Department of Economics

The influence of servitisation and digital transformation on consumer preferences in energy markets: a discrete choice experiment for digitised product-service bundles and its implications for market strategies

By

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Dedicated to my children,

Emma Elisabeth Mull & Jonas Evert Mull

…and to my wife,

Anja Mull

Declaration of authenticity

This thesis is the result of the author’s original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed:

Date: 10.02.2025

Abstract

This thesis is motivated by the need to gain a clearer understanding of the competitive landscape for the energy consumer market. The concept of digital servitisation (product-service bundles) is offered as an approach to create additional consumer benefits. The thesis is based on a discrete choice experiment (DCE) involving digitalised electricity product-service bundles.

The first part of the thesis (Chapters 1-2) presents the research motivation and objectives. It lays the theoretical and methodological foundations by discussing the evolution of economic theories. It also covers the basics of DCEs, traces their theories and examines different estimation models. Finally, the survey design based on a servitisation model is presented.

The second part and first application (Chapter 3) investigates influences on preference reliability. It tests whether preferences are subject to change due to situational context prior to a purchase decision. The investigation is based on a split sample DCE survey where respondents were asked to evaluate different attributes of a purchase alternative either before or after the preference elicitation. Two logit model estimations are used to test for preference differences between the two sample groups. Statistically significant estimates for a measurable effect of context on preferences are found.

The third part and second application (Chapter 4) focuses on product and service attributes within a DCE. It assesses whether there are synergies between the product and service attributes in a bundled offer. Particular attention is paid to servitisation and hybrid value creation. Methodologically, multiple conditional logit models are estimated to examine interaction effects for all attribute combinations. This is done to identify significant interaction effects and to provide evidence for the impact of bundling on positive or negative customer utility. Based on defined synergy cases, statistical evidence for synergies and antagonisms in specific cases and attribute combinations is found.

The fourth part and third application (Chapter 5) examines how different attribute levels, which differ in their degree of digitisation, can be compared by evaluating the

alternatives with their respective perceived utilities. Methodologically, this is done by applying a Hierarchical Bayes (HB) routine, which is used to estimate the part-worth utilities from the observed choices. A correlation analysis between the categories in the HB estimation is also performed, as well as a multiple regression analysis and a conditional logit model estimation. These methods are used to establish a relationship between perceived utility and perceived digital maturity of product attributes. The results show that respondents tend to derive utility from digitised service attributes across many service dimensions. Nevertheless, the influence of the price attribute, which dominates decision-making in our context, remains high.

Overall, as set out in the concluding chapter, all the chapters build on one another to investigate the economic relationship between servitisation, digitisation and preferences. They add to the quantitative body of research on servitisation. A new perspective based on the economic utility evaluation of servitisation is offered. The main contribution of the thesis is that technology and digitisation affect utility and preferences either directly or through attitudes. Under certain conditions, customers value digital product-service bundles more than their non-digital counterparts.

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List of Abbreviations

AI	Artificial Intelligence
AIC	Akaike information criterion
ASC	Alternative specific constant
BA	Bayesian analysis
BM	Bayesian methods
BIC	Bayesian information criterion
B2B	Business-to-Business
B2C	Business-to-Customer
CA	Conjoint Analysis
CBC	Choice Based Conjoint
CBA	Cost Benefit Analysis
CHARGE	DCE attribute: Additional charge to the monthly basic rate
CL	Conditional Logit (model)
CRM	Customer relationship management (system)
DCE	Discrete choice experiment
DCM	Discrete choice models
DEVICE	DCE attribute: All attribute level with additional devices included in the contract
DEVICE0	DCE attribute level: No additional plug adapter
DEVICE1	DCE attribute level: Manually adjustable electric plug adapter
DEVICE2	DCE attribute level: Local connected electric plug adapter
DEVICE3	DCE attribute level: Smart plug adapter incl. smartphone app
DEVICE4	DCE attribute level: Smart plug adapter incl. smartphone app and algorithm
DM	Digital maturity
DM1	Digital maturity sample group, ‘Treatment Group’
DM2	Digital maturity sample group, ‘Control Group’
ERP	Enterprise resource planning (system)
EEX	European Energy Exchange
GMNL	Generalised Multinomial Logit model
H1 … H6	Hypothesis 1 … hypothesis 6
HB	Hierarchical Bayes (model)
HHI	Herfindahl-Hirschman Index
HLM	Heteroskedastic Logit model
HTML	Hypertext Markup Language (standard markup language for documents designed to be displayed in a web browser)
IIA	Independence of irrelevant alternatives
ICS	Instructional choice sets
i.i.d.	Independently and identically distributed
IMo	Interaction model

IoT	Internet of Things
LC	Latent class (model)
LED	Light-emitting diode
LL	Log-Likelihood
mCHC	Micro combined heat and power, also CHP
MHA	Metropolis Hastings Algorithm
MLM	Mixed logit model
ML	Machine Learning
mlhs	Modified Latin hypercube sampling
MRS	Marginal rate of substitution
mWTP	Marginal Willingness to Pay
MNL	Multinomial logit model
NIE	New Institutional Economics
OFGEM	Office of Gas and Electricity Markets (UK)
OLM	Ordered Logit Model
PLC	Panel Latent Class Models
PRICECALC	DCE attribute: Source of price calculation per kWh
PRICECALC1	DCE attribute level: Changing of prices based on a pre-defined plan (e.g., different prices on weekdays)
PRICECALC2	DCE attribute level: Decreasing prices per kWh each month with increase or decrease of overall consumption
PRICE_	DCE attribute: All price communication and access to bills attributes
PRICEMAIL	DCE attribute: Prices and monthly bills are sent via email
PRICEPORTAL	DCE attribute: Prices and monthly bills made available through an online portal (login necessary)
PRICEAPP	DCE attribute: Prices and monthly bills made available through mobile app
PSS	Product-service-systems
PV	Photovoltaic
QCA	Qualitative Comparative Analysis
rDM	Relative digital maturity
RUM	Random utility model
RUT	Random utility theory
SC1 … SC6	Synergy case 1 … synergy case 6
SERV_	DCE attribute: All service infrastructure attributes
SERVEMAIL	DCE attribute: Service infrastructure via email
SERVCHAT	DCE attribute level: Service infrastructure via chat agent (also video chat)
SERVEAPP	DCE attribute level: Service infrastructure via message service within smartphone app
SML	Simulated Maximum Likelihood
WTP	Willingness to pay

WTA	Willingness to accept
ZCD	Zero-centered Differences

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1 Introduction

1.1 Motivation for the thesis and the research

The initial motivation for this thesis has been the question of what types of digitally enhanced offers from energy sellers may increase customer loyalty and, therefore, provide the seller an advantage within a competitive market. In contrast to most management and business contributions in this area, this work approaches the question from the consumer perspective and quantifies this perspective based on economic models. In the following, the research objectives of this thesis are established based on three areas:

(1) Identification of current developments and the general market situation of consumer energy markets,

(2) Investigation of (digital) servitisation as one important product strategy proposed by academics as well as the literature for the kind of economic environment within energy markets,

(3) Addressing the need for establishing economic foundations that provide a rationale for servitisation, as well as establishing the methodology that provides a quantitative foundation to evaluate the effects of the servitisation product strategy.

Despite its grounding within the energy consumer market, the scope of this thesis is the focus on the utility effects of the servitisation product strategy, the utility perception of digitised offerings, and the role of economic behaviour within the first two aspects. In the remainder of this introductory chapter, the three core areas of the market, product strategy, and economic grounding are described, setting the foundation for introducing the central contributions of the applications within this thesis. The sections on the central contributions will also introduce the respective research objectives of each application within this thesis.

1.1.1 Study context: energy markets as a competitive and changing environment

The increasing need for alternative energy sources and, consequently, new offerings for consumers, ones that focus on efficiency and additional value, are characteristics of the energy and electricity markets of the current millennium. Exhibits to this claim are, for example, the so-called ‘20-20-20 targets’ (European Commission, 2008) or the new European Green Deal announcing the ‘first climate-neutral continent by 2050’ (European Commission, 2021). The energy and utility industry is currently shaped at its core by the three liberalisation directives of 1996/98, 2003 and 2007 of the European Union (European Commission, 2012), which mark the starting point for the unbundling of the energy markets. Furthermore, the ongoing international energy crisis, which emerged in 2022, has further complicated the political and economic landscape, particularly as economies attempt to recover from extended periods of lockdown conditions linked to the COVID-19 pandemic. Current key drivers for this situation are also the political and economic implications of the Russian invasion of Ukraine. Specifically, this has impacted access in the Western Hemisphere to conventional energy resources such as natural gas. It also had subsequent constrained supply implications for wholesale costs and consumer prices across multiple energy markets. Consequently, households seek ways to save energy and reduce their energy costs. In a broader sense, politics and society are calling for greater independence from traditional (fossil fuel) energy resources and are proclaiming the increase of decentralised and renewable sources as necessary to reach the net-zero carbon emissions targets (The Economist, 2022a; 2022b).

All these issues collectively confront energy providers with a kaleidoscope of challenges, ranging from cost efficiency (operations and cost-cutting) to energy efficiency (strategy and investing) issues that need to be addressed in business strategies, offerings, and customer interactions. Moreover, technological progress will result in an increasing demand for electricity, despite or even because of improved energy efficiency (IEA, 2013; Sorrell, 2009; Turner, 2013). Nevertheless, or even so, the general task of energy utilities is to ensure a balanced amount of energy generation and energy consumption (Connor, et al., 2014; Clastres, 2011). Every energy provider will need to provide the bespoke energy congruence with minimal operational costs while offering a sustainable added value for its customers (Giordano & Fulli, 2011; Guthridge, et al., 2012). All these factors have created a competitive situation that energy companies need to cope with today. Looking at the UK as an example, within only six years, the ‘Big Six’[1] lost almost 30% of the market share of the electricity and gas market between 2012 and 2018, while the number of new market entrants is continuously rising (OFGEM, 2019). One measure of the competitiveness of markets is the Herfindahl-Hirschman Index (HHI). The HHI indicates how competitive a market is by measuring the concentration of competition (Hirschman, 1964; Herfindahl, 1950). Markets with an HHI below 1,000 are regarded as unconcentrated, markets with an HHI between 1,000 and 2,000 as concentrated, and markets with an HHI above 2,000 are considered highly concentrated and monopolistic (CMA, 2017). In one of their latest ‘State of the Energy Market’ reports from 2019, Ofgem shows that the HHI for the UK electricity market was down at 987 for electricity and at 1,224 for gas (OFGEM, 2019).

As of 2019, consumer switching rates in the UK electricity market have reached a historical high of 20%, which is also higher than in other European markets. This development drives competition between suppliers (OFGEM, 2019). For the German electricity market, a similar situation is observable. Although there is no data available on the concentration of the German market, switching rates are above average within the European Union (ACER, 2021). In 2022, almost 50% of all German households (nearly 20 million) have switched their electricity provider (40% have switched their gas provider) since the liberalisation of the energy market (BDEW, 2022).

In terms of the objective of this thesis, the key takeaway in this context is that buyers in the consumer energy market have a range of buying options and face few switching barriers. In contrast, sellers face a wide variety of partly political and regulative initiated restrictions (liberation of markets) and high competition (HHI and switching behaviour). Therefore, consumer loyalty and, consequently, the value provided by the seller might be the motivation not to switch providers and to offer a mutually beneficial outcome for the involved economic actors. The underlying hypothesis in this case and from the seller’s perspective is that additional utility for the customer leads to increased loyalty towards the supplier and consequently to increased future sales (Vogel, et al., 2008).

[1] British Gas, EDF Energy, E.ON UK, npower, Scottish Power, SSE

From the customer's perspective, a greater variety of suppliers and increased transparency of prices and service features is beneficial. To remain competitive, energy suppliers have responded to this price-based decision behaviour, especially with aggressive pricing that includes different bonus payments (ACER, 2021, p. 86). However, in the past, this has happened at the expense of profitability and contract duration for each customer (Lehrke, et al., 2018; ACER, 2021). Such price-oriented behaviour is also reflected by a recent study on the British energy market, which concludes that energy customers are more likely to switch externally to another provider than internally to another tariff when offered a lower-priced contract (Tyers, et al., 2019)-

A recent study by Accenture (2022) provides assessments from energy executives from different international energy suppliers concerning the switching behaviour of customers. They expect customers to turn away from large utility companies towards new and innovative competitors. This behaviour is, for example, reflected by the British Office of Gas and Electricity Markets (OFGEM, 2019, p. 31) or by the Agency for the Cooperation of Energy Regulators on the European Level (ACER, 2021, pp. 23-25). Moreover, the implied agreement among the experts involved is that new business models and offerings no longer depend on the core commodity (e.g., electricity or gas) but rather on digital services, platforms or interactions (Lehrke, et al., 2018; Accenture, 2022; Booth, et al., 2016).

1.1.2 Research focus: (digital) servitisation as a potential product strategy

Business and management research offers the concept of 'servitisation' to cover the request that energy consumers (added value) and suppliers (competitive advantage) might have. The initial understanding of servitisation was derived from investigations of manufacturing firms and how they combine tangible products with (non-tangible) services to reach a higher degree of integrated offers (Vandermerwe & Rada, 1988).

The concept refers to the shift of a manufacturing firm's product portfolio to include a higher range of service offerings (Vandermerwe & Rada, 1988). Today's understanding of the concept has been broadened and refers to the idea that companies create additional utility by adding services or additional product components to the core product (Tukker, 2004; Oliva &

Kallenberg, 2003). Therefore, servitisation refers to the procedure of suppliers (historically manufacturers) adding services to physical product offerings to create additional utility for the customer, to increase customer linking, and thus to increase the economic success of the supplier or firm. One example of this is integrating analytic software components into printing operating systems. This enables predictive maintenance and thus reduces downtime due to encountering possible malfunctions earlier (Vandermerwe & Rada, 1988). Servitisation and its derivatives may be regarded as promising approaches for (re)gaining competitive differentiation for undifferentiable goods (‘de-commoditisation’), as they offer a platform for adding innovative attributes that are expected to increase customer loyalty (Shankar, et al., 2009; Matthyssens & Vandenbempt, 2008; Auguste, et al., 2006). While the initial concept of servitisation has been discussed for more than 40 years, the influence and acceleration of digitisation expands the possibilities of suppliers.

There are voices that see digitisation as one of the foundations of the so-called ‘Fourth Industrial Revolution’, more commonly labelled: ‘Industry 4.0’ (Schwab, 2016, p. 21; Cimini, et al., 2021)- The concept assumes that technological and innovative advancements alter the generation of value and goods in economic systems, similar to how the innovation of the steam engine led to mechanical production (First Industrial Revolution), how the introduction of electricity led to mass production (Second Industrial Revolution), and how semiconductors and computers enabled digital value generation (Third Industrial Revolution). What might be referred to as ‘Industry 4.0’ is shaped, amongst others, by mobile internet, sensors, big data, machine learning, and artificial intelligence (Schwab, 2016, pp. 11-12; Holmström & Partanen, 2014). These considerations follow the idea of an economic change based on a shift of the relative price for goods (i.e., production is less costly or the relative utility increases), which leads to a switch from one indifference curve to another, thus generating a new market equilibrium. The reasoning behind that assumption is that digitisation, in general, is often connected to the ability to reduce the information asymmetry that is inherent to analogue transactions (Nagle, et al., 2020). At its core, digitisation, or synonymously, digital transformation, has always been the accumulation of different concepts interacting with each other. The present thesis uses the following definition of digitisation: *Digitisation is the* *increasing application of technology for connecting people, systems, data, companies, products, and services*. (Coreynen, et al., 2016; Paiola, et al., 2021; Hsu & Spohrer, 2009; Porter & Heppelmann, 2015; Vendrell-Herrero, et al., 2021; Ruan, 2019).

With the help of digitisation, customers can compare suppliers and their offers more easily than before. Moreover, it is agreed that digitisation presents new service offerings, better integration, and the ability to encourage the transformation of business models (Raddats, et al., 2019; Khanra, et al., 2021). Following this reasoning, the understanding of digitisation as part of servitisation can be divided into the company's internal (1) and the external customer (2) perspective: (1) the application of digital resources and capabilities to foster servitisation (Coreynen, et al., 2016) and (2) the understanding of digitised service offers and customer needs (Porter & Heppelmann, 2014; 2015; Kohtamäki, et al., 2021).

The combination of both efficient processes and a greater variety of products may consequently lead to the desired increase of customer linking that energy providers seek. It is assumed that the customers' willingness to pay ('WTP') for digital product bundles is higher than the utility estimates for the individual bundle components or for their respective non-digital counterparts. This means, ceteris paribus, the digitisation of product bundles could increase the delta between the purchase price and WTP, hence leading to a so-called consumer surplus (Collis, 2020) or, non-economical speaking, added value.

1.1.3 Establishing the methodology: 'Back to basics' through fundamental economic reasoning and how to quantify utility

In economic terms, the concept of servitisation is based on the understanding that the consumer perceives and realises a utility surplus from a bundled combination of goods and services. This assumption can be traced back to the latter half of the 20th century when the idea emerged that products might be differentiated by characteristics (Saviotti, et al., 1982; Rothschild, 1987). Other contributions assume that not the goods themselves create utility but the services that are delivered by using those goods, such as heat/warmth, light, or entertainment (Becker, 1965). Hence, the utility of a good is derived from its properties and characteristics (Lancaster, 1966; Griliches, 1991). This concept is also applied when considering the indirect utility creation of consumer electricity (Lohse & Künzel, 2011). The core assumption of the underlying models is that utility is ‘produced’ through the combination of market goods - e.g., a heating system and the electricity (or other fuel) used to run it - with the household actor’s own time. This idea overlaps with the approach of bundling goods and services to ‘create’ additional utility as it is advocated by the concept of servitisation. Consequently, even if the bundling in both fields takes place at different times, in different locations, and through different economic actors, an economic grounding for servitisation is a legitimate assumption.

One of the mutual foundations of these approaches is the utility maximisation behaviour of the consumer, which involves the most efficient combination of goods to achieve the desired collection of characteristics at minimal costs. This means that every need can be satisfied through the consumption of both goods and services (Gallouj & Weinstein, 1997; Cassini & Robert, 2020). Therefore, considering the economic examples above, there is a clear indication of an economic grounding for the idea that product-service bundles offer additional utilities which would not be ‘accessible’ through the separate consumption of the individual involved goods. This additional utility is called ‘added value’, synergy, or consumer surplus, which is ‘created’ by or for the consumer (Brynjolfsson, et al., 2003).

To identify the different elements of the consumer´s utility function in the context of understanding servitisation, a Discrete Choice Experiment (DCE) is used as the fundamental methodology for this thesis. DCEs are a method for preference elicitation and are based on Lancaster’s (1966) theory of consumer behaviour and Thurstone’s (1927) ‘law of comparative judgement’.

1.2 Research objectives of this thesis

The three applications in this thesis are derived from a single DCE, applied with three different foci. The applications presented here capture, amongst other things, the buying behaviour and preferences for digitised electricity product service bundles from 800 respondents in Germany. The methodological foundation of the survey-based approach is a servitisation framework for energy and utility companies based on the work of Vandermerwe and Rada (1988; Grahsl, 2013; Grahsl & Velamuri, 2014). The framework includes different attribute groups that are common for energy providers when offering product-service bundles. The properties and characteristics of applied product-service bundles include different technologies (mobile internet, machine learning, sensors, digital customer interfaces, platforms, etc.), rely on important company capabilities and resources (big data, computing infrastructure, digital processes, communication protocols, etc.), and offer the potential to increase efficiency and sustainability for the consumer (energy efficiency, consumption-oriented, etc.). The survey was designed to address three areas of interest for economic and management research. It offers the foundation for investigating the following:

- If economic choice and the buying process of agents for product-service bundles can be altered by context effects (Chapter 3),
- If the combination of goods and services offers a surplus that exceeds the sum of the individual utilities of its individual parts (Chapter 4),
- If the utility difference of the digitisation of consumer offerings can be quantified and measured (Chapter 5).

The objective of the first application (Chapter 3) is the question of how preferences and expected utility can be affected by circumstances. The second application (Chapter 4) focuses especially on the attributes, i.e., products and services, and on how to quantify (if they exist) interactions or synergies between them. The third application (Chapter 5) investigates how different digitised attributes, i.e., different types of products and levels of services, offer different levels of utility. In the following sections, we will introduce the research objectives for the different chapters and applications of this thesis.

1.2.1 Objectives of Chapter 2

The second chapter of this thesis focuses on laying theoretical foundations by comprehensively addressing three areas. First, we introduce relevant economic foundations and constructs that we rely on throughout the thesis. The second part focuses on the theoretical and methodological foundations of DCEs as well as relevant estimation and modelling approaches. The last part focuses specifically on the survey design process that we used for the applications in this thesis. The different objectives of the three parts are presented in detail below.

1.2.1.1 Economic foundations

In the first part of Chapter 2, we address diverse economic theories and models to establish a robust framework for our discussions and investigations. We emphasise the critical role of the concept of preferences, which has evolved significantly from its early formulations in utility theory to contemporary interpretations that consider both marginal utility and subjective values. This evolution reflects a paradigm shift in how preferences are understood within economic theory.

We further explore how behavioural economics and expected utility theory have reshaped our understanding of consumer decision-making, particularly under conditions of uncertainty. These discussions not only highlight the limitations of traditional rational choice models but also introduce more nuanced frameworks that account for cognitive biases and probabilistic outcomes.

Our analysis also includes an examination of revealed preference theory and random utility models (RUMs). These approaches are important for empirically analysing consumer behaviour by focusing on actual choices rather than hypothesised utilities, thereby enhancing the credibility and applicability of economic models in real-world scenarios.

In discussing welfare economics, we connect the dots between individual preferences, economic efficiency, and societal well-being. Our discussions cover the implications of externalities, the importance of Pareto efficiency, and the role of social welfare functions in assessing and promoting societal welfare. At this stage, the chapter underscores the intricate relationships between economic conditions, individual choices, and overall societal outcomes.

Additionally, we elucidate the relevance of Shephard’s lemma and Roy’s Identity in our theoretical framework. These mathematical identities provide crucial links between microeconomic behaviours, such as firm input choices and consumer demand, and the broader economic variables of prices and income.

By synthesising these theories and concepts, we set the stage for a comprehensive empirical investigation in subsequent chapters of this thesis, particularly focusing on how digital transformation and servitisation influence consumer preferences and decision-making in the energy sector. The foundational chapters are crucial for presenting the methodology and the foundation for the data analysis. They have the objective of making a significant contribution to the understanding of economic behaviours in a rapidly evolving digital and service-oriented economy.

1.2.1.2 Foundations of DCE

The second part of Chapter 2 addresses the theoretical and methodological foundations of DCEs, highlighting their evolution and crucial role in understanding consumer preferences and decision-making within economic models. Anchored in the seminal theories of Lancaster (1966) and Thurstone (1927), we utilise DCEs as a robust method for estimating utility-based preference elicitations. The application of DCEs spans various sectors, effectively capturing consumer choice behaviour in environmental, health, and transportation contexts, among others.

We ground our discussion in Random Utility Theory (RUT), which posits that choices reflect the maximisation of utility, albeit influenced by random components. This theory underpins the modelling of consumer choices through logistic regressions that accommodate discrete decision variables. By comparing DCE with Choice Based Conjoint (CBC), Conjoint Analysis (CA) and Qualitative Comparative Analysis (QCA), we highlight alternative and comparable approaches that, while similar, provide distinct insights into consumer preference structures through the ranking and complex interaction effects of product attributes.

We delve further into methodological advancements within DCEs by comparing various estimation models. These include the Multinomial Logit (MNL) and Conditional Logit (CL) models. MNL models link choice probabilities to the socio-economic characteristics of respondents, while CL models are designed to handle preference homogeneity (Hoffman & Duncan, 1988). Additionally, there are more sophisticated models, such as Hybrid Choice Models (HCM), Mixed Logit Models (MLM), and Hierarchical Bayes (HB) models that capture preference heterogeneity. These models enhance the precision of utility estimation by accommodating varying decision-making contexts and individual-specific preference data.

Our narrative progresses with a critical examination of the limitations inherent to DCEs, such as design complexity and hypothetical bias, which can bias consumer responses and the interpretative power of the experiments. We advocate for conservative design and methodological reflexivity to mitigate these challenges.

In essence, the overview not only underscores the economic and psychological dimensions of DCEs but also elaborates on the theoretical and practical enhancements necessary to refine the utility estimation processes in economic models, thereby facilitating a more nuanced understanding of consumer behaviour in economic research.

1.2.1.3 Survey design process and data collection

In the next part of Chapter 2, the concept of servitisation, which serves as the guiding framework for our survey design, is explored (see Chapter 2.3). This concept is crucial in understanding how the addition of services to physical products can enhance value for customers, thereby hypothetically improving customer relationships and increasing the economic success of a supplier or firm. Initially developed from studies on manufacturing companies, servitisation involves shifting product portfolios towards greater integration of service offerings (Vandermerwe & Rada, 1988).

Our DCE survey leverages a servitisation model developed by Grahsl (2013) that focuses on product-service bundles specifically for energy and utility companies. This model categorises offerings around a core commodity – such as electricity or gas – enhanced by physical products, services, knowledge, support, and self-service components (Grahsl & Velamuri, 2014). For the development of the survey, about 200 products and services were identified and mapped to the stages and components of Grahsl's energy servitisation framework (2013).

For the DCE setup, we followed a methodology outlined by Hensher et al. (2005), which includes problem refinement, stimuli refinement, and experimental design considerations, among others. Key attributes were refined through a combination of desk research and industry consultation, aligning with real-world offerings to ensure the survey's relevance and applicability.

The part also presents the development of survey attributes. The process is based on feedback from industry professionals and was refined based on consumer feedback. The main goal was to identify how digital transformation and servitisation impact consumer preferences for bundled energy products and services. By incorporating a variety of products and services into our DCE, we aim to offer insights into consumer preferences and decision-making processes, potentially guiding energy companies in their product and service development strategies.

1.2.2 Objectives of Chapter 3

In Chapter 3, covering the first application, three main contributions for the research area of servitisation are identified and will be addressed:

- We challenge the traditional economic theories of classical preferences by demonstrating that they may be dynamic and subject to influence by situational contexts and measurement conditions.
- We employ a DCE to explore how prior digital exposure ('treatment') affects consumer choices in the energy product-service market, building on a proven application of context effects.
- We provide evidence that our context effects setup primarily influences price-related preferences, with limited impact on other decision-making aspects such as service and product choices.

In the application, we challenge the assumption held by traditional economic theory that consumer preferences are always utility maximising. Instead, we propose that preferences can be dynamic and influenced by factors such as measurement bias and situational contexts, a contention supported by various scholars (Steiner, 2007; Hensher, 2009; Grebitus, et al., 2013; Johnston, et al., 2017). Our focus shifts to the concept of the ‘context effect’, wherein prior involvement with a topic before a decision-making process (‘treatment’) alters consumer preferences and perceived utility. This exploration is particularly centred on the consumer energy market, marking a departure from previous studies that examined context effects in unrelated sectors (Kim & Park, 2017; Tourangeau & Rasinski, 1988; Tourangeau, 2021; Lubow, et al., 1967).

We utilise a discrete choice experiment (DCE) approach to investigate how this pre-exposure to digital themes influences consumer selections of energy product-service bundles. By integrating attitudinal measures with the survey, we induce context effects and hypothesise that such treatment could sway consumer decisions towards more digitally oriented services. This methodology not only builds upon but also critically evaluates the findings from previous studies like those by Liebe et al. (2016) and Pouta (2002) which reported no significant findings attributable to similar treatments.

Methodologically, our contribution lies in advancing how DCEs can be adapted to test for context effects by incorporating attitudinal questions that simulate treatment conditions. This approach is particularly pertinent to the analysis of homogeneous and intangible goods like those in the energy sector, where digital maturity as a source of competitive advantage is increasingly relevant.

In the conclusion of the application, we articulate the complexity and nuances of preference dynamics in economic decision-making. Our findings reveal that, while general preferences for services, communication, and products stay reliable, there were notable differences in how pricing-related preferences were affected among digitally pre-treated subjects. These results lend partial support to our hypothesis that a treatment can influence decision-making, albeit primarily in specific sub-domains such as price sensitivity.

1.2.3 Objectives of Chapter 4

For Chapter 4, three main contributions are identified, which will be addressed in the context of the second application:

- We provide an economic foundation for understanding the potential synergies of servitisation and hybrid value creation, grounded in economic theories and our quantitative estimates.
- We contribute to the quantitative body of servitisation research by evaluating product-service bundles, thus addressing the gap in empirical, applied research within this field.
- We apply the concept of servitisation to the B2C context, specifically within the retail electricity market, offering a new perspective on the customer-centric implications of servitisation strategies.

We start our analysis by introducing the established research field of servitisation, particularly its roots in marketing and strategy since the 1980s and its economic implications dating back to the 1930s, as discussed by Chamberlin (1933). Our investigation focuses on how manufacturing firms initially combined tangible products with services, a practice that has evolved to include a broader range of service offerings and enhanced utility through what is now termed hybrid value creation.

In the application, we employ, based on a DCE, different CL models to assess whether the integration of goods and services indeed creates additional value or consumer surplus. Our methodological approach allows us to quantify the synergetic effects within product-service bundles, offering empirical support to theoretical models that have traditionally relied on qualitative evidence.

We find significant synergies, confirming that servitisation can indeed augment customer value in specific contexts, such as in the provision of energy services. However, our results also reveal the occurrence of antagonisms, indicating that not all service additions result in enhanced value. This discovery supports the notion of the ‘servitisation paradox’, which suggests that the addition of services to products does not always lead to an increase in value output.

Our conclusions emphasise the practical and theoretical implications of our findings. For managers and policymakers, our research underscores the importance of carefully designing product-service bundles to maximise customer utility while avoiding potential pitfalls associated with inappropriate service integration. Overall, our contribution significantly advances the understanding of servitisation in the B2C sector, particularly within the energy market, challenging existing assumptions and providing a foundation for future quantitative inquiries in this domain.

1.2.4 Objectives of Chapter 5

For Chapter 5, three main contributions can be identified that are addressed in the context of the third application:

- We introduce a quantitative approach to evaluate the impact of digital servitisation on product-service bundles, employing a DCE with an HB estimation, a CL with interactions and combining the results of these models with a multivariate regression.
- We demonstrate that increased digital maturity within product-service bundles enhances consumer utility, particularly through improved service infrastructure and advanced digital features in devices.
- We offer strategic insights for businesses on focusing digital servitisation efforts where they are most effective, based on our findings that different digital attributes vary significantly in their impact on consumer utility.

In the application, we refer to the pervasive impact of digital transformation, often characterised as the 'Fourth Industrial Revolution', on business and societal structures through advanced technologies such as mobile internet, big data, and artificial intelligence. These technologies have fundamentally transformed production and service delivery, leading to increased customisation, efficiency, and decentralisation. We focus particularly on the concept of 'digital servitisation' – the integration of digital services into product offerings as a strategic response to these technological advancements. This approach not only enhances product utility but also potentially boosts competitive and financial performance by hypothetically creating additional value through integrated digital services.

We aim to quantitatively assess the digitisation of product-service bundles and their utility for consumers. We leverage economic theories to frame our analysis, hypothesising that digital servitisation offers higher utility, which we expect to be reflected in consumer preferences and captured through the HB estimation technique used in our DCE.

Our conclusion offers evidence for the role of digital maturity in enhancing consumer utility. We present quantitative evidence suggesting that higher digital maturity in product-related services correlates with increased utility of certain attributes, particularly for service infrastructure and additional devices. This finding is important for firms considering digital servitisation strategies, indicating a potential competitive advantage in focusing on these aspects. The application also highlights the variance in attribute importance, suggesting a careful approach to digital investments, where understanding consumer perceptions and preferences is crucial.

Our theoretical contributions extend to economic and business management domains, demonstrating how digital servitisation aligns with economic principles of utility and productivity enhancement. The practical implications suggest that while digital servitisation can enhance perceived utility and competitive positioning, the impact across different service dimensions varies, requiring targeted strategies.

In summary, this application underscores the transformative potential of digital technologies in servitisation, advocating for a strategic and informed approach to integrating digital services into product offerings to maximise consumer utility and firm company. Our investigation not only contributes to the academic literature by providing a quantitative framework for evaluating digital servitisation but also offers practical insights for businesses navigating the complexities of the digital economy.

1.3 Structure of the thesis

This thesis is organised into six chapters. Here, in Chapter 1, we have introduced the motivation of the thesis and provided some key concepts and relationships that are necessary for understanding the further course. We have also set out the research objectives and contributions of the thesis.

Chapter 2 covers the theoretical concepts for the different applications within the thesis. First, we introduce the relevant economic foundations that are necessary to understand the argumentation. Second, we introduce and discuss the theories and applications of DCEs, including the theoretical foundations, main contributors, different modelling and estimation approaches, and the foundations for servitisation. The third part of Chapter 2 presents the process of the survey development, including the design considerations, the administrative process of data collection and descriptive statistics. Furthermore, an overview of the specific survey-related issues that apply to two of the three different applications in this thesis is given.

In Chapter 3, we present the first application of the thesis. We investigate how pre-exposure to digital themes influences consumer choice of energy product-service bundles. In the chapter, we present the discussion of reliability and viability of preferences as well as the research on so-called context effects. We estimate three logit models, compare the estimates, and discuss the theoretical and practical implications.

In Chapter 4, we present the second application of the thesis, where we investigate the aspects of synergies within a product-service bundle. We include an extended review of servitisation research as well as present economic frameworks that connect to the foundations presented in Chapter 2. We show that both areas of research (servitisation and economic frameworks) are interlinked and can be used to respond to our research objectives.

In Chapter 5, we present the third application and contribution of this thesis. The aim is to quantitatively assess the digitisation of goods and their utility for consumers. To this end, we present the relevant theory on digital servitisation and the corresponding economic frameworks. We employ an HB and a CL model estimation as well as additional calculations to measure the consumer utility of digitally enhanced product-service bundles, compare the estimates and discuss the theoretical and practical implications.

Chapter 6 offers the conclusion of the thesis. We summarise and discuss the results from the three applications. Furthermore, we present managerial implications and takeaways for practical operationalisation.

The following Figure 1 presents the course of this thesis in a graphical illustration.

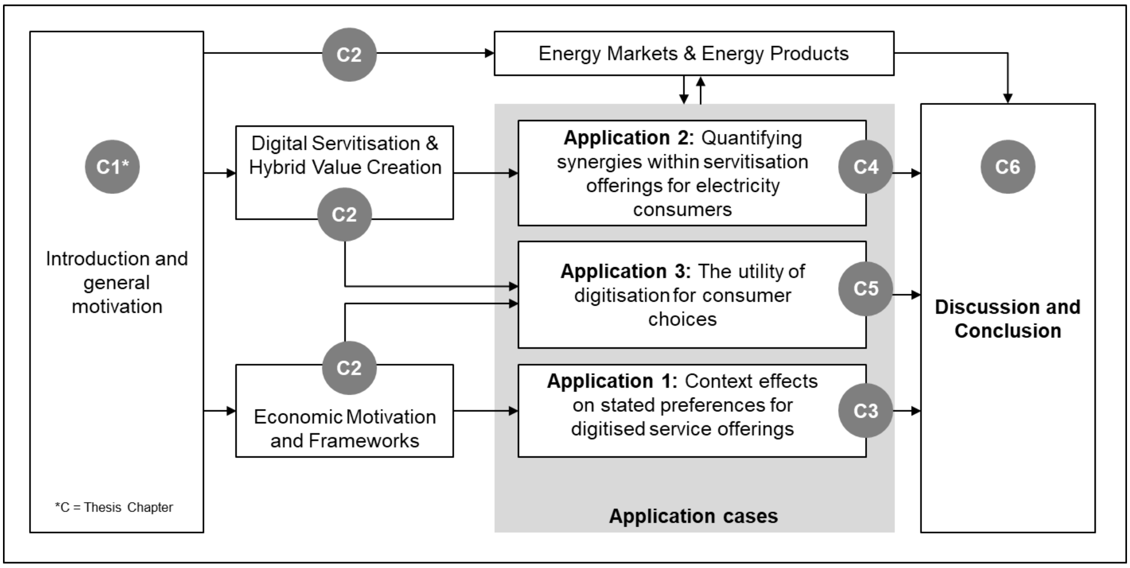


Figure 1: Structure of the thesis

2 Theoretical foundations

2.1 General economic foundations

Throughout this thesis, we are building on the foundation of different economic theories and models. The main objectives of this thesis are all related to the aspect of investigating preferences to identify the utility for parts, components, and characteristics of a service and product bundle: altering of economic choice (Chapter 3), customer surplus (Chapter 4) and preferences for digital maturity (Chapter 5). Therefore, we introduce the relevant economic concepts, such as preferences, utility, economic behaviour, and welfare economics, and their measures.

We present classical and contemporary economic theories to underpin the empirical investigations across the three chapters. Starting at the economic core, classical consumer choice and utility theories posit that consumer preferences are stable and measurable through utility functions (Varian, 2014). However, these assumptions are increasingly challenged by insights from behavioural economics and bounded rationality, which argue that decision-making is subject to situational influences and cognitive limitations (Kahneman & Tversky, 1979). This debate is central to the first application, which examines whether prior exposure and treatment can alter consumer preferences in a choice situation. By utilising random utility models that combine systematic and stochastic components, the analysis captures the dynamic nature of preferences and provides a basis for assessing shifts in measures such as willingness to pay (WTP) and willingness to accept (WTA).

In the second application, the focus shifts to the potential synergies of servitisation and hybrid value creation achieved through the bundling of products and services. While the foundational consumer choice models remain relevant, this analysis extends the framework by incorporating elements from New Institutional Economics (NIE) to account for the impact of contractual and regulatory settings on consumer decisions (North, 1990). Welfare economic measures, including consumer surplus and changes in WTP/WTA, are applied to evaluate the economic benefits of bundled offers. In this application, the concept of the servitisation paradox is mentioned, which describes how variations in service attributes contribute to an overall utility. This might be a practical manifestation of the concept of the Shephard’s lemma.

The third application investigates the effects of digital servitisation by quantifying how increased digital maturity influences consumer utility. Here, classical and behavioural models of consumer choice are adapted to incorporate digital attributes, while NIE provides the contextual framework for understanding institutional influences on digital service adoption. Welfare economic concepts, particularly compensating and equivalent variations, offer an approach for measuring utility changes induced by digital enhancements.

The task of the following chapters is to ensure that the empirical analyses are grounded in a robust conceptual framework. For each of the mentioned concepts and models, we give an explanation and definition. We point out how we apply it throughout the course of this thesis, as well as how they are linked to one another – if applicable. Thus, we align classical theories with modern behavioural insights and institutional considerations, thereby providing a comprehensive basis for examining consumer behaviour in the evolving context of digital servitisation within the energy sector.

2.1.1 Consumer preferences and behaviour

The economic concept of ‘preferences’ plays a critical role in understanding consumer behaviour and decision-making processes across various fields, such as economics, marketing, and psychology. At its core, this construct strives to explain how individuals choose between different goods, services, or alternatives.

The concept of preferences is linked to consumer behaviour, which describes in simple terms that “people choose the best things they can afford” (Varian, 2014, p. 33). The ’best things‘ or objects of consumer choice are called consumption bundles, which are all the goods and services that are relevant to the choice situation. Not only is it important to include the relevant goods in the definition of the consumption bundle, but also a description of when, where, and under what circumstances, as well as the context under which the goods become available. A good example is given by the probable preference towards the very same raft in the middle of the Atlantic Ocean vs in the middle of the Sahara Desert (Varian, 2014).

Economists often make certain assumptions regarding the ’consistency’ of consumer preferences. We assume any two consumption bundles, X (x1, x2) and Y (y1, y2), which the consumer can rank as to their desirability. It is considered illogical and contradictory to have a situation where (x1, x2) is preferred over (y1, y2) while simultaneously (y1, y2) is preferred over (x1, x2). This would imply that the consumer strictly prefers the X-bundle to the Y-bundle and vice versa, meaning that the consumer is indifferent between the two bundles (Varian, 2014). Assumptions about the nature of preference relations are typically made. Some of these assumptions can be termed axioms of consumer theory or consumer preference (Varian, 2014):

- Completeness: Two distinct bundles can be compared. Specifically, given any X-bundle and Y-bundle, we assume that either (x1, x2) ≽ (y1, y2) or (y1, y2) ≽ (x1, x2), or both, in which case the consumer is indifferent between the two bundles.
- Reflexivity: Any bundle is at least as good as itself: (x1, x2) ≽ (x1, x2).
- Transitivity: If (x1, x2) ≽ (y1, y2) and (y1, y2) ≽ (z1, z2), then we assume that (x1, x2) ≽ (z1, z2). Therefore, if the consumer considers X to be at least as good as Y and Y to be at least as good as Z, then X must be at least as good as Z.

Preference for a consumption bundle, or in our case, a product-service bundle, is not objectively determined. The perceived economic value, also called subjective value, of an alternative depends on individual preferences and choice context (Menger, 1871). The graphical representation of different and compared consumer preferences is based on so-called indifference curves. These illustrate how individuals make choices based on combinations of goods that provide them equal satisfaction (Edgeworth, 1881; Stigler, 1950a; Pareto, 1906; Varian, 2014).

In identifying preferences, economic choices need to be observed and, therefore, revealed by the consumer. DCE, the method used in this thesis, builds on the concept of revealed preferences and the theory behind it. The revealed preference theory, introduced by Paul Samuelson in his paper ‘A Note on the Pure Theory of Consumer's Behaviour’ (1938) and further developed in ‘Consumption Theory in Terms of Revealed Preference’ (1948), offers a method for analysing consumer behaviour based on observed choices rather than stated preferences or utility maximisation. This theory asserts that the choices consumers make when faced with various options reveal their preferences, allowing economists to infer preference rankings without directly measuring utility. We differentiate between ‘revealed preference’ and actual ‘preference’ in understanding economic choices. ‘Revealed preference’ occurs when an individual selects consumption bundle X over consumption bundle Y, given both are economically feasible. This choice alone does not put X as the intrinsic favourite over Y; it simply shows a decision made under certain conditions (Varian, 2014). In contrast, ’preference’ indicates a deeper, subjective preference where X is genuinely favoured over Y by the consumer. With reference to this, we say that one alternative is chosen. Therefore, we can state that ‘if bundle X is chosen over bundle Y, then X is preferred to Y.’ This statement makes it clear that the underlying behavioural model allows us to deduce underlying preferences from observed decisions. Thus, by examining choices within specific economic constraints, we can gain insights into consumer preferences (Varian, 2014). Revealed preference theory has been instrumental in empirical economics, enabling researchers to study consumer behaviour in a more objective and observable manner based on utility. Utility is a measure to describe preferences (Varian, 2014, p. 54). The concept of utility will be explained in the next subchapter.

2.1.2 The concept of utility

The concepts of utility and preferences are closely linked. It is hardly possible to explain one element without mentioning the other. The current and modern understanding of the utility concept can be seen as the summary of the consumer’s preferences by the means of a utility function (Mas-Colell, et al., 1995). A utility function is a convenient method to describe and visualise preferences. There are direct and indirect utility functions which offer different perspectives on consumer preferences and behaviour. The direct utility represents the relationship between the quantity of the consumed good and the utility that a consumer gains from that good. That means it draws a direct connection between the characteristics of the good and a utility level, which reflects the satisfaction from the consumption. The function is defined over the quantities of goods and is used to analyse how changes in consumption affect utility (Varian, 1999; Phaneuf & Requate, 2017; Mas-Colell, et al., 1995). A direct utility function assigns a numerical value to each element in X, ranking these in accordance with the individuals' preferences (Mas-Colell, et al., 1995, p. 8).

Therefore, $u: X \rightarrow R$ is a direct utility function representing the preference relation $\gtrsim$ if, for all $x, y \in X, \mathrm{x} \gtrsim y \Leftrightarrow u(x) \geq u(y)$.

The indirect utility function represents the maximum utility a consumer can achieve for a given set of prices (p) and income or wealth (m) level: $v(p, m)$. It expresses utility in terms of prices and income rather than quantities of goods. This function is useful for analysing how changes in prices and income affect a consumer's well-being without specifying the exact consumption bundle (Varian, 1999). It represents the quantity of goods that the consumer desires, given the prices for the goods and the income available (Varian, 1999; Mas-Colell, et al., 1995). This relation is described by the concept of the marginal rate of substitution (MRS). It is the rate at which the consumer is willing to substitute one good for the other (Varian, 2014). The MRS describes the slope of the indifference curve. It reflects the quantity of one good a consumer is prepared to give up in order to receive a marginal unit of another good (Varian, 2014). The concept can directly be linked to the consumer's WTP or marginal WTP (mWTP).

It is crucial, however, to understand the relation of 'marginal' and 'willingness' within the concept. The mWTP derived from the MRS represents the maximum amount a consumer is willing to pay for an incremental increase in consumption of a given good based on their preferences and budget constraints. It is independent of market prices, which are influenced by external factors such as supply and demand. mWTP stands for the value that the consumer is willing to pay in exchange for one additional consumption unit of the relevant product. The WTP for a marginal change might differ significantly from that for a substantial change in consumption, reflecting the elasticity of preferences relative to changes in quantity. Hence, the MRS as an expression of mWTP offers valuable insights into consumer behaviour and preferences, distinct from the actual transaction prices observed in the market (Varian, 2014).

To summarise, direct and indirect utility functions have different perspectives on utility and different applications in analyses. Direct utility functions are used for utility-based consumption quantities. They are central for analysing choice behaviour and preference satisfaction. Indirect utility functions, however, offer a view on the relationship between price levels and income and offer a measurement for the mWTP of consumers. They are important for examining the effects of price and income changes on consumer welfare. The indirect utility function can be derived from the direct utility function by solving the utility maximisation problem, taking prices and income as given. Conversely, recovering a direct utility function from an indirect one involves more complex procedures like expenditure minimisation (Varian, 1999, p. 130).

2.1.3 Expected utility theory and random utility

Building on our understanding of standard consumer choice theory, we now turn to choices under uncertainty. In such scenarios, the consumer's focus shifts to the probability distribution of various consumption bundles. This probability distribution is essentially a list of possible outcomes of the economic choice, each with an associated probability. For instance, when purchasing automobile insurance or investing in the stock market, consumers are not merely choosing between different bundles of goods but are instead making decisions about the distribution of probabilities across various potential consumption outcomes. This shift in perspective leads us to the concept of expected utility theory, which provides a framework for understanding how consumers make choices when faced with uncertainty (Varian, 2014). In expected utility theory, the utility of a particular outcome is weighted by the probability of that outcome occurring, and the consumer aims to maximise the sum of these weighted utilities. This approach allows us to model and predict consumer behaviour under uncertainty, providing valuable insights into decision-making processes in real-world scenarios (Biglieri, 2022, p. 203).

The expected utility theory is a cornerstone of economic decision-making under uncertainty, developed by John von Neumann and Oskar Morgenstern in their seminal work, "*Theory of Games and Economic Behavior"* (1944). This theory posits that individuals make choices not based on the potential outcomes' utility directly but on the expected utility, which accounts for the probability of each outcome. In general, it describes how a person values consumption in one state as compared to another and that it depends on the probability that the state in question will actually occur (Varian, 2014). Therefore, a utility function depends on the probabilities and on the consumption levels ('taste'). The expected value is given when weights are added to the two probability states in the context of uncertainty (Varian, 2014). The expected utility theory formalises the idea that decision-makers weigh the benefits and risks of uncertain outcomes in a rational and consistent manner, maximising their expected utility rather than merely responding to potential gains or losses. Expected utility theory has profoundly influenced various fields, including economics, finance, and psychology, providing a framework for understanding choices under uncertainty, which describes that consumers do not know the outcome of their economic choice beforehand (von Neumann & Morgenstern, 1944; Varian, 2014). One key rationale for the reasonableness of expected utility theory is its ability to handle decisions where only one outcome from several possibilities will eventually occur (Varian, 2014). However, there is the independence assumption, which critically guides expected utility theory. It implies that choices in one probability state are made independently of the potential outcomes of other probability states. This separation is important as each outcome will be experienced in isolation, making it rational to disregard non-occurring outcomes when making a decision. Nevertheless, the assumption of independence might not always hold in real-world scenarios. Real decision-making can be influenced by factors such as interdependent preferences, emotional responses to risk, or simply the amount of a product or item that the consumer already has (Varian, 2014). Expected utility theory remains a widely accepted model in economics and decision theory. It structures and models choice under uncertainty, which offers a powerful perspective, especially for economic behaviour and for our investigation of the application of preferences for digital products and services, where consequently the respondents are asked to choose exactly one alternative for each choice situation.

Having established the foundation of expected utility theory, we now turn to a more specific approach within this framework: random utility models (RUMs). While expected utility theory provides a broad understanding of decision-making under uncertainty, it assumes that consumers have precise and consistent preferences. However, in reality, consumer choices often exhibit variability and randomness due to unobserved factors and inherent uncertainties.

RUMs address this complexity by incorporating randomness directly into the utility function. It still follows the theory that a consumer chooses the product alternative that offers the highest utility (Louviere, et al., 2010). However, an observer does not have full information on the individual utility of the consumer. Therefore, these models assume that the utility a consumer derives from a particular choice is composed of two parts: a deterministic component, which captures the systematic and observable factors influencing choice and a stochastic component, which represents the random, unobserved influences (McFadden, 1974; Sammer, 2007, p. 26). Mathematically, this can be expressed as:

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{1}$$

where $U_{ij}$is the total utility of alternative j for individual i, V_{ij} is the deterministic component, and $\epsilon_{ij}$is the stochastic component (McFadden, 1974).

The deterministic component V_{ij} typically includes variables that are observable and quantifiable, such as price, income, and attributes of the goods or services, i.e., the attributes of the product bundle. The stochastic component ϵ_{ij} captures all other influences that are random or not directly measurable. By modelling utility in this way, RUMs allow us to account for the randomness in individual choices and provide a more accurate representation of consumer behaviour. The underlying economic theory of RUM is based on the work of Lancaster (1966) and Thurstone (1927). RUMs capture the probabilistic nature of decision-making, where the choice made by an individual in each context reflects the highest utility among available alternatives, considering both measured attributes and random components.

RUMs are widely used in DCEs to analyse choices among a finite set of alternatives. They enable researchers to estimate the probability that a particular alternative will be chosen, given the characteristics of the alternatives and the individual (Train, 2009). McFadden's (1974) work on RUMs, particularly in the context of transportation economics, has significantly influenced the framework of DCEs, allowing for a better understanding of how individuals value different attributes of goods or services.

2.1.4 Altering utility maximising behaviour: Behavioural economics, Bounded Rationality, and New Institutional Economics

The rational choice theory underlying traditional economic models of preferences faced criticism for its lack of descriptive accuracy, leading to the rise of behavioural economics. **Behavioural economics** challenge the concept of perfectly rational choices and highlight the role of cognitive and psychological biases in decision-making (Kahneman & Tversky, 1979). The so-called prospect theory recognises that individuals might act irrationally in an economic sense, meaning their cognitive limitations and emotions affect their decision-making processes (Simon, 1955; 1956). Behavioural economics focuses on studying how consumers make choices in practice. It uses insights from psychology to develop predictions about choices people will make. Many of these predictions are not in line with the conventional economic understanding of ‘rational’ consumers (Varian, 2014). They include, e.g., ‘framing effects’, which refers to the context of how choices are presented or framed within the buying situation. Other related concepts are anchoring effects (decisions influenced by spurious information), the impact of too much choice (increases difficulty in making choices), or, e.g., that preferences are not pre-existing but develop throughout the decision process (Varian, 2014). It can be paraphrased that behavioural economics describes the effects that lead to consumers behaving irrationally, even though if people took the time to consider their choices carefully, they would reach the ‘right’ conclusion (Varian, 2014).

The perspective of consumers using heuristics and rules of thumb to make economically irrational decisions rather than conducting exhaustive optimisations is captured by the concept of **Bounded Rationality.** This perspective helps explain why actual consumer behaviour sometimes deviates from the predictions of expected utility theory and random utility (Kahneman & Tversky, 1979; Sent, 2018). Bounded rationality posits that individuals are constrained by the information they have, the cognitive limitations of their minds, and the finite amount of time available to make decisions. In this matter, the theory is very much linked to the field of behavioural economics. Without complete information about all possible alternatives and the outcomes of each, as well as the uncertainties surrounding future events, individuals can only achieve subjective but not objective rationality. This distinction arises because, in real-world conditions, perfect knowledge is typically unattainable. As a result, when faced with complex problems that surpass their cognitive capabilities, individuals apply a strategy called 'satisficing.' (Frantz, 2020). This approach involves seeking solutions that are satisfactory rather than optimal, acknowledging that human rationality is inherently 'qualified', limited, or bounded (Frantz, 2020). This concept challenges the notion of fully rational actors in traditional economic models and provides a more realistic framework for analysing how people make choices. Bounded rationality has profound implications for the study of preferences, suggesting that preferences are not only shaped by the intrinsic attributes of the choices available but also by the decision-making context and the individual's capacity to process information, e.g. based on perception, intuition or reasoning (Simon, 1955; 1956; Kahneman, 2003).

One other concept that influences and shapes consumer preferences are institutions and how they are captured under the understanding of **New Institutional Economics (NIE)**. This field further influences the understanding of preferences, emphasising how they are shaped by institutional contexts, including legal, social, and political frameworks (North, 1990; Williamson, 2000). NIE argues that preferences are not only a result of individual choices but are also significantly shaped by the institutional contexts within which individuals operate (North, 1990). The theory extends classical institutional economics by incorporating insights from various economic theories, including transaction cost economics, agency theory, property rights, and contract theory. NIE focuses on the role of institutions, i.e., the rules, norms, and legal systems that govern interactions in society and how these influence economic performance and organisational behaviour (Canitez, 2019). For example, in our case of energy purchase decisions, there are limiting factors, such as contracts, switching procedures, or notice periods, that influence them.

This differs from classical economics by acknowledging that markets do not operate in isolation but are influenced by complex institutional arrangements (Canitez, 2019). NIE has profound implications across multiple fields. It aids in designing policy reforms by highlighting the institutional factors underlying market failures or inefficiencies, which allows for more targeted interventions. In corporate governance, NIE informs the creation of structures that minimise transaction costs and resolve conflicts between different stakeholders, such as between principal and agent (Canitez, 2019). Furthermore, NIE is critical in development economics, emphasising the necessity of robust legal and political frameworks for economic growth and corruption reduction. In environmental economics, it offers insights into how institutional frameworks affect resource management and sustainability. Overall, NIE supports economic analysis by integrating the importance of institutional dynamics into economic outcomes, making it a crucial tool for addressing a wide range of economic issues, from microeconomic cases to macroeconomic policy planning. The broad applicability of NIE demonstrates its utility in tackling complex economic challenges through an institutional lens (Canitez, 2019; North, 1990; Williamson, 2000). Critics argue that NIE tends to oversimplify the complex and often non-linear relationships between institutions and economic outcomes, sometimes overlooking the socio-political contexts within which these institutions operate (Hodgson, 2009, p. 16). Furthermore, NIE's emphasis on efficiency and rationality has been challenged for not adequately addressing power dynamics and inequality (Fine & Milonakis, 2009, p. 92). Additionally, while NIE is lauded for its interdisciplinary approach, it often borrows selectively from other disciplines, potentially leading to a fragmented understanding of institutional impacts (Fine & Milonakis, 2009). Thus, while NIE significantly contributes to economic theory, its limitations suggest the need for a more nuanced and holistic analysis of institutions within economic frameworks.

The relevance of the three concepts mentioned in this thesis is straightforward, as we are building on the understanding of behavioural economics and bounded rationality. Chapter

3 will present the investigation of the impact of context on choice and hence give a perspective on the validity of behavioural economics. We address the concept of NIE with respect to transaction costs and contractual relationships towards the hypothetical energy provider that offers the service and product bundles, which respondents from a survey are asked to choose from in the later applications.

2.1.5 Intermediate thoughts and critical aspects

Current understandings of preferences incorporate both traditional economic models and insights from behavioural economics and NIE, as well as the methodological advances provided by RUMs for DCEs. DCEs are widely used to understand how individuals value different attributes, informed by the broader context of institutional frameworks (Louviere, et al., 2000). They have become a popular method to analyse preferences, allowing researchers to understand how individuals value different attributes of a good or service. This method is used in a variety of topics, e.g. health economics (McIntosh, 2006; Ryan & Gerard, 2003), environmental economics (Mariel, et al., 2021; Bennett & Blamey, 2001), transportation applications (Hensher, et al., 2005; Ben-Akiva & Bierlaire, 1999), or marketing to inform policy and business strategy (Liebe, et al., 2016; Hainmueller, et al., 2014).

The current research and application realm also emphasises the heterogeneity of preferences among individuals, recognising that socio-demographic factors, cultural influences, and personal experiences play a significant role in shaping preferences. This has led to the development of sophisticated choice models that account for varying preference structures across different populations. Examples are Latent Class Models (Greene & Hensher, 2003; Ben-Akiva & Bierlaire, 1999; Hensher & Greene, 2002), Mixed Logit Models (Hess, et al., 2006; McFadden & Train, 2000; Greene & Hensher, 2003), Hybrid Choice Models (Abou-Zeid & Ben-Akiva, 2014; Ben-Akiva, et al., 2002; Vij & Walker, 2014), or Hierarchical Bayes Choice Models (Train, 2009; Lenk, 2014; Marshall, et al., 2010). While the study of preferences has advanced significantly over the years, incorporating insights from behavioural economics and other fields, several challenges and points of criticism remain. One major critique is the assumption of rationality in traditional economic models (Kahneman, 2003).

Despite advancements in behavioural economics, many models still rely on simplifications that may not fully capture the complexity of human decision-making. Moreover, the assumption that preferences are stable and consistent over time is often challenged (Tversky & Kahneman, 1981). Empirical evidence suggests that preferences can be context-dependent, influenced by framing effects, and subject to change over time due to factors such as learning, adaptation, and emotional state (Loewenstein & Lerner, 2003; Rooderkerk, et al., 2011; Thomadsen, et al., 2017). We are going to investigate the question of the influence of context effects on preference in Chapter 3 of this thesis.

Furthermore, the applicability and generalisability of findings from choice studies have been subjects of debate. Critics argue that laboratory settings may not accurately reflect real-world decision-making contexts, limiting the external validity of these findings (Levitt & List, 2007). Additionally, there are concerns about the ethical implications of applying economic insights in marketing and policymaking, particularly regarding the manipulation of choices and the enhancement of consumerism (Murphy, et al., 2008). The use of ’nudges’ in public policy, popularised by Thaler and Sunstein (2008), aims to guide people towards better choices without restricting their freedom. However, it also poses questions about autonomy and manipulation, especially when individuals are not aware of these influences on their decision-making processes. In marketing, the ethical implications become even more pronounced, with concerns over privacy and the potential for exploiting psychological vulnerabilities to drive consumerism. The case of Cambridge Analytica highlights the dark side of using behavioural insights, where data was used not just to influence consumer choices but to sway political opinions, raising alarms about the manipulation of preferences on a massive scale (Cadwalladr & Graham-Harrison, 2018; Sunstein, 2016). These instances underscore the need for ethical guidelines and transparency in the application of behavioural insights to protect individual autonomy and ensure that such strategies are used for genuinely beneficial outcomes rather than manipulation.

Despite these challenges, the study of preferences has undeniably enriched our understanding of economic behaviour, offering valuable insights for improving economic models, policymaking, and marketing strategies. Continuing to integrate findings from interdisciplinary research, addressing the limitations of current models, and fostering ethical considerations in the application of these insights will be crucial for the future development of this field.

2.1.6 Welfare economics: from utilities to WTP/WTA

Welfare economics is a branch of economics that focuses on the efficient allocation of resources and goods to improve social well-being. Phaneuf and Requate (2017) give the example of one factory and one laundry owner who run their business right next to each other. The factory owner's production facility pollutes the air, while the laundry owner needs to produce clean linen and thus suffers while not receiving any compensation (Phaneuf & Requate, 2017). In general, welfare economics aims at the economic well-being of individuals and societies. It investigates how different allocations of resources can affect overall happiness and economic efficiency. The concept of welfare is linked to preferences and utilities as it often relies on individuals' preferences to determine what activities lead to an increase or decrease in mutual welfare (Phaneuf & Requate, 2017).

In the area of welfare economics, behavioural economics also needs to be considered, as it offers real-world perspectives on this academic field. They reveal how cognitive biases and methods can impact welfare judgments (Kahneman & Tversky, 1979; Glimcher, et al., 2009). This emphasises the understanding of the human decision-making processes. It suggests that welfare analyses must take preferences into account for assessing political impact (Kahneman & Tversky, 1979; Thaler & Sunstein, 2008; Feldmann & Serrano, 2006). Therefore, welfare economics offers more realistic and effective recommendations for societal well-being, as it considers the complex relation between economic conditions, individual choices, and social structures. There is a connection between the individual preference within welfare economics and the concept of Pareto efficiency (Feldmann & Serrano, 2006). Pareto efficiency describes a situation where resources are allocated between market participants in a way that any change in the allocation leads to a reduction in utility for any participant. This highlights the importance of individual preferences in assessing welfare changes (Feldmann

& Serrano, 2006). A Pareto efficient (or optimal) situation can be archived for complete and perfectly competitive markets, which can be summarised as the first welfare theorem (Phaneuf & Requate, 2017).

The second welfare theorem describes that a Pareto efficient outcome can be obtained via a suitable lump sum income transfer. This connects very well to the example of the factory and the laundry owner, e.g., through the idea of having the factory owner pay some kind of compensation so that the laundry owner is not worse off in the end. Nevertheless, in real-world scenarios, absolute Pareto improvements are rare. The Kaldor-Hicks compensation criterion offers a less stringent efficiency standard. Here, an allocation is considered efficient if those who gain from the allocation could, in theory, compensate those who lose and still have a net gain. This criterion is particularly relevant in welfare economics as it provides a bridge between Pareto efficiency and practical policymaking. Therefore, while the welfare theorems focus on ideal market conditions for efficiency, the Kaldor-Hicks compensation criterion offers a pragmatic approach to evaluate policy changes and market outcomes in terms of potential overall gains, reflecting a more flexible application of efficiency principles in economic analysis (Phaneuf & Requate, 2017, pp. 649-651).

The foundations of welfare economics were laid in the early 20th century, with contributions from economists like Pigou (1920) and Pareto (1906). Pigou (1920) introduced the concept of externalities and the role of government intervention in correcting market failures to achieve social optimum. Pareto (1906) developed the Pareto efficiency or Pareto optimality, which was mentioned before.

Various measures and methods for evaluating welfare can be used. Usually, these measures evaluate the overall well-being or utility of individuals or societies. The practical goal is usually to evaluate how changes in economic policies, market conditions, or other interventions affect the welfare of different stakeholders, thus leading to an improvement or deterioration in social welfare. In the following, we are introducing some key measures that are commonly used in welfare economics.

Willingness to Pay (WTP) and Willingness to Accept (WTA) are used to quantify how much individuals value a good or service (WTP) or what minimum amount they would accept as compensation for losing it (WTA). They can offer a good understanding of welfare changes (Louviere, et al., 2000). WTP is particularly important in cost-benefit analysis and estimating compensating and equivalent variations (CV/EV). It directly reflects individuals' preferences and the subjective value for specific alternatives. WTP and WTA are very important for welfare economics as they offer a measurement unit for policies or market condition changes (Hanemann, 1984). Understanding how changes in market conditions or in the quality of goods and services affect welfare is crucial in welfare economics. It often requires considering not only the quantity but also the quality of goods consumed (captured in the concept of qualitatively different goods). This consideration is vital in evaluating the welfare impacts of policies or market changes that affect the availability or characteristics or, in our cases, attributes of goods. Therefore, the role of consumer preferences in determining the value of qualitative improvements is crucial (Lancaster, 1966). With reference to the topic of this thesis, WTP/WTA are crucial for understanding preferences and making comparisons, especially in the context of servitisation or digitisation, where traditional goods are transformed into services or digital offerings and vice versa (Kohtamäki, et al., 2021; Paiola, et al., 2021; Coreynen, et al., 2020). Chapter 5.2.2 will provide additional information on the digital transformation of servitisation to increase the utility of customers.

Compensating and Equivalent Variation (CV/EV) describe measures that show the amount of money that is needed to reach the original level of utility after a change in prices, income, or availability of goods occurs. A particular use lies in the case of policy changes or market shifts (Hicks, 1943; Feldmann & Serrano, 2006; Phaneuf & Requate, 2017). CV covers the amount of money that the aforementioned laundry owner receives from the factory owner so that their utility level remains at a ‘pre-factory’ level while the factory owner gains more utility out of the production (Feldmann & Serrano, 2006). EV accounts for how much money an individual would be willing to pay to avoid a change that would otherwise move them away from their original utility level. Within the discussion about CV/EV, the so-called Marshallian and Hicksian demand curves need to be mentioned. The Marshallian demand curve covers the aspect of how the quantity of demand for a good changes in response to a price change while the income remains constant. This means that it shows a direct relationship between price and quantity and illustrates consumers' sensitivity to price changes under the constraint of their initial income level (Marshall, 1890). The Hicksian demand curve shows how the quantity demanded of a good or service changes with price, assuming the consumer's level of utility or satisfaction remains constant (Hicks, 1943). They are also known as income-compensated demand functions. The Hicksian demand is used for calculating CV and EV in order to provide a measure for welfare changes following price adjustments or policy interventions (Hicks, 1943). By comparing the Marshallian and the Hicksian demand curves, it is possible to isolate the effects of price changes on consumption patterns to distinguish between changes in purchasing power and shifts in preferences (Varian, 1999).

The relationship between those two demand curves is called the Slutsky function (Varian, 1999). The Slutsky function is a fundamental concept in microeconomics that decomposes the effect of a price change on the quantity demanded of a good into two distinct components: the substitution effect and the income effect. This decomposition is crucial for understanding how consumers respond to changes in prices and how these changes affect their consumption patterns (Varian, 1999). The practical application of CV/EV can be found in **cost-benefit analysis (CBA).** This is a systematic approach to estimating the strengths and weaknesses of alternatives and thus is used to determine options that provide the best approach to achieve benefits while preserving savings (Mishan, 1976). It is widely used in policy evaluation, incorporating preferences to weigh the pros and cons of different actions (Boardman, et al., 2018). CBAs today rely on the Kaldor-Hicks compensation criterion to evaluate the efficiency of political actions and to compensate ‘losers’ of a policy measure (Phaneuf & Requate, 2017, p. 649).

If induced through market or policy changes, customers gain additional utility for the same price, or prices decrease for a given utility, the buyers realise a **consumer surplus**. This concept refers to the difference between the total amount that consumers are willing and able to pay for a good or service and the total amount that they actually pay. Consumer surplus is used to measure the benefit or utility consumers receive from purchasing goods and services at market prices lower than their maximum WTP (Marshall, 1890; Phaneuf & Requate, 2017; Varian, 2014). This idea becomes very relevant when talking about possible synergies of product bundling. Hence, the *combined* market price is even lower than the combined WTP, ceteris paribus or vice versa (Adams & Yellen, 1976; Phaneuf & Requate, 2017).

Understanding consumer surplus is fundamental to welfare economics, as it measures the difference between what consumers are willing to pay for a good or service and what they actually pay. This concept, alongside WTP/WTA and CV/EV, provides insight into consumer welfare and market efficiency. **Roy's identity**, a major result in microeconomics, further explains the relationship between prices, income, and consumer demand. It applies to consumer choice and the theory of the firm. It connects the Marshallian demand function to the derivatives of the indirect utility function. Specifically, for the indirect utility function $v(p, w)$, the Marshallian demand for good i is:

$$x_i^m(p, w) = -\frac{\frac{\partial v}{\partial p_i}}{\frac{\partial v}{\partial w}} \tag{2}$$

Where p is the price vector, and w is income (Varian, 1999). This identity helps to understand how price and income changes affect consumer choices and welfare. It also links to WTP and consumer surplus by quantifying the maximum amount a consumer is willing to pay for an incremental increase in utility (Mas-Colell, et al., 1995). Additionally, it aids in the measurement of CV/EVs, which reflect income adjustments needed to maintain utility after a price change (Varian, 1999; Phaneuf & Requate, 2017). Roy's identity is similar to the expenditure function's price derivatives, which are given by the Hicksian demand functions. It allows economists to derive demand functions essential for accurate welfare assessments, ensuring precise quantification of changes in consumer welfare. In a similar manner to consumer surplus**, producer surplus** measures the difference between what producers are willing to accept for a good or service and what they actually receive. It reflects the benefit or welfare producers gain from selling goods and services at market prices higher than their minimum acceptable prices (Willig, 1976).

The application of welfare economics in policymaking involves ethical considerations. For example, the distribution of resources and the potential for paternalism are important topics of discussion (Sunstein, 2016). Using welfare measures to justify certain public policies, such as taxes on unhealthy goods, raises questions about autonomy and the government's role in influencing individual preferences. It also has not been without criticism on the academic side. Critics argue that the reliance on utilitarian principles often oversimplifies the complexity of human well-being by reducing it to measurable or monetary values (Sen, 1979). Rational behaviour models have been questioned through examples like the overconsumption of sugary drinks, where consumers' consumption, influenced by advertising and lack of nutritional knowledge, leads to unfortunate health issues. This is a scenario that a rational utility maximisation model would fail to predict accurately (Thaler & Sunstein, 2008). Therefore, it is necessary to incorporate broader social, health, and ethical considerations into the analytical framework of welfare economics.

With its focus on understanding and improving social welfare, welfare economics use DCEs to capture preferences and measure changes. DCEs offer the possibility to empirically assess how individuals value different aspects of goods or services. This is of high relevance throughout this thesis, as we show that the value interpretation of servitisation and digitisation currently lacks an economic foundation. Here, much of the academic discourse refers broadly to the concept of 'value', yet a universally accepted, economically grounded definition remains unclear. This lack of precision means that while terms such as 'value creation' are frequently used in this area of research, specific metrics or parameters that could economically quantify this 'value' are often absent. Existing literature suggests a range of interpretations (Porter & Heppelmann, 2015; Rymaszewska, et al., 2017) while connecting the concept to operational benefits, including cost reductions, increased flexibility, and time savings for customers (Paschou, et al., 2020; Foubert, 1999, p. 17). This variation in understanding points towards the gap of establishing a shared, economically founded definition that would allow for consistent evaluation and measurement of 'value' within servitisation and digital transformation contexts. For further elaboration, we refer to the understanding given in Chapter 5.2.4 of this thesis.

Coming back to the understanding of quantifying individuals' WTP, DCEs provide insights into how changes in service delivery models or digital features affect consumer welfare. This empirical approach aligns with the welfare economics objective of evaluating policy or market shifts based on their impact on social welfare, allowing for a more informed decision-making process in both public policy and business strategy (Louviere, et al., 2000). Nevertheless, it is important to mention that DCEs are applied to hypothetical markets and that a real market needs to be constructed to generate real buying situations.

2.1.7 Shephard's lemma

Shephard's lemma is a fundamental result in microeconomic theory that relates to the theory of firm behaviour and production. It provides a link between a firm's cost function and its input demand functions. It states that if a firm's cost function is differentiable, then the derivative of this cost function with respect to the price of a particular input yields the firm's demand for that input, holding all other input prices and output levels constant (Varian, 1999; Diewert, 1974; Phaneuf & Requate, 2017). This means that, according to Shephard's lemma, a change in the price of a particular good means a proportional change in the quantity produced by the firm. This relationship is given by the partial derivatives of the supply function with respect to prices. These derivatives are, therefore, equal to the elasticities of demand. It allows us to understand how firms and consumers respond to changes in prices and is therefore used in empirical industrial economics to estimate demand elasticities and to analyse competition in certain markets (Diewert, 1974).

The concept is intrinsically linked to consumer theory as it has a counterpart within consumer behaviour in the Hicksian demand function. Just as Shephard's lemma describes how changes in input prices affect a firm's choice of inputs, the Hicksian demand function describes how changes in the prices of goods affect a consumer's choice of goods, holding utility constant. Therefore, Shephard's lemma serves as the firm's counterpart to Hicksian demand in consumer theory. Both are based on optimisation behaviour: firms minimise costs for a given output level, while consumers maximise utility for a given income level. The duality between cost minimisation by firms and utility maximisation by consumers underpins much of microeconomic theory, offering deep insights into market behaviours and economic welfare (Varian, 1999).

2.2 Foundations of Discrete Choice Experiments

2.2.1 Introduction to DCEs

2.2.1.1 Economic foundation of DCEs

For the valuation and formal economic modelling of the consumer utility of servitisation, we apply a DCE. DCEs are a method for preference elicitation and are based on Lancaster's (1966) theory and Thurstone's (1927) 'Law of comparative judgement'. Thurstone's (1927) work offers applications for the measurement of psychological values, e.g., attitudes or expected utilities, based on pairwise comparisons, which still is a commonly used procedure in recent publications (Saaty, 2008; Kadıoglu, et al., 2022). Furthermore, it has led to the introduction of random utility models, exploring the theoretical implications for choice probabilities of maximisation of utilities that contain some random elements (McFadden, 1974). Lancaster's, Thurstone's, and McFadden's contributions are the theoretical foundation of all DCE contributions and the derived model approaches in research and literature. The contemporary understanding and application of DCEs has been developed by Louviere and Hensher (1982) as well as Louviere & Woodworth (1983), all of whom assume, very much like the choice-based approach of consumer theory, that the observed choices of respondents reveal the preferences of the individuals.

Here, we provide an appropriate introduction to the theory and approaches to Discrete Choice models (DCM) for the purposes of this thesis. DCMs deal with the selections made by decision-makers among various options or choices. These can include individuals, households, companies, or other decision-making entities in the context of selecting choices between competing products, courses of action, or other alternatives that require decision-making.

The set of alternatives, which is also called a choice set, must satisfy three conditions. First, that alternatives are mutually exclusive. Second, alternatives need to be exhaustive, which means that all possible alternatives are included in the choice set. Third, alternatives are finite and can, therefore, be counted. Given these preconditions, DCMs are typically modelled under the behavioural assumption that decision-makers aim to maximise their utility (Train, 2009). Specifically, choice experiments frequently use metrics such as WTP, WTA, or other measures of preferences for goods as well as for scenarios that are not publicly available yet (Johnston, et al., 2017, p. 344). Choice experiment approaches are commonly used in environmental or political contexts (Mariel, et al., 2021), for logistic or transportation applications (Hensher, et al., 2005), or in the case of health economics (McIntosh, 2006). Especially in the social and behavioural sciences, the use of choice models is an established approach for estimating the influence of attributes on decisions. With the help of this approach, (social) choice situations can be presented within a realistic setting (Liebe, et al., 2016).

DCEs are not the only methods for evaluating consumer preferences. Other approaches are, for example, Conjoint Analysis (CA) and Qualitative Comparative Analysis (QCA). CAs, which are similar to DCEs, evaluate consumer preferences for product attributes but differ in the way attributes are presented and analysed. They are often used to rank product alternatives rather than to choose them. This means that they offer insights into the relative importance of different attributes. QCAs help to identify complex interaction effects among attributes that may not be apparent in DCEs. They are useful for exploring how combinations of attributes lead to a particular outcome, thus providing a nuanced understanding of decision-making processes (Berg-Schlosser, et al., 2009). In this way, these approaches focus on the conditions leading to outcomes and thus try to reveal complex attribute interactions that cannot be modelled by CBC or DCE approaches (Berg-Schlosser, et al., 2009).

Within CA, CBC analyses represent a specific approach closely aligned with DCE. In CBC, respondents also choose from presented alternatives, thus simulating a decision process (Orme, 2020; Auspurg & Liebe, 2011). CBC and DCE share a common foundation in the random utility theory. However, there are minor differences within the application and interpretation. The term CBC is mainly used in marketing and market research. It mainly focuses on measuring the trade-offs consumers make when selecting among sets of alternatives. In contrast, DCE is a term more frequently used in economics, often with a stronger focus on estimating monetary values, such as WTP or WTA, for specific attributes or policy changes.

As choices are based on discrete variables (e.g., selection or discard of an alternative), classical regression analyses, which rely on continuous variables, lead to incorrect results. DCMs take this aspect into account and model discrete variables via logistic regressions that are based on explicit behavioural assumptions of the decision maker (Temme, 2009).

As introduced earlier, DCEs are mainly based on two theories: Lancaster's consumption theory and McFadden's random utility theory. Lancaster's consumption theory neglects the fact that goods are direct objects of utility and that the properties or characteristics are rather the source of utility (Lancaster, 1966, p. 133). Applying Lancaster's theory and assuming the investigated attributes have two or more different levels which vary between good alternatives, the behaviour of consumers can be assumed to be utility maximising. McFadden (1974) provides, based on these assumptions, the following utility function U_i with different alternatives i:

$$U_i = x_i\beta + \epsilon_i = V_i + \epsilon_i \tag{3}$$

Within the function U_i, X_i stands for a vector that is comprised of the attribute levels in the alternative $i(x_{1i}, x_{2i}, \dots)$, and β represents a vector of the associated parameters. Technically speaking, the vector β comprises the utility weights. The term ϵ_i captures all effects on utilities that cannot be described by the observed variables. Therefore, statistically, ϵ_i is an error term. For simplification, $X_i\beta$ – the observed part of the utility – is denoted as V_i. This model is known as the RUM (or RUT for random utility theory) that we introduced earlier, which follows the theory that, based on utility maximisation, the consumer chooses the product alternative that offers the highest utility. However, an observer does not have full information on the individual utility of the consumer. Therefore, the corresponding utility function consisting of deterministic and stochastic components and displayed utility is not an apparent value but a non-observable, latent, and random variable (McFadden, 1974; Sammer, 2007, p. 26).

Louviere, et al. (2010, p. 62) summarise that *“random utility theory provides an explanation of the choice behaviour of humans, not numbers”.*

Ben-Akiva and Bierlaire (1999, p. 2) extend and clarify this understanding: the total utility for the consumer consists of independent partial utilities of single products in different markets, which means that customers do not receive value from the product itself, as attributes represent the cumulative costs and benefits of one alternative. This aligns with the view of Lancaster (1966, p. 133) stated above and refers to the properties and the characteristics of a good as being relevant for the utility.

We have introduced the theoretical background of preferences earlier. The measurement of preferences is based on monetary trade-offs, following the core question of how willing the customer is to pay for a certain product, offer or service (Golsteyn & Schildberg-Hörisch, 2017, p. 2). According to Helm et al., preference measurement *“is needed to design new products or adopt [sic!] existing goods to the customers’ needs”* (2004, p. 3). In general, preference measurement methods are separated into two different groups: decomposing and composing approaches. Composing preferences measurement methods investigate sub-attributes to estimate an overall preference level (e.g., used in CA approaches) while decomposing approaches ask for the values of a good to construct the preferences for the sub-attributes.

DCEs can be designed as a decomposing approach, which means that the total utility of the investigated good is broken down into the individual utilities of the good’s characteristics or attributes. DCE approaches belong to the field of behavioural theory, more specifically to the area of choice behaviour (Louviere, et al., 2010). DCEs are, practically speaking, survey-based methods for collecting preferences, utility shares, WTP, and WTA for defined attributes of a product or service alternative. Within the process of a DCE, respondents are repeatedly shown two or more product alternatives that consist of different attribute level combinations. Usually, there are six to 16 iterations, so-called choice tasks, where each respondent can select the most preferred alternative for each iteration. The different attribute levels vary across the alternatives and throughout the whole choice design (choice design = all choice tasks combined).

2.2.1.2 Estimation and execution of DCEs

After conducting a choice experiment, different estimation methods can be used. Multinomial Logit (MNL) and Conditional Logit (CL) models assume that individuals choose the option that provides the highest utility, treating choices as mutually exclusive events (McFadden, 1974). MNL models model a choice as a function of the chooser's characteristics, whereas CL models present the choice as a function of the alternatives' characteristics. Some CL models include socioeconomic characteristics as explanatory variables to account for observable taste heterogeneity, and thus, in the literature, MNL and CL are often used as synonyms. However, a choice model using only socio-economic covariates can only estimate choice probability and cannot decompose the probability effects of choice attributes, which are the elemental constituents of preference analysis. CL models are directly derived from the random utility theory introduced by McFadden (1974).

Latent Class (LC) models build on these approaches and try to identify segments within the population of respondents that share similar preferences (Temme, 2009; Greene & Hensher, 2003). LC models build on the approach that not all respondents are influenced by attributes in the same way. They group homogenous preferences within heterogeneous classes that need to be selected beforehand. (Temme, 2009; Greene & Hensher, 2003). Hybrid Choice Models (HCM) integrate latent variables and decision processes, allowing the inclusion of psychological factors and other unobserved heterogeneity in the choice process (Ben-Akiva, et al., 2002). This approach enhances the explanatory power by considering both observed and unobserved variables that influence decision-making.

Mixed Logit Models (MLM) allow for random preference variation of the individual respondents, unrestricted substitution patterns, and the correlation in unobserved factors over time (Train, 2009; Hensher & Greene, 2002; Greene & Hensher, 2003). Within the area of MLM, there are specific applications, such as Panel Latent Class Models (PLC), that mix utility over discrete groups of homogeneous preference ("preference classes") rather than over a continuous random variable. This segmentation approach enables the identification of distinct preference patterns within finite classes, allowing researchers to model heterogeneity in a structured way. By contrast to the continuous distribution in standard MLMs, PLCs focus on classes with similar attribute sensitivities, providing a useful framework for studying discrete heterogeneity within populations (Andrews, et al., 2002). Within MLM, individual-level parameters can also be computed. These are estimated using frequentist methods (statistical approaches that interpret probability as the long-term frequency of observed events and assume fixed unknown parameters). One common frequentist technique is Simulated Maximum Likelihood (SML), which approximates complex likelihood functions by generating random draws from the distribution of random coefficients and averaging these to estimate model parameters. MLMs are inherently hierarchical, as they integrate population-level parameters (e.g., the means and variances of random coefficients) with individual-level data to infer conditional distributions of tastes. As Train (2009, p. 263) explains, "the density of β in the subpopulation of people who would choose sequence y_n when facing x_n is proportional to the density of β in the entire population *times* the probability that y_n would be chosen if the person's coefficients were β". This means that individual preferences are inferred by conditioning the population-level distribution on observed choices. SML facilitates this process by approximating the likelihood of observing a sequence of choices through simulation. By taking random draws from the population distribution of preferences and weighting them by the likelihood of observed choices, the model estimates individual-specific parameters. These estimates become more precise as more choices are observed, resulting in tighter conditional distributions and more accurate predictions.

Hierarchical Bayes (HB) models represent an advanced approach to choice modelling, estimating individual-level preferences by combining population-level parameters with individual-specific data, typically using Monte Carlo Markov Chains (MCMC) methods (Allenby & Ginter, 1995; Sawtooth Software, 2021).

In the next section, we will compare the different estimation methods and elaborate on the methods that are going to be used within this thesis.

For running DCEs, it has become common to use software tools for creating the experimental design, e.g. Ngene (ChoiceMetrics, 2024), for setting up the survey, e.g. Sawtooth (Chrzan & Orme, 2000), and for data handling and running the estimation, e.g. Sawtooth, Apollo, or STATA (Sawtooth Software, 2017; Hess & Palma, 2022; StataCorp, 2023). In this thesis, we will use Sawtooth and Apollo, as the combination of these tools gives us the possibility to build an adequate setup for our research objectives. Sawtooth Software is a leading provider for choice analytics, offering a suite of tools for creating, conducting, and analysing DCEs. Its capabilities include efficient design generation, survey programming, and sophisticated analysis techniques (Sawtooth Software, 2021; 2017; Orme, 2020; Chrzan & Orme, 2000). We use Sawtooth in this thesis for the setup of the choice design, for the management of the survey, and for the execution of an HB estimation. Apollo is an open-source package for R which does not rely on commercial statistical software as a host environment. It offers the possibility to run a variety of choice model estimates (e.g., MNL, CL, LC, MLM, HCM, etc.) with different restrictions, requirements, and setups (e.g., revealed preferences, stated preferences, nested logits, utility space, WTP space, ordered data, etc.). Due to its foundation on the open-source statistics and data management tool “R”, a lot of individual adjustments of the models are possible. There is also a big and active user community, including the researchers responsible for Apollo, that can offer support and guidance (Hess & Palma, 2022; 2019).

2.2.1.3 Limitations of DCM and future research directions

By using DCEs, researchers face different challenges and limitations. One significant challenge is the design complexity of choice setups. For example, the selection and number of attributes and attribute levels need to be balanced to avoid biases. The inclusion of irrelevant information also needs to be avoided, or the fatigue of respondents needs to be acknowledged while ensuring the experiment's relevance (Hensher, et al., 2005; Train, 2009). Furthermore, there is the issue of hypothetical bias, where responses in a survey context may not accurately reflect real-world decisions (Liebe, et al., 2016; Hensher, 2009; Kim & Park, 2017). Another limitation is the assumption of rationality in decision-making, which may not account for all factors influencing consumer choices, such as emotional or irrational considerations (Hensher, et al., 2005). Additionally, the interpretation of results can be complicated by the presence of unobserved heterogeneity among respondents, challenging the generalisability of findings. Addressing these challenges requires careful experiment design, consideration of alternative modelling approaches, and ongoing methodological advancements (Train, 2009; McFadden & Train, 2000). The field of DCE and DCM continues to evolve, with recent advances focusing on enhancing model accuracy, flexibility, and applicability (Wang, et al., 2023). Developments in machine learning and artificial intelligence have introduced new possibilities for analysing choice data, allowing for the identification of complex patterns and interactions that traditional models may overlook (Ali, et al., 2023; CranenburghI, et al., 2022; Wang, et al., 2020).

2.2.2 Estimation approaches for choice methods

As already introduced in this chapter, different estimation approaches are used for DCEs or DCMs. Roughly speaking, they can be separated into methods that account for preference homogeneity (MNL, CL) and preference heterogeneity (LC, HCM, MLM, HB). In the following, we offer a short comparison of the different methods based on the following criteria:

- Application context, including flexibility and type of preferences,
- Independence of Irrelevant Alternatives (IIA),
- Data and sample size requirements.

2.2.2.1 Application context, incl. flexibility and type of preferences

The application context of the choice modelling techniques differs based on their fit for research and practical scenarios. MNL models do have a rather simple structure. They are best suited for applications within transportation, market research, and environmental evaluation (McFadden, 1974). CL models find their application in scenarios where choices are significantly impacted by the characteristics of the options, such as in environmental economics and transportation planning (McFadden, 1974). MNL and CL models estimate preferences assuming they are homogeneous across individuals, not capturing variability in tastes (Train, 2009). Both models offer limited flexibility in modelling complex choice scenarios due to certain restrictions (‘IIA’, see next sub-section 2.2.2.2) and the assumption of homogeneous preferences (McFadden, 1974; Train, 2009). CL models are useful in the case that there are many possible alternatives from which a choice can be made. Here, CL models allow for the analysis of how specific features of the alternatives influence the choice outcome (Hoffman & Duncan, 1988; McFadden, 1974). This distinction makes the CL model particularly suitable for DCEs, where choices between alternatives that are defined based on certain attribute combinations are analysed. In contrast, MNL models are used for choice modelling where alternatives are not characterised by attributes, focusing instead on the choice as a function of the individual's characteristics.

Therefore, MNL models explain choice behaviour between a finite set of alternatives based on the characteristics of the decision-maker, while CL models explain choice using differences between the attributes of alternatives (Hoffman & Duncan, 1988; McFadden, 1974).

LC models are very useful for determining segments within a population. They mark one of the first approaches to incorporate heterogenous preferences within a population. Under certain conditions, LC models are able to estimate individual-level parameters. However, these models are mainly used to identify certain groups within a sample. Therefore, LC models are ideal for market and customer segmentation as well as market strategies targeted at specific audiences (Greene & Hensher, 2003). They estimate preferences by segmenting the population into distinct classes with homogeneous preferences within each class but allowing for heterogeneity across classes. They offer a middle ground in capturing preference diversity (Kamakura & Russell, 1989; Temme, 2009). LC models have some application flexibility by allowing for heterogeneity through latent segmentation (Kamakura & Russell, 1989).

HCMs are particularly suited where context or underlying psychological or sociological factors drive choice. HCM may provide insights beyond traditional choice models, as they include not only the choice data but also behavioural aspects (e.g. attitudes, perceptions or decision protocols) in the estimation (Abou-Zeid & Ben-Akiva, 2014; Ben-Akiva, et al., 2002). HCMs estimate heterogeneous preferences by acknowledging that individuals' choices are influenced by a combination of observed factors and unobserved latent constructs. This means they can capture a wide spectrum of behavioural shades (Abou-Zeid & Ben-Akiva, 2014; Ben-Akiva, et al., 2002). Hence, HCMs offer superior flexibility in modelling complex choice situations, thus allowing for a more comprehensive understanding of decision-making processes (Abou-Zeid & Ben-Akiva, 2014; Ben-Akiva, et al., 2002).

MLMs are particularly effective in handling preference heterogeneity, owing to their ability to simulate random parameters across individuals. These models rely on SML, which approximates the likelihood function by generating random draws from the population distribution of coefficients. This approach enables researchers to handle complex integrals that arise from incorporating random effects into utility functions (Train, 2009). They are particularly valuable in advanced market research, healthcare, and environmental studies (Train, 2009; Hess, et al., 2006). MLM take a further step in accommodating heterogeneity by estimating distributions of preferences across individuals (McFadden & Train, 2000; Hess, et al., 2006). For instance, Train (2009) analysed energy supplier choice data, demonstrating how MLM could effectively incorporate random coefficients for attributes like price, contract length, and supplier reputation. This highlights the ability of mixed logit models to predict choice behaviour while accounting for diverse preferences within a population. Therefore, MLM significantly increases flexibility by including correlations in unobserved factors and allowing for random preference variation (McFadden & Train, 2000)**.**

HB models are also able to model individual and highly personalised and even ‘extreme’ preferences. They are used, for example, for customised product design, personalised marketing, and precision medicine (Allenby & Ginter, 1995; Allenby & Rossi, 1999). HB models represent the high end of preference heterogeneity estimation. They allow for individual-level parameter estimation that reflects the unique preferences of each respondent (Allenby & Rossi, 1999; Train, 2009). HB models offer the highest flexibility because they can handle complexity with interactions between attributes and non-linear effects. In addition, they can build upon and incorporate prior information (Allenby & Rossi, 1999; Lenk, 2014; Marshall, et al., 2010).

2.2.2.2 Independence of Irrelevant Alternatives

In logit models, the Independence of Irrelevant Alternatives (IIA) says that individual choice alternatives need to be strictly independent from each other as the consumer's preference is not subject to relative comparison (McFadden, 1974; Luce, 1959; Ben-Akiva & Bierlaire, 1999). This property implies that the relative probabilities of different outcomes do not change when certain options are added or removed from the choice set. This means that the inclusion or exclusion of irrelevant alternatives will not affect the predicted probabilities of the remaining alternatives. One of the consequences of such characteristics of IIA is that it can sometimes lead to counter-intuitive predictions. For example, if two options are equally preferred by a decision-maker and a third option is added that is clearly inferior to both options, the predicted probabilities of the first two options may not change at all. This goes against usual human intuition, as we would expect the addition of a clearly inferior option to make the other options more attractive. Another consequence is that it can be difficult to compare the relative importance of different factors that influence a decision using IIA. In logit models, the predicted probabilities of different outcomes are determined by the relative weights of the various factors that are included in the model. However, if the inclusion or exclusion of irrelevant alternatives does not affect the predicted probabilities, it becomes difficult to assess the relative importance of these factors. Overall, while the independence of irrelevant alternatives is a useful property of logit models, it can lead to unrealistic and counter-intuitive substitution patterns in certain contexts and can make it difficult to compare the relative importance of different factors (McFadden, 1974; Train, 2009).

MNL and CL models are subject to the IIA property. Nevertheless, to navigate the inherent limitations of IIA, a nested logit approach extends MNL models by grouping choices into 'nests' that can share similar characteristics (Hensher & Greene, 2002; McFadden, 1981).

LC models partially circumvent the IIA limitation by allowing for heterogeneous choice behaviour across segments, which can introduce some level of flexibility in substitution patterns (Kamakura & Russell, 1989). HCMs are designed to overcome IIA by integrating latent variables that capture unobserved preference heterogeneity, thus allowing for more realistic substitution patterns among choices (Abou-Zeid & Ben-Akiva, 2014; Ben-Akiva, et al., 2002).

MLM overcome the IIA limitation by allowing for correlation in unobserved factors across alternatives and incorporating random coefficients. This enables more realistic substitution patterns and flexibility in modelling choice behaviour (McFadden & Train, 2000; Train, 2009).

Like MLMs, HB models do not assume IIA. This is because HB models account for individual-level heterogeneity by estimating individual-specific parameters, which allows them to accommodate variations in preferences that violate the IIA assumption (Train, 2009, pp. 141,300). They offer the most freedom in modelling substitution patterns and capturing complex choice dynamics through their flexible specification and estimation at the individual level (Allenby & Rossi, 1999; Train, 2009).

2.2.2.3 Data and sample size requirements

In this chapter, several DCMs are compared in terms of their data requirements, and their applicability to the DCE used in this thesis, which investigates digital servitisation in the energy sector based on 800 respondents from Germany. Although each estimation model differs in its theoretical foundations, practical relevance depends on aligning these foundations with the empirical context in our context. The discussion here, therefore, focuses on the specific design and data of our DCE (12 choice tasks, eight attributes, see Chapter 2.4) while highlighting key features such as sample size, demographic composition, and level of engagement in energy markets.

The sample for this thesis consists of 800 participants, whose demographic and behavioural characteristics are described in detail in Chapter 2.6. In brief, the group is slightly skewed toward male respondents, predominantly under 51 years of age, and more than half report household incomes below 3,000 € per month. Around half are employed full-time, and most have switched their energy provider only once or never, which suggests relatively low engagement in the energy market. Approximately one-third of the sample identifies as innovation-oriented, while others prefer to wait for market maturity or require incentives to adopt new offerings, indicating heterogeneous attitudes towards digital services.

MNL and CL models are considered efficient with smaller sample sizes because they rely on relatively few parameters and assume homogeneous preferences across individuals, thereby reducing the complexity of the estimation process (Train, 2009; Bhat, et al., 2000). Therefore, they do not require the level of detail needed in more advanced models that capture heterogeneity (e.g., Mixed Logit or Latent Class), which typically demand larger datasets to reliably estimate additional variance or latent group parameters. However, the same simplifying assumptions that make MNL or CL efficient with smaller samples mean that they are not well equipped to handle sparse data, where certain attribute levels appear infrequently or the sample is highly imbalanced. In such cases, the parameters estimated by an MNL or a CL model may become unstable or imprecise because the limited variation in the data does not sufficiently support reliable coefficient estimation (Louviere, et al., 2000; Train, 2009).

CL models are nonetheless well suited to the aims of this thesis via the applied work in Chapters 3, 4 and 5. Chapter 3 applies a split sample approach to assess whether survey items presented before the choice tasks influence stated preferences, taking advantage of CL's interpretability and relatively low computational complexity. Chapter 4 builds on several CLs by including interaction terms between attributes, thus allowing a focused investigation of synergetic effects in bundled energy-service products. Chapter 5 uses the CL with interactions to offer an integrated perspective of the impact of digitisation of preferences.

LC models divide the population into classes with distinct preference structures (Kamakura & Russell, 1989). which can be beneficial when multiple latent segments (for example, cost-sensitive versus technology-savvy consumers) are believed to exist. However, estimating LC models generally requires a larger dataset to reliably identify parameters for multiple classes and, thus, offer significant results. LC models can partially balance small data input through segmentation. However, a significant estimation depends on the ability to support clear class distinctions (Kamakura & Russell, 1989). Although LC modelling provides a powerful framework for exploring discrete preference segments, this thesis focuses on continuous heterogeneity in individual-level preferences rather than segment-level distinctions. It does not, therefore, employ an LC approach.

Hybrid Choice Models (HCMs) incorporate latent variables (such as attitudes or trust) and multiple data sources into the choice modelling process and thus demand detailed data on psychosocial constructs (Abou-Zeid & Ben-Akiva, 2014; Ben-Akiva, et al., 2002; Vij & Walker, 2014). By leveraging latent variables and incorporating prior information, HCMs can effectively deal with sparse data, making predictions more robust in cases with less or incomplete data (Abou-Zeid & Ben-Akiva, 2014; Ben-Akiva, et al., 2002). Although HCMs can efficiently deal with moderate sample sizes if robust psychometric measures are available, our data collection does not feature the extensive latent variable measures required for a full HCM approach.

Another widely used technique are MLM estimations, which accommodates random taste variation and can work with both individual-level and aggregate data, accommodating varying degrees of preference heterogeneity (McFadden & Train, 2000; Hess, et al., 2006). However, MLMs typically require sufficient observations or repeated choice tasks per individual to robustly estimate the distributions of preference parameters (Hess, et al., 2010). In addition, MLM can be computationally intensive (Train, 2009). As the main objective of this thesis is to compare simpler average trends (Chapters 3 and 4) and to explore individual-level preference heterogeneity specifically linked to digital maturity (in Chapter 5), the thesis does not include an MLM estimation. Instead, we estimate an HB model to examine the role of perceived digital maturity on individual customer utility. HB estimations can capture heterogeneity by allowing for individual-specific parameters (Allenby & Rossi, 1999; Train, 2009). Also, they can incorporate prior information to improve parameter stability. It is, therefore, particularly suited to addressing how perceived digital maturity might vary across respondents and influence utility (Rossi & Allenby, 2003; Huber & Train, 2001). MLMs and HB Models are the most computationally intensive models, MLMs due to the large number of draws and HB models due to the iterative nature of Bayesian estimation and the use of Markov Chain Monte Carlo (MCMC) methods (Allenby & Rossi, 1999; Train, 2009; McFadden & Train, 2000).

Throughout the empirical applications in this thesis, the decision to rely on CL and HB estimations is based on two considerations. First, CL provides a clear baseline for identifying how attributes and interactions between them affect choice probabilities. It is less computationally demanding and suits contexts where the main interest is in average effects (McFadden, 1974; Louviere, et al., 2000). Second, HB supplies a powerful framework for capturing finer-grained heterogeneity, which is essential when the thesis aims to link perceived digital maturity to individual preferences (Huber & Train, 2001). The flexible Bayesian setting can incorporate prior information and is robust to smaller or less balanced datasets, although the dataset in this thesis is relatively balanced and of moderate size. Moreover, the test statistics for the comparison of the model fit that is based on the LL ratio test in the second application (see Chapter 4.1) show that the relevant interaction effects can be adequately detected without resorting to more complex or data-demanding models.

In conclusion, the final choice of models reflects both theoretical alignment with the research questions and an assessment of practical data requirements. CL models are appealing for their interpretability and moderate data demands, while an HB estimation provides deeper insights into how perceived digital maturity impacts choice behaviour at the individual level. Other modelling approaches, such as MNL, LC, HCM, or MLM, offer alternative ways to handle preference heterogeneity or latent constructs but were not pursued within the thesis, given our primary focus on attribute-level analysis and individual-level digital maturity.

2.2.2.4 Summary of estimation approaches

As this thesis progresses, we are going to focus on CL and HB modelling approaches to investigate different aspects of consumer preferences and behaviours.

We apply CL models in Chapters 3, 4 and 5, as well as an HB model in Chapter 5. Here, we compare the selection of these models to other approaches that have been discussed above.

In Chapter 3, we investigate whether survey items presented before the choice procedure influence respondents' preferences. To achieve this, we have adopted a split sample procedure based on a CL modelling approach. This approach is particularly suitable for the analysis in this chapter due to its ability to handle choice data where alternatives are characterised by attributes. We see the following three main criteria for our selection:

- Simplicity and interpretability: The CL model provides straightforward estimates of attribute-level effects on choice probabilities, which is crucial for understanding the direct influence of survey items on preferences (McFadden, 1974).
- Established methodology: The CL model has a well-established theoretical foundation and is extensively used in empirical studies, making it a reliable choice for investigating the influence of survey items (Train, 2009).
- Efficiency in estimation: Given the split sample approach, the CL model allows for efficient estimation and comparison across different sub-samples without the computational complexity associated with more advanced models.

In Chapter 4, we explore the interaction effects between different attributes to quantify synergetic effects within product bundles. Here, again, the CL model was chosen for its suitability in analysing attribute interactions within choice experiments. We identify the following three main criteria for our selection:

- Ability to model interaction effects: The CL model can be easily extended to include interaction terms between attributes, enabling the analysis of synergies within product bundles (Louviere, et al., 2000).
- Empirical validation: The CL model's results can be directly interpreted to assess the significance and magnitude of interaction effects, facilitating straightforward empirical validation and hypothesis testing.

- Comparative baseline: Using the CL model provides a baseline comparison for more complex models, ensuring that the identified interaction effects are robust and not some artefacts of model complexity.

In Chapter 5, we aim to do a regression analysis based on individual utility estimates obtained from the DCE with an individual digital maturity assessment to examine the influence of perceived digital maturity on preferences. For this analysis, we employ an HB model as well as a CL model. We establish the following main criteria for our selection:

- Individual-level parameter estimates: The HB model excels in estimating individual-level parameters, allowing for a detailed analysis of how perceived digital maturity influences preferences at the individual level (Rossi & Allenby, 2003).
- Handling heterogeneity: By incorporating random coefficients, the HB model effectively captures heterogeneity in preferences that may arise from variations in digital maturity, which is crucial for understanding diverse consumer behaviours (Train, 2009).
- Bayesian framework advantages: The Bayesian framework of the HB model provides a flexible approach to incorporate prior information and achieve robust parameter estimates, particularly useful in cases with smaller sample sizes or complex model structures (Huber & Train, 2001).
- Ability to model interaction effects: We apply the CL model again as it can be easily extended to include interaction terms, which can directly be interpreted to assess the significance and magnitude of interaction effects. Moreover, the CL model serves as the double-check approach for the HB estimation regression results.

In contrast, we decided not to include MNL, LC, HCM, and MLM models. MNL models model preferences based on the buyers' characteristics, not on the alternatives'. LC models are powerful in identifying segments with distinct preference patterns. Even though it is possible to obtain individual-level estimates, we decided not to use an LC model, as the core research questions do not revolve around explicit market segmentation but rather on the influence of specific attributes and individual-level heterogeneity. Nevertheless, in panel-data applications, which are common in stated choice experiments, LC models are able to generate individual-level estimates by combining estimates of class membership probabilities with within-class parameters (Scarpa & Thiene, 2005; Scarpa, et al., 2005; Sarrias & Daziano, 2017). Scarpa and Thiene (2005) show how LC models capture different intensities of preference in environmental-choice contexts, while Scarpa et al. (2005) incorporate error components to address status quo effects. There are different approaches how to produce individual-level utility parameters and WTP estimates for LC specification in both open source, such as the gmnl package for R (Sarrias & Daziano, 2017), and commercial software tools, such as NLOGIT (Greene, 2016).

For determining the number of latent classes in a LC model no universally accepted approach exists that predefines the exact number of classes prior to model estimation. Existing methods rely on approximation procedures that evaluate statistical fit ex-post, such as the Bayesian Information Criterion (BIC), the Akaike Information Criterion (AIC), and likelihood ratio tests (Nylund, et al., 2007). While BIC is a consistent model selection criterion favouring parsimonious models, AIC tends to identify models that better fit the data by imposing lower penalties for complexity. Andrews and Currim (2003) demonstrated that modified criteria like AIC3, which increases the penalty term, can significantly improve segment retention accuracy in finite mixture logit models by reducing over-parameterisation errors. In addition, Yang and Yang (2007) emphasised the limitations of traditional criteria, showing that adjusting for sample size and complexity can improve class separation accuracy in LC models. Additionally, a Bootstrap Likelihood Ratio Test offers a robust alternative to address non-regularity conditions in LC models and improve the precision of class estimation, particularly for studies with limited sample sizes (Tekle, et al., 2016). Despite their strengths, these methods require iterative estimation of models with varying numbers of classes to identify the most appropriate fit, underscoring their computational intensity (Nylund, et al., 2007).

Even though HCMs combine psychological constructs with choice data, which offers insights into decision-making processes, their complexity and data requirements make them less practical for the scope of this thesis (Ben-Akiva, et al., 2002). Like HB models, MLMs handle preference heterogeneity and relax the IIA assumption; however, they require significant computational power and can be challenging to estimate, especially for large datasets (Train, 2009).

To summarise, the selection of the CL model for all chapters of the thesis is justified by that approach’s simplicity, interpretability, and efficiency in modelling attribute-level effects and interactions. The HB model used in Chapter 5 is chosen for its superior capability in estimating individual-level parameters and handling heterogeneity, making it ideal for analysing the influence of perceived digital maturity on preferences. These choices align with the specific objectives of each part of the thesis, ensuring robust and meaningful insights into consumer preferences.

Table 1 summarises the different characteristics of all models and estimation approaches that we presented throughout the previous subchapters. In the following chapters, we present in more detail the theoretical foundations of CL and HB models.

Table 1: Comparison of DCE/CBC models

Chapter/Aspect	MNL or CL	LC	HCM	MLM	HB
Application Context	Transportation, market research, environmental evaluation	Market/customer segmentation targeted market strategies	Contextual, psychological/sociological factors in choices	Advanced market research, healthcare, environmental studies	Customised product design, personalised marketing, precision medicine
Flexibility & Type of Preferences	Limited flexibility, assumes homogeneous preferences	Incorporates heterogeneity for segments, not individuals	Superior flexibility, includes behavioural aspects for individualised preference modelling	Captures individual preferences and complex choice behaviour through random coefficients	Models individual and highly personalised preferences, highest flexibility
Independence of Irrelevant Alternatives (IIA)	Subject to IIA, issues can be partially addressed with nested logit	Partially circumvents IIA through segmentation, introducing flexibility	Designed to overcome IIA by integrating latent variables for realistic substitution patterns	Overcomes IIA with correlation in unobserved factors and random coefficients	Does not assume IIA, offers freedom in modelling substitution patterns
Data and Sample Size Requirements	Requires less detailed data, efficient with smaller samples	Requires data supporting segmentation, more data than MNL and CL	Requires detailed information on preferences and socio-psychological factors, can be efficient with moderate samples	Flexible with data requirements, can work with individual and aggregate data	Highly data-intensive, requires detailed choice data at the individual level
Sources	McFadden (1974) Train (2009) Louviere, et al. (2000) Ben-Akiva & Bierlaire (1999) Bhat, et al. (2000) Hensher, et al. (2005) Hensher & Greene (2002)	Greene & Hensher (2003), Temme (2009) Kamakura & Russell (1989) Ben-Akiva & Bierlaire (1999) Hensher, et al. (2005) Hensher & Greene (2002)	Abou-Zeid & Ben-Akiva (2014) Ben-Akiva, et al. (2002) Ben-Akiva & Bierlaire (1999) Vij & Walker (2014)	Hess et al. (2006) McFadden & Train (2000) Greene & Hensher (2003) Revelt & Train (1998)	Allenby & Ginter (1995) Allenby & Rossi (1999) Train (2009) Lenk (2014) Marshall et al. (2010)

2.2.3 Multinominal and Conditional Logit Models (MNL, CL)

MNLs are based on the assumption that ϵ_i is distributed according to an extreme value type I distribution, while X_i stands for a linear and additive form of the observed attributes (Kim & Park, 2017; Sarrias & Daziano, 2017). For this approach, choice is modelled as a function of the characteristics of the individuals, which means that a different individual choice is a result of individual preferences (Hoffman & Duncan, 1988).

MNL models are restricted by two major drawbacks: First, the assumption of IIA requires that the individual choice alternatives need to be strictly independent from each other as consumers' preferences are no subject to relative comparison (McFadden, 1974; Luce, 1959). Second, MNL models cannot capture the heterogeneity of the respondents, i.e., β in the utility function is the same for all the respondents (Temme, 2009; Hensher & Greene, 2002). Nevertheless, MNL models estimate a function of the individual's characteristics. This assumes that individuals behave differently and have different preferences in the case of identical situations with identical alternatives (Hoffman & Duncan, 1988).

The conditional logit model (CL) is based on the assumptions that all ϵ_i within the RUM are identical and independently attributed. Given these preconditions, the selection probabilities of McFadden's so-called conditional logit model can be formulated as follows (McFadden, 1974, p. 113, Sammer, 2007, p. 30):

$$Prob\ (ij) = \frac{\exp\ (V_i)}{\sum_{j=1}^{j=J} \exp\ (V_j)} \tag{4}$$

The model is a function of the probability of choosing alternative j, which represents a non-linear expression of probabilities which is always between 0 and 1.

For MNL and CL models, the estimation of the values of β is achieved through the maximum likelihood method (McFadden, 1974, p. 115; Temme, 2009). Interpretation aids are necessary for comparing the estimated values. Thus, ratios of the utility weights can be interpreted as the MRS, i.e., the customer's willingness to give up one attribute in favour of one more unit of another attribute to keep his/her utility constant ($\Delta U_i = 0$). Within this understanding, WTP values stand for the MRS between an attribute and the costs and can be calculated by the first derivative of the utility function with respect to an attribute and the cost attribute. This leaves WTP as the quotient of the parameter of the attribute β_x and the parameter of the cost attribute β_c (Sammer, 2007, p. 30):

$$WTP_x = -\frac{\frac{\partial U}{\partial x}}{\frac{\partial U}{\partial C}} = -\beta_x / \beta_C \quad (5).$$

2.2.4 Hierarchical Bayes estimation (HB)

In the realm of market research, understanding individual consumer preferences is important for accurately predicting market behaviours and preferences. Traditional methods often assume a homogeneity among consumers that fails to capture the diverse landscape of individual decision-making processes. As noted by Frischknecht et al. (2014, p. 499) *"[a] primary motivation for studying individuals, even when the aggregate behaviour such as the prediction of market share is the object of interest, is that individuals behave differently from one another both in terms of their preferences and also in terms of their decision processes.*" Here, we introduce the HB estimation method for a DCE/CBC analysis, exploring why it is essential, how it differs from other methods, and its theoretical underpinnings.

Preference simulations often rely on several assumptions that may not fully align with real market conditions. These include equal awareness and availability of all products, no product scarcity, the inclusion of all relevant attributes, and the absence of budget constraints for respondents. Hein et al. (2022) caution that the choice shares derived from such simulations are better seen as relative indicators of preference rather than direct estimates of WTP. Consequently, if we assume that individuals are similar, we might have inaccurate conclusions at the individual or aggregate level (Frischknecht, et al., 2014; Islam, et al., 2009; Marshall, et al., 2010; Sawtooth Software, 2017). Furthermore, only making choices is an inefficient way to elicit preferences, as we gain less information from letting the respondents rate every alternative in the set individually (Sawtooth Software, 2017). Therefore, it might be helpful to introduce a layer of individual-level random effects to capture the heterogeneity in consumer preferences. This allows for a more flexible model that can account for differences in tastes among consumers.

The evolution of choice models has seen a significant shift from the initial 'top-down' models conceptualised based on McFadden's work (1974). These models start with an aggregate population choice model, assuming a distribution of population preferences from which individual-level parameters are derived. Over time, the exploration of top-down models has expanded from basic, fixed-effects models to more complex forms involving random parameters, such as LC or MLM models (Kamakura & Russell, 1989; Temme, 2009; Hensher & Greene, 2002; Hess, et al., 2006).

In this thesis, we use, amongst others, a top-down approach based on an HB analysis, which uniquely adjusts the results for each respondent based on the aggregate distribution of choices. This method not only yields a model for each individual respondent but also incorporates the influence of aggregate choices in the estimation of the individual's preferences (Marshall, et al., 2010; Sawtooth Software, 2021).

As noted earlier, HB models offer several advantages for analysing consumer choice data. Firstly, the ability to model individual-level preferences allows for a very detailed understanding of consumer behaviour. (Allenby & Rossi, 1999; Allenby, et al., 2005). Secondly, HB models are flexible in handling complex models that include, for example, interaction or non-linear effects. This means they are more suitable to simulate real-world decision-making scenarios (Lenk, et al., 1996). Furthermore, HB models can use prior information, which enhances the robustness and reliability of the estimation. Thirdly, unlike the MNL or CL models, HB models do not suffer from the IIA assumption (McFadden & Train, 2000). Moreover, the Bayesian framework of HB estimation allows for the explicit quantification of uncertainty in parameter estimates, providing valuable insights into the confidence of the model's predictions (Train, 2009).

The successful application of an HB estimation in DCE/CBC analysis depends significantly on the type and quality of data. The robustness and flexibility in modelling individual preferences requires data that is rich in both depth and complexity (Allenby & Rossi, 1999). The analysis is particularly well-suited to data emerging from queries where respondents are presented with sets of alternatives and asked to choose their preferred option. The data must capture a wide range of attributes and levels to ensure the model can accurately estimate individual-level utilities (Lenk, et al., 1996). It should be free from biases such as non-response bias or selection bias, which can distort the estimation of preferences (Train, 2009). It is also crucial that the data accurately reflects the population of interest to ensure the generalisability of the findings (Orme, 2020). Generally, a larger number of observations per respondent leads to more precise individual-level estimates.

HB approaches also have challenges and downsides. The computational complexity of HB models requires considerable processing power in Bayesian statistics, making it potentially inaccessible without the necessary computational resources or software applications. Additionally, the iterative nature of HB estimation, typically involving MCMC methods also used in this thesis, can lead to long calculation procedures, especially in the case of large data sets. This means it is necessary to ensure that the model accurately reflects the underlying decision processes of consumers. Misspecification can lead to biased estimates or overfitting, particularly in cases where the model complexity does not match the data. These challenges necessitate a careful balance between model complexity and interpretability, as highlighted by Train (2009).

To summarise, the key differences between HB and other estimation methods lie in HB's individual-level modelling capabilities and its flexibility in handling preference heterogeneity. Unlike the MNL or CL models, which estimate a single set of utility parameters for the entire sample, HB approaches capture individual variations in preferences. This differs from traditional logit models, which can cover significant variations in consumer preferences. Furthermore, HB does not rely on the IIA assumption, providing a more realistic representation of choice behaviour. These distinctions are crucial for researchers and practitioners who want to understand consumer decision-making, as discussed in McFadden and Train's (2000) work, which compares various DCMs and highlights the methodological innovations brought about by HB estimation.

Later in the thesis, we report the average relative importance of the attributes (see Table 25) to indicate how much each attribute influences respondents' overall choices. These importance values are calculated at the individual level using the part-worth estimates derived from the HB model and afterwards averaged across the entire sample. The average relative importance, by definition, sums to 100 across all attributes in the model, reflecting each attribute's share of influence on choice (Sawtooth Software, 2017).

To compute an attribute's relative importance, first, the range of part-worth utilities for each attribute (i.e., the difference between the highest and lowest utility estimates) is determined. The relative importance of an attribute is the ratio of its range to the sum of the ranges across all attributes, then expressed on a 0 to 100 scale. Therefore, attributes with larger utility ranges are more influential on choice, whereas attributes with smaller ranges have less influence on choice.

While these importance scores can offer a straightforward summary of how each attribute influences choice probability, they do not map directly to choice probabilities themselves. Instead, they reflect how much movement across an attribute's levels (e.g., going from a low to a high price) affects the utility of a given product profile. Actual choice probabilities are typically calculated by applying these part-worths within a logit model framework, where the exponentiated sums of part-worths for each alternative are compared (Orme, 2020).

It is also important to exercise caution when interpreting the relative importance across studies. They are sensitive to the range of levels defined for each attribute. For instance, if the price attribute spans from 4.99 € to 9.99 € in one study and from 4.99 € to 19.99 € in another, the price in the first study may appear to have a smaller influence simply because of the narrower range. In addition, if one study includes three attributes and another includes six, the average importance in the second study will generally be lower per attribute because the sum of all attributes' importances is normalised to 100 within each study (Sawtooth Software, 2017).

In the further course of this chapter, we elaborate more on the foundations of Bayesian estimation and the hierarchical model, including the MCMC, as these are the groundwork for one application in this thesis.

2.2.4.1 Bayesian estimation

The connection between choice (or conjoint) studies and Bayesian estimation originates in utility theory (Lenk, 2014). Like the foundation of DCEs by Luce (1959) and Lancaster (1966), Bayesian analysis (BA) is based on utility theory, which was further developed by Savage (1972) to incorporate subjective probability. Savage's work extended the rational preference axioms outlined by von Neumann and Morgenstern (1944), providing a framework where probability becomes a subjective measure of belief (1972). He applied this framework to inference, deriving decision rules that optimise expected utility (or minimise expected loss) based on the decision maker's subjective probability assessments of parameters.

Central to the BA lies Bayes' theorem, a fundamental concept in probability theory. Bayes' theorem describes how to update beliefs in the face of new evidence (Bayes, 1763). It mathematically formalises the process of refining prior beliefs based on observed data. Initially, the decision maker starts with prior beliefs about the parameters of interest, represented by prior distributions. As new data become available, Bayes' theorem allows for the updating of these prior distributions to obtain posterior distributions, which reflect the incorporation of the new evidence (Lenk, 2014; Gelman, et al., 2013; Sawtooth Software, 2021). The theorem mathematically expresses how the likelihood of observing the data given the parameters (the likelihood function) is combined with the prior beliefs (about the parameter) to obtain the updated posterior beliefs about the parameter.

This iterative process of updating beliefs using Bayes' theorem is central to BA, allowing decision-makers to make informed decisions based on both prior knowledge and observed data. In conjoint models, BA provides a unique framework where both the mechanism for generating data and the philosophy of inference are derived from shared theoretical foundations (Lenk, 2014).

Bayesian methods (BM), compared to conventional ones like MNL or CL models, offer several advantages. HB estimation, for instance, provides better individual value estimates by incorporating hierarchical structures and sharing information across individual respondents (Rossi, et al., 2005). This leads to more precise estimates, especially in situations with limited data or diverse populations. In CA, BM maintain equivalent accuracy with shorter questionnaires compared to traditional approaches (Train, 2009). This is achieved by utilising the hierarchical model structure to effectively pool information across respondents, thereby enhancing parameter estimation by borrowing strength from shared data characteristics. As a result, BA reduces the need for extensive data collection while preserving statistical power (Allenby & Ginter, 1995). Additionally, BM allow for the extraction of valuable individual-level estimates where aggregate estimates were previously predominant. This is particularly beneficial in fields like customer satisfaction research or laboratory choice experiments in psychology, where understanding individual preferences and behaviours is essential for decision-making (Frischknecht, et al., 2014). The goal of having individual preferences is something that we want to utilise for this thesis, as we want to investigate if there is a connection between individual preferences for an offer (part-worth utility) and the stated evaluations (DM assessment) by the buyer for the attributes of that offer.

BA builds on three kinds of probabilities: (1) prior probabilities are the probabilities we would assign before we see the data, (2) likelihood is the probability of the data, given a particular hypothesis or model and (3) posterior probabilities, which are the probabilities we would assign after we have seen data. Posterior probabilities are based on the priors as well as information in the data (Johnson, 2000; Sawtooth Software, 2021; Gelman, et al., 2013). For a BA, the so-called 'Baye's Rule' is applied (Johnson, 2000):

$$\mathrm{p}(\mathrm{X} \mid \mathrm{Y}) = \frac{p(Y \mid X) * p(X)}{p(Y)} \quad (6),$$

where:

p(X) = is the marginal probability of X (e.g., without respect to Y),

p(Y) = is the marginal probability of Y (e.g., without respect to X),

$p(X|Y)$ = is the conditional probability of X given Y.

Bayes' Rule gives us the conditional probability of X given Y if we know the conditional probability of Y given X and the two marginal probabilities. In a practical context, the probability in the denominator in equation (6) is often hard to compute, especially as it often depends on arbitrary factors like the way measurements are made and data are coded. Therefore, the denominator is often regarded as a constant, which is expressed as:

$$\mathrm{p}\,(\mathrm{X} \mid \mathrm{Y}) \propto \mathrm{p}(Y \mid X) * p(X) \tag{7}$$

where the symbol ∝ means 'is proportional to'. Thus, equation (7) states that posterior probabilities are proportional to likelihoods times priors, which is an expression of the 'Bayes theorem' that illustrates the core understandings of BA (Johnson, 2000; Sawtooth Software, 2021; Allenby, et al., 2005; Train, 2001):

- $p(X)$ is the probability of the hypothesis that is known as its 'prior probability', which describes the assumption about that hypothesis before the data is seen.
- $p(Y \mid X)$ represents the likelihood of the data, which is the conditional probability of observing the specific dataset given the hypothesis. It quantifies how probable it is to encounter that exact set of values under the hypothesis about the data.
- $\mathrm{p}\,(\mathrm{X} \mid \mathrm{Y})$ denotes the "posterior probability" of the hypothesis about the data. It represents the likelihood of the hypothesis after integrating both prior knowledge and the insights derived from the data.

The posterior probability of a hypothesis is determined by multiplying the likelihood of observing the data, assuming that the hypothesis is true, by the initial probability of the hypothesis. This process of BA allows for the refinement of probability estimates. It begins with a preliminary assessment of a hypothesis's likelihood. Then, it incorporates data-based evidence to produce an updated, posterior estimate that merges prior beliefs with the insights gained from the data (Sawtooth Software, 2021).

BAs are associated with different characteristics and advantages. They are expected to offer 'subjective probabilities', where prior beliefs are specified, potentially affecting the outcome of the analysis. However, in large-scale applications using HB, the impact of priors is often minimal due to the abundance of data. This allows for robust posterior estimates even when sensible priors are unavailable. In BA, the concept of 'inverse probabilities' is employed, where parameters are treated as random variables and data are fixed after observation. This contrasts with conventional analysis, which views parameters as fixed and data as variable. By treating parameters as random variables, BA allows for more flexible and intuitive inference, enabling a deeper understanding of uncertainty in the model. While Bayesian models may seem conceptually simple, their practical implementation often requires complex computer simulations. These simulations can be computationally intensive and time-consuming, potentially taking hours to complete. Despite these challenges, the computational complexity of BM is justified by their ability to provide more accurate and nuanced estimates (Johnson, 2000; Allenby, et al., 2005; Train, 2001).

2.2.4.2 The Hierarchical Model and the Monte Carlo Markov Chain

We now turn our attention to an overview of the hierarchical model that is used in combination with the HB estimation applied in this thesis. In Chapter 2.2.4.2, we give an overview of the calculation procedures that are carried out for the HB estimation on CBC by the Sawtooth Software, which we used to obtain the individual HB part-worth estimates (2021). For more details and further technical explanations, we refer the reader to the relevant technical papers (Sawtooth Software, 2017; 2021; 2024a; Marshall, et al., 2010).

Bayesian updating of probabilities is the conceptual apparatus that enables estimating the model parameters, which builds on the relationship between priors, likelihoods, and posterior probabilities introduced in the previous chapter.

The term 'hierarchical' within the HB model that is used in this thesis refers to two levels: a higher overall and a lower individual level. The assumption is that at a higher level, the individual part-worth utilities are described by a multivariate normal distribution, which is characterised by a vector of means and a matrix of covariances. The concept of part-worth utilities refers to numerical scores that measure how much each attribute level influences the customer's decision to select an alternative. Part-worth utilities refer to the individual utilities of each part of the alternative. They are also known as attribute importance scores and level values or simply as conjoint analysis utilities and show only mean (average) preferences and importances. For the second, lower, and individual level, it is assumed, based on the individual's part-worths, that the probabilities of choosing particular alternatives are governed by a multinomial logit model (Sawtooth Software, 2021; Lenk, 2014). It is further assumed that individual part-worths have the multivariate normal distribution

$$\beta_i \sim \mathrm{Normal}(\alpha, \mathrm{D}) \tag{8},$$

where:

β_i = is a vector of part-worths for the individual i,

α = is a vector of means of the distribution of individuals' part-worths,

D = is a matrix of variances and covariances of the distribution of part-worths across individuals.

At the individual level, choices are described by an MNL model. Equation (9) specifies the probability of observing the entire sequence of choices $k_1, k_2, \dots, k_T$ made by individual i across T repeated choice tasks. Under the MNL model and the assumption of conditional independence given β_i the probability of each chosen alternative k_t in task t is given by the standard MNL formula. The overall (joint) probability is then the product of these per-task probabilities, reflecting that the same individual makes all T choices (i.e., panel data).

$$P_i^T(k_1, k_2, \dots, k_T) = \prod_{t \in T} \frac{exp(x'_{k_t}\, \beta_i)}{\sum_j exp(x'_j\, \beta_i)} \tag{9}$$

where:

i = denotes the individual.

T = is the set (or number) of choice tasks in which the same individual i participates.

k_t = is the chosen alternative at choice task t.

x_{k_t} = is the vector of attributes associated with the chosen alternative k_t.

β_i = is the vector of coefficients

Equation (10) thus provides the joint probability of respondent i's entire sequence of choices across T tasks. Each individual-level probability in the product is computed using the standard MNL model. Concretely, for each task t, the part-worths (i.e., the elements of β_i) associated with a specific alternative k_t are multiplied by its attribute-level descriptors to obtain the individual's utility for that alternative (Sawtooth Software, 2021). This utility is then exponentiated, and the same exponentiation procedure is carried out for all competing alternatives in that choice task. Dividing the exponentiated utility of alternative k_t by the sum of exponentiated utilities of all alternatives yields the probability of choosing k_t in task t. When repeated for tasks 1 to T, the product of these per-task probabilities gives the overall likelihood of observing the sequence of choices $\{k_1, k_2, \ldots, k_T\}$ made by respondent i. In an HB estimation, these individual-level parameters β_i (i.e., part-worths) are assumed to come from a higher-level distribution with mean vector α, representing the average part-worths in the population, and the covariance matrix D, which captures the variance and covariance structure among the part-worths across individuals (Sawtooth Software, 2021).

The parameters β_i, α, and D are estimated by an iterative process which does not depend on starting values. Hence, all elements are set equal to zero. Each iteration consists of three phases: (1) estimation of α, given β and D; (2) estimation of D, given α and β; and (3) estimation of β, given α and D. Therefore, in each phase, one set of parameters is conditionally re-estimated (α, D or β), given current values for the other two sets. The procedure converges to the correct distributions for each of the three sets of parameters. This technique is known as "Gibbs sampling", which belongs to the area of MCMC algorithms and goes back to the work of Geman and Geman (1984) who used it to study image processing models. It is a technique mainly used in the case of BM for indirectly generating random variables from a marginal distribution without having to calculate the density (Casella & George, 1992).

For the first phase (1), It is assumed α is distributed normally with a mean equal to the average of the betas and a covariance matrix equal to D divided by the number of respondents. A new estimate of α is drawn from that distribution with a mean equal to the mean of the current betas and with a covariance matrix 1/n D (Sawtooth Software, 2021). In the second phase (2), based on existing estimates of the betas and α, a new estimation for D is drawn from an inverse Wishart distribution, which is used in Bayesian statistics as the conjugate prior for the covariance matrix of a multivariate normal distribution (Bodnar, et al., 2016; Sawtooth Software, 2021). In the third phase (3), updated betas are estimated based on the present estimates of α and D. For this purpose, the procedure of the Metropolis-Hastings algorithm (MHA) is used, which is a Markov chain method to simulate multivariate distributions (Chib & Greenberg, 1995; Sawtooth Software, 2021). Successive draws of the betas generally provide a better fit of the model to the data until the model converges (i.e., the model fit cannot be further improved)

The MHA in the HB model is used to obtain a new set of betas, which is performed for each respondent in turn. β_O (for 'beta old') is employed to denote the prior iteration's estimate of individual part-worths. Then, a tentative value for the new estimate is created, designated as β_N (for 'beta new'), and evaluated according to its improvement over the previous estimate. The acceptance of β_N as the subsequent estimate depends on its comparative improvement or, in cases of inferiority, a probability-based decision. To derive β_N, a random vector d is extracted, representing differences from a zero-mean distribution with a covariance matrix scaled by D, setting $\beta_N = \beta_O + d$. The data's likelihood for both β_O and β_N part-worths is assessed through the logit model's formula, calculating individual choice probabilities using the logit equation for p_k and aggregating these probabilities to obtain values p_O and p_N, respectively (Sawtooth Software, 2021).

Afterwards, the relative density of the beta distribution for β_O and β_N is determined based on current parameter estimates α and D, which act as priors in Bayesian updating. These densities are referred to as d_O and d_N, respectively. The relative density at a specific point β is given by the following formula (Sawtooth Software, 2021):

$$Relative\ Density = \exp\left[-\frac{1}{2}(\beta - \alpha)'\, D^{-1}(\beta - \alpha)\right] \tag{10}$$

Which leads to the calculation of the ratio:

$$r = \frac{p_N\, d_N}{p_O\, d_O} \tag{11}$$

Within the Bayesian updating approach, the posterior probabilities of the beta estimates β_N and β_O are determined by multiplying the likelihoods by the priors. The probabilities p_N and p_O, corresponding to the parameter estimates β_N and β_O, respectively, are proportional to these estimates' likelihoods and serve as priors. The ratio r between the posterior probabilities of β_N and β_O, given current estimates of α and D and the data, guides the acceptance of β_N as the new beta estimate. If r is greater than or equal to one, β_N is preferred for its higher or equal posterior probability. If r is less than one, indicating β_N has a lower posterior probability than β_O, it is decided randomly, accepting β_N with a probability equal to r (Sawtooth Software, 2021).

In deciding to accept a new beta estimate, both data fit and relative densities against current parameters α and D are assessed. A better fitting β_N or a higher relative density gives an estimate for the advantage. Ignoring densities would lead to choices based purely on maximising likelihoods, similar to individual estimates. However, incorporating densities accounts for variations in the higher-level distribution across iterations, leading to significant differences in successive beta estimates. These variations reveal information about the individual-specific random variance in the part-worths (Sawtooth Software, 2021; Allenby & Rossi, 1999; Allenby, et al., 2005).

The software Sawtooth uses an adaptive algorithm for the 'jumping distribution' of the difference vector d, aiming for an acceptance rate of around 0.30. Starting with a scale factor of 0.1, the jump size is adjusted based on the acceptance rate of β_N, ensuring convergence efficiency by modifying the jump size to keep the acceptance rate near the target. A jumping rate between 0.2 and 0.44 is also suggested in the literature (Sawtooth Software, 2021).

The first sequence of the three phases is carried out with numerous iterations until convergence is ascertained. In the second phase, further numerous iterations of the draws are carried out, but this time, the actual draws for each individual observation and the estimates of α and D are saved. The final values of the part-worths (betas) for each individual, as well as of α and D, are calculated by averaging the sequence of the two values that have been saved (Sawtooth Software, 2021). This means that (average) point estimates from the saved iterations are created, as well as variances and covariances of the distribution of respondents.

For further details on the drawing and estimation procedure, we refer to Appendix 1 of the technical paper for the HB estimation on CBC by Sawtooth Software (2021). Here, the random draws of α from a multivariate normal distribution and Cholesky decomposition for D are presented for the first iteration sequence.

2.3 Servitisation as the guiding framework for the survey design

The DCE survey in this thesis is based on a model for product-service bundles, especially for energy and utility companies (Grahsl, 2013; Grahsl & Velamuri, 2014). This approach is based on the concept of ‘servitisation’, which says that adding services to physical product offerings adds value for the customer, improves customer relationships, and thus increases the economic success of the supplier or firm (Vandermerwe & Rada, 1988). The initial understanding of servitisation was derived from investigations of manufacturing firms and how they combine tangible products with (non-tangible) services. Servitisation refers to the shift of a manufacturing firm’s product portfolio towards a higher degree of integrated service offerings (Vandermerwe & Rada, 1988). Although numerous other definitions of servitisation were subsequently developed, these still fundamentally align with the core definition of Vandermerwe and Rada (1988), as the delivery of product-based services can be stated as a universal feature (Baines et al., 2009). The current understanding can, therefore, be presented in light of the basic consideration that companies create value by adding services or additional product components to their core product offerings (Tukker, 2004; Oliva & Kallenberg, 2003). We will elaborate on the topic of servitisation in the further course of this thesis within the different applications.

Grahsl (2013) used the concept from Vandermerwe and Rada (1988) for developing a business-to-customer (B2C) servitisation approach for energy and utility companies that groups different components around the core commodity offering (electricity, gas, warmth, etc.): physical products, service, knowledge, support, and self-service (Grahsl & Velamuri, 2014). Based on a case study approach, the research showed that utilities tend to combine the core commodity with service components. Additionally, other components (e.g., physical products, knowledge, support or self-service) are added for respective consumer offerings (Grahsl & Velamuri, 2014).

For the survey setup of this thesis, Grahsl's (2013, p. 206) analysis of German and Austrian energy providers was expanded with additional desk research, which led to a long list of product and service offers within the German-speaking consumer electricity market. In total, about 200 products and services have been listed and assigned to the stages and components of the energy servitisation framework. The mapping of the products according to the components of the model is displayed in Table 2.

Table 2: Classification of products and services examples

Stage	Components	Market offerings of energy providers
1	Commodity	Electricity, gas, heat, water
2	Service	Contractual time, notice period, fixed prices, fixed generation source (e.g. green energy), bonuses, flat rate tariffs, financing for decentral generation, commodity bundles (electricity and gas), certifications, electricity for heating
3	Product	Metering devices, storage systems/batteries, tablet/mobile phone, recharge infrastructure for e-mobility, scooter (e-mobility), smart whiteware, mCHC devices, photovoltaic devices, media streaming subscription, 'cloud' storage of PV generation, LED light bulbs, smart plugs, telecommunication and mobile phone contracts, smart thermostats, internet contracts
3	Knowledge	Operation models for maintenance, sponsor support for renewables, energy performance certificates, ecological restoration counselling, energy efficiency consulting
3	Support	Service hotline (call centre), invoice counselling, energy efficiency consulting, moving service, information for tariffs, peer-to-peer-support, communities, e.g. for e-mobility, switching service (for new customers)
3	Self-service	Online customer portal, mobile phone app, online efficiency tips based on consumption, calculation of tariff optimisation, app with list of public charging infrastructure, malfunction notification to provider, online shop for smart home devices

Source: Own data collection and aggregation.

Based on these different products and services, we designed a first draft of the choice attributes and attribute levels, which we discussed with professionals from the energy industry. In this discussion, we very much focused on the ‘product’ dimension, as product bundling or servitisation is not very common in the industry. We wanted to find out what physical offers energy executives would regard as relevant for a go-to-market approach.

Below, we elaborate on the attribute development together with industry executives and present the further refinement of the attributes based on the customer perspective.

2.4 Questionnaire development

For the process of the survey design and the DCE setup, we follow the approach proposed by Hensher et al. (2005, p. 104) that gives guidance for the setup of our DCE:

1. Problem refinement
2. Stimuli refinement (alternative identification, attribute identification, attribute level identification)
3. Experimental design consideration (type of design, model specification (additive vs interactions), reducing experiment size),
4. Generation of experimental design
5. Attribute allocation to design columns (main effects vs interactions)
6. Generation of choice sets
7. Randomisation of choice sets
8. Construction of survey instrument

The problem refinement and definition (step 1) of the survey’s research goals have been discussed in the previous chapters. According to Hensher et al. (2005), a carefully formulated problem definition is necessary to create a solid understanding of the research.

2.4.1 Stimuli refinement for the DCE

The second step in designing a DCE is the stimuli refinement (2005) of the relevant attributes for the research subject (Hensher, et al., 2005). Attributes in a DCE can be quantitative, such as cost, or qualitative, such as a service or colour of the product (Kløjgaard, et al., 2012). For the identification of the attributes and attribute level, typically primary and secondary data is collected, which should also be grounded in relevant theory and literature

(Szinay, et al., 2021; Mangham, et al., 2009). For our survey and the DCE, we covered both perspectives, i.e., secondary and primary data. Based on the literature (secondary data), we collected services and products for energy offers, as illustrated in Chapter 2.3. We supplemented this finding by doing desk research and collecting product and service offerings of major energy and utility providers (primary data). We used this database to construct a first draft of the attributes and attribute level that we wanted to use for the research. This draft is presented in Figure 2.

<table>
<tr><th>Attributes for energy services</th><th colspan="4">Level 1</th><th colspan="4">Level 2</th><th colspan="4">Level 3</th></tr>
<tr><td>Contractual time</td><td colspan="4">0,5 years</td><td colspan="4">1 year</td><td colspan="4">2 years</td></tr>
<tr><td>Billing and communication</td><td colspan="4">Monthly bill and communication is send by letter to the customer</td><td colspan="4">D I
Monthly bill and communication is send by E-Mail to the customer</td><td colspan="4">P C D I
Monthly bill and communication is available through online portal</td></tr>
<tr><td>Electricity and change of €/kWh compared to status quo</td><td colspan="4">Green energy, fixed €/kWh
Range of -5%/+5%</td><td colspan="4">P C D I
Smart energy, Changing €/kWh throughout the day
Range of -15%/+10%</td><td colspan="4">Flat energy, fixed amount per month
Range of +15%</td></tr>
<tr><td>Additional devices leading to energy savings compared to status quo</td><td colspan="4">I
5 light saving LED light bulbs
Pot. energy saving 10%</td><td colspan="4">C D I
2 smart thermostats and sensors for automatically adjusting heat
Pot. energy Saving 12%</td><td colspan="4">P C D I
Smart Home tablet device with real time consump-tion information and home device controlling interface
Pot. energy Saving 15%</td></tr>
<tr><td>Availability of service infrastructure and request fulfillment time</td><td colspan="4">Service point,
Travel time 1,5 hours
10 am to 6 pm, Mo - Fri,
immediate request fulfillment</td><td colspan="4">I
Call Center,
10 minutes waiting line
8 am to 8 pm, Mo - Sat,
request fulfillment 12 to 24h</td><td colspan="4">P C D I
Online portal,
no waiting or travel time
24/7,
request fulfillment within 36h</td></tr>
<tr><td>Additional monthly charge to electricity bill</td><td colspan="3">6,00 €</td><td colspan="3">10,99 €</td><td colspan="3">14,50 €</td><td colspan="3">19,95 €</td></tr>
</table>

Process: Software resources for digital representation **Infrastructure:** Connection of the computing systems
Data & Knowledge : *Digital representation of persons/production factors* **Computing:** Collaborating computation platforms

Figure 2: First draft of attributes and attribute levels.

Based on this initial draft, we further reworked the attribute and attribute level based on further primary data research. Our focus was on selecting components that are digital or technology-driven but assumed to be common to most energy customers. The choice set draft was shown to top-level energy industry executives (n = 17; e.g., CEOs, CMOs, sales team leaders, etc.), who were asked what product and service components they regarded as relevant for a consumer offering. Some screenshots of the survey are displayed in Figure 3.

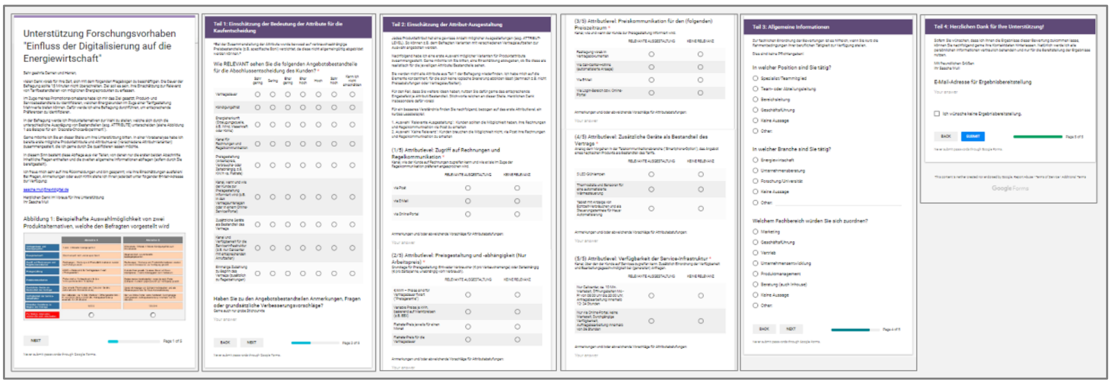


Figure 3: Focus group survey - energy industry executives

Based on this feedback, a second draft of the choice set was developed, which is presented in Figure 4. Building on the feedback suggestions, we eliminated some attributes (e.g., contract time, notice period, and source of energy) and attribute levels (red frames in Figure 4), as well as added new attribute levels (green frames in Figure 4).

Attributes for energy services	Attribute Levels				
~~Contractual time~~ ~~Notice period~~ ~~Source of electricity/energy~~	*All the presented products have the same contraction and notice period. All tariffs are 100% green energy generated. The are no tariffs that are cheaper or in other ways more advantageous that the presented.*				
Access to billing and Communication	Bills and advertisements/ product information are send via mail	Bills and advertisements/ product information are send via E-mail	Access to bills and product information through an online portal		
Pricing	Fixed Price per kWh – prices are defined for the contractual time	~~Variable prices per kWh depending on market prices (e.g. EEX)~~	Flat rate price per month – no dependence on consumption	Flat rate price for contractual time – no dependence on consumption	Prices depending on individual consumption profile/behavior
Price communication	Prices are itemized within the initial contract documents	~~Prices are made available through hotline (automatic information)~~	Prices are send to customer via E-Mail on a daily base for the next day	Prices are constantly made available through an online portal	Prices are made available through automated inbound hotline
Additional devices included in the contract	~~5 light saving LED light bulbs~~	~~2 smart thermostats and sensors for automatically adjusting heat~~	Device with real time consumption information and home controlling interface	Tablet device (incl./excl. data plan)	TV-Gaming device
Availability of service infrastructure	Call Center, 10 minutes waiting line, 8 am to 8 pm, Mo - Sat, request fulfillment 12 to 24h	Online portal, no waiting or travel time 24/7, request fulfillment within 36h	Chatbot, no waiting time 24/7, fulfillment for standard requests	Chat agents, 10 minutes waiting line, no opening ours	
Additional monthly charge to electricity bill	6,00 €	10,99 €	14,50 €	19,95 €	

Figure 4: Second draft of attributes and attribute levels

Even though the energy executives marked these attributes as very relevant for an energy offer in general, we excluded the contractual issues from our attribute draft as the research objective of this thesis focuses on the identification of the impact of digitisation on product and service bundles in the energy sector. We decided that the aspect of having attribute levels that can be designed to be digitally enhanced so that a proper attribute level differentiation was possible was more important than having a highly correct representation of real energy offerings. Furthermore, it was important for us to reduce the number of attributes and attribute levels to keep the survey and thus the cognitive engagement manageable for the respondents (Mangham, et al., 2009; Hensher, et al., 2005). From the first draft, we excluded highly irrelevant, e.g. ‘price communication via hotline’ or technically too complex, e.g. prices per kWh based on real market prices, attributes, as well as attributes that we could not differentiate very well with respect to the digital maturity which we assigned to them, e.g. light bulbs and sensors. The adjusted choice set was shown to possible consumers (n = 55), who were asked to evaluate the second draft choice set components from a consumer’s perspective. This second pre-questioning focused on the component group ‘(physical) product’, as several energy executives had new ideas for the component segment. Screenshots of this second survey are displayed in Figure 5.

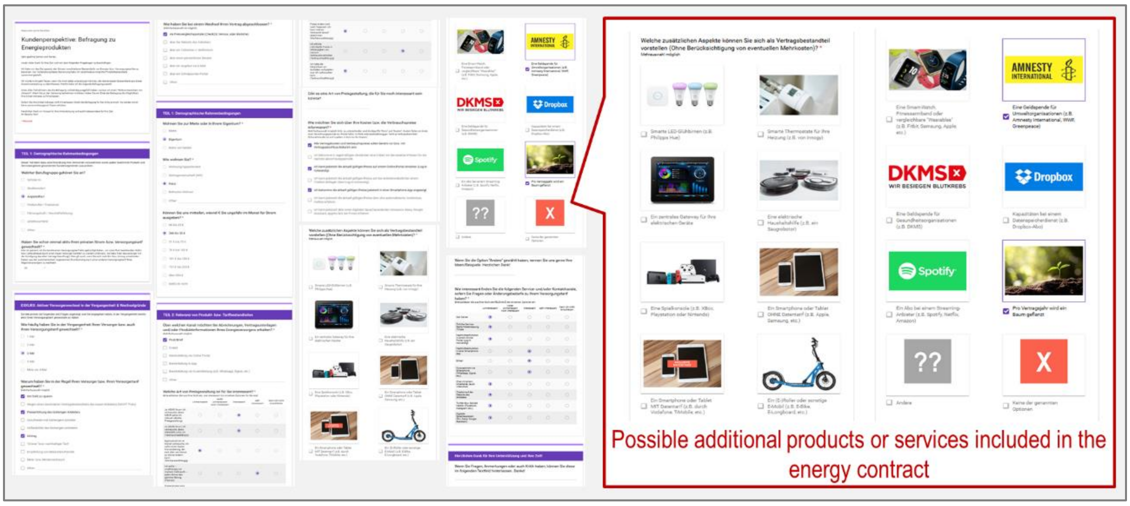


Figure 5: Survey customer perspective.

The combined evaluation of the additional product and service components, either by the customers or the professionals, is shown below in Table 3:

Table 3: Evaluation of relevance of additional product and service components

Additional product or service components	Share of answer items ‘rather high’, ‘high’ and ‘very high’ (perceived relevance)	
	Customers (n=55)	Professionals (n=17)
Smart thermostats and sensors for automatically adjusting heat	13.18%	47.06%
Tree planted for each contractual year	13.18%	-
Robotic/connected vacuum cleaner	10.45%	-
Tablet device (excl. data plan)	9.09%	-
Connected LED light bulbs	8.18%	11.76%
Donation for environmental protection organisation	8.18%	-
Donations for health organisation	8.18%	-
Video stream service subscription (e.g. Netflix)	7.27%	-
E-bike or other electronic mobility devices	6.36%	-
Smartwatch or fitness tracker	4.55%	-
TV gaming device (e.g. Sony PlayStation)	3.64%	-
Tablet device (incl. data plan)	2.73%	-
Data storage service subscription (e.g. Dropbox)	2.27%	-
Smart home controlling interface	0.00%	64.71%
Donations for charity organisations	0.00%	-

Source: Author’s own analysis.

Based on the evaluation by executives and the customer side, the most relevant perceived attributes and attribute levels were included in the final choice design. The two surveys were the foundation for creating a realistic and relevant DCE choice set, as the preferences and utilities of the respondents depend on attributes, not on the product itself (Lancaster, 1966; Temme, 2009). Hence, the attributes and attribute level needed to be realistic and relevant to the topic.

Nevertheless, the levels should allow for trade-offs among attributes (Hensher, et al., 2005). A trade-off happens when respondents give up some of one attribute to get more of another (Ratcliffe & Longworth, 2002). Also, if some attributes have more levels than others, they seem more important (Yang, et al., 2021). Simpler designs have fewer levels, easing the burden on respondents and helping identify which attributes are most important. On the other hand, more complex designs, with more levels, offer greater statistical precision. They are better at showing how attributes trade off against each other (Yang, et al., 2021).

As previously discussed, standard contract elements – such as energy source (e.g., renewable, fossil, or nuclear), contract duration, notice period, and bonuses – are excluded from the choice set. By omitting simpler contractual features that are less relevant to our general hypothesis, the design avoids unnecessary complexity that could detract from the analysis. Respondents were informed that they could select these conventional options later in the hypothetical purchasing process and that none of the attributes in the choice set limits these choices. This approach minimises the risk of excluding relevant, unobserved attributes (Hensher, et al., 2005, pp. 73-74). Since this thesis primarily investigates preferences in electricity supply-service bundles, particularly the impact of servitisation on WTP and customer loyalty, the design decision is methodologically sound. Additionally, including all typical energy contract components would have resulted in an unmanageable number of attribute combinations, complicating the model while offering limited analytical value.

For our design, there was one major divergence in the choice design given the pre-survey evaluation results. After discussing the evaluation results with researchers from the field of hybrid value generation, we decided not to include smart thermostats, instead opting to put smart electricity plugs into the choice set. The reason for this change is the idea that smart plugs are perceived to be useful in the case of variable pricing, which might lead to the identification of possible synergetic relations in addition to the additive linkage within the bundle.

The definition of the price attribute level is based on market prices for the different smart plug versions and displayed as a monthly fee (foundation for calculation: four-room apartment, total costs for the devices calculated over 12 months) for four devices for each alternative with no additional fees included. The final variants can be seen in Figure 6.

Type of plug		Description/ features	Average Price per piece
	Manually Adjustable electricity plugs	• *On-/Off-Programs e.g. based on daytime or days*	*4,00 €*
	Connected Plugs	• *On-/Off-Programs e.g. based on daytime or days* • *Connection to switches or other devices within a closed in-house network*	*10,00 €*
	Smart Plugs incl. App	• *On-/Off-Programms e.g. based on daytime or days* • *Remote Control via smart phone app from the outside* • *Open connection to other home steering systems* • *Measurement of consumption*	*30,00 €*
	Smart plug adapter incl. smartphone app and algorithm	• *On-/Off-Programs e.g. based on daytime or days* • *Remote Control via smart phone app from the outside* • *Open connection to other home steering systems* • *Measurement of consumption* • *Automatization programming ("If this than that")* • *Consumption pattern analysis e.g. based on tariff information, location or behavior*	*80,00 €*

Figure 6: Electricity plugs that are used for the attribute 'additional device'.

The final design of the choice set is shown in Table 4. We also included the names of the variables that we are using throughout the thesis.

Table 4: Attributes included in the DCE

Attribute	**Variable**	**Attribute Level**
Source of price calculation per kWh	PRICECALC0	• Fixed Price per kWh – prices are defined for the contractual time
	PRICECALC1	• Changing prices based on a pre-defined plan (e.g. different prices on weekdays)
	PRICECALC2	• Decreasing prices per kWh each month with an increase or decrease in overall consumption
Price communication and access to bills	(default)	• Prices are itemised within the initial contract documents, and bills are sent via mail
	PRICEMAIL	• Prices and monthly bills are sent via email
	PRICEPORTAL	• Prices and monthly bills made available through an online portal (login necessary)
	PRICEAPP	• Prices and monthly bills made available through a mobile app
Service infrastructure	(default)	• Call centre
	SERVEMAIL	• Email
	SERVCHAT	• Chat agent (also video chat)
	SERVEAPP	• Message service within a smartphone app
	DEVICE0	• No electric plug adapter included

Attribute	Variable	Attribute Level
Additional device included in the contract	DEVICE1	• Manually adjustable electric plug adapter
	DEVICE2	• Local connected electric plug adapter
	DEVICE3	• Smart plug adapter, incl. smartphone app
	DEVICE4	• Smart plug adapter incl. smartphone app, and algorithm
Additional charge to the monthly basic rate	CHARGE	• 0.00 €
		• 4.99 €
		• 9.99 €
		• 14.99 €
		• 19.99 €
		• 24.99 €

Source: Author's own analysis.

With this setup, we combined the structure obtained from the servitisation model and the requirements of a DCE setup. An illustration of the different considerations that have been made is presented in Figure 7.

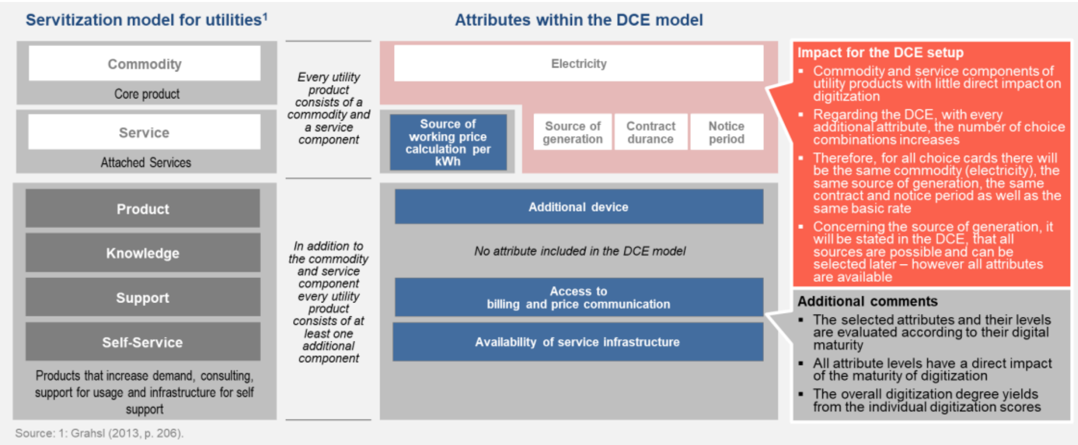


Figure 7: Attribute design and servitisation framework.

It must be mentioned that for attribute groups "price communication and access to bills" as well as "service infrastructure", instead of having two attributes with four attribute levels each, we decided to have a survey design that has six attributes with two attribute levels each: 'yes' or 'no' for being presented within the alternative combination of the choice cards. In addition, we used a default attribute for 'price communication' (-> mail) and 'service infrastructure' (-> call centre) so that at least one default contract component exists for these two items within the alternatives. The reasons for this decision are of a practical nature: If the attributes are presented as 'joint' levels (A, (A+B), (A+B+C) and (A+B+C+D)), we are not able to analyse the individual utility share of the components. This is especially important as we want to identify interaction effects in the second application of this thesis. It could not be determined without a doubt whether the perceived utility (share) of the 'C' in the combination of, e.g. (A+B+C) is the same as in a combination of (A+C+D). Thus, a more conservative and safer approach was chosen. Furthermore, with joint levels, only a limited number of attribute combinations is possible. If we use the binary approach, we can present at least eight possible combinations (example for service infrastructure):

1. Call centre
2. Call centre + Email
3. Call centre + chat
4. Call centre + app
5. Call centre + email+ chat
6. Call centre + chat + app
7. Call centre + email+ app
8. Call centre + email+ chat + app

2.4.2 Experimental design considerations

Having identified the alternatives, attributes, the number of attribute levels, and the attribute-level labels, in the third step of Hensher et al.'s (2005) approach to setting up a DCE, decisions regarding the design to be used must now be made. For this purpose, the understanding of the behavioural impacts should guide the decision-making process, considering the statistical characteristics of the design. Although this approach yields the best outcome, it is often found that the available designs may limit the behaviours that can be explored. One of these designs is a full factorial design, defined as a design where all possible treatment combinations are enumerated (Hensher, et al., 2005).

A full factorial design of all attribute-level combinations is generally defined as N = L*A, where L is the number of levels, while A is the number of attributes. For our survey, this would result in N = 3 * 2 * 2 * 2 * 2 * 2 * 2 * 5 * 6 = 5,760. The full calculation accounts for how these alternatives can be combined in pairs in different choice tasks: $5{,}760^2$ = 33,177,600. The 5,760 combinations with identical pairs are deducted from this. This leads to N = 33,171,840. This is divided by the number of possibilities (2) with which a pair can be obtained by ordering the alternatives. This will determine the total number of unique alternatives available:

$$\frac{N^2 - N}{2} = \frac{(3 \times 2^6 \times 5 \times 6)^2 - (3 \times 2^6 \times 5 \times 6)}{2} = \frac{5760^2 - 5760}{2} = 16{,}585{,}920 \qquad (12).$$

As these treatment combinations would by far exceed the limits of the survey and conventions, we worked with a fractional factorial design (Hensher, et al., 2005, p. 112). It was thus ensured that there is a) no imbalance of the selected attribute levels (i.e., one or more levels are shown more than others) and b) no correlation between the attributes and attribute levels. A survey design that is not fully factorial but respects the mandatory requirements (no imbalance, no correlation) is called orthogonal (Hensher, 2009, p. 115). Some researchers are in favour of fixed orthogonal designs, where a single version of the questionnaire is typically used for all respondents, even though respondents may be randomly assigned to groups with different questionnaire versions (‘blocks’). Orthogonal designs offer maximum efficiency in measuring main effects and specific interactions, especially in symmetric designs, where all attributes have the same number of levels for all attributes (Sawtooth Software, 2017). Other researchers prefer random designs where each respondent encounters a unique set of questions (mainly used with web- or CAPI-administered interviews). These designs, though termed ’random’, are not chosen arbitrarily but are ‘nearly’ orthogonal. While the ‘random’ design is slightly less efficient than truly orthogonal designs in symmetric setups, random designs can be more efficient in asymmetric designs. They allow for the measurement of all interactions, including those not recognised as important at the time the survey is designed, and neutralise psychological context as well as order effects due to a wider variety of choice tasks across respondents (Sawtooth Software, 2017).

Fractional factorial designs have been traditionally employed due to their ability to produce orthogonal designs where the attributes are statistically independent, thereby simplifying the estimation process. These designs allow for a reduction in the number of choice sets, which minimises the cognitive burden on respondents and reduces the likelihood of fatigue. However, the orthogonality of these designs often fails to be preserved through the estimation process, which can result in biased parameter estimates (Rose & Bliemer, 2004).

The literature suggests moving towards statistically optimal designs, such as D-efficient designs, which maximise the information about the parameters of interest, specifically mWTP, while minimising the loss of orthogonality. Huber and Zwerina (1996) and Kanninen (2002) have shown that these designs can provide more efficient parameter estimates even with smaller sample sizes. However, the construction of optimal designs typically involves iterative processes and may require prior knowledge of the parameters, which can be challenging to obtain.

A neutral option ('opt-out') was not included in the choice design. This makes our research a 'forced choice' approach (Dhar & Simonson, 2003). The advantage of an opt-out option is the potential to simulate a real-world context where individuals can exercise their right to make a choice (Szinay, et al., 2021). Furthermore, the literature suggests that if uncertainty in choices is seen as a stress and discomfort factor, the availability of an opt-out takes preference share away from the choices that are made to avoid stress in a forced choice scenario (Dhar & Simonson, 2003). Nevertheless, when a respondent chooses to opt-out, no data regarding preferences and trade-offs are provided. Moreover, as respondents and customers always need to have an energy contract, for our case, we decided to go with the 'forced choice' scenario. In this case, we also did not include an alternative answer choice for the respondents to stay with their existing contract, as this would have been no 'real' opt-out and would have made it difficult to compare preferences. Because of these design decisions, this experimental design may lead to results that are different from those of decisions in the real world. However, it can be argued that an opt-out alternative is not relevant for the case of retail electricity pricing as it can be convincingly stated that consumers may not be aligned to choose any contract at all. This approach is comparable to other studies on consumer preferences and decision-making, where the experimental design is characterised as forced choice design (Dhar & Simonson, 2003).

2.4.3 Generation of the experimental design

The next stage in Hensher et al.'s (2005) experimental design process is the generation of the experimental design (Stage 4). An experimental design is the method of generating the choice sets that are presented to respondents. When creating the experimental design, there are some aspects that need to be taken into account (Szinay, et al., 2021):

(1) The analytical model specification,
(2) Consideration of only main effects or also interaction effects,
(3) Labelling of the design,
(4) Number of choice tasks and blocking options to be used, and
(5) Type of design of the choice matrix.

The **analytical models** used for this DCE are CL models and an HB estimation for a third application. We presented the theoretical foundations of these models in the previous chapters and will introduce the specific applications for the individual research approaches throughout the thesis.

In the following stage, we set out the approach if we want to analyse only **main effects or if we want to uncover interaction effects**. The estimation of main effects within a model only shows the preference estimates for the presented attributes and attribute level. However, it does not show whether there are moderating or interaction effects between the different attributes, more precisely if one attribute level impacts the preference for another attribute level ('two-way-interactions'). Main effects reveal how attribute levels influence the choice outcome, while Interaction effects show the combined impact of two or more attribute levels on preference (Hensher, et al., 2005). As we will investigate the effects of interactions between the attributes and attribute level in the second application, we emphasise this topic below in section 2.7, where we elaborate on the specific survey-related issues for each application. The decision to include interaction effects is also the fifth stage of Hensher et al.'s (2005) experimental design process.

Labelling of the design: In a labelled setup, the presented alternatives are different (e.g. travelling by train or by car). This allows for the use of specific attributes for each alternative. For instance, certain attributes might only apply to train travel, while others are specific to car travel. This approach contrasts with an unlabelled design, where the options are generic (e.g. travelling with Train 1 or Train 2) and must share the same attributes across alternatives. Thus, in a labelled experiment, it is essential to incorporate these specific parameters into the experimental design. Conversely, in an unlabelled experiment, since specific parameters do not apply, they are omitted from the design (Hensher, et al., 2005; Szinay, et al., 2021). For this survey, we used an unlabelled setup, as we are showing two energy products that rely on the same attributes and attribute levels.

Number of choice tasks and blocking options: Our design includes 12 randomised tasks per version (each with two alternative attribute-level combinations to choose from) and one 'fixed task' that consists of the same attribute-level combination for all respondents (Orme, 2014). The following Figure 8 shows the relevant interface of the tool we used to create the design.

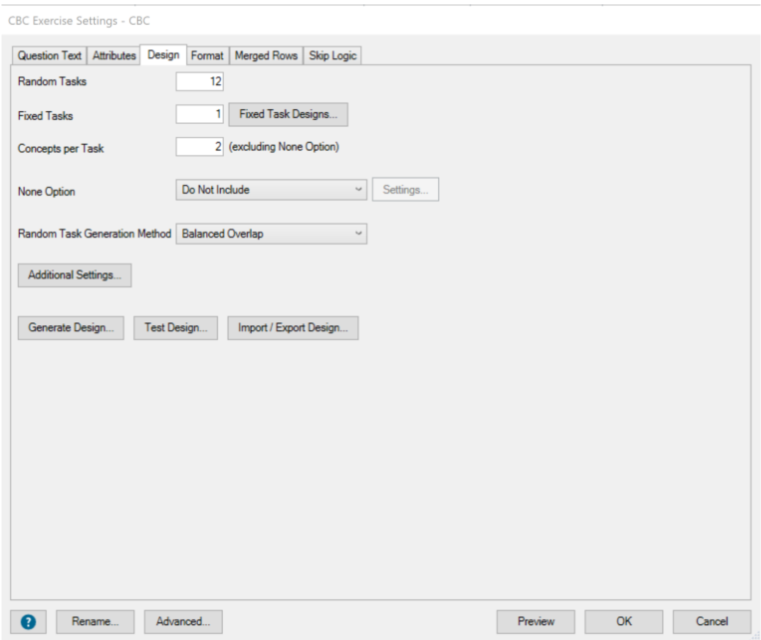
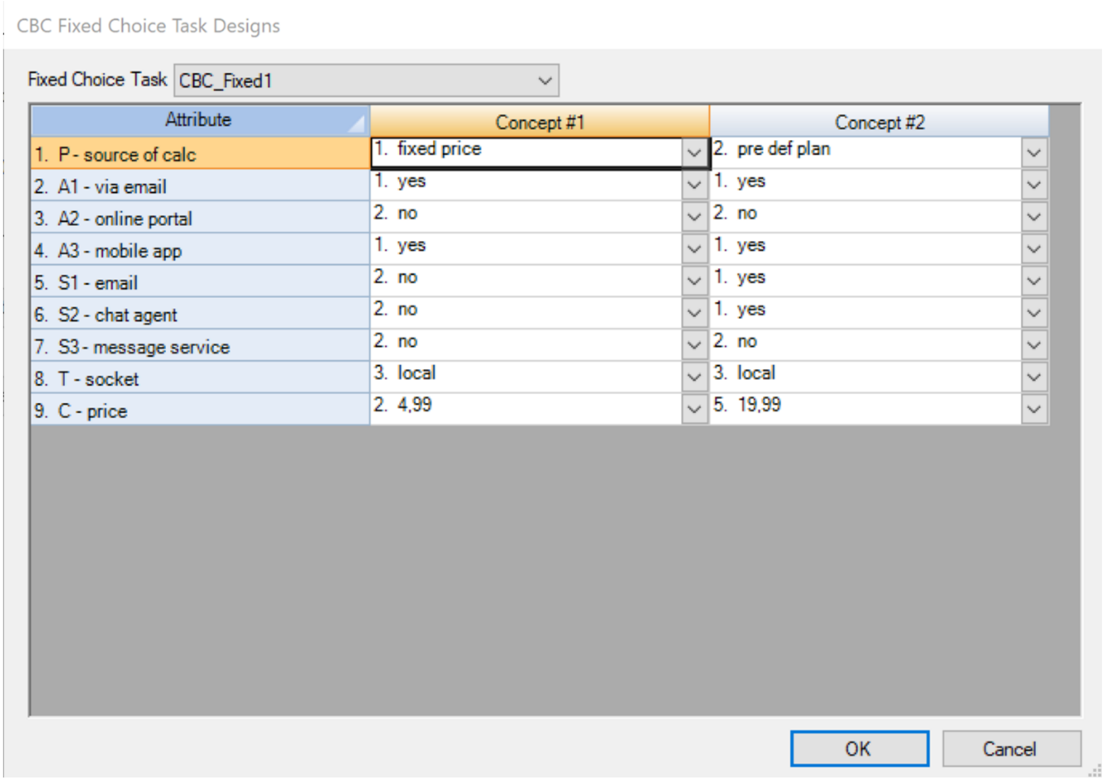


Figure 8: Choice design settings (Sawtooth Software).

The fixed task is not used for utility estimation. A fixed task refers to the very same choice that every respondent is shown. All attributes and attribute levels are defined in exactly the same way. This approach is suggested directly by Sawtooth for conjoint interviews, even though they may not appear to be needed for the main purpose of the thesis. Sawtooth lists some reasons for including a fixed task (Sawtooth Software, 2024). Amongst others, a fixed task

- Gives an indication of validity, measured by the utilities' ability to predict choices not used in their estimation,
- Enables identification and removal of inconsistent respondents,
- Can be used for direct testing specific product configurations under consideration and
- Can be used for testing the accuracy of market simulators, e.g. when it is necessary to compare different models (MNL, CL, LC, or HB, adjustment of the scale parameter as a prerequisite).

The structure of the fixed task used in this survey is shown in Figure 9. We decided not to use any extreme attribute combinations but rather an average setup with no extreme trade-off possibilities.


CBC Fixed Choice Task Designs

Fixed Choice Task CBC_Fixed1

Attribute	Concept #1	Concept #2
1. P - source of calc	1. fixed price	2. pre def plan
2. A1 - via email	1. yes	1. yes
3. A2 - online portal	2. no	2. no
4. A3 - mobile app	1. yes	1. yes
5. S1 - email	2. no	1. yes
6. S2 - chat agent	2. no	1. yes
7. S3 - message service	2. no	2. no
8. T - socket	3. local	3. local
9. C - price	2. 4,99	5. 19,99

OK Cancel

Figure 9: Fixed choice task design (Sawtooth Software).

Using the software Sawtooth, we created a randomised orthogonal design for the survey ('Balanced Overlap') that is optimised regarding 1-way-frequency (balanced appearance of all single attribute levels within the design) and 2-way-frequencies (balanced appearance of two combined attribute level). This approach is a compromise between a high degree of orthogonality (complete enumeration) and some degree of overlap within the attribute combinations (random distribution) to capture and estimate all main and possible interaction effects within the model (Chrzan & Orme, 2000, pp. 6-7). The randomisation of the choice sets refers to stage 7 in Hensher et al.'s experimental design process (2005).

We decided to split the survey into two samples of each n = 400. This means that, in total, we included 800 respondents in our survey. We created 400 blocks (survey versions) of different alternatives and tasks. Thus, each block of choice tasks was shown to two respondents: one in Sample 1 and one in Sample 2. An example of a choice task from the survey is shown in Table 5. The interface for the setup is shown in Figure 10. All socio-demographic questions were the same for the groups. The generation of the choice sets refers to stage 6 in Hensher et al.'s experimental design process (2005).

Table 5: Example of a choice task used in the survey

	Alternative 1	**Alternative 2**
Source of price calculation per kWh	Changing prices based on a pre-defined plan	Fixed price per kWh – prices are defined for the contractual time
Price communication and access to bills	• Via mail • Via email • Through an online portal • Through smartphone mobile app	• Via mail • Via email • Through smartphone mobile app
Service infrastructure	• Call centre • Message service within a smartphone app	• Call centre • Message service within a smartphone app
Additional device included in the contract	Manually adjustable electric plug adapter	Smart plug adapter incl. smartphone app, and algorithm
Additional charge to the monthly basic rate	4.99 €	0.00 €
	○	○

Source: Author's own analysis.

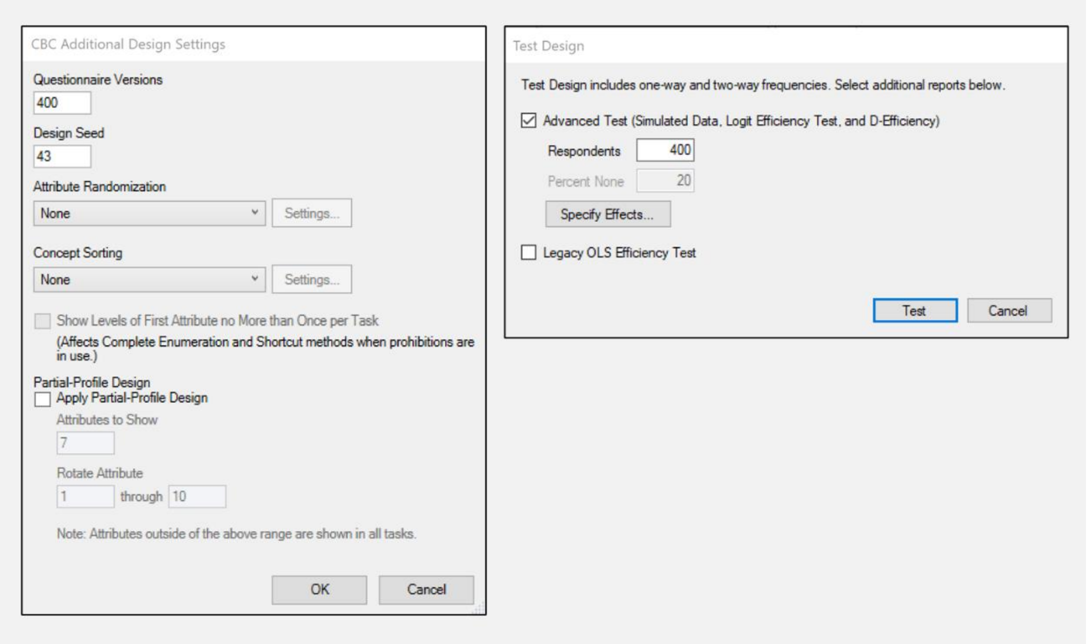


Figure 10: Design settings and test (Sawtooth Software).

The total population of households that need to make decisions about their energy supply contract in Germany is very much the same number of total households in Germany, which is currently about 41.3 million (DESTATIS, 2024). For the calculation of the necessary sample size, we assumed a confidence interval of 95% and a maximum standard error of 5%.

With these parameters, the minimal amount of 385 measurements is needed to have a confidence level of 95% that the real value is within ±5% of the measured values (Sawtooth Software, 2024). As mentioned earlier, we followed a split sample approach, as we wanted to investigate the relationship between two populations. It was important to make sure that each of the samples could stand on its own, i.e., if we identified statistically significant differences between the two samples, we could keep on working with the samples independently. This is also suggested by Orme (2010). Therefore, the minimal number of respondents, according to the sample size calculation above, would be 772. For convenience issues, we used n = 2x400.

Based on the minimal sample size (400), the number of attributes (5), the total number of attribute levels (22), the number of choice tasks (12), the alternatives per choice task (2), as well as the split sample approach (2), we use the design test provided by Sawtooth (Sawtooth Software, 2024a) to test our design[2].

Sawtooth's test design procedure, amongst others, reports standard errors for the parameters. When we refer to these standard errors reported in the test design, we are discussing coefficient estimates derived from the logistic regression model underlying the DCE. In contrast, in the context of calculating the initial sample size (i.e., ensuring a margin of error of at least ±5% for the estimated proportions), the maximum standard error refers to the probability of selection of a particular option. This is a common survey-based determination of how accurate the estimation of a proportion in the final sample should be. These two concepts of standard error serve different purposes: the first (test design) is to ensure accurate parameter (coefficient) estimation within the statistical model used to analyse choice behaviour, and the second (sample size) is intended to guarantee the precision of proportions at the aggregate level (respondents' choices)."

For the test design, the software simulates "dummy" respondent answers and reports the standard errors (derived from a logistic regression analysis) as well as the D-efficiency metric for the experimental design. The test uses a logistic regression approach to estimate simulated coefficients and their corresponding standard errors for each attribute level (Sawtooth Software, 2024a). The key purpose of this simulation is to assess how efficiently (or precisely) the proposed design can estimate the parameters, given the number of respondents expected, the number of attributes and levels, the number of tasks each respondent completes and the model specification (e.g., main effects, interactions). As the procedure uses random (i.e., 'dummy') respondent answers, it does not assume any particular 'true' effect sizes. Instead, it artificially assigns choices to emulate a range of possible preferences, allowing the software to calculate the expected precision of the design in an average or theoretical sense. Therefore, the reported standard errors indicate potential precision, not the actual significance of the coefficients. They reflect how precisely the design

[2] See appendix 8.1

could estimate each parameter if the true preference patterns were similar to the random data generation process. Without knowing the actual (real-world) coefficient values, these standard errors cannot reveal whether an attribute level's effect is truly significant in practice, only how precise the estimates might be if the attribute has a measurable effect (Sawtooth Software, 2024a).

An interpretation of normal standard errors would heavily depend on the magnitude of the corresponding coefficient values. For instance, a standard error of 0.0377 would be substantial if the coefficient value is 0.02, indicating low precision and minimal confidence in the estimate. Conversely, the same standard error would be acceptable if the coefficient value is 0.7, signifying a proportionately lower relative error (Orme, 2025).

To assess the significance and practical impact of the estimated effects, a common rule of thumb is to consider a t-value of approximately 2, which corresponds to 95% confidence that the effect is different from zero. The t-value is calculated as the ratio of the coefficient to its standard error. For example, a standard error of 0.05 and a coefficient value of 0.1 would yield a t-value of 2. This gives 95% confidence about an effect being different from zero. For that, we take: Exp(0.1) / [Exp(0.1)+Exp(0.0)]= 52.5%, which is the MNL equation for the share that an alternative with 0.1 utils would get if in competition with an alternative with an effect of 0.0. The ratio of 52.5/(100-52.5) is 1.11, or an 11% increase in share. So, having a standard error of 0.05 gives us 95% confidence for effects of a magnitude that can lift share by 11% for a product alternative (Orme, 2025).

While a standard error of 0.05 is often considered an acceptable threshold for precision, achieving a standard error of 0.025 would provide higher confidence. At this level, 95% confidence could be established for effects that lead to a 5% increase in share, a change of practical significance in competitive markets. Therefore, as the test design is based on simulated data, the absolute size of any reported coefficient is merely a byproduct of the simulation, not the real-world relationship. The tool's objective is to give an indication of how well the design can measure differences in attribute levels if those differences exist in practice.

Therefore, the standard error reported in the test is only meant to show how precise the design is likely to be, given a certain number of respondents and tasks (Orme, 2025).

The outcomes of the test can be seen in Figure 11. In our case, the levels within the three-level attributes (PRICECAL, PRICE_, SERV_) all have standard errors between 0.015 and 0.025. The five-level attribute (DEVICE) has standard errors for its levels around 0.038. We are able to observe higher standard errors for DEVICE as each attribute level appears fewer times in the design than for the other attribute level. Regarding the results and our design, the suggested guidelines from Sawtooth are that standard errors within each attribute should be roughly equivalent and that standard errors for main effects should be no larger than about 0.05 (Sawtooth Software, 2024a).

Logit Efficiencies
Using main effects only
Respondent Count

Label	**Std. Error**
PRICECALC	
PRICECALC0	0.0254
PRICECALC1	0.0255
PRICECALC2	0.0253
PRICEMAIL	0.0158
PRICEPORTAL	0.0156
PRICEAPP	0.0157
SERVEMAIL	0.0158
SERVCHAT	0.0158
SERVEAPP	0.0159
DEVICE	
DEVICE0	0.0377
DEVICE1	0.0377
DEVICE2	0.0379
DEVICE3	0.0379
DEVICE4	0.0380
CHARGE	
0	0.0429
4,99	0.0426
9,99	0.0429
14,99	0.0430
19,99	0.0429
24,99	0.0431

A general guideline is to achieve standard errors of 0.05 or smaller for main effect utilities and 0.10 or smaller for interaction effects or alternative-specific effects.

The strength of design for this model is 1471.58554913637.

(The ratio of strengths of design for two designs reflects the D-Efficiency of one design relative to the other.)

Figure 11: Results from test design.

Based on this preparatory work, the questionnaire was developed using the Sawtooth software. A copy of the final list of survey questions is included in the appendix.

2.5 Administrative process of data collection

The DCE was conducted as an online survey in December 2020. The resulting data was collected with the help of a market research firm. The data collection was performed based on the final questionnaire, which included changes based on the results of a pre-test. We carried out the pre-test to ensure that relevant and quality data could be collected. Pre-testing or pilot questionnaires for collecting empirical data is a common procedure in the social sciences, especially in the context of surveys (Porst, 2013, p. 190; Hensher, et al., 2005, p. 256; Saunders, et al., 2019).

It must also be mentioned that the sample was also controlled for private household decision-makers for electricity and was balanced for gender and age clusters in between the ages of 18 to 69 following the represented age and gender distribution in Germany. All respondents are part of the market research organisation's national panel with, according to the information provided, over 500,000 panellists. The respondents received a small reimbursement from the organisation for their participation. As the number of respondents (n = 800) for our design was pre-defined, the web survey was kept open until the necessary amount for each gender and age group was collected.

The survey was separated into two split samples, each addressing 400 respondents. Based on the survey design, each respondent was assigned to his or her own choice task group. This means that in both samples, all respondents interacted with different choice cards, and therefore, each task group consists of two respondents, each for one sample. All socio-demographic questions (see Chapter 8.2 in the appendix for the full list of questions) and the choice tasks were the same for the groups. The only difference between the sample groups was that both received some attitudinal questions either before the choice tasks or afterwards to identify the effect of these questions on preference.

As some of the attributes and attribute levels required some explanation (e.g., the sources of price calculation or the different plug alternatives), we established an interactive 'mouseover' description (short information when the user moves the pointer over the attribute (or attribute level) for nearly all attributes and attribute levels within the choice set. In addition, before initiating the choice tasks, respondents were shown and provided with an explanation of all attributes. For each choice task, the respondents were told that there is no connection to previous or later choice tasks and that respondents only need to consider the current given alternatives.

Additional questions were also introduced as part of the questionnaire. These are supposed to provide further information on the general attitude and position of the respondents towards relevant issues, e.g., digitisation, innovation or buying behaviour.

2.6 Descriptive statistics of the survey

Table 6 presents the different sample characteristics of the sample groups (split samples) and the pooled data set. It becomes evident that the characteristics of the two sample groups are homogeneously distributed, with no marked differences. In the pooled dataset of 800 participants, the gender distribution is slightly directed towards males, with 53.25% (407 respondents) male and 46.75% female (392 respondents), including one respondent picking a third option.

The majority, 61.3% of the respondents (490 individuals), are below the age of 51, suggesting a predominantly youthful to middle-aged demographic. This trend is consistent across both sample groups, underscoring the generalisability of the findings across different age groups.

In terms of income, the largest segment of both samples earns between 2,000 and 2,999 € monthly. This indicates more than half of the respondents, 57% (456 individuals), have a household income below 3,000 €, a figure that holds steady across both samples.

The employment status across the samples shows that half of the respondents (48.75%, 405 individuals) are in full-time employment, which is a trend mirrored in both sample groups. The portion of those employed part-time is also closely matched between the groups, accounting for 18.25% of the total.

When considering energy and innovation-related behaviours, 61.3% of respondents across both samples report having switched their energy provider never or only once, which suggests a low level of engagement in the energy market across the board. We see this value as an indication that the majority of the respondents are not highly involved in the energy market. Hence, we assume that the respondents approach the choice tasks unbiased by experience or high interest.

We asked the respondents with the objective of identifying synergetic effects, whether they consider themselves rather ecologically or economically oriented. This self-assessment reveals minor differences between the samples. While the proportion of respondents in Sample 1 who consider themselves to be ecologically inclined is higher compared to Sample 2 (35.5% in Sample 1, 30.0% in Sample 2), those identifying as economically oriented are slightly more prevalent in Sample 2 (25.3%) compared to Sample 1 (19.5%). Almost half of the survey sample (45.0%, 359 respondents) had no preference for each of the two extremes.

Table 6: Socio-demographics characteristics of the samples.

Demographic category		Sample Group 1		Sample Group 2		Total	
		Number	%	Number	%	Number	%
Survey statistics	Survey time (Mean)	00:18:11		00:18:26		00:18:18	
	Survey time (Median)	00:11:05		00:10:55		00:11:01	
n	Respondents	400	100.00%	400	100.00%	800	100.00%
Gender	Male	213	53.25%	194	48.50%	407	50.87%
	Female	187	46.75%	205	51.25%	392	49.00%
	Diverse	0	0.00%	1	0.25%	1	0.13%
Age	Under 30	90	22.50%	101	25.25%	191	23.88%
	31-40	67	16.75%	76	19.00%	143	17.88%
	41-50	84	21.00%	72	18.00%	156	19,50%
	51-60	95	23.75%	96	24.00%	191	23.88%
	61 and older	64	16.00%	55	13.75%	119	14.88%
	Mean (age)	44.56	-	43.30	-	43.93	-
Household income	Under 1,000 €	45	11.25%	37	9.25%	82	10.25%
	1,000 - 1,999	85	21.25%	87	21.75%	172	21.50%
	2,000 - 2,999	101	25.25%	101	25.25%	202	25.25%
	3,000 - 3,999	67	16.75%	84	21.00%	151	18.88%
	4,000 - 4,999	54	13.50%	47	11.75%	101	12.63%
	5,000 - 5,999	35	8.75%	31	7.75%	66	8.25%
	6,000 and more	13	3.25%	13	3.25%	26	3.25%
Employment	Full time job	195	48.75%	210	52.50%	405	50.63%
	Part time job	73	18.25%	65	16.25%	138	17.25%
	currently unemployed	18	4.50%	19	4.75%	37	4.63%
	Retired	64	16.00%	49	12.25%	113	14.13%
	Househusband/wife	18	4.50%	21	5.25%	39	4.88%
	Student	32	8.00%	36	9.00%	68	8.50%
Education Level	2nd School, no vocational training	11	2.75%	12	3.00%	23	2.88%
	2nd School with vocational training	86	21.50%	95	23.75%	181	22.63%
	University entrance qualification with vocational training	78	19.50%	62	15.50%	140	17.50%
	High School, no university entrance qualification	59	14.75%	62	15.50%	121	15.13%
	Uncompleted university studies	77	19.25%	82	20.50%	159	19.88%
	Completed university studies	89	22.25%	87	21.75%	176	22.00%
Switching Behaviour	never	139	34.75%	154	38.50%	293	36.63%
	once	106	26.50%	91	22.75%	197	24.63%
	twice	85	21.25%	75	18.75%	160	20.00%
	three times	39	9.75%	39	9.75%	78	9.75%
	four times or more	26	6.50%	29	7.25%	55	6.88%
	no response	5	1.25%	12	3.00%	17	2.13%
Self assesment: Ecologocal vs. economical behviour	Full ecological	8	2.00%	7	1.75%	15	1.88%
	Mostly ecological	45	11.25%	46	11.50%	91	11.38%
	Slightly ecological	89	22.25%	67	16.75%	156	19.50%
	Same share	180	45.00%	179	44.75%	359	44.88%
	Slightly economical	47	11.75%	58	14.50%	105	13.13%
	Mostly economical	28	7.00%	38	9.50%	66	8.25%
	Full economical	3	0.75%	5	1.25%	8	1.00%
Self assesment: Innovation First Mover vs. Late Follower	Instant purchase of services/products (First Mover)	33	8.25%	21	5.25%	54	6.75%
	Purchase after tests and user reviews are available	111	27.75%	117	29.25%	228	28.50%
	Purchase products/services have proven useful	128	32.00%	130	32.50%	258	32.25%
	Purchase only on discount	83	20.75%	76	19.00%	159	19.88%
	Sticks with existing products until no choice left (Late Follower)	45	11.25%	56	14.00%	101	12.63%

With respect to a first mover vs. a late follower self-assessment, a roughly equal share of respondents in each category has been found. About 35.3% regard themselves as innovation-oriented (282 respondents), 32.3% wait until new products and services have gained a certain market maturity and have proven useful (258 respondents), while the other third (32.5%, 260 respondents) of the respondents is rather reluctant to innovate their product or service usage or needs incentives (discounts) to use innovative services and products.

2.7 Specific remarks regarding survey-related issues of the applications in the thesis

In this thesis, we leverage the results of the DCE across three distinct applications, utilising data from 800 respondents under varying scenarios and through three methodological approaches. In the following chapters, we summarise unique aspects of the survey design relevant to these applications. For the first application (Chapter 3), we employ a split sample approach to examine varying respondent segments alongside integrating attitudinal items within the survey to generate context effects. In the second application (Chapter 4), we apply interaction effects to capture potential synergies among attributes, providing insights into attribute combinations that enhance utility beyond individual effects. For the third application (Chapter 5), we follow the standard HB estimation as outlined in Section 2.2.4. However, we apply an auxiliary regression based on the estimation results, which requires additional methodological grounding in addition to the necessary structural aspects of the data gathering.

2.7.1 Remarks regarding Application 1: Attitudinal items for activating context effects

The first application focuses on the impact of context effects on choice. Here, we will make special use of the introduced split-sample approach. To test for context effects, the experimental design follows the work of Pouta (2002) and Liebe et al. (2016), who each designed an approach for investigating context effects in a choice setup based on attitudinal measures.

The hypothesis for our investigation is that one sample shows significant evidence of so-called treatment effects. Treatment effects refer to treatments, interactions, and activities that take part before the preference elicitation, allowing the identification of differences within the preference elicitation. Examples of groups that have been subject to treatments are, e.g. clinical studies or randomised control trials, with one sample group receiving a treatment while the other one being the control group to investigate the effect of the treatment (Houle, 2015).

For the investigation in this thesis, we use the treatment as a method to frame the choice situation in terms of making the respondents think about their attitude and perspective on digital maturity.

Typically, relevant questions such as attitudinal measures are added to a choice survey in addition to the choice tasks. Including attitudinal measures is recommended to validate stated preferences (Bateman, et al., 2002). Attitudinal measures refer to the concept of individual attitudes. In microeconomics, attitudes lead to the preferences and subjective judgements of agents regarding different choices or outcomes. Attitudes can influence decision-making processes, including the valuation of goods and services, risk assessment, and the overall behaviour in markets. Attitudes in microeconomics are also closely linked to the concept of 'tastes and preferences', which are fundamental assumptions in the theory of consumer choice. These assumptions help to predict how changes in economic variables like prices and income affect the demand for various goods and services (Nicholson & Snyder, 2007).

The structure of the attitudinal approach is not the same in the studies from Pouta (2002) and Liebe, et al. (2016). While Pouta (2002, p. 234) constructs one of the split samples with two attitudinal questions and the other with no attitudinal questions before the choice tasks, Liebe, et al. (2016) let both samples answer the attitudinal questions; however, one sample before the choice tasks and the other afterwards.

The survey setup for Chapter 3 follows the approach of Liebe et al. (2016), allowing both sample groups to interact with the same attitudinal items. The first group gets the attitudinal item presented before their choice tasks, and the second group sees the question after the choice assignment. Figure 12 illustrates the structure of the survey for both sample groups:

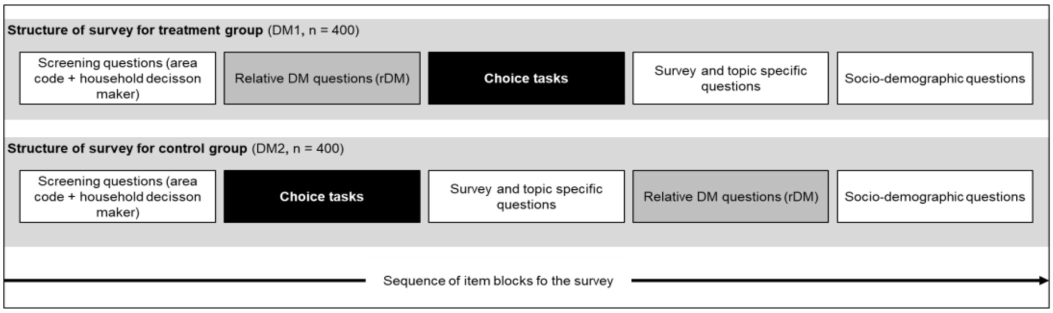


Figure 12: Item blocks of survey for the two samples.

We call the first group DM1 and the second group DM2. DM is the abbreviation for 'digital maturity'. The term digital maturity receives particular attention in the work of Westermann et al. (2014). The researchers provide evidence that companies with higher digital maturity show superior performance. They separate the concept of digital maturity into digital capabilities (e.g., strategy, technological expertise, business models, customer experience) and leadership capabilities (e.g., governance, change management, culture) and point out that both areas need to be addressed for a high maturity level. In this thesis, we use the concept as an individual measurement of the 'degree of adoption and application of digital technologies' of a service offering and follow a definition from Rossmann (2018, p. 3), who performed a systematic literature review on the topic. For this thesis, it is important that we use the concept for the evaluation of services and do not focus on the capabilities of a firm. Hence, we ignore the aspects of leadership from the work of Westermann, et al. (2014) and Rossmann (2018) at this part. However, we address the question of digital capabilities in conducting the third application (Chapter 5). Nevertheless, we used the presented definition in line with similar works on digital transformation (Davenport & Redman, 2020; Hsu & Spohrer, 2009) to introduce the attitudinal items. Thus, we are using the concept of digital maturity therefore as a subjective and individual measure and evaluation of the respondents for the attributes used in our DCE. This means that we do not include the DM in the DCE estimation but use it as a different kind of stated evaluation.

To simplify, we refer to the notation of 'DM questions' when talking about the attitudinal items to induce context effects before or after the choice tasks.

For the DM questions, we used a four-point scale asking the respondents to evaluate, in the case of the DM1 group, the yet unknown attributes and attribute levels of the later choice tasks according to their perceived digital maturity. Due to the different approach, the DM2 group was familiar with the attributes and attributes levels at the point they received their DM questions. For simplification, we will state that group DM1 received a ‘treatment’, even though group DM2 received the same attitudinal questions, just at a later stage of the survey. This implies that we do not expect an impact of the stated answers to the attitudinal questions in DM2 on preference estimates as we see the results from this sample group as a baseline or the control group for our comparison.

With the setup of the DM questions, we follow closely the approach chosen by Liebe et al. (2016), which builds on an approach to identify context effects. Context effects denote the phenomenon that answers to a target question depend on whether it is asked before or after relevant context questions (see Chapter 3.2.2 for details). Question context is likely to affect stated preferences because surveying relevant attitudes prior to choice tasks might provide an ‘interpretive framework’ regarding the choice questions, leading to possible judgment effects (Tourangeau, et al., 2000; Tourangeau & Rasinski, 1988; Tourangeau, 2021). This implies that a modelling approach that includes the DM questions and scores would not offer insights for that objective as we are investigating the effect on preferences. For example, an ordered logit model (OLM), which is a type of regression model used for ordinal dependent variables, where the response categories have a natural order, but the intervals between them are not assumed to be equal, might not be an ideal choice due to its underlying assumptions and limitations in handling the complexity of context effects (Long & Freese, 2001). OLM estimate the probabilities of the dependent variable falling into different categories while assuming that the relationship between each pair of outcome groups is the same (Long & Freese, 2001; Williams, 2006). This assumption might not hold in the presence of context effects, where the influence of previous questions can lead to varying response patterns that do not conform to a single underlying ordinal structure. For example, survey respondents could be asked to rate their preference for different energy-saving technologies after being presented with questions about their environmental attitudes. If a context item leads respondents to think more critically about environmental issues, their preferences may be affected, which may lead to biased parameter estimates of the OLM. This approach would fail to capture the differential impact of the context on the choice, resulting in misleading conclusions about preferences.

For our survey, pre-tests showed that a certain number of participants, especially in the DM1 group, were confused with the task of initially evaluating the different attribute levels. Therefore, we included a short description, pointing out the subjectivity of the evaluation and that there is no right or wrong answer. Moreover, we provided some assistance to aid in understanding the concept of ‘digital’. With a simplified approach based on the core areas of digital transformation (Davenport & Redman, 2020; Hsu & Spohrer, 2009), we stated as an instruction that respondents should think of the degree of technology and/or data involved in the allocation of specific attribute level in case of doubtfulness.

2.7.2 Remarks regarding Application 2: definition of interaction effects

The second application of the thesis focuses on interaction effects as an extension to the understanding of main effects. We define main effects as the direct, independent influence of each attribute level on choice probability, estimated without considering the effects of other attributes (Hensher, et al., 2005). Accordingly, an effect can be formally expressed as the difference in the estimated utility parameters for different attribute levels, often relative to a baseline level (Hensher et al., 2005). Therefore, for the purpose of this thesis, we define an effect as the difference in preference estimates. To obtain the difference, we do not consider numerical means for ordinal attributes but rather differences in the preference estimates assigned to each attribute level (Hensher, et al., 2005).

The estimation of main effects within a model only shows the preference estimates for the presented attributes and attribute levels. However, it does not show whether there are moderating or so-called interaction effects between the different attributes, more precisely, if one attribute level impacts the preference for another attribute level (two-way interactions). Interaction effects can be applied in a choice model context, for example, to show the impact of contextual factors on the perception of attributes. This means that an interaction effect is an effect upon a response variable (choice probability) obtained by combining two or more attributes, which would not have been observed if each of the attributes had been estimated separately. One example of interaction effects is the impact of travel motivation (leisure vs. business) on the perceived quality of the accommodation (Kim & Park, 2017): The perceived quality of a room can be different depending on the motivation of the journey. If, for example, there is no balcony or mountain view, a business traveller's perspective on the room would differ from that of a family on holiday.

A basic form of a utility function that includes an interaction effect between two attributes, x_1 and x_2 can be written as:

$$U\ (x_1, x_2) = \alpha x_1 + \beta x_2 + \gamma x_1 x_2 \tag{13}$$

where,

$U\ (x_1, x_2)$	represents the utility derived from having quantities x_1 and x_2 of two attributes.
$\alpha + \gamma x_2$	is the coefficient representing the marginal utilities of x_1
$\beta + \gamma x_1$	is the coefficient representing the marginal utilities of x_2
γ	is the coefficient representing the interaction effect between x_1 and x_2.

The term $\gamma x_1 x_2$ captures the interaction effect. If $\gamma > 0$, the attributes are complements, meaning the utility increases when both attributes come together. If $\gamma < 0$, the attributes are substitutes, meaning the presence of one attribute reduces the additional utility of having more of the other attribute.

This basic form can be expanded or modified to fit specific contexts or more complex interactions. For instance, in more advanced models, interaction effects might be nonlinear or involve more than two attributes.

2.7.3 Remarks regarding Application 3: digital maturity, regression analysis

We have already introduced the DM questions in the remarks for Application 1 in Chapter 2.7.1. Prior to the choice task, we asked the respondents to evaluate the DCE attributes according to their perception of the attribute's digital maturity (DM). We set it up as a comparison between the different levels of one attribute (scale: most digital, second most digital, third most digital, least digital; notation for the parameter: ‘rDM’ – relative digital maturity, see Figure 13 and Figure 14). We did not offer any ‘no answer’ (opt-out) option. This would have increased the risk of generating flawed results within the evaluation and would have made the evaluation invalid for later analysis. The evaluation of the DM took place for each attribute on individual screens with the help of interactive drop-down fields (i.e., when the answer ‘most digital’ is chosen once, it does not appear anymore for the other attribute levels).

Figure 13: rDM question screen for attribute PRICECALC (“What do you perceive as the most, second-most and least digital product attribute?”).

Figure 14: rDM question for attributes PRICEEMAIL, PRICEPORTAL, PRICEAPP.

We are using the obtained DM scores from each respondent and for each attribute in the third application. The core idea is to identify if there are any relationships between customer utility and the perceived digital maturity of a digital servitisation offer.

We investigate the correlations between the attribute estimation and DM value differences and apply a multiple regression analysis to investigate the impact of the DM perception on individual utilities. This means that the utility difference for the complete attribute combinations (the chosen alternative in contrast to the dismissed alternative) is used as a dependent variable, while the attributes related to perceived digital maturity, as well as demographic and other factors, are used as independent variables.

We found one similar approach that has been applied in the field of housing and building research, which investigates how the part-worth utilities of housing attributes are related to socio-economic variables and current housing environments (Molin, et al., 2001). Those researchers adopt a two-stage methodological framework that first extracts part-worth utilities from a stated choice experiment and then regresses these utilities on socio-demographic variables. In the first stage, each respondent's part-worth utilities are estimated using a CBC design. In the second stage, the individual-level utility estimates serve as the dependent variables in a multivariate regression, with socio-demographic factors (e.g., age, income, education) as key predictors. The goal was to investigate how and why certain respondent segments assign different utilities to particular attributes. By explaining variation in the part-worth utilities rather than in raw choice data, this approach offers clearer insights into how personal and contextual factors drive differences in attribute importance. From a methodological perspective, the regression of part-worth utilities on socio-demographic characteristics is particularly useful in studies seeking to explore preference heterogeneity. It provides direct interpretations of whether, for instance, older respondents place higher utility on user-friendly technology or if higher-income participants favour premium service options. In their study, Molin, et al. (2001). employed a multiple regression framework in which the dependent variables are individual-level part-worth utilities estimated from the stated choice experiment. To address the observed pattern that, for certain three-level attributes, only the first and the third levels exhibit significant (and opposing) relationships with explanatory variables, the authors opt to use the range between the lowest and highest part-worth utilities rather than individual level-specific part-worths. In doing so, they interpret this range as an indicator of how important the particular attribute is to respondents (Molin, et al., 2001).

Given the methodological challenges associated with using utility estimates derived from an HB model for the regression, we apply a bootstrapping method to obtain correct standard errors to interpret the regression results. While HB estimates are widely recognised for capturing individual-level preferences, they are not raw data points but Bayesian estimates that incorporate assumptions, priors, and uncertainty inherent to the model. This presents a methodological challenge when applying ordinary least squares (OLS) regression, as OLS assumes that predictor variables are error-free and that residuals are independently and identically distributed (i.i.d.). However, these assumptions may not hold for HB utilities due to their underlying dependency structure and estimation variability.

Specifically, the standard errors obtained from OLS regression might be inadequate because they do not account for the uncertainty and variability introduced during the HB estimation process. Furthermore, the sampling distribution of the OLS regression coefficients might deviate from the asymptotic normality assumed in traditional inference procedures. These issues can lead to underestimated standard errors and potentially biased statistical conclusions.

To address this limitation, we applied a bootstrapping approach to calculate robust standard errors for our regression coefficients. Bootstrapping is a resampling technique that allows for an empirical estimation of the sampling distribution of the coefficients without relying on the assumption of asymptotic normality. By repeatedly resampling the data with replacement and performing the regression analysis on each bootstrap sample, this method captures the variability in the HB estimates and provides more reliable standard errors.

Practically, bootstrapping offers a straightforward and flexible solution to account for the uncertainties in HB utilities, as it does not require modifications to the Bayesian estimation process or specialised hierarchical regression models. The implementation involves resampling the original dataset, re-estimating the regression coefficients for each bootstrap sample, and calculating the empirical standard errors from the distribution of the bootstrap estimates.

3 Application 1: Influence of context effects on stated preferences for digitised service offerings

Abstract

This chapter investigates influences on preference reliability. It tests if preferences are subject to change due to situational context prior to the buying decision. The investigation is based on a split sample DCE survey where respondents are asked to evaluate different attributes of a purchase alternative either before or after the preference elicitation. Two logit model estimations are used to test for preference differences between the two sample groups. Statistically significant estimates for a measurable impact of the context on preferences are found.

3.1 Introduction

The understanding of preferences relies on the assumption that customers tend to maximise their utility when deciding between different options (Golsteyn & Schildberg-Hörisch, 2017, p. 2). In pursuing the maximisation of utility, consumer preferences are traditionally considered stable in neoclassical economic theory: "changes in consumers' choices over time cause changes in relative prices but not on consumers' preferences that remain stable over time" (Calle, et al., 2020, p. 2). Indifference curves are used to represent equal utility levels for different combinations of two consumption goods with preferences being assumed as stationary or stable (Mankiw, 2018, p. 438). Some researchers consider different preference outcomes that are a result of repeated measurements under the same conditions as 'volume level differences' (Golsteyn & Schildberg-Hörisch, 2017, p. 3). However, there is a debate in the research community whether preferences are, in fact, stable or they are subject to change due to dynamic conditions, measurement bias, personality, emotional involvement, or situational context, which has an impact on the reliability of the preference estimates (Steiner, 2007, p. 19; Hensher, 2009; Grebitus, et al., 2013; Johnston, et al., 2017, p. 321). For details on this debate, we refer to the concepts presented in Chapter 2.1.4.

In this chapter, we investigate the impact of a so-called context effect on the reliability of preference. It assumes that by creating involvement ('treatment') with a topic prior to a buying decision with preferences not yet been stated by the consumer, a different preference estimate occurs in contrast to a buying decision in which such involvement has not been created. We understand the concept of involvement as the measure of the cognitive control customers can exercise when making a decision (Felser, 2015, p. 111). We assume that the context effect, therefore, impacts preferences, behaviour, and, consequently, the perceived utility of a product or service. With this assumption, we build on the contributions of Pouta (2002) and Liebe et al. (2016), but with a different product-service focus. While these studies mentioned focus on environmental offers or consumption products that serve as a political proxy and investigate how context effects influence choice, we focus on the consumer energy market. Other studies on context effects within choice situations focus, e.g.

- In the hospitality sector (Kim & Park, 2017), where the authors explore the moderating role of context on the effects of choice attributes on hotel choice using a DCE. This research reveals that the choice context significantly influences consumer preferences and decision-making processes in hotel selection. For instance, leisure travellers with family emphasised price and overall atmosphere, while business travellers focused on room quality and comfort. This illustrates the critical role of context in shaping consumer behaviour, aligning with the broader research area of context effects by demonstrating how situational factors can alter the importance of product attributes.
- On birth control (Tourangeau & Rasinski, 1988), where the authors investigate the cognitive processes underlying context effects through an attitude measurement, which emphasises that attitudes should be considered as structures stored in long-term memory. Their research examines how the context of preceding survey questions can influence respondents' interpretations and answers to subsequent questions, thereby affecting survey results. This work is important in the research area of context effects as it provides a detailed model of the cognitive mechanisms that lead to context effects in survey responses.
- On psychological testing (Lubow, et al., 1967), where the authors investigate how the relationship between stimulus preexposure and environmental preexposure affects

subsequent learning. It is significant in the research area of context effects because it elucidates the conditions under which previous exposure to a stimulus either facilitates or inhibits new learning based on the familiarity of the stimulus and the environment.

This means that our approach is one of the few that is completely based on economic goods within markets with full access, where understanding, influencing, and modelling customer (buying) behaviour is a desire of corporations and sales managers. Here, nearly the most important question is, ‘what brands or services are selected by customers in any given (comparable pairwise) choice situation, and if there are influencing factors for the purchase decision process’ (Temme, 2009, p. 299).

For this application, we build on the established DCE setup that we introduced earlier in Chapter 2.4. Usually, a DCE describes not only the choice tasks itself but also includes additional questions to capture the influence of socio-demographic issues or further insights. Those questions may serve as screening criteria or as attitudinal items for validating the stated preferences (Johnston, et al., 2017, p. 353). We use these attitudinal items to create the involvement (a measure of cognitive control) for one part of the sample of the respondents with the topic digitisation prior to the actual preference elicitation task and thus to examine the existence of context effects. The other part of the sample receives the attitudinal items after this preference elicitation task. Our approach focuses on consumer preferences for digitised energy product-service bundles (see Chapter 2.3 and Chapter 2.4), and the involvement is created by asking the respondents to evaluate the perceived digital maturity of the different attribute levels of the product. Our hypothesis is that respondents who are faced (or received a ‘treatment’) with the topic of digitisation before preference elicitation will have different, presumably stronger, preferences for digital services in their choices for energy service bundles compared to respondents who have not yet been exposed to this topic beforehand (i.e., have not received a treatment). We state this assumption in contrast to the results from Liebe, et al. (2016) and Pouta (2002), where the difference between each of the two treatments did not offer statistically significant evidence. However, we believe that a treatment in the course of a purchase decision for economic goods is going to have an impact on preferences.

As introduced in Chapter 2.7.1, we are using a split sample approach for this application. For analysing the data, we use a CL model, which allows us to estimate the impact of product attributes on choices. We estimate the model three times: once for each split sample and once for both samples combined ('pooled sample'). Afterwards, we discuss any differences in the estimates of WTP across the split samples and test for differences between the treatment groups with the help of Poe et al.'s (1994) test.

We organise the remainder of Chapter 3 as follows: first, the theoretical foundations and literature for reliability and viability of stated preferences (Chapter 3.2.1) and context effects (Chapter 3.2.2) are reviewed. Afterwards, we present our methodological approach for the study design and the underlying considerations (Chapter 3.3). In Chapter 3.4, we present the modelling results and test for the differences between the treatments and sample groups. Finally, the discussion and conclusion (Chapter 3.5) critically presents the study results with reference to the research objective, lists limitations, and offers practical and methodological implications as well as aspects for further research.

3.2 Theoretical foundations and methods

3.2.1 Preference reliability and viability

"The results of CE studies are often used to inform public and private decision-makers. It is, therefore, important that these results be valid and reliable. Otherwise, decision-making will be based on misleading estimates of stated preferences and WTP estimates, leading to poor policy choices." (Liebe, et al., 2016, p. 136).

Mariel, et al. (2021, p. 114) use the metaphor of shooting arrows at a target to describe the aspects of reliability and validity. Within this picture, while the arrows are the utility estimates, reliability stands for the closeness of the arrows to each other. It does not mean that they are 'on target' (the bullseye) or even close to it. However, it is important that the arrows are shot in the same direction. A low reliability means that the different arrows are spread across the whole target area. Validity refers to the metaphorical closeness of the arrows to the bullseye, and hence, a low validity means that the arrows are far away from the bullseye. Therefore, “reliability is about variance and validity is about bias” (Bishop & Boyle, 2018, p. 590). In this application, we focus on testing the reliability of preferences for digitised product-service bundles in the case of the appearance of so-called context effects. To stay within the metaphor, we want to find out if and how the direction of the arrow that Robin shoots changes when Lady Marian distracts him at the moment of the arrow’s release in the 1991 movie ‘Robin Hood: Prince of Thieves’. In our case, the ‘distraction’ is conceptually realised within the setup of our survey through the evaluation of the attributes by the respondents (treatment for the first split sample group). Three conceptual approaches to ensuring the reliability of choice experiments are proposed in the literature (e.g. Bateman, et al. (2002, p. 296):

- Test-retest to obtain estimates for the same individuals at two different points in time,
- Comparison of estimate distributions from two independent but statistically equivalent samples from the same population or
- Comparison of the bid function in repeated samples.

In this chapter, we use the conceptual approach of comparing the estimated distribution of the two samples for testing reliability and testing to what extent stated preferences, especially their reliability, are influenced by context effects. A typical DCE study includes socio-demographic and attitudinal items that frame the actual choice tasks for validating and better understanding preferences as well as the characteristics of the sample and the population. However, the inclusion of these items might influence the context in which the respondents interact with the choice tasks and, hence, the reliability of the preferences and the estimates of the DCE (Liebe, et al., 2016). We test whether stated preferences differ when there is a certain interaction with the attributes of the DCE before rather than after the choice tasks.

3.2.2 Context effects

“*There is substantial evidence that people make decisions that deviate strikingly and systematically from the predictions of the standard random utility model”* (Rooderkerk, et al., 2011, p. 767). This statement implies that (consumer) choices might be influenced by context and that individual utility is – at least partly – subject to situational context rather than recalled from subconscious memories (Rooderkerk, et al., 2011; Thomadsen, et al., 2017). The statement, however, implies a shift of the understanding from the neoclassical economic perspective towards NIE or bounded rationality with the presence of other variables (e.g., information, attitude, context) to explain behaviour other than by the sheer utility of a good (Lancaster, 1966).

To examine the effects and interrelations of these variables, literature and research in various academic fields offer different approaches to how decision behaviour is influenced, such as dynamic conditions, measurement bias, personality of the respondents, emotional involvement[3], or situational context. The investigation of context effects has been explored, including experimental psychology, where early references can be found for the investigation of the relationship between stimulus preexposure and environmental preexposure and how that affects subsequent learning (Lubow, et al., 1967). It showed with the help of shapes and colours of the environment and of the interaction items, small plaster pieces, that there is an intuitive connection between actions, selection of items, the shape and colour of the item, and the shapes and colours of the environment. Thus, the interaction differed according to context (Lubow, et al., 1967). The phenomena now known as latent inhibition and perceptual learning describe the effects of certain cognitive processes. Latent inhibition arises when a previously encountered neutral stimulus, one that initially bears no specific outcome, is later associated with a consequence. Perceptual learning, on the other hand, refers to the enhanced capacity to discern information from one's surroundings, a skill that improves through continued exposure to and interaction with environmental stimuli (De la Casa & Timberlake, 2006).

Context effects can refer to influencing choices, for example, via the use of framing, composition, or sequencing (Thomadsen, et al., 2017). Research has shown that context contains and predicts a conditioned stimulus (Nadel & Willner, 1980). Therefore, the

[3] Meaning that actors are staying with an economic choice for emotional reasons (memories, comfort, etc.), even though a – rationally seen – better choice is presented.

experiments showed how context can affect actions. However, it does not show if there is an impact on mid- to long-term behaviour.

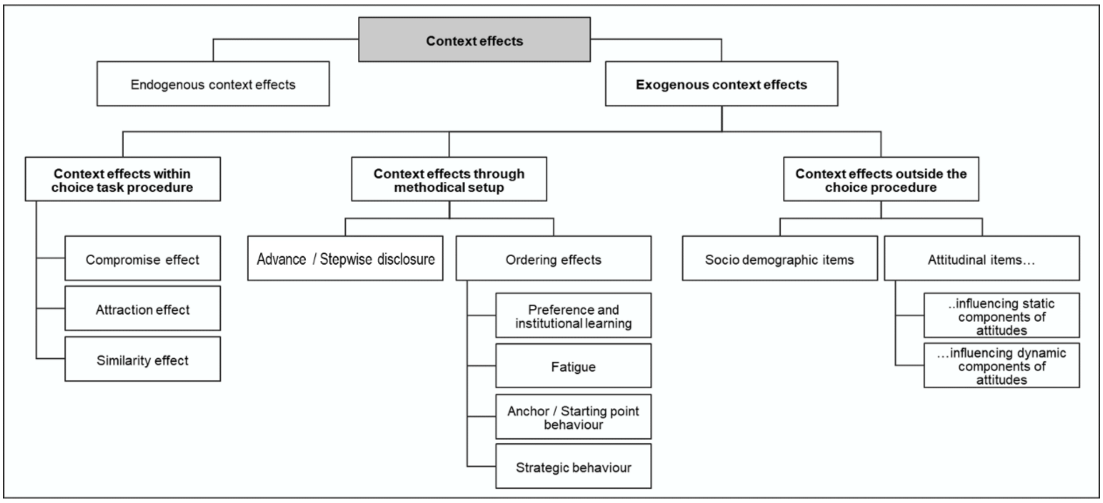


Figure 15: Classification of context effects.

Source: Author's own analysis based on literature review, esp. based on Rooderkerk et al. (2011), Thomadsen et al. (2017), Bateman et al. (2008), and Meyerhoff & Glenk (2013).

As presented in Figure 15, context effects can be separated into endogenous and exogenous effects. This division is based on the work of Thomadsen et al. (2017). Endogenous effects are initiated by the decision maker, e.g., actively hiding information, pausing or interrupting the choice situation, or creating habits while making choices (Thomadsen, et al., 2017). As these activities can hardly be controlled or captured through revealed preferences, we assume within our model that endogenous effects are captured through the error term (ϵ_i, see equation (3)). For (survey-based) consumer choice experiments, based on our research, we divide exogenous context effects into three segments, as this is a mutual exclusive separation of the different effects that we found:

- Context effects created within the choice task procedure
- Context effects created through the methodological setup
- Context effects created outside the choice task procedure.

3.2.2.1 Context effects created within the choice task procedure

According to research from Rooderkerk et al. (2011), there are three dominant inside context effects:

- The compromise effect: adding an alternative that offers an average of two extreme alternatives,
- The attraction effect: adding an alternative that is similar but inferior to another alternative, which makes the superior item more attractive and
- The similarity effect: adding an alternative that is similar but superior increases the choice share of that new item.

All these can affect consumer choice and may be intentionally used. However, manually integrating those items into the choice set would intentionally violate the IIA assumption for choice experiments (McFadden, 1974; Luce, 1959; Dhar & Simonson, 2003; Rooderkerk, et al., 2011). For a more extensive discussion and further definition of IIA, we refer to Chapter 2.2.2.2 of this thesis.

3.2.2.2 Context effects created through the methodological setup

Methodologically induced context effects are mostly addressed by the concepts of advanced/stepwise disclosure and ordering effects (Bateman, et al., 2008; Carlsson, et al., 2012; Meyerhoff & Glenk, 2013). Research shows that both belong to the category of context effects, as there is an impact on preference even if the choice set stays identical. When investigating ordering effects, several explanations can be found that lead to an impact on preference (or to a decrease of the error variance) due to the sequence of the choice tasks:

- Preference and institutional learning (respondents become familiar with the choice tasks after being uncomfortable in the first iterations),
- Fatigue (repetition of the alternative choice behaviour leads to fuzzy results in later tasks; see also Czajkowski, et al. (2014)),

- Anchor or starting point behaviour (especially for prices; the respondent compares later attribute combinations with earlier attribute appearances by means of price) or
- Strategic behaviour of the respondents (rejection of similar alternatives that have been presented before at a lower price) (Carlsson, et al., 2012).

In the case of advanced (the whole series of tasks is revealed) or stepwise (each task at a time) disclosure, respondents are informed beforehand about the attributes, attribute levels, alternatives, prices, or question structure (Meyerhoff & Glenk, 2013). This might be done through instructional choice sets (ICS, also called 'warm-up-tasks') that enable the respondents to understand the task and anchor comparison and might even reduce certain biases (Abate, et al., 2018; Pouta, 2002; Carlsson, 2010; Czajkowski, et al., 2014). As research shows, an increase in model estimate precision can be observed when the first choice task is not included in the estimation calculation (Meyerhoff & Glenk, 2013; Bateman, et al., 2008). Common approaches for advanced disclosure are, for example, telling or showing what the respondents will face in the following choice situation before each task. Moreover, at least for computer-based surveys, the possibility to go back on previous questions and alter these is a kind of advanced disclosure as well. For paper-based surveys that are answered without supervision, chances are also elevated that respondents look through all the instructions and choice tasks beforehand (Bateman, et al., 2008).

3.2.2.3 Context effects created outside the choice tasks

Context effects that are induced outside the choice task procedures are usually triggered by the socio-demographic and attitudinal items in the survey design. Liebe et al. (2016) argue that these kinds of survey items alter the question context and, therefore, affect the stated preferences of the respondents.

Tourangeau and Rasinski (1988) identify a four-phased process for how context – represented as survey items – affects the response process stages. For that, they use so-called attitudinal survey items, i.e., questions that are likely to activate and condition relevant attitudes from the respondent. According to them, attitudes are part of long-term memory and need to be stimulated to be recalled by the respondent. The four phases of the cognitive process for answering a question are (Tourangeau & Rasinski, 1988, p. 299; Tourangeau, et al., 2000, p. 8; Tourangeau, 2021):

- Interpretation phase: interpretation of the question (locating and activating the relevant attitude structure in the case of familiar issues – in the case of unfamiliar issues, comparable structures need to be identified),
- Retrieval phase: retrieval of suitable beliefs from the attitude structure (sampling process for the most accessible beliefs or situational cues like, for example, in the case of a nuclear phaseout where the occurrence of a catastrophic event might lead to a change of existing beliefs),
- Judgement phase: rendering of judgement in order to make the decision (scaling and weighting of the beliefs in the case of the question and or the context) and
- Answer phase: reporting of the answer (mapping of judgements onto the response options and checking for consistency within the answer).

The model has regularly been referred to in the last years when discussing attitude measurement within survey projects in different research fields (Baum, et al., 2022; Tourangeau, et al., 2000; Ashok, et al., 2022; Jen-Yi, et al., 2015; Jaeger & Cardello, 2022; Harnois, 2022; Liebe, et al., 2016). The attitude process consists of two parts: a long-term static and a dynamic component (Tourangeau & Rasinski, 1988). The latter needs to be 'activated' to affect decisions and actions by the static general attitudes and beliefs. This implies that attitudes are not fully stable, and impulses from the dynamic component could even backfire through a feedback loop on the static part if the judgment or answer phase leads to cognitive dissonance. Cognitive dissonance in this context means the psychological tension that arises when a person's new judgment or decision conflicts with their long-held attitudes or beliefs, potentially prompting them to alter or justify those attitudes to reduce the inconsistency.

The earlier introduced hypothesis, stating that respondents who are treated with the topic of digitisation before preference elicitation will have different preferences for digital services, builds on the idea of a dissonance in which context effects lead to an alternative preference elicitation of the respondent. We illustrate this concept in Figure 16 and Figure 17.

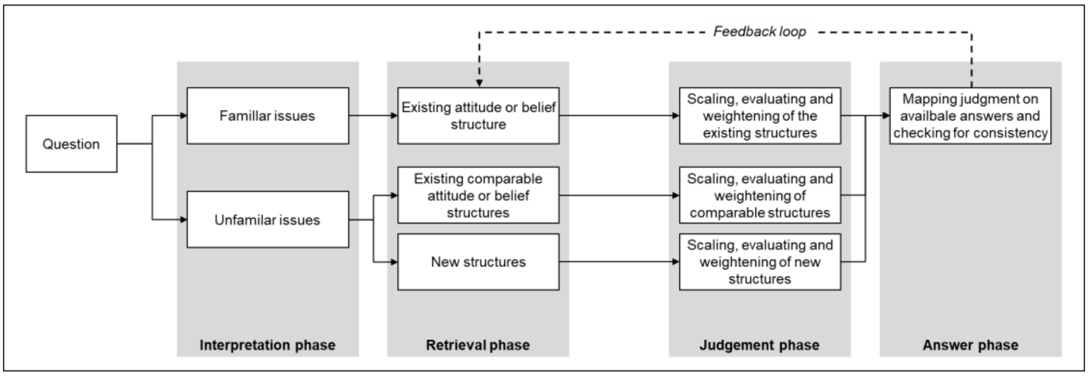


Figure 16: Stages of the cognitive process.

Source: Own illustration after Tourangeau and Rasinski (1988) and Tourangeau, et al., (2000).

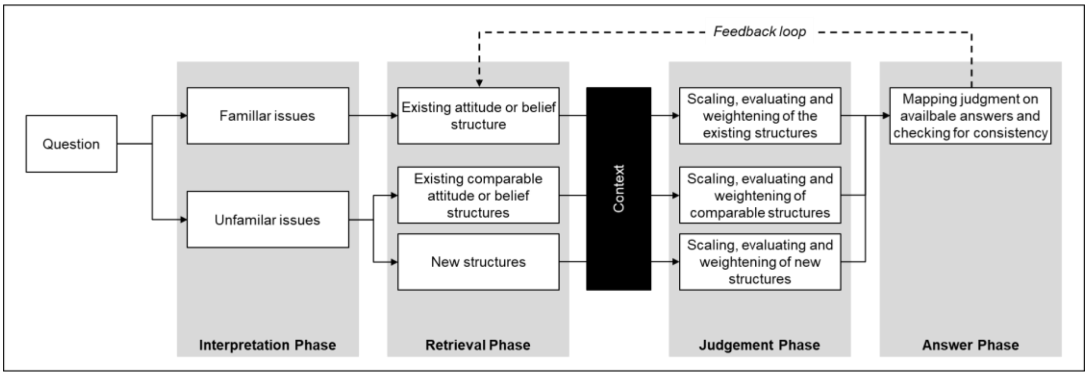


Figure 17: Stages of the cognitive process, including context.

Source: Own illustration after Tourangeau and Rasinski (1988) and Tourangeau, et al., (2000).

A change in preferences, which is stated within the answer phase, has been shown to depend on several different reasons (Grüne-Yanoff & Hansson, 2009; Jun, et al., 2019), such as through product experience in the past or payment timing. These reasons are based on previous experiences and influence repeated decisions. For this investigation, we focus on change effects that are based on situational context within the survey, which ‘conflicts’ the decision process between the retrieval and the judgement phase (see Figure 17).

The experimental design of our contribution focuses, therefore, on context for the judgement stage of the cognitive process. Thus, we ask the respondents to evaluate the digital maturity[4] of the attribute levels of the choice set without knowing that the items are presented later in the survey as attributes. Based on this evaluation, we assume that we have observed a preference shift towards the attribute levels that are perceived to have a higher digital maturity.

Within the choice tasks, the attributes, and the attribute levels from our survey, there is no notation of any kind for the terms ‘digitisation’ or ‘digital maturity’. Instead, the expected connection must be unconsciously made by the respondents. Hence, we understand this connection as an effect or influence of context. This idea is comparable to the findings of Pouta (2002), who used belief and attitudinal questions within a choice situation for forest recreation. The study showed that there is an increased probability that an environmentally friendly alternative is chosen if there have been prior questions addressing the importance of regeneration cutting, personal beliefs concerning different cutting alternatives, payment, and environmentally friendly policy (Pouta, 2002). Nearly all of the presented research focuses on non-economic issues, e.g., forest regeneration (Pouta, 2002), olive oil as a political proxy (Liebe, et al., 2016), or birth control attitudes (Tourangeau & Rasinski, 1988). Existing stated preference experiments differ greatly and do not take the issue of context effects into account (Liebe, et al., 2016). The approach in our application focuses on the retail electricity market, a market that is increasingly characterised by product differentiation instead of the classical understanding of electricity as a homogenous commodity product (Eakin & Faruqui, 2000) Therefore, from a practical perspective, context effects might give suppliers the possibility to influence preference for or against certain services within the buying decision process.

3.3 Methodological approach

The experimental design for this part of the investigation follows the work of Pouta (2002) and Liebe, et al. (2016) with a split sample approach. We already introduced the

[4] See chapter 2.7.1 for the definition of digital maturity and the scope for it in this thesis.

structure of the survey design for this application in Chapter 2.7.1 of this thesis. This means in the further course of this chapter and for the first application, we refer to the established labels of the treatment group for split sample 1 (‘DM1’), which received the attitudinal questions before the choice tasks, and the control group (‘DM2’) for split sample 2, which received the attitudinal questions after the choice tasks, and rDM for the assessment of the relative digital maturity.

For our model, we did not consider the different durations of the surveys. Although the treatment group (DM1), which encountered attitudinal questions prior to the discrete choice tasks, exhibited a slightly shorter median completion time (11:05 minutes, see Table 6) compared to the control group (10:56 minutes, see Table 6), the mean completion times were similar for both groups (18:11 minutes for treatment group vs. 18:26 minutes for control group). This marginal difference in survey duration suggests that the potential fatigue effect, if present, would be minimal at best. Given that both groups completed the same number of choice tasks and faced identical attribute structures, the modest differences in timing observed do not align with substantial fatigue effects. Instead, it is more plausible that slight variations in respondent reading patterns or comprehension rates, rather than systematic context-related fatigue, account for the minor discrepancies in completion time.

DCEs vary in length and complexity, and completion times are influenced by multiple factors, including the number of choice tasks, the complexity of attributes and levels, and the cognitive effort required from respondents (Bekker-Grob, et al., 2012). They typically allow for variation in completion times, recognising that respondent engagement, reading speed, and cognitive processing differ between individuals and even between randomised survey conditions.

Nevertheless, we want to note that we did not conduct a formal statistical test to confirm the insignificance of the timing differences, as the narrow margin of difference and the overall similarity in completion profiles across DM1 and DM2 support the decision to proceed without modelling fatigue explicitly.

In a similar manner to Liebe, et al. (2016) we estimated a CL model for the full sample (n = 800) and compared the estimated parameters with two CL estimations on the two groups, treatment (n = 400) and control (n = 400), separately. With this approach, we investigated if there are differences within the WTP estimates for both DM groups.

For the comparison of the preference estimates of the two samples, the aspects of taste and scale need to be considered (Swait & Louviere, 1993; Ben-Akiva & Morikawa, 1990). Two choice modelling samples may differ not only in terms of taste intensities (β) but also in terms of scale parameter estimate σ.

Differences in scale can arise from variations in choice uncertainty between samples, as the scale parameter is inversely proportional to the Gumbel error variance. Thus, even when the taste parameters are identical between the two samples, differences in scale may distort comparisons of preference estimates.

One might assume that scale heterogeneity could be neglected when comparing WTP estimates, as WTP represents a ratio of coefficients (e.g. β_1/β_2) in which the scale parameter cancels out:

$$\frac{\beta_1}{\beta_2} = \frac{\frac{\beta_1^*}{\sigma}}{\frac{\beta_2^*}{\sigma}} = \frac{\beta_1^*}{\beta_2^*} \tag{14}$$

where the subscripts refer to the first and second coefficients (Train, 2009, p. 41). Consequently, WTP estimates and other measures of MRS are unaffected by the scale parameter. This assumption allowed the focus to remain solely on taste differences as the source of variation in WTP.

While this assumption holds when examining the treatment (DM1) and control (DM2) samples individually, it becomes important when looking at the pooled model. In the pooled models, differences in scale between groups can bias the estimated coefficients (and consequently the MRS) if not properly accounted for, as differences in unobserved utility variance between samples are conflated with differences in taste parameters (Swait & Louviere, 1993).

To address potential biases caused by scale heterogeneity in the pooled model, two approaches are available: the heteroskedastic logit model (HLM) and the Generalised Multinomial Logit (GMNL) model. Both methods enable the separation of taste parameters and scale parameters, ensuring that differences in unobserved utility variance do not distort preference estimates.

The HLM explicitly accounts for differences in scale parameters between subgroups by introducing a scale parameter that varies across groups. In this approach, the treatment group is assigned a scale parameter (λ_t) that is estimated as part of the model, while the control group serves as the reference group with its scale parameter fixed to 1 ($\lambda_t = 1$). The pooled model assumes identical taste parameters (β) for both groups while allowing for differences in scale. This structure enables the utility function for each subgroup to be expressed as:

$$U_{i,j} = \lambda \times \left(\beta X_{i,j} \right) + \epsilon_{i,j} \quad (15),$$

where λ captures group-specific scale heterogeneity and $\epsilon_{i,j}$ is the Gumbel-distributed error term. Without adjustments for scale heterogeneity, the pooled model produces estimates of β that are weighted by a mixture of the taste parameters from each group (β_t and β_c). Consequently, measures such as the MRS and WTP become biased. By explicitly including a scale parameter and fixing one group's scale as the reference, the HLM separates scale heterogeneity from preference differences, ensuring unbiased preference estimates.

The GMNL model offers another way to address scale heterogeneity. This model extends the multinomial logit framework by simultaneously accounting for scale and preference heterogeneity. The GMNL introduces a parameter that combines individual-specific scale and taste heterogeneity, allowing for a highly flexible modelling structure. However, the GMNL model is computationally intensive and requires additional assumptions about the distribution of scale parameters across individuals, which can introduce unnecessary complexity when our primary concern is group-level scale heterogeneity (Fiebig, et al., 2009).

For this analysis, the heteroskedastic logit model was applied to the pooled data, incorporating a scale parameter (λ) to capture differences in the variance of unobserved utility between the two DM groups. This scale parameter ($\lambda_t =$ 'scale_treat') was estimated for the treatment group, while the control group's scale parameter was fixed to 1. The model assumes identical taste parameters (β) across the two groups, reflecting shared preferences while accounting for group-specific differences in scale.

The results of the HLM showed that the scale parameter for the treatment group was estimated at 1.00177 (robust t-statistic = 12.636, p<0.0001, see Table 7). This indicates a statistically significant but minor difference in scale between the two groups, suggesting a slightly higher variance in unobserved utility for the treatment group. Importantly, the inclusion of the scale parameter did not substantially alter the preference estimates or WTP values, reaffirming that the observed differences between the groups primarily reflect variations in taste rather than scale.

Based on the results of the CL model, we applied further estimations to identify whether the difference we might find between the estimates of the two sample groups is statistically significant or just based on chance. First, based on the z statistic, we compare the WTP estimates for both samples, thus finding the first indication for our research objective. Afterwards, an N = 1000 bootstrap replication was drawn for the DM1 and DM2 datasets to replicate the original distribution of the initial CL model. The resulting new simulated distribution was then assessed based on Poe et al.'s (1994) test with the aim to detect potential and statistically significant differences in the WTP between the DM1 and the DM2 group as a result of the different treatments of the two sample groups. This is used to confirm the hypothesis that the different treatments may impact the buying decision in electricity consumer markets so that consumers are in favour of technologically advanced products.

3.4 Results: Context effects on stated preferences

In the following sections, the results for the CL models are presented. This includes an initial standard restriction test and, furthermore, the results from the Poe et al. (1994) test, which was applied to the DM groups to evaluate if significant differences between the samples may exist.

Our hypothesis is that for the sample group DM1 (or: ‘treatment group’), the treatment (or framing) significantly influences consumers’ WTP for the attributes. Therefore, the null hypothesis can be stated as:

$$H0: WTP_{DM1} - WTP_{DM2} = \Delta WTP = 0$$

We estimate WTP in separate CL models for the two sample groups, derive robust standard errors using the delta method, and compare group-level WTPs with a z statistic:

$$z = \frac{WTP_{DM1} - WTP_{DM2}}{\sqrt{SE_{DM1} + SE_{DM2}}}, \qquad (16).$$

This means we are testing whether H0 is rejected at conventional significance levels. We also report 99.7% confidence intervals for the group-level differences, enabling an examination of whether the intervals overlap in a region that includes zero.

Nevertheless, before testing for H0, we take a look at the results of the three CL models and thus the three sets of estimates (treatment group, control group, pooled model; all models estimated in the preference space, WTP approximated through delta method) for the complete sample and the two split samples in Table 7 further below. Here, marginal WTP values that have been obtained post-estimation from parameter estimates are shown. The models were estimated using Apollo Choice Modelling for R (Hess & Palma, 2019)[5]. The alternative specific constant (‘ASC’, asc_alt1) is positive and statistically significant for all three sets of estimates at the 0.001 level. The ASC captures the differences between the utilities of the two alternatives that cannot be explained by the given parameters. The ASC being significant might be an indicator that one alternative is selected significantly more often than the other (Mariel, et al., 2021, p. 63; Hess & Beharry-Borg, 2012; Train, 2009). However, in our case, alternative 1 is chosen with 51.07% (4,903 times), and alternative 2 is chosen with 48.93% (4,697 times), which we still regard as a coincidence (Δ = 2.14%). It is also possible

[5] See appendices 8.4.1 for the applied R scripts.

that this observation is caused by the left-right bias, a bias which is caused by the reading order where respondents show a particular preference for an alternative that is displayed on a certain spot. This is a common bias in discrete choice experiments (Veldwijk et al., 2023, p. 307).

Table 7: Estimation results CL models (WTP, heteroskedastic logit model)

		Total			Treatment Group (DM 1)			Control Group (DM 2)		
Parameter	Name	WTP	pVal	Rob.s.e.	WTP	pVal	Rob.s.e.	WTP	pVal	Rob.s.e.
ASC_alt1		0.9729	0.0002	0.2574	1.1063	0.0019	0.3562	0.8356	0.0236	0.3691
PRICECALC0	Fixed Price per kWh – prices are defined for the contractual time	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PRICECALC1	Changing of prices based on a pre-defined plan	-3.0720	0.0000	0.4750	-1.5030	0.0181	0.6361	-4.6653	0.0000	0.6832
PRICECALC2	Decreasing prices per kWh each month with consumption change	-1.0987	0.0171	0.4609	-0.2320	0.7177	0.6416	-1.9897	0.0023	0.6533
(default)	Prices are itemized within the initial contract documents, bills are sent via mail	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PRICEEMAIL	Prices and monthly bills are sent via email	1.2911	0.0000	0.2699	1.2675	0.0011	0.3869	1.3168	0.0004	0.3747
PRICEPORTAL	Prices and monthly bills made available through an online portal	0.9623	0.0001	0.2435	0.6245	0.0578	0.3291	1.3158	0.0003	0.3600
PRICEAPP	Price communication and access to bills through mobile app	1.1594	0.0000	0.2445	1.1860	0.0005	0.3410	1.1380	0.0012	0.3502
(default)	Service Infrastructure: Call centre	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SERVEEMAIL	Service infrastructure: E-Mail	1.2729	0.0000	0.2595	1.1893	0.0010	0.3605	1.3675	0.0002	0.3722
SERVCHAT	Service infrastructure: Chat Agent (also video Chat)	0.5937	0.0149	0.2437	0.6632	0.0515	0.3406	0.5151	0.1396	0.3486
SERVAPP	Service infrastructure: Message service within smart phone app	1.1524	0.0000	0.2608	1.5435	0.0000	0.3706	0.7485	0.0384	0.3614
DEVICE0	No electric plug adapter included	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
DEVICE1	Manually adjustable electric plug adapter	2.6266	0.0000	0.5002	2.2914	0.0010	0.6966	2.9603	0.0000	0.7151
DEVICE2	Local connected electric plug adapter	2.0775	0.0000	0.5101	2.1586	0.0022	0.7043	1.9930	0.0067	0.7350
DEVICE3	Smart plug adapter incl. smart phone app	3.6384	0.0000	0.5396	3.7753	0.0000	0.7279	3.5150	0.0000	0.7957
DEVICE4	Smart plug adapter incl. smart phone app and analysis	4.4523	0.0000	0.5604	4.5843	0.0000	0.8034	4.3346	0.0000	0.7771
scale_treat	scale_treat	9.5676	0.0000	1.1835						
Log Likelihood (final)		-5076.85			-2532.10			-2531.79		
Observations		9600			4800			4800		
n		800			400			400		

Note: WTP = Willingness to pay; ***p < 0.001; **p < 0.01; *p < 0.05; DM1 and DM2 refer to the two different sample groups: Treatment Group (DM1) and Control Group (DM2)

Source: Author's own analysis.

In the following section, we will briefly discuss and compare the estimation results of the two sample groups.

The results from Table 7 show that both groups experience disutility from the deviation of a fixed price per kWh, such as in the case of a change in prices based on pre-defined plans (PRICECALC1), where prices might be different depending on the weekdays. Also, service bundles are less attractive if they are based on consumption-based discounts or premiums in case of higher vs. lower electricity consumption (PRICECALC2). Here, the control group shows higher disutility than the treatment. Respondents are willing to pay more or less, respectively, for consumption-based prices than for the other price option. However, the estimates for the consumption-dependent prices (PRICECALC2) are statistically significant only for the control group, while there is no statistical significance for the coefficients in the treatment group. The analysis of the parameters for PRICECALC and PRICECALC2 shows rational consumer behaviour. For PRICECALC1, consumers experience disutility from variable pricing, preferring stable pricing to manage budgets effectively (Train, 2009; Varian, 2014). The greater disutility for the control group suggests that familiarity with variable pricing in the treatment group mitigates negative perceptions if we assume the presence of context effects. For PRICECALC2, higher WTP for consumption-based pricing indicates a preference for control and potential savings, aligning with consumer sovereignty (Hanemann, 1991). The statistical significance in the control group but not in the treatment group implies context effects could alter perceptions. Practically, these findings suggest energy plans should offer stable pricing and customised consumption-based plans, with educational campaigns to increase acceptance.

For the price communication attributes, results show that utility for the treatment group (DM1) seems to be lower for PRICEEMAIL and PRICEPORTAL (not statistically significant for the treatment group) but higher for PRICEAPP, which might be an indicator that price communication through a smartphone app is perceived differently due to the treatment. This effect may be caused by the context effect before the preference elicitation.

Regarding the service infrastructure attributes, we see a higher WTP for SERVCHAT (not statistically significant for the treatment group) and SERVAPP for the treatment group compared to the control sample and a lower WTP for SERVEMAIL.

The parameter for the attribute levels of the additional device shows a lower WTP for the DEVICE1 in the treatment group. This is a manual adjustable electric plug adapter, hence the non-digital version of a plug. All other device attribute levels show a higher WTP.

The parameter results for price communication, service infrastructure, or additional devices seem plausible, given that the relevant attributes with a higher WTP value in the treatment group provide additional service or functionality to the consumers.

When just interpreting and comparing the individual results of the two samples, evidence for context effects might be visible, as the WTP values and the statistical significance differ between the two groups. The results are, therefore, methodologically comparable to the results of Liebe et al. (2016), albeit in a different context.

Nevertheless, based on the test for differences, it is necessary to further statistically investigate the existence of differences between the treatment and the control group, as the different WTPs could also be a result of chance. Therefore, based on estimation results from Table 7, we calculated the z statistic for the samples. The results can be seen in Table 8.

Table 8: Differences in sample group estimations

Parameter	WTP (DM1)	SE (DM1)	WTP (DM2)	SE (DM2)	Diff (DM1-DM2)	SE (Diff)	z-Value	p-Value	*	CI99.7% (Low)	CI99.7% (High)
ASC_alt1	1.1063	0.3562	0.8356	0.3691	0.2707	0.5129	0.5277	0.5977		-1.2681	1.8095
PRICECALC1	-1.5030	0.6361	-4.6653	0.6832	3.1623	0.9335	3.3876	0.0007	***	0.3619	5.9627
PRICECALC2	-0.2320	0.6416	-1.9897	0.6533	1.7577	0.9157	1.9196	0.0549		-0.9893	4.5047
PRICEEMAIL	1.2675	0.3869	1.3168	0.3747	-0.0493	0.5386	-0.0915	0.9271		-1.6651	1.5665
PRICEPORTAL	0.6245	0.3291	1.3158	0.3600	-0.6913	0.4878	-1.4173	0.1564		-2.1546	0.7720
PRICEAPP	1.1860	0.3410	1.1380	0.3502	0.0480	0.4888	0.0982	0.9218		-1.4184	1.5144
SERVEEMAIL	1.1893	0.3605	1.3675	0.3722	-0.1782	0.5182	-0.3439	0.7309		-1.7327	1.3763
SERVCHAT	0.6632	0.3406	0.5151	0.3486	0.1481	0.4874	0.3039	0.7612		-1.3140	1.6102
SERVAPP	1.5435	0.3706	0.7485	0.3614	0.7950	0.5176	1.5358	0.1246		-0.7579	2.3479
DEVICE1	2.2914	0.6966	2.9603	0.7151	-0.6689	0.9983	-0.6700	0.5028		-3.6638	2.3260
DEVICE2	2.1586	0.7043	1.9930	0.7350	0.1656	1.0180	0.1627	0.8708		-2.8883	3.2195
DEVICE3	3.7753	0.7279	3.5150	0.7957	0.2603	1.0784	0.2414	0.8093		-2.9749	3.4955
DEVICE4	4.5843	0.8034	4.3346	0.7771	0.2497	1.1177	0.2234	0.8232		-3.1035	3.6029

Note: ±3 * SE for ~99.7% confidence intervals. p-Value from two-sided z-test. '*' indicates significance at *p < 0.05, **p < 0.01, ***p < 0.001.

Source: Author’s own analysis.

In Table 8, we present the WTP differences between the treatment group and the control group. Most attributes show no statistically significant WTP difference. The exception is PRICECALC1, where the WTP difference is statistically significant (p = 0.0007). This suggests that the treatment group is significantly less averse to pre-defined variable pricing schemes than the control group. Hence, H0 can be rejected for PRICECALC1. However, when taking the 99.7% confidence intervals into consideration, the results for PRICECALC1 can be stated as follows:

$$Treatment\ group\colon -1.503 - 3 \times 0.6361 = -3.4113\ and\ -1.503 + 3 \times 0.6361 = 0.4053,$$

$$Control\ group\colon -4.6653 - 3 \times 0.6832 = -6.7149\ and\ -4.6653 + 3 \times 0.6832 = -2.6157.$$

This means the two samples overlap for PRICECALC1 in the interval [−3.4113, −2.6157]. Therefore, there is a chance that the two samples might have, indeed, in some instances the same estimation. Therefore, we take one step back and apply a rough standard restriction test on the full models by initiating a Chi-squared statistic based on the likelihood-ratio test. Afterwards, we follow the comparison approach presented by Poe et al. (1994), which is based on the method of convolutions.

From Table 7, we extract the three relevant log-likelihoods (LL) for the pooled (restricted model) and the two sample (unrestricted) models:

Model	**LL value**
Treatment Group (DM1)	-2532.10
Control Group (DM2)	-2531.79
Sum of DM1 + DM2	*-5063.89*
Pooled	-5076.85

Twice the difference of the LL value between the restricted model and the sum of the unrestricted models gives the value of the test for the hypothesis of the implied restrictions:

$$2\ x\ (5076.85 - 5063.89) = 25.92 \tag{17}$$

Based on the likelihood-ratio-test statistic for H0 of no joint difference across the 13 restrictions in WTP and the further restriction in scale, we obtain 14 restrictions in total ('degrees of freedom'). Based on a confidence interval of 95% (= critical value of 5%), we calculate the following threshold: 23.68479[6]. As our test statistic based on the LL values is higher than this threshold (25.92 > 23.68), we are able to reject H0 (no difference between the samples).

Now, we want to turn to the approach presented by Poe et al. (1994) in order to validate the results from the overall Chi-squared statistic for all attributes individually. The input of this evaluation are the WTP values from the CL model, which tries to describe the outcome by the choice variables such as PRICECALC, SERVEMAIL, or DEVICE, with the variable CHARGE being used to describe the outcome. The ratio

$$WTP = -\frac{\hat{\beta}}{\widehat{\beta_\$}}, \qquad (18),$$

where $\hat{\beta}$ is the estimated coefficient corresponding to a choice variable and $\hat{\beta}_\$$ the estimated coefficient of the CHARGE variable, has here been used as a measure for WTP. For the treatment (WTP1) and the control group (WTP2), different estimates of WTP, namely

$$WTP_1 = -\frac{\widehat{\beta_1}}{\widehat{\beta_{\$1}}}, \quad WTP_2 = -\frac{\widehat{\beta_2}}{\widehat{\beta_{\$2}}}, \qquad (19),$$

were obtained (as provided in Table 7). The estimators for the standard error were provided by means of the delta method, assuming that WTP is asymptotically normal distributed. This means that as more data is added, the distribution of the WTP estimates approaches a normal (bell-shaped) distribution. One approach to simulate such an increase of data points to generate a normal distribution is the so-called bootstrap procedure. To check if the WTP is significantly different in the treatment and control group, we follow Poe et al. (1994). Poe et al.'s test is based on bootstrapping methods, for this application we use 1000 replications, and applies a computational method (convolution approach) to measure the difference of independent empirical distributions and to find an estimate of the distribution of the following difference Δ:

[6] R command: qchisq(p=.05, df=14, lower.tail=FALSE).

$$\Delta = WTP_1 - WTP_2 \quad (20).$$

To do so, first n = 1000 bootstrap replications were drawn from the dataset corresponding to DM1 and DM2, providing N estimates of WTP_1 and N estimates of WTP_2. The empirical distribution of those bootstrap estimates is expected to replicate the distribution of the delta method used in Table 7. By calculating the mean and standard deviation of the bootstrap distribution of the estimates of WTP, the following results were obtained as depicted below in Table 9 following Poe et al. (1994, p. 912):

Table 9: Results for the bootstrapping estimates.

	DM1			***DM2***		
parameter	**mean**	**se**	**p**	**mean**	**se**	**p**
ASC_alt1	1.1064	0.3544	0.0040	0.8483	0.3683	0.0120
PRICECALC1	-1.4894	0.6193	0.0160	-4.6640	0.6922	0.0000
PRICECALC2	-0.2090	0.6348	0.7680	-2.0110	0.6586	0.0020
PRICEEMAIL	1.2542	0.3722	0.0000	1.3289	0.3797	0.0000
PRICEPORTAL	0.6179	0.3314	0.0600	1.3188	0.3633	0.0000
PRICEAPP	1.1958	0.3346	0.0000	1.1528	0.3381	0.0000
SERVEEMAIL	1.1838	0.3773	0.0000	1.3681	0.3619	0.0000
SERVCHAT	0.6655	0.3365	0.0500	0.5274	0.3587	0.1320
SERVAPP	1.5485	0.3591	0.0000	0.7516	0.3514	0.0220
DEVICE1	2.2873	0.6731	0.0020	2.9589	0.7411	0.0000
DEVICE2	2.1497	0.6874	0.0040	1.9708	0.7543	0.0120
DEVICE3	3.7545	0.7210	0.0000	3.5325	0.8168	0.0000
DEVICE4	4.5784	0.8191	0.0000	4.3526	0.7422	0.0000

Source: Author's own analysis.

It can be seen that, indeed, the statistical parameters mean, standard deviation, and the p-value for the test if the mean is zero coincide with the estimation results of Table 7. Histograms of the bootstrap distributions of the estimates of WTP for both groups DM1 and DM2 are given in the following Figure 18:

It can be observed that statistically relevant differences only occur for the variables PRICECALC1, PRICECALC2, PRICEPORTAL, SERVAPP, and DEVICE1. For the other variables, the bootstrap distributions seem to match quite closely for the two treatment groups.

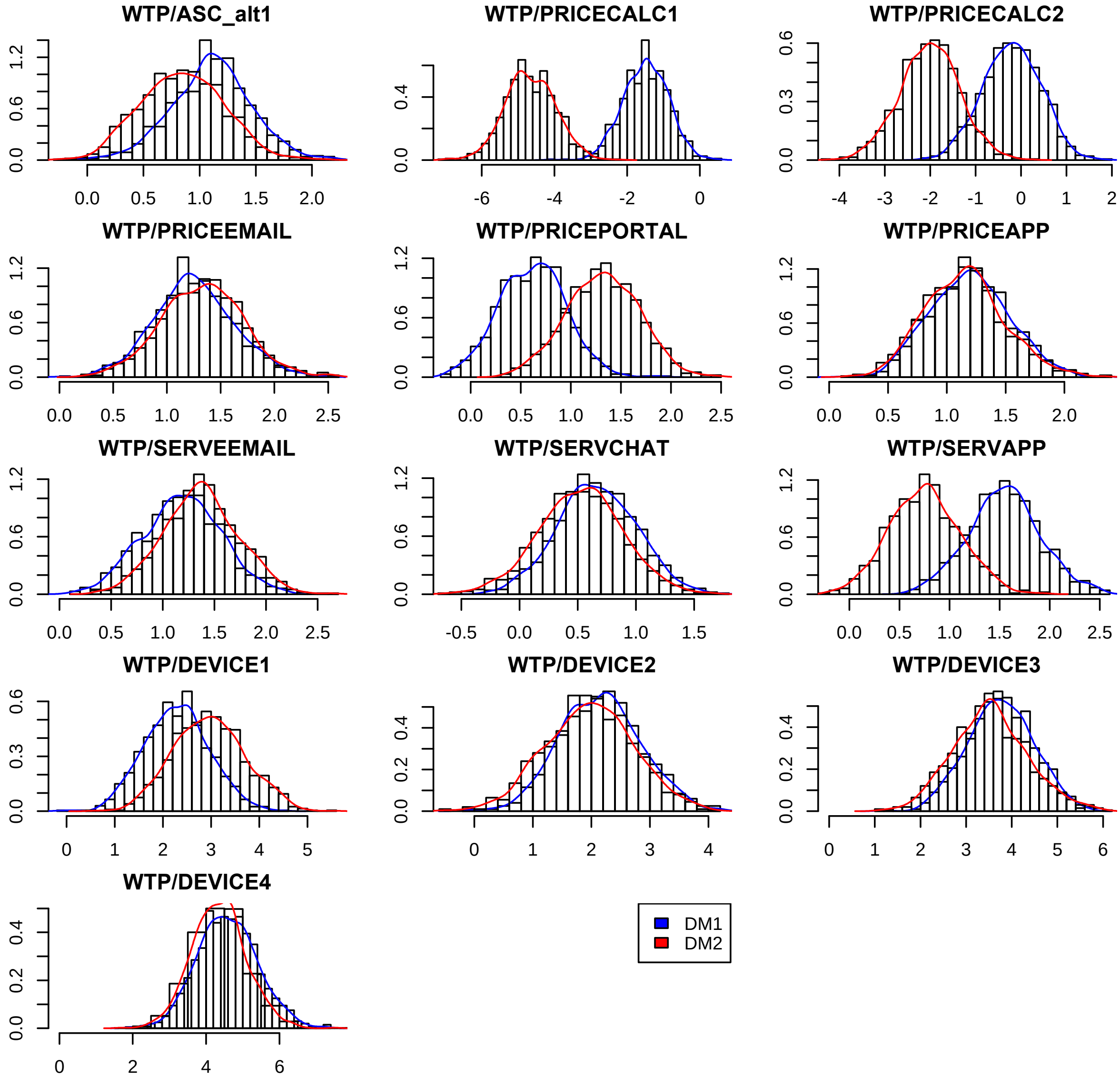


Figure 18: Histograms for the bootstrapping estimates for DM1 and DM2.

Source: Author's own analysis.

Following Liebe, et al. (2016), we apply Poe et al. (1994) test, where the cumulative distribution function and the density of $\Delta = WTP_1 - WTP_2$ for independent variables WTP_1 and WTP_2 is obtained by the convolution integral:

$$F_{\Delta}(d) = \int_{-\infty}^{d} f_{\Delta}(v)dv, \quad f_{\Delta}(v) = \int_{-\infty}^{d} \int_{-\infty}^{\infty} f_{WTP1}(v+y) \cdot f_{WTP2}(y)dy, \tag{21}$$

where f_{WTP1}, f_{WTP2} denote the densities of WTP_1, WTP_2, respectively (Poe, et al., 1994, p. 908). These densities are now approximated by the bootstrap distribution densities (histograms), while the integral is approximated by a discrete sum. For both approximations, a support of [-10,10] was assumed for the densities, and the lattice on which approximation took place consisted of 2001 equidistant points, that is, the lattice was given by $\frac{i}{M}, i = -10M, \ldots, 10M$ with $M = 1000$. The estimators obtained for the densities f_Δ of Δ are given in the following figure. Additionally, the corresponding symmetric 95% confidence regions consisting of the 0.025 and the 0.975 quantiles are depicted below in Figure 19:

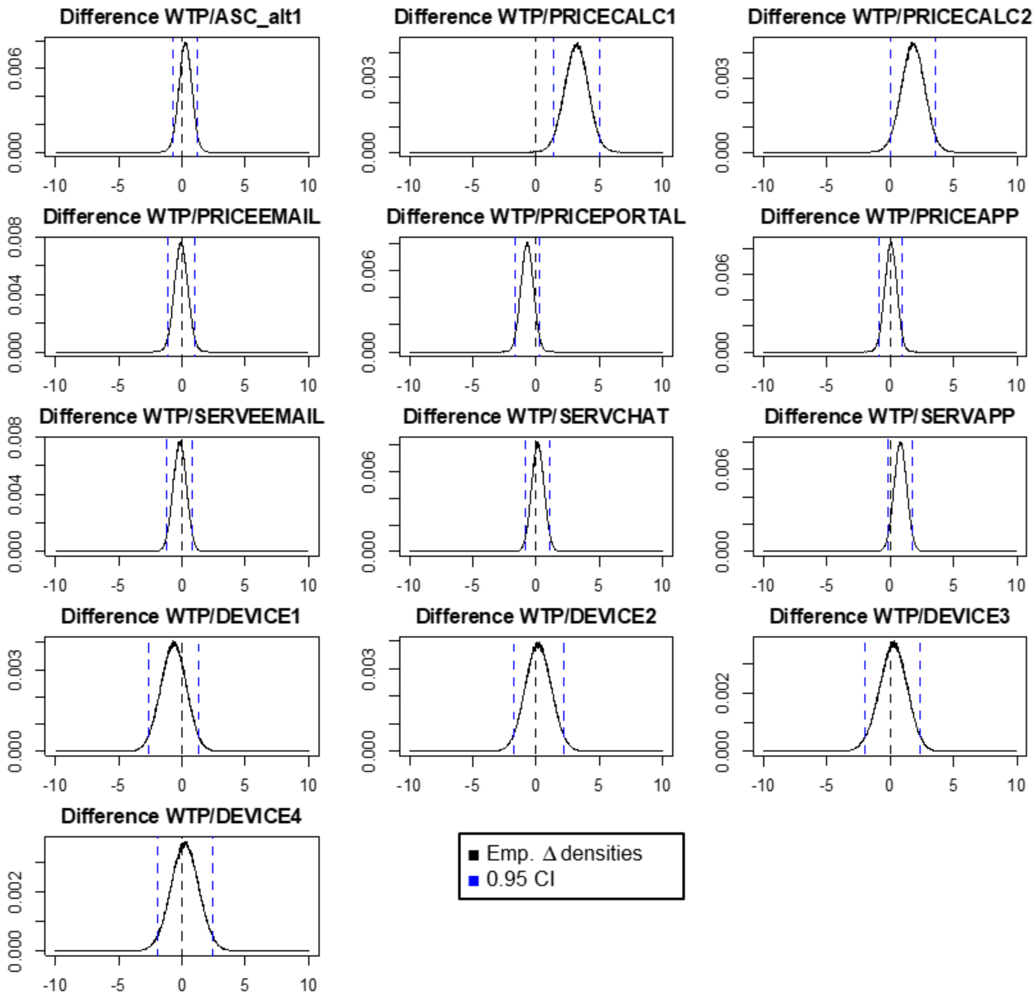


Figure 19: Densities for the differences of the WTP per attribute.

Source: Author’s own analysis.

To check if the difference Δ is zero, the p-values for this hypothesis were calculated based on the above empirical densities. The results are given in the following table.

Table 10: Group differences between DM1 and DM2

	DM1-DM2		
Parameter	**mean**	**se**	**p**
ASC_alt1	0.2582	0.2609	0.6131
PRICECALC1	3.1746	0.8618	0.0011
PRICECALC2	1.8020	0.8359	0.0498
PRICEEMAIL	-0.0744	0.2824	0.8755
PRICEPORTAL	-0.7010	0.2417	0.1522
PRICEAPP	0.0428	0.2260	0.9305
SERVEEMAIL	-0.1843	0.2731	0.7234
SERVCHAT	0.1383	0.2415	0.7897
SERVAPP	0.7969	0.2520	0.1171
DEVICE1	-0.6716	1.0011	0.5036
DEVICE2	0.1788	1.0401	0.8716
DEVICE3	0.2224	1.1858	0.8300
DEVICE4	0.2258	1.2210	0.8425

Source: Author's own analysis.

The results show only significant differences for the variables PRICECALC1 (p = 0.0011) and PRICECALC2 (p = 0.0498). All other parameters do not show a statistically significant difference between the treatment and the control group. This implies that the treatment has not yielded any statistically significant difference in the price communication, service infrastructure, and device attributes. The results of our tests, therefore, show that, with the exception of the price calculation attributes, the two samples do not have large differences in conditioning, as WTP are similarly distributed for most of the attributes.

This result complements the findings of Liebe et al. (2016) in their research on ethical consumption goods, who found evidence for certain context effects (p. 144) of certain attributes. Nevertheless, the results cannot be directly compared as the ethical consumer context is different and connected to socially undesired behaviours. In the case of this research, the treatment with the DM items appears to not increase awareness for digitised service, communication, and device attributes and thus does not influence WTP values as a result of individual treatment. Therefore, we observe that, apart from the impact on the price calculation components, the context effect treatment does not induce a shift in preferences.

The difference in perceived preference for both DM groups might, therefore, be translated into the following statement:

Electricity contract buyers that engaged with digitisation right before the buying decision are not enticed to increasingly choose technologically advanced product components in terms of service, communication, and product features.

Consequently, it can be stated that the hypothesis of a treatment leading to increased WTP for technologically advanced attributes and products can only be supported for two attributes: PRICECALC1 (pre-defined price plans) and PRICECALC2 (variable prices based on consumption). This means that in our approach, there is a significant difference in the WTP for variable tariffs after a direct treatment before the buying decision. We see these tariffs as more technologically advanced than a static tariff that uses a per-kWh calculation.

3.5 Discussion and Conclusion

3.5.1 Discussion of the results

The goal of this application was to identify whether context influences choice behaviour for economic goods, namely consumer energy product-service bundles. Evidence for the occurrence of context effects was found by other researchers, albeit in non-energy-related settings (Pouta, 2002; Liebe, et al., 2016; Kim & Park, 2017). The main objective of this application has been the question of whether preferences are reliable within the classical economic understanding of utility maximisation or if preferences and perceived utilities are, in fact, subject to change due to dynamic conditions or situational context. In our case, the dynamic condition was simulated by attitudinal questions that were supposed to induce context effects and thus impact perceived utilities by the respondents.

We investigated the occurrence of contextual effects using a CL model estimation. We found that in the categories of service, communication, and added devices, preferences remain stable as no significant differences have been found between the treatment (DM1) and the control group (DM2). Generally, the sample group that evaluated the product attributes and attribute levels according to their perceived digital maturity before the actual choice tasks

(DM1) showed a similar utility perception as the other group (DM2). However, differences have been found for pricing-related items. This implies that the treated group's preferences are different from the preferences of the control group when it comes to price calculation attributes (instead of services, support, or product-related items). Therefore, the use of attitude items prior to the choice task in this application leads to a different WTP for the price calculation items, particularly in favour of the more digitised and technologically advanced variations. Thus, this finding shows partial support for the general hypothesis that digitalised treatment impacts preferences in the context of retail electricity contracts. Consequently, a treatment that addresses digital attitudes does not necessarily induce a higher WTP for digital attributes apart from pricing-related items. This might lead to the result that a treatment is of little use to promote novel electricity contracts, except the novelty is price-related.

3.5.2 Limitations of the research

In total, our research is limited by five factors. First, we do not address the aspect of the (temporal) stability of preferences in our setup. This would provide information as to whether there are context effects that appear after a choice decision and can possibly be experienced in the case of later choice situations. Second, if we take the difference of the price-related attributes as an example of context effects, it would be interesting to see whether there is still a significant difference in preference between the sample groups after the purchase decision has been made and usage has started. Third, we did not control for endogenous context effects in our setup. Fourth, a setup with physical products and not energy contracts might be of interest. As these products are the original foundation for the area of servitisation, a split sample approach addressing physical products and adjacent services might lead to other results than for the case of contract-based intangible consumption offers, which are enriched with physical components and services. And finally, the limiting factor is the mechanism of the attitudinal questions. In other contributions, e.g., from Liebe et al. (2016) or Pouta (2002), these questions were statements that were evaluated by the respondents according to their individual approval or consent[7]. In our case, the attitudinal questions provided a framing to the choice tasks.

3.5.3 Managerial and methodological implications

Managerial and methodological implications can be drawn from the findings. For sales and marketing professionals, forcing customers into a pre-purchase decision-making situation may not be very helpful. Given the results of this application, a treatment could only be useful for price-related elements, as no impact on the level of services, communications or physical devices was found in our investigation. Consequently, no evidence was found to support the main hypothesis that context effects can alter preference under certain circumstances.

On the methodological side, our application adds to the relatively few contributions on context effects in choice experiments that focus on homogeneous and intangible economic goods. Thus, we add to the contributions of Pouta (2002) and Liebe, et al. (2016), who each called for an application with other economic goods.

The findings of this application, focused on whether preferences are reliable within classical utility maximisation or influenced by situational context, offer significant insights for energy providers and operators. The research demonstrated that while preferences for service, communication, and product attributes seem to be reliable, pricing-related preferences can be influenced by a treatment. This implies that targeted interventions can shift customer preferences for advanced pricing models, even if other attributes remain unaffected. In the following paragraphs, we will offer some practical suggestions for energy providers that might build on our results.

By recognising that treatments affect price mechanism preferences, energy providers can better segment their customers and tailor marketing strategies. For instance, customers showing higher interest in advanced digital maturity can be targeted with dynamic pricing models or time-of-use tariffs, which we perceive as technologically advanced and beneficial.

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[7] For example, with phrases such as: “I can understand that…”, “In my opinion…”, or “I would not have any problems with…”.

While the treatments did not significantly alter preferences for communication and service attributes, there remains a high WTP for services accessed via smartphone apps. Energy providers should develop comprehensive mobile applications offering features like real-time energy consumption analytics, personalised energy-saving tips, and dynamic pricing notifications. One example could be a ‘Smart Savings Plan’ that includes a mobile app with features like real-time usage tracking, energy-saving tips, and dynamic pricing alerts. This plan can be marketed to technology-savvy consumers, highlighting the benefits of advanced technology and potential cost savings. Given the impact of the treatment on pricing preferences, promoting flexible pricing plans such as peak and off-peak rates or weekend discounts might be beneficial. Marketing should emphasise the technological sophistication and cost-saving potential of these plans to attract and retain customers. Although preferences for service communication channels like email have not been affected by the treatment, the significant WTP for app-based interactions suggests a trend towards mobile communication. Enhancing mobile app features with 24/7 chat support, FAQs, and direct contact options can improve customer satisfaction and loyalty.

The higher WTP for advanced pricing models suggests the potential for integrating smart devices into energy service offerings. Energy providers should consider bundling advanced devices with their plans, emphasising the added value and functionality to attract consumers. Educating consumers on the benefits and ease of use of these advanced devices can further enhance their WTP. For that, energy providers can partner with smart home device manufacturers to offer bundled packages that include energy contracts and smart devices at discounted rates. This offers the possibility to leverage data from digital interactions and smart devices, which can provide deeper insights into customer behaviour. These insights could be very helpful for future product development and marketing strategies.

In conclusion, our results provide valuable insights for energy providers seeking to enhance their commercial strategies. By focusing on flexible pricing plans, developing advanced digital platforms, promoting smart device integration, and leveraging data-driven insights, companies can better meet the evolving preferences of their technology-savvy customers, enhancing satisfaction and driving business growth in a competitive market.

4 Application 2: Quantifying synergies within servitisation offerings for electricity consumers

Abstract

This chapter focuses specifically on product and service attributes. It evaluates if there are synergies between the product and service attributes in a bundled offer for energy products. This investigation particularly addresses the issues of servitisation or hybrid value generation. Methodologically, multiple conditional logit models are estimated to investigate interaction effects for attribute combinations. This is performed to identify significant interaction effects and to gain evidence for the impact on a positive or negative customer utility as a result of the bundling of goods and services. Statistical evidence for synergies in certain cases and for some attribute combinations are found.

4.1 Introduction

The concept of servitisation has been a prominent research focus in marketing and strategy since the 1980s. However, the foundational economic question regarding the utility derived from combining products, commodities, and services has deeper roots in economic theory, dating back to the 1930s. For instance, Chamberlin (1933) introduced the notion of product differentiation within markets, which serves as an early conceptual precursor to servitisation. His work highlighted the significance of heterogeneous goods and marked a shift towards understanding how differences in product attributes influence market structures and competition.

Building on this, later studies emphasised that heterogeneous product markets consist of goods that are similar but not perfect substitutes, thus creating opportunities for firms to compete by offering differentiated products (Saviotti, et al., 1982; Rothschild, 1987). A defining feature of these markets is the distinctiveness of products based on their unique characteristics, which can include functional features, design, or complementary services. This differentiation allows firms to appeal to diverse consumer preferences, fostering competition on factors beyond price alone. Consequently, servitisation, a concept where firms enhance their offerings by bundling services with products, emerges as a strategic approach to capture value in such markets.

By positioning servitisation within this broader historical and theoretical context, it becomes evident that the integration of goods and services represents a natural evolution of market differentiation. This perspective supports the relevance of servitisation in addressing the dynamic relationship between consumer needs and competitive pressures.

We will make two important contributions with this application. First, we offer an economic overview to help understand the possible synergies of servitisation and hybrid value creation. We show that utility is created by combining products and services, which supports the ideas, especially of Becker (1965) as well as Adams & Yellen (1976). Second, we add to the quantitative body of servitisation research, specifically offering a new perspective involving the evaluation of the product-service bundle based on customer utility.

The existing research on servitisation within management literature often highlights the potential benefits of integrated solutions for firms, such as enhanced customer value and competitive advantage. This narrative is frequently supported by theoretical arguments and anecdotal evidence rather than robust empirical analysis. For example, Ceci and Masini (2011) critique the so-called "integrated solution advantage hypothesis," observing that the advantages of such solutions are "mostly supported by theoretical arguments and anecdotal evidence only" (2011, pp. 29-30).

In addition to Ceci and Masini’s critique, while this mentioned predominant hypothesis is valuable for exploring qualitative aspects of servitisation, it lacks the quantitative foundation to support its claims. This gap points towards the need for approaches that provide data-driven insights into the preferences and trade-offs made by customers when selecting offerings that are distinguished by varying attribute components. Therefore, this application aims to address this limitation by quantifying customer preferences through evaluating the utility surplus of servitisation, measured in terms of increased WTP for combined attributes.

The initial understanding of servitisation was derived from the investigations of manufacturing firms and how they combine tangible products with (non-tangible) services.

(Vandermerwe & Rada, 1988). Servitisation refers to the shift of a manufacturing firm's product portfolio to include a higher range of service offerings (Vandermerwe & Rada, 1988). Today's understanding of the concept has been broadened and refers to the idea that companies create additional utility by adding services or additional product components to the core product (Tukker, 2004; Oliva & Kallenberg, 2003). This extended understanding is summarised, for example, by the concept of 'hybrid value creation' (Ulaga & Reinartz, 2011; Velamuri, et al., 2011), which concerns the issues of product bundling and the related question of whether product bundling impacts utility (Becker, 1965; Adams & Yellen, 1976). The idea of bundling is part of Lancaster's theory of consumer behaviour (1966), which proposes that goods are not direct objects of utility but that utility is derived from a bundle of properties and characteristics, which consequently could also be own products or services. However, here, the key point is that the focus for differentiation between bundles or products is based on their respective quality (Lancaster, 1966; Apps & Rees, 2009, p. 23).

Even though the research field of servitisation can be regarded as an established area, most of the contributions are conceptual or qualitative (Ceci & Masini, 2011, pp. 29-30). In this thesis, we argue that the research field lacks applied or quantitative contributions that add to the economic body and reasoning of servitisation. Therefore, this chapter investigates whether the hypothesis of a consumer surplus arising from combining goods, services, and attributes holds true in an applied economic model estimation. Within a business management context, the result of this question could be that servitisation or hybrid value creation is a suitable approach for energy providers to offer additional utility to customers and (re)gain competitive advantage as it is assumed and proposed in the literature (Lightfoot, et al., 2013; Raddats, et al., 2019; Ambroise, et al., 2018; Oliva & Kallenberg, 2003; Gebauer, et al., 2011; Vandermerwe, 2000; Grahsl & Velamuri, 2014; Baines, et al., 2017).

Statistically significant interaction effects in our data set would indicate the existence of synergies within product-service bundles, so-called synergetic bundles. Therefore, we test for the combination of attribute levels in order to capture possible interaction effects within our DCE setup. We approach the question for interactions from an attribute-level perspective, as this offers richer insights. The different device attribute levels that have been part of the choice setup offer great potential for synergetic effects in private household use, i.e., smart plugs with app control or even with an algorithm included. Moreover, the design enables the estimation of direct utility effects for each attribute level.

In accordance with conventions in the literature, for estimating the DCE, we use conditional logit models (CL) with interaction effects to test if the components of energy product-service bundles offer synergies and thus a customer surplus (Hensher, et al., 2005; Louviere & Hensher, 1982; McFadden, 1974). The data for this investigation was captured by the already presented survey that involved 800 respondents from a German research panel. The DCE is structured according to a three-stage servitisation framework for utility companies introduced in Chapter 2.3, which offers directions for creating bundled offerings for consumers (Grahsl, 2013; Grahsl & Velamuri, 2014; Vandermerwe & Rada, 1988).

Based on the assumptions derived from business servitisation literature set in combination with economic foundations set out in Chapter 2, we expect our models to show synergetic effects between the different parts of the product-service bundles, hence generating additional customer utility surplus as the result of the bundling.

We organise the remainder of Chapter 4 as follows: first, we review the theoretical foundations and literature for servitisation and hybrid value creation (Chapter 4.2). Here, the economic foundations that support the idea of servitisation are treated as well. In Chapter 4.3, the methodological approach for the specific case of our research objectives will be presented in more detail. We then discuss and explain the estimation results of the models in Chapter 4.1. At this point, we take a deeper look at the observed interaction effects (= synergies) of our framework and give a practical-oriented interpretation of the estimation results while referring to the validity of the research hypotheses. Finally, the conclusions provided in Chapter 4.2 will consider the practical and methodological implications of the modelling results with reference to theory and practical application. Furthermore, limitations are discussed, and directions for further research are presented.

4.2 Literature review and theoretical foundations

4.2.1 Servitisation in business and management literature

Numerous notations and terms were established which are comparable to the concept of 'servitisation' introduced earlier. These include: 'service operations', 'service integration', 'service economy', 'integrated solutions' (Baines, et al., 2017), 'service infusion', 'transition from product to services' (Raddats, et al., 2019; Forkmann, et al., 2017), 'hybrid value creation', 'dematerialisation', 'hybrid product or solution' (Ulaga & Reinartz, 2011; Velamuri, et al., 2011) or 'PSS – Product-Service-System' (Tukker, 2004). The variety in terminology implies that the initial understanding of 'servitisation' has gained attention from different fields within management and operational studies (Raddats, et al., 2019; Baines, et al., 2017; Baines, et al., 2009; Lightfoot, et al., 2013; Velamuri, et al., 2011). Within the course of this chapter, we use 'servitisation' as the fundamental nomenclature. However, references to other expressions within the given context and definitions can be made in some cases. Nevertheless, the definition of servitisation in the remainder of this contribution refers to the understanding that servitisation is the combination of different (and potentially differentiable) product and service attribute bundles that are offered to customers.

Within the literature, different approaches for categorising services are proposed. One example is the segmentation based on value creation complexity by Baines et al. (2017): base services (e.g. installation), intermediate services (e.g. maintenance) and advanced services (e.g. outcome contracts or service level agreements). Other understandings blur the hierarchy of tangible and intangible components within the offer, for instance, separating services into smoothing services (facilitate product purchase without altering functionality, e.g., insurance service when renting a car), adapting services (can be integrated into the product and expand functionality, e.g. GPS usage for smartwatches) and substituting services (instead of purchasing a product, customers pay per use, e.g. in the case of Microsoft 365) (Frank, et al., 2019).

Besides the categorisation of services, management research has also focussed on the motivation for offering servitisation. Companies may increase revenue and profit, improve response to customer needs, improve product innovation, build new revenue streams, increase customer loyalty, or set barriers to competition (Lightfoot, et al., 2013; Raddats, et al., 2019; Ambroise, et al., 2018; Baines, et al., 2017). The diversification of product-heavy firms into service-based operations offers firms opportunities for sustained growth and enhances competitiveness. The expansion of the service business is hereby heavily connected to an array of new digital technologies which are part of the ongoing digital transformation. In this context, the current evolutionary stage of servitisation can also be referred to as digital servitisation (Gebauer et al., 2021).

In the remainder of this section, we reply to this chapter's second research objective of adding to the quantitative area of the servitisation research area. Thus, we summarise key quantitative studies on servitisation while identifying the quantitative methods, the underlying data, and the key results of the research. In conducting and structuring this literature review, we identify three major research topics: The impact of servitisation on the basic financial performance of the firm, the impact of the firm's capabilities and resources on servitisation offerings, and the performance of servitisation strategies.

The first research area of servitisation is the investigation of the impact on financial performance and shareholder value. The studies within this field are built on the hypothesis that servitisation increases turnover and competitive differentiation for the firm. The data of the relevant studies is captured from annual performance reports (Suarez, et al., 2013; Fang, et al., 2008; Visnjic, et al., 2016) and self-assessment surveys (Eggert, et al., 2014). The studies focus on IT providers (Suarez, et al., 2013), manufacturing (Fang, et al., 2008; Visnjic, et al., 2016), and engineering firms (Eggert, et al., 2014). Different quantitative methods are used within the studies: fixed effects models and dynamic panel data estimations (Suarez, et al., 2013), a correlation analysis between the service intensity and the firm's value based on the replacement costs of the firm's assets (Fang, et al., 2008), latent growth models (Eggert, et al., 2014), and panel data analysis with fixed effects (Visnjic, et al., 2016). Key results and arguments emerging from these studies are as follows:

- The profitability of heavily integrated services does not exceed the profits associated with focusing simply on products, with the implication that the high importance of services as the result of market maturity may be overrated (Suarez, et al., 2013)
- There is a correlation between the service intensity and the firm's value when service turnover reaches a share of 20% to 30% of the company's total turnover (Fang, et al., 2008)
- A balanced product-service combination serves the long-term performance of the firm, while an isolated focus on either services or products improves the short-term performance (Visnjic, et al., 2016)
- Servitisation strategies increase both the absolute level and the growth of manufacturing firms' revenue streams while reducing the level but improving the growth of profits (Eggert, et al., 2014)

The findings within this research topic are in line with the wider consensus about the impact of servitisation. The studies above find evidence for the impact of integrated service-product strategies on the financial performance of the firm (Fang, et al., 2008; Visnjic, et al., 2016; Eggert, et al., 2014; Suarez, et al., 2013). However, due to the nature of the data, a customer perspective is missing, as the development of the financial performance may have had different market drivers. The studies use market share, market maturity, and margins (Suarez, et al., 2013); share price, service turnover, market dynamics, or R&D sales ratios (Fang, et al., 2008; Visnjic, et al., 2016; Eggert, et al., 2014) as variables and controlled these by company size indicators. Based on the findings, we assume product-service bundles have a positive impact on financial performance. However, the source of the increased financial performance still needs further clarification. We still need to investigate the impact on the WTP from consumers, with a focus on whether product-service bundles offering a utility surplus lead to better financial performance for the firm.

The second area of quantitative servitisation research concerns the impact of the firm's capabilities and resources on servitisation offerings. Empirical research in relation to this issue is mostly conducted based on survey data (Kohtamäki, et al., 2013; Parida, et al., 2014), case studies (Parida, et al., 2014; Ceci & Masini, 2011), executive interviews (Ceci & Masini, 2011), or industry panel data (Santamaria, et al., 2011). The studies focus on manufacturers (Santamaria, et al., 2011; Kohtamäki, et al., 2013; Parida, et al., 2014) and IT companies (Ceci & Masini, 2011). The methods used are factor analyses (Parida, et al., 2014; Kohtamäki, et al., 2013), regression models (Kohtamäki, et al., 2013), cluster analyses (Ceci & Masini, 2011), and a multivariate probit model (Santamaria, et al., 2011). Key results of the studies in this research area are:

- Service strategy configurations for IT providers and service offerings, in addition to hard- and software sales, increase financial performance in contrast to not offering services (Ceci & Masini, 2011)
- The existence of networking capabilities facilitates the relationship between sales performance and servitisation (Kohtamäki, et al., 2013)
- Human resource management and customer links are the main facilitators for service innovations (Santamaria, et al., 2011)
- An organisational transformation based on distinctive capabilities and associated key learning activities is necessary if a positive financial performance of added services is to emerge (Parida, et al., 2014)

Important takeaways of this research field are the findings that for increased performance, providers need to have the capability to combine services and physical products in-house (Santamaria, et al., 2011; Ceci & Masini, 2011). Moreover, it shows that integrated services are an offering that supports competitive advantages in homogenous markets (Ceci & Masini, 2011). Other findings are in line with the established knowledge, e.g., that there is a non-linear or even negative effect of service offerings on sales growth if not implemented thoughtfully (Kohtamäki, et al., 2013; Parida, et al., 2014). This effect is known as the ‘servitisation paradox’, which we address later in Chapter 4.2.2.

The third research area within the subject of quantitative servitisation focuses on the performance of servitisation strategies. Data in this field are captured through surveys

(Gebauer, et al., 2011; Eggert, et al., 2011; Steiner, et al., 2014) and interviews (Gebauer, 2008). All studies focus on manufacturing companies. Methods include correlation analyses (Gebauer, et al., 2011; Gebauer, 2008), factor analyses (Gebauer, 2008; Steiner, et al., 2014), and latent growth and group models (Eggert, et al., 2011). The key results of selected studies can be summarised as follows:

- There is evidence that companies which have a strong service differentiation approach are less sensitive to a change in customer needs (Gebauer, et al., 2011)
- Distinct service strategies emerge based on after-sales, customer support, outsourcing and development (Gebauer, 2008)
- Services that are added to or combined with a product directly increase firm profitability, while services supporting the clients' actions do not display any link with long-term profitability (Eggert, et al., 2011)
- There is a higher WTP for individually tailored and negotiated services in B2B sales than for the very same services combination that is only presented as ‘pre-packaged’ (Steiner, et al., 2014)

This research cluster takes the customer perspective (e.g. ‘customer centricity’) into account. However, for measuring customer centricity, financial performance indicators are used, which have been gathered through interviews with firm executives (Gebauer, et al., 2011). Again, direct customer preferences are not collected to assess the success of service-product bundles. Nevertheless, the studies (Gebauer, et al., 2011; Eggert, et al., 2011) confirm that a proxy for consumer centricity as well as for innovativeness of service offerings of a firm has an impact on financial performance, which supports the assumption that the (long-term) financial effects of servitisation. We find evidence that there is a higher WTP for product-service bundles, which also supports the underlying assumption of our research (Steiner, et al., 2014).

The review of the quantitative literature on servitisation identifies several characteristics that directly lead to the research gap that we want to address with this application. It becomes obvious that the majority of the quantitative servitisation studies focus on manufacturing companies. There are some studies on IT companies; however, all of them are B2B focused. While only one study (Steiner, et al., 2014) emphasises the value for the (corporate) customer, most equate better financial performance or profitability with higher value, implying that this addresses the customer perspective as well.

4.2.2 Hybrid value creation for commodities and electricity

We begin by introducing electricity based on its characteristics as a good, which makes it hard to offer a competitive advantage for the supplier. We then introduce servitisation and hybrid value creation as one way to increase customer linkage in order to gain that competitive advantage. We also introduce a servitisation framework specifically aimed at product differentiation and servitisation strategies for energy and utility companies and discuss common pitfalls of the concept, known as the servitisation paradox. Consistent with the general approach to servitisation, the energy and utility servitisation framework is built in part on the assumption of synergies generated from product bundles, which we want to investigate in the further course of this application.

Electricity can generally be regarded as showing the characteristics of private goods (Nikander, et al., 2020). Customers can be excluded from the consumption if they do not pay for the supply. Furthermore, the volume of electricity consumption must be the same as the production volume and must take place roughly at the same time[8] (Lohse & Künzel, 2011, p. 384; Kempener & de Vivero, 2015). It can be argued that electricity is a good that has a low competitive differentiation (Rangan & Bowmann, 1992). Nevertheless, some authors argue that, based on the characteristics, a differentiation might be possible (Woo, et al., 2014). For example, customers may be willing to pay a premium for electricity if it is produced from renewable energy sources (Kim, et al., 2013). The electricity market demonstrates the typical characteristics of a commodity market. Consumers perceive energy providers and their products to be interchangeable, mainly based on the standardised quality of: 'if the light

[8] The organisation of this connection is done by the balancing group management.

switches on or not', which makes the price an important switching criterion (Rangan & Bowmann, 1992, p. 217; Haller, et al., 2022; Littlechild, 2018; Amenta, et al., 2022). However, recent research suggests that price is no longer the dominant reason for switching decisions and that non-price attributes (e.g., call waiting time, length of the fixed-rate contract, renewable energy, loyalty rewards, etc.) also have an important influence on the consumer decisions to switch their electricity provider (Ndebele, et al., 2019). Thus, energy and electricity suppliers need foster differentiation strategies by emphasising discounts, bonuses, different tariff configurations, non-price product attributes as well as product bundles (Woldeab, 2014, p. 63; Bruhn & Zimmermann, 2022).

From a business and management perspective, electricity can be regarded as a so-called 'born commodity' as it does not offer the objective potential for competitive differentiation itself. Some researchers argue that 'born commodities' can be 'de-commoditised' by adding additional attributes or new functionalities (Enke, et al., 2010, pp. 8-10), a strategy that is at the core of the classical servitisation understanding. Consumer electricity is a 'low-involvement-product', as it is available in nearly every household and company and as it is essential for daily life (Lohse & Künzel, 2011, p. 384). There are five characteristics that shape electricity offers:

- Intangibility: There are no tangible aspects such as shape, colour, smell or taste. Branding or packaging is not possible on the core product.
- Homogeneity: Electricity is standardised, and the supplier is fully exchangeable for the consumer within a deregulated energy market, where switching is facilitated.
- Indirect value creation: Electricity alone does not offer any value or utility to consumers. Value creation is achieved through the usage of electrical devices.
- Grid boundedness and instability: Even though storage technologies have become more common in recent years (Kempener & de Vivero, 2015, p. 4), energy generation and consumption need to align within a limited time period (balancing group management).
- Low involvement of consumers: Personal involvement of consumers for electricity increases when it is not available and electric devices cease to function. However, on a

political level, in recent years, different moments emerged (e.g. Fridays For Future) that created high involvement in energy and sustainability-related issues.

To summarise, there are different characteristics of electricity that might serve as a starting point for differentiation. Given the characteristics of electricity, servitisation can be regarded as a promising approach for gaining competitive differentiation in the case of de-commoditisation, as it describes the combination of different goods and services and, therefore, offers a platform for adding innovative attributes that might increase customer loyalty (Shankar, et al., 2009; Matthyssens & Vandenbempt, 2008; Auguste, et al., 2006). Matthyssens and Vandenbempt (2008) argue that there are three main value propositions that lead to competitive differentiation: a) product innovation, b) customer linking, and c) cost leadership. While the business of commodities is mostly driven by price competition, cost leadership can only lead to sustainable competitive advantage if operational efficiency, economies of scale, and cost reduction are archived and maintained on a continuous level. Apart from this, product innovation, customer linking and engagement through implementing innovative services can very much result in the de-commoditisation of a product (Matthyssens & Vandenbempt, 2008; Nauen & Enke, 2022). The application of commoditised and intangible offers in the area of servitisation is addressed by a few qualitative contributions (Shankar, et al., 2009; Grahsl, 2013; Grahsl & Velamuri, 2014). It can be argued that a service extension of existing offerings, e.g., building a product-service combination as a source for new income or for increasing customer loyalty, can also be applicable in fields other than manufacturing. This broader understanding is addressed by the concepts product-service systems (Tukker, 2004), ‘hybrid value creation’ (Velamuri, 2011; Grahsl & Velamuri, 2014; Velamuri, et al., 2011) or ‘hybrid solutions’ (Shankar, et al., 2009). The concept of hybrid value creation in the case of electricity offerings is based on the understanding that the value creation of energy providers can be understood as ‘manufacturing’ electricity (Grahsl, 2013, p. 106). Therefore, the theoretical foundation of servitisation as proposed by Vandermerwe and Rada (1988) can be applied in this case. A three-stage process of servitisation for manufacturing companies is proposed (Vandermerwe & Rada, 1988, pp. 315-316; Grahsl, 2013, p. 108) that also serves as the foundation for our approach on energy product-service bundles:

- Stage 1: Companies offering products, goods or services,
- Stage 2: Product companies adding services to their offering or service companies adding products based on advanced technology or converging trends (goods + services) and
- Stage 3: Companies offering bundles, combining goods, services, support, self-service and knowledge; services being the dominant component (goods + services + support + knowledge + self-service).

Grahsl (2013; Grahsl & Velamuri, 2014) used Vandermerwe and Rada's (1988) approach to add to the existing variety of industry perspectives provided on servitisation with a special focus on better serving end-customers in the energy sector and identified two approaches on how servitisation offerings can be systematically conceptualised into additive- and synergetic-bundles.

While the differentiation of the three servitisation stages is straightforward, the parts may overlap or might be interconnected, which becomes even more apparent for the more detailed framework and the description of the components for each stage that are used in this chapter and which are displayed in Table 11.

Table 11: Servitisation model for utilities

Stage	Components	Description	Examples
1	Commodity	Traditional core offering of energy and utility companies.	Electricity, gas, heat
2	Service	Service aspects provided around the commodity electricity or new offerings.	Special electricity tariffs, e.g., green electricity, price guarantees
3	Product	Physical products that lead to an increase in electricity demand or are essential to increase new offerings.	E-scooter, batteries, solar panels
3	Knowledge	Individual consulting services and/or know-how transfer.	Consulting services like a business case calculation regarding a new heating insulation investment
3	Support	Customer support to use its offerings more efficiently.	Tips for saving energy, support to use new offerings most efficiently
3	Self service	Enabling users to substitute formerly paid services like energy consumption optimisation with self-service tools.	Online tool to monitor electricity consumption

Source: Grahsl & Velamuri (2014, pp. 4-5).

Customer-focussed bundles of goods and services can be offered, which aim to offer value for the customers in the form of support, knowledge, or self-service applications (Vandermerwe & Rada, 1988). The core product of energy and electricity providers is the commodity (electricity, gas, heat) itself, Grahsl (2013) uses it within the understanding of Vandermerwe and Rada's (1988) Stage 1 definition. Building on this foundation, Stage 2 adds complementing services, such as green tariffs or blackout insurance (Grahsl, 2013; Kim, et al., 2013; Baik, et al., 2020). In contrast to the original framework by Vandermerwe and Rada (1988), Grahsl defines physical products (e.g., smart plugs, smart thermostats, home automation sensors, or e-scooter) as part of Stage 3 for energy and utilities (Grahsl, 2013, p. 115). She argues that in the case of energy supply contracts, the prevalence of physical products increases demand for the core good and, therefore, are complementary to electricity (Grahsl, 2013, p. 116). Electric vehicles are a prime example of this (Gilleran, et al., 2021). However, it must also be mentioned that the servitisation approach for retail electricity does not necessarily entice customers to use more electricity because of complementary or additional attributes or features of the product. For example, some of the servitisation features effectively provide options for energy saving (Grahsl & Velamuri, 2014), while others are effectively based on environmental preferences such as for renewable energy source use (Kim, et al., 2013).

In Grahsl's (2013) framework, the categories of possible bundles are distinguished into additive ('combinations') and synergetic ('solutions') bundles (see also Grahsl & Velamuri (2014, p. 9)). Additive bundles are a combination of two or more single services or physical products sold together in a bundle. Examples of additive bundles are peace-of-mind bundles, which offer best-of-breed offerings with low complementarity and high independence of components. The configuration logic can be written as 1+1 equals 2. There are two reasons for additive bundles from the customer perspective: the convenience aspect in purchasing several offers within a single point of contact and in most cases a price advantage as companies tend to offer bundles at a special price (Grahsl & Velamuri, 2014, p. 9). Synergetic bundles are a combination of components that are integrated to create a utility surplus for the customer that exceeds the sum of the individual utilities of the bundle components. Examples are so-called 'flexible bundles', which combine independent but highly complementary components (Shankar, et al., 2009; Grahsl & Velamuri, 2014). The configuration logic might be understood as 1+1 equals 3. Synergetic bundles are assumed to offer additional values for the user based on their interconnection and integration.

The hypothesis for synergetic bundles is that the combination of the different components leads to an optimised outcome for the customer, hence a higher WTP and – according to servitisation literature – an increase in commercial performance. However, any energy savings features within a servitisation bundle may lead to an antagony from the viewpoint of the provider - at least in the short run and without taking any loyalty effects into account. This might happen if the respective feature (e.g., a mobile app for transparency, a remote-controlled device or even a smart device that optimises consumption) leads either to lower consumption of the commodity good in the form of electricity use or to consumption with lower prices. This example is very relevant for the theme of the 'servitisation paradox', which refers to the empirical observations that additional services may not necessarily correspond to higher returns for producing firms (Gebauer, et al., 2005).

The servitisation paradox has been observed within manufacturing companies. Gebauer et al. (2005) identify four different factors for the appearance of the paradox. First, cognitive and behavioural challenges, such as an overemphasis from managers on tangible products, economic scepticism about the viability of the services business model, and risk aversion to develop new organisational capabilities, restrain firms from fully developing a service-oriented model. Second, organisational and strategic misalignment, including the lack of a strategy that has services as a core component as well as the underestimation of the need to transform from a product-centric to a service-oriented company, which requires substantial changes in organisational structure, culture, and employee skills (Dmitrijeva, et al., 2022; Brax, et al., 2021; Kaczor, et al., 2017). Third, operational and implementation challenges like resource misallocation and inadequate service design fail to meet market demands or customer needs effectively (Kaczor, et al., 2017). Fourth, market dynamics and customer perceptions can also contribute to the paradox, as customers may not perceive sufficient value in the services provided, especially if not well integrated with the core products. Also, competitive pressures in saturated markets can lead to reduced profitability (Gebauer, et al., 2005). New insights from Brax et al. (2021). emphasise the importance of a configurational approach in understanding the servitisation paradox. They propose that different strategic, processual, and environmental configurations can distinctly impact a firm's performance when adopting servitisation strategies. This configurational theory helps explain the varying outcomes observed in firms' servitisation efforts, suggesting that success in servitisation is not merely about adding services but about finding the right combination of factors that work harmoniously within the specific context of each firm.

For the servitisation paradox, it might be reasonable to consider Shephard's lemma as a potential theoretical underpinning. It can offer an economically grounded perspective on the phenomenon. Shephard's lemma, by exploring the relationship between cost functions and input demand, provides insights into cost minimisation behaviour (Varian, 1999; Diewert, 1974;

Phaneuf & Requate, 2017). When firms transition from pure manufacturing to a service-oriented model, the production and input mix inevitably changes, emphasising labour, technology, and other service-related inputs over traditional raw materials. By analysing these shifts through the lens of cost functions and input demand, as articulated by Shephard's lemma, we could conceptualise the economic impacts of servitisation. This approach suggests that the observed challenges and reduced profitability in the servitisation paradox may stem from the complex adjustments in input costs and demands. Thus, while not directly resolving the paradox, Shephard's lemma offers a theoretical framework to understand the cost dynamics and input reconfigurations inherent in the organisational servitisation process.

However, it is crucial to recognise the limitations of directly linking the two concepts. The lemma operates within the confines of neoclassical economic theory, assuming rational behaviour and smooth adjustment of inputs, which may not fully capture the dynamic and often non-linear factors influencing servitisation outcomes. Servitisation involves complexities such as market competition, customer behaviour, and internal organisational changes, which extend beyond the scope of traditional cost minimisation models. Servitisation challenges often stem from strategic and operational misalignments rather than purely economic factors (Baines, et al., 2009). Additionally, the servitisation paradox arises from practical difficulties in implementing service-oriented strategies, suggesting that a broader, multi-disciplinary approach is necessary to fully understand and address the challenges (Brax, et al., 2021).

A similar concept has also been hypothesised specifically for digitalised offerings as well and is known as the ‘digitisation paradox’ (Gebauer et al., 2020).

4.2.3 Discussion of the theoretical foundations of random utility models for servitisation, value added and hybrid value creation

There are different theoretical approaches that relate to servitisation. A recent study names (1) resource-based theory, (2) game theory, (3) transaction cost theory, and (4) the contingency theory as the most used perspectives in servitisation research (Ruiz-Martín & Díaz-Garrido, 2021).

(1) Resource-based theory builds on the assumption that the firm's resources and capabilities are the source of its offers and, consequently, its competitive advantage. This understanding follows the motivation of servitisation to differentiate based on unique product-service-combinations to increase utility for customers (Barney, 1991).
(2) The consideration of game theory builds on the need to analyse the return of servitisation strategies through understanding the provider and seller relationship as well as consumer (choice) behaviour (Wagstaff, et al., 2021).
(3) The transaction cost theory is used to consider operating cost for supply chain integration to offer product-service bundles that are composed by different market actors (e.g. call centres for service, third party field service, etc.) and are of complex nature by definition (Ruiz-Martín & Díaz-Garrido, 2021).
(4) The contingency theory describes the need for an ideal fit of the (product) strategy for meeting external requirements based on the firm's capabilities and resources (Ruiz-Martín & Díaz-Garrido, 2021).

Before concentrating on the economic models that underly the research field of servitisation, we need to consider that there is no servitisation logic for the household and consumer level, yet. The majority of servitisation literature builds on the perspective of the firm ('theory of the firm') and hence does not emphasise household behaviour and consumer preferences. However, there are examples in the academic literature that the concept of servitisation can be applied within the understanding of household and consumer consumption as well (Shankar, et al., 2009). Applications in the literature include cases of smartphone leasing (Rousseau, 2020), laundry services (Rombouts, 2019), upgradable whiteware (Michaud, et al., 2017), airport food courts (Pullman, et al., 2001), hotel membership services (Ordanini, et al., 2014) or consumer energy offerings (Grahsl & Velamuri, 2014; Grahsl, 2013). Kreye and van Donk (2021) name the following aspects that differentiate B2C servitisation from the dominant B2B characteristics. They conclude that an application of servitisation on the consumer and household level is reasonable.

A B2C service provider needs to be aware of the increased volume of interaction with consumers. Thus, service operations might be shifted to third-party intermediaries due to a higher distribution of physical service and selling facilities. This might not be as crucial in times of digital sales and service platforms. However, as the predominant value is not the economic payoff but increased customer life cycles or reduced environmental impact of the good-service bundle, the focus shifts towards less transaction- and more relationship-based consumer interactions. In the end, the interactions between seller and buyer become less complex. In the case of energy products, all three aspects can be observed (Kaastra, et al., 2020): Energy retailers still make use of physical sales stores, even though a high share of sales and interactions is performed online, relationship-based consumer interactions (e.g. the concept of 'customer lifetime value') are the dominant success measure, and the relationship still remains on the aspects of "trust, simplicity, transparency and affordability" (Kaastra, et al., 2020, p. 4). However, the situation has become more complex in comparison to earlier times, where customers merely have been looked at as just 'metering points'.

Crucially, the understanding of servitisation as a concept for private markets and the household level offers a starting point for investigating economic consumer and household theories. This perspective can be traced to the work of Chamberlin (1933), which offered a turning point towards an economic understanding of heterogeneous goods within markets. It suggested that products might be differentiated by characteristics (Saviotti, et al., 1982; Rothschild, 1987) by conceptualising two market types, of which one is an industry structure that is made up of groups of goods, each with less than perfect substitutes. It implied that competition offers similar but not identical products (Rothschild, 1987). Therefore, for this theory to hold true, the source of utility needs to come from certain characteristics that each group of products features and not from the product itself.

Becker's (1965) household production model assumes that utility is not created by the goods themselves but from the delivery of services such as heat/warmth, light, or entertainment, which is very close to the mentioned indirect value creation characteristic of electricity (Lohse & Künzel, 2011). Becker's model assumes that utility is 'produced' through the combination of market goods with time spent within the household (an individual unit but potentially involving more than one individual). For our DCE, this means that the respondent uses the time to interact with the product-service bundle, e.g. to generate energy savings.

Adams and Yellen's (1976) model of commodity bundling offers different bundling portfolio strategies for firms: either (1) just bundles of two or more goods or (2) bundles as well as single goods, whereas the bundled goods might be purchased separately. Within their approaches, they acknowledge the possibility of a utility surplus of the bundle that exceeds the individual utility of the bundled parts. Nevertheless, Adams and Yellen show that bundling might be inefficient according to Pareto standards, leading to an over- or undersupply of particular goods. The reason is that bundling (in contrast to Becker's model) is applied before entering the household and without knowledge of the reservation prices and exact preferences of the household (and its individual members).

Lancaster's Theory of Consumer Behaviour (1966) is one of the later applications of Becker's theory, however, with a focus on the quality of goods and not time (Apps & Rees, 2009, p. 23). Lancaster postulates that goods are not direct objects of utility. He defines the utility of a good as derived from its properties and characteristics (Lancaster, 1966). In his formulation of the theory, Lancaster uses the situation of a dinner party as an example for his idea: i.e., the conjuncture of a meal and social company as a combination of attributes offers a different utility than both goods would if consumed individually (Lancaster, 1966).

Furthermore, the hedonic price indexes of Griliches (1991) must be mentioned at this point with respect to the economic foundations. These refer to the valuation of different product characteristics from the perspective of the consumer. This approach is not directed at the analysis of the overall good but rather at the change of quality of attributes. The approach offers a combination of the individual specifications into a single composite measure that leads to a pricing index (Griliches, 1991; Goodman, 1998).

Samuelson's household theorem (1956) can be mentioned as another theoretical underpinning of relevance in our context as well. This theoretical model assumes that a household might consist of different agents (i.e., within the 'family') who pool their income in deriving their budget constraint for reaching the household's optimum level of utility. On an abstract level, we can observe the combination of different utilities ('decentralisation', sharing rule) that leads to a utility maximisation of the household utility function ('aggregation'). This assumes preference heterogeneity in the household, as individual tastes and preferences for a good or service vary across consumers (Feick & Higie, 1992). However, this preference heterogeneity is merged through consensus into one household welfare function (Apps & Rees, 2009, p. 39; Samuelson, 1956). For our application, effects such as energy efficiency or monetary savings that generate household utility can be applied to all members of the household.[9]

With reference to servitisation, one of the shared foundations of the approaches considered above is the utility maximisation behaviour of the consumer, which involves the most efficient combination of goods to achieve the desired collection of characteristics at minimal costs. Therefore, every need can be satisfied through the consumption of both goods and services (Gallouj & Weinstein, 1997; Cassini & Robert, 2020). We argue that the presented contributions share some characteristics with the concept of servitisation. Furthermore, these contributions indicate that there is an economic grounding for the idea that product-service bundles offer additional utilities that would not be available through the isolated consumption of the goods. We call this additional utility 'added value', synergy, or consumer surplus, which is 'created' by or for the consumer. In Becker's model of household production (1965), which defines goods and services (and time) as not directly generating utility themselves, this idea of a customer surplus is an explicit assumption. The characteristics of goods and services are the input to a household 'production process' that creates the desired utility through the services that are demanded (Becker, 1965). Based on this assumption, Lancaster's model assumes a linear relationship between physical characteristics and products. In the Lancaster model, the consumer maximises utility by choosing his or her ideal product quantity. Mathematically, the product characteristics and the consumption

[9] It must be mentioned that this attribution depends on the household structure, especially regarding household size, i.e. number of people within the household.

technology provide necessary inputs for the utility-maximising decision (Wierenga, 1984, pp. 264-265).

Therefore, Lancaster’s model inherits a multidimensional view that can be applied to the multi-attribute models that are used by behavioural science-oriented consumer researchers (Wierenga, 1984), e.g., in the case of random utility models (McFadden, 1974).

While Lancaster’s model clearly offers an economic foundation for the application of servitisation, Wierenga (1984) indicates two limitations of the model in an empirical context. First, Lancaster does not differentiate between the perceived and experienced utility. Therefore, Wierenga (1984) suggests an additional ‘perception vector’ that accounts for socio-psychological cues fabricated from external (advertising, word-of-mouth, etc.) and personal contexts (attitudes, experiences, etc.), which adds to our discussion regarding the relevance of bounded rationality earlier in this thesis. Second, Wierenga (1984) claims that Lancaster ignores the ‘variety-seeking behaviour’ of consumers in choice situations, thereby neglecting the creation of utility through the consumption of many different goods and services in addition to the needed characteristics.

4.2.4 Selected servitisation research based on choice experiments

Based on the results from the literature review, it has become obvious that the concepts of value and utility are very relevant to the research area of servitisation. The source of the value understanding originates within neoclassical economics as ‘utilities’. It concentrates on the buyer’s side and assumes that under rational circumstances, customers have a preference to maximise their utility when deciding between different options (Woll, 1993, p. 121; Varian, 1999, p. 33; Coase, 1937, p. 387; Golsteyn & Schildberg-Hörisch, 2017, p. 2).

In this application, we use CL estimations to test for synergies within a product-service bundle. We formulate different synergy cases that describe different scenarios between the attributes. To identify synergies, we investigate interactions between the different attribute levels. The term synergy is widely used in marketing, while in statistics, the same concept is referred to as interaction effect (James, et al., 2021, p. 60). Furthermore, interactions in statistics can be positive (synergistic) or negative (antagonistic). In this contribution, we use the concepts of synergy and interaction interchangeably. The synergy cases serve as the qualitative description of our research hypotheses for the estimation of the so-called main and interaction effects.

There are several contributions that apply preference measurement and choice approaches in the field of servitisation (Easton & Pullman, 2001; Verma, et al., 2004; Pullman, et al., 2001; Rombouts, 2019; Rousseau, 2020; Michaud, et al., 2017; Ndebele, et al., 2019). We introduce these below. For example, different studies combine choice preferences with the organisational view. Verma et al. (2001; 1999) argue that the advantage of choice experiments for service and product designs is that it gives a good understanding of the market share, optimal profit or product costs in dependence on specified operating procedures. They combine different choice-based approaches (for different stakeholders) to give suggestions for an effective product/service design.

Easton and Pullmann (2001) develop a comprehensive model for optimising service attributes by connecting attribute levels directly to expected profits, thus facilitating the design of service configurations that maximise profitability. Their approach integrates realistic service delivery cost models with a conjoint analysis to derive a seller’s utility function. The function aims at the optimal level for each service attribute, balancing consumer preferences with cost implications. By employing this model, service designers are supposed to manipulate attribute levels to optimise both market share and profitability.

The specific modelling approach used in the study involves a sophisticated application of conjoint analysis combined with the development of a heuristic for a complex service design problem (‘NP-hard’). This heuristic considers nonlinear and discontinuous cost functions and the indirect influence of process decisions (like employee recruitment and training) on consumer perceptions and costs. The results from their simulations indicate that the proposed service configurations not only align closely with consumer preferences but also enhance profitability significantly by optimising both technical and process-related service attributes.

This model represents a significant advance in the strategic design of service offerings, particularly in how it quantifies the impact of various service attributes on both market share and cost efficiency.

Verma et al. (2004) explore customer preferences for e-finance services using DCE to understand the importance of various service features, both online and traditional. Their study offers insights into how different attributes influence customer choices and how businesses can leverage this knowledge to design effective service offerings. The DCE methodology involves creating hypothetical service scenarios with varying attributes which participants evaluate, allowing researchers to capture detailed preference data.

In their analysis, Verma et al. use MNL models to estimate the relative importance of each service attribute included in their experiments. This method helped identify the trade-offs customers are willing to make among various service features and price levels. Attributes studied include price per transaction, availability of in-depth research and analysis, real-time product information, and access to local branches, among others. The study suggests that customers value a mix of both traditional and online features, indicating that companies should not exclusively focus on competitive pricing or digital services alone but should integrate these with traditional service aspects to enhance customer value and market share.

The results of this research provide a comprehensive understanding of customer preferences in e-finance services, which is crucial for businesses aiming to tailor their offerings to meet customer needs effectively. This approach not only helps in aligning service attributes with customer expectations but also in finding strategic market positioning and competitive differentiation.

Pullmann et al. (2001) examine the complexities of designing service offerings for multicultural markets, focusing on the balance between standardisation and customisation to optimise economic success. Their contribution specifically addressed cultural preferences in service attributes, employing a mixed-method approach that combines conjoint analysis with real-world experimentation in a multicultural setting. This enabled the identification of optimal service configurations that align with cultural diversity and enhance profitability.

The modelling approach used in their approach was based on a DCE that integrates probabilistic MNL modelling. These models helped quantify the trade-offs customers from different cultural backgrounds are willing to make among various service attributes. By doing so, the study not only provided insights into how different cultural groups perceive and value service attributes but also allowed for the strategic manipulation of these attributes to optimise service offerings for heterogeneous markets. The findings support the necessity for service providers to adapt their offerings to respect cultural differences effectively, thereby aligning service design with the diverse expectations and preferences of multicultural consumer segments.

Rousseau (2020) investigates the factors that influence young people's willingness to lease smartphones under a PSS, employing a discrete DCE to investigate preferences and decision-making processes. The research identifies key drivers and barriers impacting the adoption of PSS, revealing that while some respondents are driven by environmental concerns or the allure of the latest technology, significant barriers include financial concerns and attachment to ownership, which reflect deep-rooted values around self-identity and possession. The DCE of this application is estimated by the application of a CL and an LC model. The CL model assesses choice probabilities assuming homogenous preferences across respondents, providing baseline preference data. The LC model identifies segments within the consumer base, recognising heterogeneity in preferences and allowing for the differentiation of consumer groups with distinct preference patterns. This dual-model approach offers an understanding of the millennial market, highlighting the diversity of attitudes towards leasing smartphones within a specific demographic group of 'millennials'.

Rombouts' (2019) study focuses on consumer acceptance of PSS within the washing machine market in a B2C context. The work offers an understanding of the extent to which consumers are willing to transition from traditional ownership models to more sustainable consumption patterns through PSS. The study investigates the most significant attributes influencing consumer decisions, such as payment models, product quality, flexibility, sustainability, convenience, and efficiency of resource use. A DCE was used with 1,061 Dutch consumers to measure preferences across different PSS offerings. The study employed an MNL model to analyse consumer choices, allowing for the estimation of utility values for different attributes and the ability to predict choice probabilities. By incorporating also an LC analysis, the research identifies customer segments, thus identifying heterogeneous preference patterns.

Michaud et al. (2017) investigate WTP for sustainable and innovative products. They assess preferences for upgradeable products such as washing machines, vacuum cleaners, and laptops. The choice experiment is designed to understand how consumers value the option to upgrade products, which can lead to extended product life and potentially reduce environmental impact, thus applying a PSS idea. The specific modelling approach used in this application involves an MLM to catch the preference heterogeneity of the respondents. The research provides insights into how much more consumers are willing to pay for the capability to upgrade products compared to non-upgradable versions.

There are very few publications that include preference and choice experiments in the field of servitisation for electricity offerings. An example of such research is provided by Ndebele et al. (2019) who conducted a study on consumer switching in retail electricity markets in New Zealand. The study tries to understand the determinants of switching behaviour and estimates the WTP for non-price attributes of electricity services. Attributes that are analysed are, e.g., call waiting time, length of the fixed-rate contract, renewable energy, loyalty rewards, supplier ownership, and supplier type. The study highlights the significant role of non-price attributes in influencing consumer decisions to switch providers. This challenges the prevailing notion that price is the predominant factor driving consumer behaviour in deregulated electricity markets. The study used a latent class model to analyse the choice data, allowing for the identification of heterogeneous preference segments within the consumer base. This approach facilitated the modelling of varying sensitivities to power bill savings across different consumer segments, thus providing an understanding of consumer behaviour.

The currently available research, while comprehensive in evaluating individual attributes, typically overlooks the potential synergies that could arise from the combination of service attributes. This gap highlights a need to investigate attribute interactions explicitly. It needs to be understood how bundled attributes interact to influence consumer decisions, as this is crucial for optimising servitisation strategies. This exploration of the effects of attribute interaction is essential to advance servitisation research. It offers comprehensive guidance for the design of servitisation offerings that fit consumer needs and expectations. Therefore, the majority of the servitisation research, even with applied DCE approaches, focuses on the output and individual estimates of product-service systems and does not scrutinise the origin of the value-add- or synergy assumption.

4.3 Methodological approach and development of hypotheses

The attribute and attribute level definition follows the setup that we established for this thesis in Chapter 2. We allocated the presented attributes to the different stages of the servitisation framework for utilities (Grahsl & Velamuri, 2014), as presented in the following Table 12.

Table 12: Choice Setup with reference to the servitisation framework for utilities

Attribute		Attribute level	Stage	Component
Source of price calculation per kWh	PRICECALC0 (p0)	Fixed Price per kWh – prices are defined for the contractual time	2	Service
	PRICECALC1 (p1)	Changing of prices based on a pre-defined plan (e.g. different prices on weekdays)		
	PRICECALC2 (p2)	Decreasing prices per kWh each month with an increase or decrease in overall consumption		
Price communication and access to bills	(default)	Prices are itemised within the initial contract documents; bills are sent via mail	2	Service
	PRICEMAIL (a1)	Prices and monthly bills are sent via email		
	PRICEPORTAL (a2)	Prices and monthly bills are made available through an online portal (login necessary)		
	PRICEAPP (a3)	Prices and monthly bills are made available through a mobile app		
Service infrastructure	(default)	Call centre	3	Support
	SERVEMAIL (s1)	Email		
	SERVCHAT (s2)	Chat agent (also video chat)		
	SERVAPP (s3)	Message service within the smartphone app		
Additional device included in the contract	DEVICE0 (d0)	No electric plug adapter is included	3	Product
	DEVICE1 (d1)	Manually adjustable electric plug adapter		
	DEVICE2 (d2)	Local connected electric plug adapter		
	DEVICE3 (d3)	Smart plug adapter incl. smartphone app		
	DEVICE4 (d4)	Smart plug adapter incl. smartphone app, and algorithm		
Additional charge to the monthly basic rate	CHARGE (C)	0.00 €, 4.99 €, 9.99 €,14.99 €,19.99 €, 24.99 €	-	-

Source: Author’s own analysis.

As was stated earlier, for the DCE setup, we used a randomised orthogonal design ('Balanced Overlap') that is optimised regarding 'one-way-frequency' and 'two-way-frequency', as it offers us a compromise between a high degree of orthogonality ('Complete Enumeration') and some degree of overlap within the attribute combinations ('Random' distribution) in order to capture also interaction effects that might occur within the model (Chrzan & Orme, 2000, pp. 6-7).

Interaction effects identify the effect of two or more combined attributes (or attribute levels) on the utility generated by alternatives in the choice set (see also Chapter 2.7.2). An example within the survey design of this thesis is a higher preference for one alternative if it offers the exact combination of the attribute level 'Smart plug adapter incl. smartphone app and algorithm' and the attribute level 'Decreasing prices per kWh each month with increase or decrease of overall consumption', having the other alternative offering just one or none of the attribute combinations. With reference to the introduced energy servitisation framework as well as the two classes of bundles from Grahsl and Velamuri (2014), we assume that there are attribute combinations that either result in synergetic or additive interactions. To test for these specific interaction effects, we developed four synergy cases (SC1, SC2, SC3, SC4) based on two considerations. First, as suggested throughout traditional servitisation literature, we wanted to investigate possible synergies with the physical component. Second, we looked at all other possible origins of synergies, e.g., based on the same interaction channel, to capture all potential sources of synergetic effects:

- SC1: All 'service' attributes share synergies with all other attributes ('support' and 'product'), as that relation reflects the transition from Stage 2 to Stage 3 in Grahsl's servitisation framework (Table 12).
- SC2: Out of DEVICE, the two attribute levels DEVICE3 ('Smart plug adapter incl. smartphone app') and DEVICE4 ('Smart plug adapter incl. smartphone app and algorithm') share synergies with PRICECALC2 ('Decreasing prices per kWh each month with increase or decrease of overall consumption').

- SC3: As PRICE ('Price communication and access to bills') and SERV ('Service infrastructure') offer the same technological interaction channels (email, web presence (chat/online portal) and mobile phone app), we assume shared synergies across the corresponding attributes: PRICEEMAIL with SERVEMAIL; PRICEPORTAL with SERVCHAT as well as PRICEAPP with SERVEAPP.
- SC4: We expect shared synergies of DEVICE with all other attributes, as we perceive the bundling with a smart and even controllable plug as the most basic example of a synergetic bundle, which helps customer to optimise their individual energy consumption and available household budget.

To test these synergy cases, we establish different models that combine attributes to capture all possible interaction effects. We pursue a two-stage process. First, we estimate all possible models with interaction effects in a structured manner to identify models that offer a better fit than our basic main effect model. Therefore, we first test for joint restrictions of the interaction effects within the model. Second, we test for the single interactions of the models that show a significant increase in model fit.

An exemplary utility function for the interaction effects of all attributes with PRICEEMAIL (a1) can be denoted as (for all the other attribute levels the same structure is applied):

$$
\begin{aligned}
U_{,j} &= \overbrace{\beta_{p1}p1_j + \beta_{p2}p2_j + \beta_{s1}s1_j + \beta_{s2}s2_j + \beta_{s3}s3_j + \beta_{d1}d1_j + \beta_{d2}d2_j + \beta_{d3}d3_j + \beta_{d4}d4_i}^{attribute\ main\ effects\ subject\ to\ interactions} \\
&+ \overbrace{\pi_{a1}^{1}p1_j a1_j + \pi_{a1}^{2}p2_j a1_j}^{attribute\ interaction\ effects\ for\ a1\times p} + \overbrace{\sigma_{a1}^{1}s1_j a1_j + \sigma_{a1}^{2}s2_j a1_j + \sigma_{a1}^{3}s3_j a1_j}^{attribute\ interaction\ effects\ for\ a1\times s} \\
&+ \overbrace{\delta_{a1}^{0}d0_j a1_j + \delta_{a1}^{1}d1_j a1_j + \delta_{a1}^{2}d2_j a1_j + \delta_{a1}^{3}d3_j a1_j + \delta_{a1}^{4}d4_j a1_j}^{attribute\ interaction\ effects\ for\ a1\times d} \\
&+ \overbrace{\alpha^2 a2_j + \alpha^3 a3_j + \gamma C_j}^{attribute\ main\ effects\ no\ subject\ to\ interactions} + \epsilon_j
\end{aligned}
\tag{22}
$$

.

where

j = alternative,

p1	=	PRICECALC1,
p2	=	PRICECALC2,
a1	=	PRICEEMAIL,
a2	=	PRICEPORTAL,
a3	=	PRICEAPP,
s1	=	SERVEEMAIL,
s2	=	SERVCHAT,
s3	=	SERVAPP,
d0	=	DEVICE0,
d1	=	DEVICE1,
d2	=	DEVICE2,
d3	=	DEVICE3,
d4	=	DEVICE4,
C	=	CHARGE,
β	=	Coefficient vector for main/direct attribute effects,
π	=	Coefficient vector for attribute interaction effects with P (p1; p2),
σ	=	Coefficient vector for attribute interaction effects with S (s1; s2; s3),
δ	=	Coefficient vector for attribute interaction effects with D (d0; d1; d2; d3; d4),
α	=	Coefficient vector for attribute interaction effects with A (a1; a2; a3),
γ	=	Coefficient for attribute effects of C.

For testing of the joint restrictions, we use the likelihood-ratio test. The likelihood-ratio test is based on the -2LL ratio. It is used to test for the significance of the difference between the likelihood ratio of models that include interactions minus the likelihood ratio for the base model that includes no interaction effects.

To test the individual restrictions of the models that show a significantly better fit than the base model, we test for the hypotheses based on the presented SC. With reference to the general assumption that servitisation in general leads to synergies within the product-service bundle, we test for the following H0, which assumes that there are no synergetic effects. This means that only find evidence for additive service bundles:

$$H0\text{: } testing\ for\ the\ restrictions\ on\ the\ vectors\ \ \pi\ =\ 0\ and\ \ \sigma\ =\ 0\ and\ \ \delta\ = 0\ and\ \ \alpha\ = 0$$

Based on the servitisation stage models proposed by Grahsl (2013) as well as Vandermerwe and Rada (1988), we test if there are significant synergies between Stage 2 and Stage 3 of the servitisation model. Earlier, we allocated the attributes PRICECALC1, PRICECALC2, PRICEEMAIL, PRICEPORTAL and PRICEAPP to Stage 2 (servitisation framework category: ‘service’) and the attributes SERVEEMAIL, SERVCHAT and SERVAPP to Stage 3 (servitisation framework category: ‘support’) and the attributes DEVICE0, DEVICE1, DEVICE2, DEVICE3 and DEVICE4 also to Stage 3 (servitisation framework category: ‘product’). The allocation is presented in Table 12. For SC1, we test whether we find significant interactions between the servitisation framework Stage 2 attribute level and the servitisation framework level attributes for ‘support’ (Stage 3) and/or between the servitisation framework Stage 2 attribute level and the servitisation framework level attributes for ‘product’ (Stage 3). We expect the effects to be different than 0, which would be a clear action point and policy advice for energy providers to offer attribute combinations as we found evidence for synergies. The perceived utility in case of significant interaction effects may increase, and hence, the interaction effect would lead to a synergetic bundle. Or we observe an antagony. Thus, we find evidence of the servitisation paradox. We are testing for the following four hypotheses:

$$H1\ :\ at\ least\ one\ index\ i\ (\mathrm{p1;\ p2})\ such\ that\ \pi_i \neq\ 0\ and\ at\ least\ one\ index\ i\ (\mathrm{s1;\ s2;\ s3})\ such\ that\ \sigma_i \neq\ 0$$

$$H2\!:\ at\ least\ one\ index\ i\ (\mathrm{p1;\ p2})\ such\ that\ \pi_i \neq\ 0\ and\ at\ least\ one\ index\ i\ (\mathrm{d1;\ d2;\ d3;\ d4})\ such\ that\ \delta_i \neq\ 0$$

$$H3\!:\ at\ least\ one\ index\ i\ (\mathrm{a1;\ a2;\ a3})\ such\ that\ \alpha_i \neq\ 0\ and\ at\ least\ one\ index\ i\ such\ that\ \sigma_i\ (\mathrm{s1;\ s2;\ s3})\ \neq\ 0$$

$$H4\!:\ at\ least\ one\ index\ i\ (\mathrm{a1;\ a2;\ a3})\ such\ that\ \alpha_i \neq\ 0\ and\ at\ least\ one\ index\ i\ (\mathrm{d1;\ d2;\ d3;\ d4})\ such\ that\ \delta_i \neq\ 0$$

For SC2, we want to test if there are interactions between two attribute levels of DEVICE and PRICECALC2, as we assume that a product-service bundle that combines the ability to remote control electricity consumption through the two smart plug attributes: DEVICE3 (‘Smart plug adapter incl. smartphone app’) and DEVICE4 (‘Smart plug adapter incl. smartphone app and algorithm’). We expect to see comparable interaction effects for both model variations (given that the responding models offer a better fit than our base model as tested with the first iteration of this investigation). We expect all effects to be positive; hence, the perceived utility in case of significant interaction effects increases in the case of synergetic bundles. If the effects are negative, we will find evidence for the effects of the servitisation paradox. Both results would imply clear policy advice for energy providers, either offering variable price tariffs in the case of synergies or analysing in-depth what investments in infrastructure and capabilities are necessary for not creating an antagony. We are testing for the following two sets of hypotheses.

$H5\colon\ \delta_{p2}^{3} > 0\ and\ \pi_{d3}^{2} > 0$

$H6\colon \delta_{p2}^{4} > 0\ and\ \pi_{d4}^{2} > 0$

For SC3, we concentrate on the attributes PRICEEMAIL, PRICEPORTAL, PRICEAP, SERVEMAIL, SERVCHAT, and SERVAPP. We want to test for interaction effects between the responding pairs of the attribute effects, namely PRICEEMAIL (a1) and SERVEEMAIL (s1); PRICEPORTAL (a2) and SERVCHAT (s2) as well as PRICEAPP (a3) and SERVEAPP (s3). Hence, we are testing for the following hypotheses: H7, H8, and H9. We expect all effects to be positive, and hence, the perceived utility in case of significant interaction effects increases in the case of synergetic bundles. If the effects are negative, we find evidence for the effects of the servitisation paradox. Again, both results would indicate a piece of clear policy advice for energy providers, hence harmonising and assessing the communication and service channels that are used to approach the customers.

$H7\colon\ \alpha_{s1}^{1} > 0\ and\ \sigma_{a1}^{1} > 0$

$H8\colon\ \alpha_{s2}^{2} > 0\ and\ \sigma_{a2}^{2} > 0$

$H9\colon \alpha_{s3}^{3} > 0\ and\ \sigma_{a3}^{3} > 0$

For testing SC4, we can take a general approach addressing all attribute levels of DEVICE. This means we can develop the following hypothesis. One possibility for SC4 is already addressed very specifically by H5 and H6 (SC2, PRICECALC2 & DEVICE3/DEVICE4). However, we do not only want to test for a specific attribute combination but for the existence of any synergy between certain attributes, as the combination of physical products and services holds a prominent position in servitisation research. This gives us the perspective if the combination of intangible services and tangible devices is advisable in the case of an aspired synergetic service bundle. We are testing for the following hypothesis:

$H10$: $\delta^{0}_{p,a,s} < 0$ and it exists at least one index i such that $\delta^{i}_{p,a,s} > 0$

It is important that any interaction effects in combination with the attribute level DEVICE0 (“No electric plug adapter included”) need to be interpreted with regards to the sign of the estimation. As the attribute level refers to the *absence* of a device, a positive vector would imply an increase in utility if the device is left out of the product-service bundle.

As a summary, we provide the discussed hypotheses, including the relevant synergy cases, the relevant coefficients, and the expected direction of the effects, in Table 13.

Table 13: Summary of hypotheses

Hypothesis	Relation to be tested	SC	Relevant coefficients	Effect direction
H0	$\pi = 0\ and\ \sigma = 0\ and\ \delta = 0\ and\ \alpha = 0$	All	All interaction coefficients	Positive or negative
H1	$at\ least\ one\ index\ i\ such\ that\ \pi_i \neq 0\ and\ at\ least\ one\ index\ i\ such\ that\ \sigma_i \neq 0$	SC1	Interaction effects with (PRICECALC1 (p1) or PRICECALC2 (p2)) and (SERVEEMAIL(s1) or SERVCHAT(s2) or SERVAPP (s3))	Different from 0
H2	$at\ least\ one\ index\ i\ such\ that\ \pi_i \neq 0\ and\ at\ least\ one\ index\ i\ such\ that\ \delta_i \neq 0$	SC1	Interaction effects with (PRICECALC1 (p1) or PRICECALC2 (p2)) and (DEVICE1(d1) or DEVICE2 (d2) or DEVICE3 (d3) or DEVICE4 (d4))	Different from 0
H3	$at\ least\ one\ index\ i\ such\ that\ \alpha_i \neq 0\ and\ at\ least\ one\ index\ i\ such\ that\ \sigma_i \neq 0$	SC1	Interaction effects with (PRICEEMAIL (a1) or PRICEPORTAL (a2) or PRICEAPP (a3)) and (SERVEEMAIL(s1) or SERVCHAT(s2) or SERVAPP (s3))	Different from 0
H4	$at\ least\ one\ index\ i\ such\ that\ \alpha_i \neq 0\ and\ at\ least\ one\ index\ i\ such\ that\ \delta_i \neq 0$	SC1	Interaction effects with (PRICEEMAIL (a1) or PRICEPORTAL (a2) or PRICEAPP (a3)) and (DEVICE1(d1) or DEVICE2 (d2) or DEVICE3 (d3) or DEVICE4 (d4))	Different from 0
H5	$\delta^3_{p2} > 0\ and\ \pi^2_{d3} > 0$	SC2	DEVICE3_p2 PRICECALC2_d3	positive
H6	$\delta^4_{p2} > 0\ and\ \pi^2_{d4} > 0$	SC2	DEVICE4_p2 PRICECALC2_d4	positive
H7	$\alpha^1_{s1} > 0\ and\ \sigma^1_{a1} > 0$	SC3	PRICEEMAIL_s1 SERVEEMAIL_a1	positive
H8	$\alpha^2_{s2} > 0\ and\ \sigma^2_{a2} > 0$	SC3	PRICEPORTAL_s2 SERVCHAT_a2	positive
H9	$\alpha^3_{s3} > 0\ and\ \sigma^3_{a3} > 0$	SC3	PRICEAPP_s3 SERVEAPP_a3	positive
H10	$\delta^0_{p,a,s} < 0$ and it exists at least one index i such that $\delta^i_{p,a,s} > 0$	SC4	A: Interaction effects with DEVICE0 (d0) B: Interaction effects with DEVICE1 (d1), DEVICE2 (d2), DEVICE3 (d3), DEVICE4 (d4)	A: negative B: positive

Source: Author’s own analysis.

4.1 Results

Chapter 4.1 is divided into two parts. In the first part (Chapter 4.1), we present the estimation and hypotheses test results. In the second part (Chapter 4.1.2), we discuss regulatory measures with which, on the one hand, the economic policy framework for energy suppliers can be adjusted and, on the other hand, the corporate policy decisions of the energy suppliers can be aligned.

4.1.1 Estimation results

The choice of the individuals in the stated preference experiment was analysed using discrete choice modelling. Again, we used the R package for 'Apollo Choice Modelling' with maximum likelihood estimates to estimate the models (Hess & Palma, 2019)[10]. As we discussed earlier, we followed a two-staged approach, first estimating all models to identify if models that include interaction effects show a better statistical fit than our 'Base Model' (BMo). For this purpose, we use the Chi-squared statistic based on the Likelihood-ratio test (see Table 14). We then analyse the interaction models (IMo[11]) that show either a significant or close to a significant increase in model fit compared to the BMo. For the discussion of the results, we only look at three models that are most relevant for the discussion on interaction effects. For each of the models, we look at all the remaining research hypotheses that have not been rejected already.

Before investigating the individual models and their divergence in contrast to the BMo, two general aspects are observable: (1) The overall fit of all the models based on their log-likelihood (LL) scores does not differ greatly from the BMo. This is expected, as by adding coefficients to a base model, the degrees of freedom in the model increase, and the likelihood of the sample achieves higher maxima. This leads to the fact that all IMo show slightly higher LL scores compared to the BMo. This means that by adding interactions, the relative explanatory power of the models is increased. (2) In contrast to the hypotheses prior to the

[10] See Appendix 8.4.2 for the applied R script.

[11] In the reminder of the investigation, IMo_PRICEEMAIL refers to the interaction model that estimates the impact of the attribute level PRICEEMAIL (Price communication via email). The other attribute levels are similarly combined with the prefix IMo_ (e.g. IMo_DEVICE1 etc.).

investigation, only a few statistically significant interaction effects can be observed within the models that have been investigated more deeply. This means that the assumption of having comprehensive synergetic product-service bundles cannot be regarded as valid for all model estimates which have been calculated. The test statistics for the comparison of the model fit based on the LL ratio test are shown below in Table 14.

Table 14: Log likelihood (LL) scores for all model variants

Model	LL	DoF	Chi	p_value	p_sig
Base Model	-5076.85	0	0.00	1.0000	
IMo_PRICECALC0	-5071.27	10	11.16	0.3452	
IMo_PRICECALC1	-5073.71	10	6.28	0.7912	
IMo_PRICECALC2	-5074.10	10	5.50	0.8554	
IMo_PRICEEMAIL	-5068.82	9	16.06	0.0656	
IMo_PRICEPORTAL	-5071.14	9	11.42	0.2480	
IMo_PRICEAPP	-5074.76	9	4.18	0.8992	
IMo_SERVEMAIL	-5067.61	9	18.48	0.0300	*
IMo_SERVCHAT	-5074.79	9	4.12	0.9033	
IMo_SERVAPP	-5070.79	9	12.12	0.2066	
IMo_DEVICE0	-5070.08	8	13.54	0.0946	
IMo_DEVICE1	-5071.09	8	11.52	0.1739	
IMo_DEVICE2	-5071.64	8	10.42	0.2368	
IMo_DEVICE3	-5072.58	8	8.54	0.3826	
IMo_DEVICE4	-5073.37	8	6.96	0.5410	

[a] LL = Log Likelihood; DoF = Degrees of Freedom; Chi = Chi-Squared Statistic; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Source: Author’s own analysis.

Given the results from Table 14, it can be concluded that there are three models which are most relevant for the discussion on interaction effects: IMo_SERVEMAIL, IMo_PRICEEMAIL, and IMo_DEVICE0, where IMo_SERVEMAIL is the only model out of the collection that shows a statistical significance of the improved model fit. We choose also to investigate the other two models as their p-value is below 0,1, which we regard as weak evidence of statistical significance. (Ganesh & Cave, 2018).

With regards to our research hypotheses, we can reject H0 immediately, as we find evidence for a statistically significant model, including interaction effects (IMo_SERVEMAIL). In addition, we are able to reject H8 and H9, as these cover the interaction effects of α_{s2}^{2} and α_{s3}^{3} as well as σ_{a2}^{2} and σ_{a3}^{3}, which means that even at this level, we see that there are no interaction effects between PRICEPORTAL and SERVCHAT or between PRICEAPP and SERVAPP that statistically significantly improve the explanatory power of the model. We are not able to reject H7 yet, as we find evidence for an improved and statistically significant model fit through IMo_SERVEMAIL compared to BMo, and hence, there is the possibility of having a significant interaction effect between SERVEMAIL and PRICEEMAIL. Even though we further investigate the models IMo_DEVICE0 and IMo_PRICEEMAIL to prove H2, we are already able to reject H5 and H6 as these address a hypothetical interaction relationship between PRICECALC2 and DEVICE3 or DEVICE4, which are not addressed by these two interaction models.

In the remainder of this section, we analyse the estimates of the mentioned three models in particular. We investigate the development of the main effects in contrast to the BMo, look at possible significant interaction effects, and the relation of the conjunct main and interaction effects for each model. At the end of each section of the model discussion, we offer a practical-oriented interpretation of the estimation results while referring to the validity of the research hypotheses.

4.1.1.1 Interpretation of interaction effects for IMo_SERVEMAIL

IMo_SERVEMAIL is the statistically most significant model from the list of all possible models for which interaction effects have been evaluated, and it is the only model where the

LL score has provided a statistically significant result. In IMo_SERVEMAIL, we test whether the availability of just the “email” channel as service infrastructure for contract requests interacts (‘impacts’) with the other attribute levels, thus leading to a change in WTP. The WTP for other attributes such as for the specific devices (DEVICE), for the availability of options for price communication (PRICEMAIL, PRICEPORTAL, PRICEAPP), or other attributes of the electricity contract services package must therefore be evaluated for this model, where service is only provided by email. The results of the model estimation for IMo_SERVEMAIL are shown below in Table 15.

Table 15: Estimates for main and interaction effects for IMo_SERVEMAIL (s1)

Estimation results IMo_SERVEMAIL

Paramter	WTP	Rob. s.e.	Rob. t-ratio	p Value (2-sided)		pVal WTP > 0	pVal WTP < 0
ASC_alt1	1.0010	0.2575	3.8874	0.0001	***	0.9999	0.0001
PRICECALC1	-3.4688	0.6372	-5.4440	0.0000	***	1.0000	0.0000
PRICECALC2	-1.6682	0.6062	-2.7519	0.0059	**	0.9970	0.0030
PRICEEMAIL	0.8784	0.4997	1.7580	0.0787		0.9606	0.0394
PRICEPORTAL	1.9879	0.5161	3.8516	0.0001	***	0.9999	0.0001
PRICEAPP	0.9350	0.5053	1.8506	0.0642		0.9679	0.0321
SERVEMAIL	2.7442	1.1210	2.4480	0.0144	*	0.9928	0.0072
SERVCHAT	0.6002	0.2437	2.4631	0.0138	*	0.9931	0.0069
SERVAPP	1.1610	0.2602	4.4624	0.0000	***	1.0000	0.0000
DEVICE1	3.9966	0.7298	5.4765	0.0000	***	1.0000	0.0000
DEVICE2	2.7317	0.7367	3.7080	0.0002	***	0.9999	0.0001
DEVICE3	4.3266	0.7462	5.7985	0.0000	***	1.0000	0.0000
DEVICE4	5.9940	0.7735	7.7490	0.0000	***	1.0000	0.0000
PRICECALC1_s1	0.7636	0.8341	0.9154	0.3600		0.8200	0.1800
PRICECALC2_s1	1.1724	0.8305	1.4117	0.1580		0.9210	0.0790
PRICEEMAIL_s1	0.7893	0.8241	0.9578	0.3382		0.8309	0.1691
PRICEPORTAL_s1	-2.1037	0.9108	-2.3098	0.0209	*	0.9896	0.0104
PRICEAPP_s1	0.4984	0.8752	0.5694	0.5691		0.7155	0.2845
DEVICE1_s1	-2.7331	1.1113	-2.4593	0.0139	*	0.9930	0.0070
DEVICE2_s1	-1.3052	1.0693	-1.2206	0.2223		0.8889	0.1111
DEVICE3_s1	-1.3965	1.0962	-1.2740	0.2027		0.8987	0.1013
DEVICE4_s1	-3.0937	1.0737	-2.8812	0.0040	**	0.9980	0.0020

[a] WTP = Willingness to pay; LL = Log Likelihood; ***p < 0.001; **p < 0.01; *p < 0.05

Source: Author’s own analysis.

The results from Table 15 show significant interaction effects for PRICEPORTAL (Prices and monthly bills made available through an online portal), DEVICE1 (Manually adjustable electric plug adapter), and DEVICE4 (Smart plug adapter smartphone app and algorithm). All these significant attributes are associated with a negative WTP. Within the context of the electricity contract choice model, the interpretation of the negative WTP values for these attributes provides insights into how individuals perceive and value these attributes relative to others in the choice set. The following issues can specifically be pointed out:

- The negative WTP for the interaction with the availability of prices via an online portal (PRICEPORTAL_s1) suggests that individuals might not prefer or value contracts where prices are made available via the price portal while having only the possibility to have support or service requests by email.
- In contrast, the main effects for PRICEPORTAL show a positive WTP value, and thus, the respondents do not dislike the availability of prices via an online portal per se. It is particularly worthwhile to note that the main effects of price communication via email (PRICEEMAIL) and through an app (PRICEAPP) are also associated with a positive WTP value. Therefore, the dislike comes from the specific combination of these two attribute levels. The negative value of the WTP of the interaction effect indicates that individuals might have a preference for contracts that offer additional service infrastructure when prices are available only via an online portal.
- Generally, the result suggests that more complicated manners of price communication are less attractive or provide less WTP if service is only available through email. This is, in principle, comparable to the situation where the WTP for a complex product depends on the service level offered (Jain & Bala, 2018).
- For the interaction effects DEVICE1_s1 (interaction of SERVEMAIL with manually adjustable electric plug adapter) and DEVICE4_s1 (interaction of SERVEMAIL with smart plug adapter incl. smartphone app and algorithm), we also report negative WTP values. The WTP for the interaction with DEVICE4 has a higher negative value than for DEVICE1. This implies that individuals might perceive these devices as offering lower value or being less preferable compared to other device options available in the electricity contract choices when offered within a contract where email is the only service/support infrastructure. Given that the interaction effects with the DEVICE attribute level all show a negative WTP value in the IMo_SERVEMAIL model, it can be pointed out that by limiting service communication to email, customers experience a negative WTP from additional

device functionalities (even though the other interaction effects involving DEVICE2 and DEVICE3 do not show statistical significance).

- This is an important result, especially as it was found that the main effect WTP for the DEVICE attributes is positive. Furthermore, while the main effect for DEVICE4 has the highest positive value compared to the other device attribute levels, it also has the second highest negative WTP for the interaction with SERVEMAIL, and hence, we see at least a non-linear effect (= the effect value of the interaction is not the same for all attribute level). A similar effect can be seen for DEVICE1, which switches positions from having the second lowest WTP (main effect, even though it arguably offers less functionality than the lowest device attribute level DEVICE2) to having the second highest negative interaction effect with SERVEMAIL. Therefore, it can be argued that the complexity of the device within the bundle is not a driver for the WTP, either in one or the other direction, as the device with the highest technical abilities might be the less desirable option by individuals.
- In particular, the values of the interaction effects between SERVEMAIL and the devices imply the existence of the servitisation paradox, as adding a specific service infrastructure to a product-service bundle leads, in our case, to a decrease of WTP, which was already mentioned in the literature review of this application (Gebauer et al., 2005; Gebauer et al., 2020).

In essence, the negative WTP values for PRICEPORTAL_s1, DEVICE1_s1, and DEVICE2_s1 show that these attributes might be perceived negatively as they provide – in combination with a specific and maybe less interactive service infrastructure – less utility to individuals in the electricity contract context of our investigation. This result is helpful for understanding consumer preferences in the retail electricity market, especially in the context of servitisation. It can be emphasised that by designing electricity contracts with hybrid service options, a low-level service is offsetting the benefits from other potentially useful service options. Companies are, therefore, encouraged to implement and provide adequate service channels to meet customers' demands and cater to their preferences. It seems that users do not value email service interaction and, therefore, ‘punish’ the other associated attribute level of the interaction by not selecting it. There might be different reasons why email interaction has its disadvantages in current times (e.g., non-personal interaction, danger of misinterpretation, spam, danger of viruses, etc.), which could give direction for further research.

According to the estimation results and with reference to our research hypotheses, we reject H0 (no interaction effects). Furthermore, the results of this model support H4, as we found significant interaction effects of SERVEMAIL with PRICEPORTAL (α) and/or DEVICE (δ). We validate H3 as we found evidence for interaction effects between PRICEPORTAL (α_i) and SERVEMAIL (σ_i). We must reject H7 as we did not find significant evidence for an interaction between PRICEEMAIL and SERVEEMAIL. Moreover, IMo_SERVEMAIL does not offer evidence for the validity of H1.

4.1.1.2 Interpretation of interaction effects for IMo_PRICEEMAIL

Like IMo_SERVEMAIL, for which the results were shown above, significant interaction effects have also been found for IMo_PRICEEMAIL. The estimation results for this model are presented in Table 16.

Table 16: Interaction effects for IMo_PRICEEMAIL

Estimation results IMo_PRICEEMAIL

Paramter	WTP	Rob. s.e.	Rob. t-ratio	p Value (2-sided)		pVal WTP > 0	pVal WTP < 0
ASC_alt1	0.9412	0.2574	3.6574	0.0003	***	0.9999	0.0001
PRICECALC1	-4.0815	0.6274	-6.5059	0.0000	***	1.0000	0.0000
PRICECALC2	-1.9524	0.6256	-3.1208	0.0018	**	0.9991	0.0009
PRICEEMAIL	-0.1039	1.1443	-0.0908	0.9277		0.5362	0.4638
PRICEPORTAL	0.9509	0.2436	3.9030	0.0001	***	1.0000	0.0000
PRICEAPP	1.1635	0.2445	4.7595	0.0000	***	1.0000	0.0000
SERVEMAIL	0.9045	0.4764	1.8984	0.0576		0.9712	0.0288
SERVCHAT	0.9687	0.4678	2.0706	0.0384	*	0.9808	0.0192
SERVAPP	1.3886	0.4966	2.7961	0.0052	**	0.9974	0.0026
DEVICE1	2.5801	0.7515	3.4330	0.0006	***	0.9997	0.0003
DEVICE2	1.0101	0.7520	1.3433	0.1792		0.9104	0.0896
DEVICE3	4.0966	0.7802	5.2508	0.0000	***	1.0000	0.0000
DEVICE4	4.0081	0.7959	5.0358	0.0000	***	1.0000	0.0000
PRICECALC1_a1	2.0467	0.8541	2.3965	0.0166	*	0.9917	0.0083
PRICECALC2_a1	1.6868	0.8669	1.9458	0.0517		0.9742	0.0258
SERVEMAIL_a1	0.7580	0.8257	0.9181	0.3586		0.8207	0.1793
SERVCHAT_a1	-0.7797	0.7969	-0.9784	0.3279		0.8361	0.1639
SERVAPP_a1	-0.4701	0.8172	-0.5753	0.5651		0.7175	0.2825
DEVICE1_a1	0.0181	1.1016	0.0165	0.9869		0.5066	0.4934
DEVICE2_a1	2.0584	1.0862	1.8950	0.0581		0.9710	0.0290
DEVICE3_a1	-0.9283	1.0977	-0.8457	0.3977		0.8011	0.1989
DEVICE4_a1	0.8461	1.1245	0.7524	0.4518		0.7741	0.2259

[a] WTP = Willingness to pay; LL = Log Likelihood; ***p < 0.001; **p < 0.01; *p < 0.05

Source: Author's own analysis.

Within IMo_PRICEEMAIL, we only find one significant interaction effect estimate: PRICECALC1_a1, i.e., the combination of having prices ‘changing based on a pre-defined plan’ (PRICECALC1), which is provided through email on a monthly base (PRICEMAIL). Therefore, a use case of this combination could be a different price scheme for each month, which offers the energy provider and the consumer a certain degree of planning security (trading prices and consumption prices). The result implies that if customers are offered the option of having a pre-defined plan for their energy consumption prices, they are willing to pay for the possibility of having these price plans provided on a regular/monthly basis. Additionally, a positive but lower WTP is observable (albeit not statistically significant) in this case for the other method of price calculation PRICECALC2_a1 (Decreasing prices per kWh each month with an increase or decrease of overall consumption). The result might be interpreted in the sense that a regular availability of valid price schemes (both variants of PRICECALC) that *are sent* to the customers increases a sense of control and transparency for them. Furthermore, this interpretation can be seen as a contrast to the scenario where customers need to become active to retrieve current prices, e.g., from a website or from an app. With this interpretation in mind, we notably did not find a significantly better model with interaction effects that address exactly a combination of proactive retrieving prices for the different price schemes (e.g. IMo_PRICEPORTAL and IMo_PRICEAPP, see Table 14). Moreover, it can be argued that preferences for the use of digital technology, such as apps, exist so that email communication is regarded as more transparent or easier compared to other forms of digital communication. This interpretation can be rooted in research on this field, albeit from other topics, such as where apps are used for informative purposes on personal data (Ahmad, et al., 2022; Giebel, et al., 2022).

Statistically significant evidence for interaction effects with the attributes in connection with the devices (DEVICE), such as in the case of the IMo_SERVEMAIL model, was not found for the IMo_PRICEEMAIL. In addition, the evidence for the non-significant estimators is mixed regarding whether there is a positive or negative impact on the WTP. In particular, the WTP for DEVICE3_a1 is negative, while the other devices at least show a positive value. It can be argued that there might be no significant interaction effect of PRICEEMAIL on the DEVICE attribute levels, but further research might uncover more insights in the future. Nevertheless, it is reasonable to assume that in contrast to the attributes of the service infrastructure (the IMo_SERVEMAIL model), the way how prices and bills are communicated is less relevant to the choice of a smart electricity device. Instead, the choice of smart devices for retail electricity clients generally depends on issues such as perceived ease of use, perceived usefulness, customer satisfaction, as well as on the attitude towards smart energy in general (Zamrudi, et al., 2019). It is, therefore, more likely to assume a more prominent role for selected service channel attributes over price and bill communication attributes. Referring to the servitisation level framework (see Table 11), certain attribute combinations may be irrelevant in the context of hybrid value creation. Specifically, the combination of ‘price communication’ and the added device (DEVICE1_a1, DEVICE2_a1, DEVICE3_a1, DEVICE4_a1) does not exhibit a statistically significant synergistic relationship. This lack of significance suggests that these attributes, when combined, may not contribute above the sum of their individual means to the overall value proposition of the alternative.

Similar to the dimension of the devices, the service infrastructure dimension shows no statistically significant relationships for the IMo_PRICEEMAIL model. Here, the estimates show a negative WTP for SERVCHAT and for SERVEAPP and a positive WTP for SERVEMAIL. Given that this result is obtained for the PRICEEMAIL attribute, it is possible that customers prefer to use a single communication and service channel such as email. The effect is particularly interesting as we found evidence within the estimation results of IMo_SERVMAIL that customers do not seem to value complicated forms of price communication if the service is only available through email. Therefore, we find evidence for a dependency between the service component and communication channel: In general, customers value uniform and no-frills channels. However, in combination with advanced bundling components, this preference seems to change, which supports again the findings from Jain and Bala (2018). With reference to our research hypotheses, we reject H0, as we found evidence for an interaction effect in the model. We cannot reject nor support other hypotheses based on the results of this interaction model that have not been rejected or supported before.

4.1.1.3 Interpretation of interaction effects for IMo_DEVICE0

IMo_DEVICE0 addresses the interaction effects of the attribute that stands for the *absence* of an electric plug adapter in the offered bundle of attribute level. The results for this model are shown below in Table 17.

Table 17: Interaction effects for Imo_DEVICE0

Estimation results IMo_DEVICE0

Paramter	WTP	Rob. s.e.	Rob. t-ratio	p Value (2-sided)		pVal WTP > 0	pVal WTP < 0
ASC_alt1	0.9833	0.2564	3.8355	0.0001	***	0.9999	0.0001
PRICECALC1	-3.1589	0.5013	-6.3009	0.0000	***	1.0000	0.0000
PRICECALC2	-1.1775	0.4941	-2.3833	0.0172	*	0.9914	0.0086
PRICEEMAIL	1.4079	0.3240	4.3449	0.0000	***	1.0000	0.0000
PRICEPORTAL	0.9254	0.2931	3.1568	0.0016	**	0.9992	0.0008
PRICEAPP	1.1881	0.3067	3.8735	0.0001	***	0.9999	0.0001
SERVEMAIL	0.8750	0.3054	2.8655	0.0042	**	0.9979	0.0021
SERVCHAT	0.5481	0.3007	1.8229	0.0683		0.9658	0.0342
SERVAPP	1.6303	0.3185	5.1185	0.0000	***	1.0000	0.0000
DEVICE1	2.4037	1.3319	1.8046	0.0711		0.9644	0.0356
DEVICE2	1.8811	1.3141	1.4315	0.1523		0.9239	0.0761
DEVICE3	3.4156	1.3316	2.5651	0.0103	*	0.9948	0.0052
DEVICE4	4.2369	1.3469	3.1457	0.0017	**	0.9992	0.0008
PRICECALC1_d0	0.2921	1.0177	0.2870	0.7741		0.6129	0.3871
PRICECALC2_d0	0.2525	1.0029	0.2518	0.8012		0.5994	0.4006
PRICEEMAIL_d0	-0.5637	0.8670	-0.6502	0.5156		0.7422	0.2578
PRICEPORTAL_d0	0.2064	0.8299	0.2487	0.8036		0.5982	0.4018
PRICEAPP_d0	-0.2603	0.8560	-0.3041	0.7610		0.6195	0.3805
SERVEMAIL_d0	2.0036	0.8569	2.3382	0.0194	*	0.9903	0.0097
SERVCHAT_d0	0.2139	0.8405	0.2545	0.7991		0.6005	0.3995
SERVAPP_d0	-2.3708	0.8489	-2.7928	0.0052	**	0.9974	0.0026

[a] WTP = Willingness to pay; LL = Log Likelihood; ***p < 0.001; **p < 0.01; *p < 0.05

Source: Author’s own analysis.

The results in Table 17 show that there are two significant interaction parameters with service infrastructure attributes: SERVEMAIL_d0 and SERVEAPP_d0. Given these significant interaction effects for the case that no electric plug adapter is included (DEVICE0), customers show a preference for service communication via email, as evidenced by a positive WTP value. On the other hand, service communication by app is connected to a negative WTP value. It can be argued that IMo_DEVICE0 shows the highest level of commoditisation (with reference to the understanding of ‘commodities’ provided in Chapter 4.2.2) of an energy contract within our setup. No physical device is included in the product bundle. Therefore, the device does not serve as a differentiating selling point against other providers. In this environment, a strong preference for less technology-intense service infrastructure (technology intensity: SERVEMAIL < SERVCHAT < SERVAPP) can be observed, as evidenced by the positive WTP for SERVEMAIL. This can be interpreted as a typical case for the existence of the digitalisation paradox (Gebauer, et al., 2020) as there is a higher WTP for a less digitised service bundle than for a higher digitised offer (= negative WTP for SERVEAPP_d0). The results show that the quest for hybrid value creation is difficult and that the simple introduction and implementation of new technological features may not necessarily contribute to the utility that is perceived by consumers. This effect is mentioned in the literature with respect to B2B-producing firms (Gebauer, et al., 2005; Cusumano, et al., 2015; Brax, et al., 2021). However, the results from our investigation provide evidence that this effect might also be relevant in the case of B2C retail electricity contracts. This means that it is vital for suppliers to understand and meet customer expectations when offering services or service bundles. This includes designing services that add real value to customers and are well-integrated with existing products. Failing to do so can result in services that customers see as inadequate or irrelevant, which can dilute brand value and customer loyalty (Brax, et al., 2021). Moreover, the pricing of services needs to be appropriate. Unlike products, services often involve ongoing customer engagement and variability in delivery costs. Companies need to develop pricing models that reflect the value of the service to customers while covering costs. Moreover, shifting toward services increases the provider's risk, particularly in terms of maintaining service quality and managing long-term customer contracts. Effective risk management strategies must be in place to handle these issues (Kaczor et al., 2017).

Furthermore, we reject H0 due to the evidence of interaction effects. We find support for one part of H10, however, only for the interactions with DEVICE0 and not for the other device attribute level. In addition, we did not anticipate an interaction effect between any attribute level of DEVICE and SERV.

4.1.2 Summary of hypotheses test

A summary of the observed and discussed interaction effects is presented in Table 18. In contrast to the number of synergy cases and responding hypotheses, only two of our hypotheses are fully confirmed by statistical evidence. One hypothesis can be seen as partly confirmed by evidence; however, it is just for one interaction effect in one model. Surprisingly, we found evidence of an interaction effect we did not anticipate, namely an effect between the device and the service infrastructure attributes, which offers an additional understanding and evidence for the digitisation paradox.

Based on the overall results, we reject H0, as we found significant interaction effects throughout the models and within our research design. Even if we expected a higher number of interactions due to the nature and origin of the attribute level, we were able to find some evidence for the presence of synergetic bundles as proposed in the literature (Grahsl & Velamuri, 2014; Grahsl, 2013).

Table 18: Results of hypotheses

Hypothesis	Relation to be tested	Relevant Model	Statistically significant result (coefficients)	Validation vs. Rejection
H0	$\pi = 0 \; and \; \sigma = 0 \; and \; \delta = 0 \; and \; \alpha = 0$	All Models	-	Rejection
H1	$at\ least\ one\ index\ i\ such\ that\ \pi_i \neq 0$ $and\ at\ least\ one\ index\ i\ such\ that\ \sigma_i \neq 0$	All Models	-	Rejection
H2	$at\ least\ one\ index\ i\ such\ that\ \pi_i \neq 0$ $and\ at\ least\ one\ index\ i\ such\ that\ \delta_i \neq 0$	All Models	-	Rejection
H3	$at\ least\ one\ index\ i\ such\ that\ \alpha_i \neq 0$ $and\ at\ least\ one\ index\ i\ such\ that\ \sigma_i \neq 0$	IMo_SERVEMAIL	PRICEPPORTAL_s1 DEVICE1_s1 DEVICE4_s1	Validation
H4	$at\ least\ one\ index\ i\ such\ that\ \alpha_i \neq 0$ $and\ at\ least\ one\ index\ i\ such\ that\ \delta_i \neq 0$	IMo_SERVEMAIL	PRICEPPORTAL_s1	Validation
H5	$\delta_{p2}^{3} > 0 \; and \; \pi_{d3}^{2} > 0$	IMo_PRICECALC2 IMo_DEVICE3	-	Rejection
H6	$\delta_{p2}^{4} > 0 \; and \; \pi_{d4}^{2} > 0$	IMo_PRICECALC2 IMo_DEVICE4	-	Rejection
H7	$\alpha_{s1}^{1} > 0 \; and \; \sigma_{a1}^{1} > 0$	IMo_PRICEEMAIL IMo_SERVEMAIL	-	Rejection
H8	$\alpha_{s2}^{2} > 0 \; and \; \sigma_{a2}^{2} > 0$	IMo_PRICEPORTAL IMo_SERVCHAT	-	Rejection
H9	$\alpha_{s3}^{3} > 0 \; and \; \sigma_{a3}^{3} > 0$	IMo_PRICEAPP IMo_SERVAPP	-	Rejection
H10	$\delta_{p,a,s}^{0} < 0$ and it exists at least one index i such that $\delta_{p,a,s}^{i} > 0$	IMo_SERVEMAIL IMo_DEVICE0	DEVICE1_s1 (negative) DEVICE4_s1 (negative) SERVEMAIL_d0 (positive) SERVEAPP_d0 (negative)	Validation for $\delta_{p,a,s}^{0} < 0$ in IMo_DEVICE0 Rejection for $\delta_{p,a,s}^{i} > 0$ in all other models
Additional	$at\ least\ one\ index\ i\ such\ that\ \delta_i \neq 0$ $and\ at\ least\ one\ index\ i\ such\ that\ \sigma_i \neq 0$	*IMo_DEVICE0*	*SERVEMAIL_d0 (positive)* *SERVEAPP_d0 (negative)*	*Validation*

Source: Author’s own analysis.

4.2 Discussion and Conclusion

The first objective of this application was to offer an economic overview to understand possible synergies of servitisation and hybrid value creation. We investigated if there is a theoretical foundation and if servitisation can lead to a higher value for customers in the form of synergies. Literature implies that offering a higher value for customers also leads to more value for companies (longer customer relationships, higher willingness to pay, enduring loyalty, etc.). Therefore, we wanted to offer an economic foundation for the understanding and find evidence for possible synergetic effects of servitisation and hybrid value creation.

For the second objective, we wanted to show that the concept of servitisation and the inherent assumption of synergies can be applied to the case of private customers in the market for retail electricity. Thus, we wanted to add to the body of quantitative servitisation research by offering a new perspective for product-service bundles based on the economic understanding of customer utility.

In the following chapter, we will address the different research objectives within the discussion of the results and give managerial and theoretical implications. We also address the limitations of the application.

4.2.1 Discussion of the results

We found statistical evidence for synergies in the transition from Stage 2 to Stage 3 of Vandermerwe and Rada's servitisation (1988) framework, e.g., through the validation of our research hypothesis H3, which is based on the interaction effect between PRICEPORTAL (Availability of prices through an online portal, Stage 2: 'Service') and SERVEMAIL (Service infrastructure through email, Stage: 3 'Support'). Our example of such a synergy is the offering of a price calculation option based on a pre-defined plan in the case that prices and bills are communicated via email. Therefore, we can validate the assumption that certain services lead to synergies when added to a product offering bundle (Vandermerwe & Rada, 1988; Grahsl & Velamuri, 2014). In addition, we found antagonisms. For example, if email is solely used to provide service, customers will exhibit a negative WTP for smart devices. Complicated devices with superior functionality are affected by this. The results confirm the servitisation paradox (Gebauer, et al., 2005) and the digitalisation paradox (Gebauer, et al., 2020) in the sense that the provision of additional features does not necessarily add value to a product bundle. The contribution of our analysis does confirm this in the context of retail electricity markets. It supports findings from the literature which have been gained within other market environments (Jain & Bala, 2018).

In addition, we found some evidence that customers do not prefer comparably advanced technological touch points such as apps or price portals at all times over less advanced technologies such as mail or email. Such findings have already been uncovered from other areas of research, such as in the field of using apps for health-related personal data (Ahmad, et al., 2022; Giebel, et al., 2022). One contribution of this application is that it is able to provide hints on the existence of similar impediments in the context of information provided to customers, specifically information in the form of prices and bills via email.

Another issue concerned the role of transparency. We found that if information is provided by email, customers show a positive WTP for an electricity tariff that allows them to have prices based on a pre-defined plan and which allows charging different prices on weekdays (in contrast to the established € per kw/h, that is still widely used in real-life market environments). We assume that this transparency provides a benefit as it allows customers to align their electricity use behaviour with the price that is being charged at specific times. However, from the perspective of the provider, this bundled offer would potentially lead to a lower revenue per unit of electricity due to the provision of such a smart electricity tariff, as customers consume electricity at a low price point. Consequently, there is a conflict of interest between the increase of utility for consumers through servitisation, the necessary investment in relevant service capabilities, and the goal of profit increase by the supplier. In this sense, hybrid value creation does not necessarily work in both ways if the investment in capabilities does not lead to economies of scale for additional service offerings and thus equalises the decrease of income from the lower price point. The suppliers' income in this scenario comes from the additional services and an increase in the number of customers due to the increased utility of the offer.

It can be pointed out that recently, there has been a public discussion on energy efficiency and climate change in the public and in academics. These are considered as some of the major challenges for economies, corporations, and households (Fischer, 2021) while also being very present in the minds of consumers (Noth & Tonzer, 2022; Wallis & Loy, 2021). From our perspective, the ability of households to control consumption via smart devices, as well as benefit from intelligent pricing tariffs of electricity, not only provides household synergies but can also contribute to overall welfare goals. Surprisingly, our results might point towards a concept that is known as the energy-efficiency gap or energy-efficiency paradox, which postulates the effect that there is a gap between current or expected future energy use and optimal current or future energy use (Jaffe & Stavins, 1994; Aznar & Vindel, 2023; Sorrell, 2009). The question arises as to why available energy-saving and low-emission devices or efficient insulation applications are not more widely used. This relation can be seen as the opposite of the so-called rebound effects, where energy consumption volume does not decrease (or even increase) despite the usage of efficiency measures (Sorrell, 2009; Turner, 2013). Literature offers three potential explanations for the energy-efficiency paradox: (1) private failures (households underestimate saving potential); (2) market failures (low information or insufficient labelling on energy efficiency); and (3) social failures (energy operating costs are inefficiently priced and/ or understood) (Gerarden, et al., 2017; Jaffe & Stavins, 1994). As we are not able to ask the respondents whether the energy efficiency paradox is applicable in our case, we can only assume the reasons for the results from this perspective. It may be possible that, in our case, the respondents did not see the energy and budget-saving potential or did not value it highly enough to impact the emerging result. Hence, in our case, the explanations ‘(1)’ and ‘(2)’ for the energy efficiency gap might be applicable.

A key aspect that needs to be emphasised at this point relates to the observation of antagonisms and, thus, the loss of utility and WTP in the case of paired attributes. Examples of this have been pointed out in the preceding paragraphs on the individual estimates for the

WTP in the discussed interaction models. It must particularly be pointed out and emphasised that the majority of the statistically significant estimates of WTP in the models are negative. The results seem puzzling, especially as, in most cases, the main effect of that attribute level is positive and statistically significant for most models. These results have striking implications as they show that hybrid value creation attempts can easily result in what we can call hybrid value destruction (Velamuri, et al., 2010).

4.2.2 Managerial and theoretical implications

We began by presenting different economic models that offer strong foundations and links to characteristics that are incorporated by servitisation literature. We showed that the product-service bundles do have an economic grounding and serve as one of the first alternative perspectives to the idea of homogeneous goods by assuming that the combination of different characteristics offers utility to the consumer (Saviotti, et al., 1982; Rothschild, 1987). We showed that the bundling of different products (Adams & Yellen, 1976) as well as the idea of synergies (Becker, 1965) can be grounded in economic literature. Further evidence also contributes to the key theme in the literature that servitisation or the bundling of additional digital components into the provision of a product does not necessarily lead to a positive impact in terms of utility increase or an increase of WTP (Gebauer et al., 2005; Gebauer et al., 2020).

Generally, the identification and understanding of interaction effects in a DCE model is important as it helps researchers and analysts to get a comprehensive understanding of how different attributes interact and jointly influence individuals' decision-making processes, such as the choices of products with multiple attributes. These insights are valuable in designing products and services as hybrid synergetic bundles so that these align in the best possible way with consumers' preferences. By deriving WTP estimates for interaction effects, researchers and practitioners can understand the relative importance of attribute interactions in choice situations and assess how individuals value specific combinations of servitisation in terms of monetary units or WTP. This means that when combining different services, products, or bundles, DCE approaches can help to identify synergies within the offering before the market launch or quickly afterwards. Therefore, product managers or sales executives can analyse the synergy hypothesis, e.g. in our case the idea of combining smart electricity plugs with variable tariffs and compare it to the obtained WTP estimates. If the assumed preference reaction does not appear, we know from our discussion of the servitisation paradox what aspects to consider first in order to realise the desired synergy perception of potential customers. Therefore, the results and the procedure from this application are valuable for companies and marketers in product development, such as in the field of pricing strategies.

This application offers another specific assessment of a particular market and is generally based on Lancaster's (1966) Theory of Consumer Behaviour, which serves as the interface between servitisation on one side but also as the source of the evaluation method that we use for this thesis. Lancaster's ideas are the core and standard foundation for the applications of DCE models, which offer a path to combine the aspects of consumer utility, servitisation and discrete choice experiments. Particularly, in our findings of synergetic effects between the different components of our product-service bundle, we establish evidence to support Becker's (1965), Adams and Yellen's (1976) as well as Lancaster's (1966) models and theories. Moreover, the application of the DCE with our sample of 800 respondents offered a quantitative application in the field of servitisation. We used a RUM that offered evidence of consumer utilities for different components of a product-service bundle. Thus, we added to the small body of quantitative servitisation research on the consumer and household level. We also contribute to the quantitative stream of the servitisation literature by confirming the assumed synergies between the product and service components according to the predominant servitisation framework.

Crucially, this application is the first DCE on servitisation that focuses on B2C applications in the energy market, specifically regarding retail electricity contracts. This means that our approach is one of the few that approaches servitisation from the customer's perspective and is not based on company performance indicators, as these are not automatically determined by the added value that could be created by a servitisation market approach.

For energy managers, it is important to know that it is possible to increase the value of the commodity by adding services and products. They should work on synergetic bundles to create additional value for the customer and consequently build up customer loyalty, which would increase competitive differentiation. Ultimately, this approach offers opportunities for long-term de-commoditisation. Nevertheless, managers need to be careful not to create antagonisms, as evidenced in multiple instances in this chapter. They should carefully select service touchpoints and evaluate if the relevant interaction channels are available. In such cases, an additive bundle might be better for the time being than an antagonistic bundle. In reference to the issue of the energy-efficiency gap that potentially has become visible in this research, managers should invest in resources (e.g., energy efficiency consultants for households, technical energy efficiency analyses, educational roadshows), capabilities (e.g., information hotlines, education and training for the sales and support team) and infrastructure (e.g., gamification approaches for energy efficiency, test and learn showcases for energy efficiencies, information snippets within the buying process) for offering context interaction and information – may be prior to the buying process – for educating customers in the matter of energy efficiency.

4.2.3 Limitations and suggestions for future research

A central limitation of the application is the fact that we did not include an attribute for electricity (i.e., the source of energy generation) in the choice design[12]. The consideration of the energy supply arrangement as one attribute in the product-service bundle would have created more insights and maybe evidence for synergies between the first two stages of the utility servitisation framework. This would be particularly relevant as, for example, renewable energy sources have been found as a relevant criterion for the WTP (Kim et al., 2013).

Another suggestion for further research is the question of whether synergies are quantifiable throughout the life cycle of the product. Here, our approach is based on perceived synergies and not realised effects. Hence, for the real user experience of the product-service

[12] See the discussion and reasoning for this choice in chapter 2.4.1 and Figure 7.

bundle, either a post-purchase investigation or objective measures, e.g., consumption behaviour, could be included in the evaluation.

The setup of the survey with other physical products, e.g., loading infrastructure, electric scooters, all boxes, or batteries, might be of interest for further research as well. As physical products are the core of the research area of servitisation, an approach addressing physical products and adjacent services might lead to results other than those in this application. Our case of contract-based intangible consumption offers that are enriched with physical components and services might be a very unique application. With reference to the majority of the servitisation literature, preference measurement approaches for manufacturing servitisation cases might also be of additional interest.

Moreover, additional research could connect the evidence for synergies in the B2C or potentially even in the B2B environment to the long-term financial performance of the firm. This would close the gap between customer value and the firm's performance and would greatly serve the overall servitisation literature. This could be extended towards the consideration of additional product segments of firms, thereby touching on the issue of product or service cannibalisation concerns that might arise when multiple segments are served by one entity (Jain & Bala, 2018).

5 Application 3: The utility of digitisation for consumer choices

Abstract

This application investigates how preferences for attributes might be influenced by the perceived digital maturity of the same attributes. Methodologically, this is performed by applying a hierarchical Bayes (HB) routine, which is used to estimate the part-worth utilities from the observed choices. Furthermore, a correlation analysis is provided between the categories in the HB estimation, as well as a multiple regression analysis. Also, we apply a CL model with interactions. By using these methods, a connection was made between the perceived utility and the perception of digital maturity of product attributes. The results show that the respondents tend to derive utility out of digitised service attributes across many service dimensions. However, there is still a profound influence via the price attribute, which dominates decision-making in our context.

5.1 Introduction

In the literature and common discourse, there are perspectives that see the digital transformation as the ‘Fourth Industrial Revolution’ (Schwab, 2016, p. 21; Cimini, et al., 2021). Others talk about ‘Industry 4.0’ or the ‘Age of Digital’. Even though in our days, the focus on zero emission, green technology, and social responsibility foreshadows the next industrial revolution, it is unlikely that the influence of digitisation on business and society is going to fade out.

The concept of an industrial revolution is based on the impact that technology and innovation have on the creation of value and goods in economic systems. For example, the impact of the steam engine that led to mechanical production is commonly seen as the First Industrial Revolution. It is agreed that electrification in production processes led to mass production and thus to the Second Industrial Revolution, while semiconductors and computers enabled digital value generation, which is referred to as the Third Industrial Revolution. The now enduring fourth revolution is shaped amongst others by mobile internet, sensors, big data, machine learning, and artificial intelligence, which lead to co-creation of products, individualisation, increase of production speed and decentralisation of production (Schwab, 2016, pp. 11-12; Holmström & Partanen, 2014; Porter & Heppelmann, 2014). Due to digitisation and/or Industry 4.0, we enjoy advantages on a private, business, and social level in major parts of our daily lives that we did not anticipate decades before (Brynjolfsson & Collis, 2019).

With the application described in this part of the thesis, we want to add to the very small body of quantitative literature that investigates approaches to measure and evaluate the digitisation of goods (Vendrell-Herrero, et al., 2021; Brynjolfsson, et al., 2019; Katz & Koutroumpis, 2013; Mammadli & Klivak, 2020; Jamison & Wang, 2021). For this purpose we apply the concept of digital servitisation, which refers to the shift of companies' product portfolios towards a higher degree of integrated digital services and applications within a product-service combination (Vandermerwe & Rada, 1988; Oliva & Kallenberg, 2003; Porter & Heppelmann, 2014; Vendrell-Herrero, et al., 2017). Examples of digitalised services can be found in numerous markets, including B2B and B2C environments, where physical products are increasingly being connected with digitalised servitisation options. For example, in the B2B market, aircraft producers are embedding digitalised solutions such as predictive maintenance, performance improvements, or similar digitalised solutions as a servitisation strategy. Similarly, in the B2C market, television screen manufacturing firms design their products to be platforms where digital content is being sold and on which advertising can be placed (Bossert & Laartz, 2017, p. 5). Researchers and practitioners assume that on a microeconomic level, (digital) servitisation can lead to an increase of utility for the customer, an increase of the financial performance as well as a competitive advantage for the firm (Lightfoot, et al., 2013; Raddats, et al., 2019; Ambroise, et al., 2018; Oliva & Kallenberg, 2003; Gebauer, et al., 2011; Vandermerwe, 2000; Baines, et al., 2017). A competitive advantage (i.e., being 'better' than competition, see e.g. Porter (1987)) as well as the closely linked concept of comparative advantage (i.e., generating comparable output, like products, through lower input, such as less capital or human resources, see Ricardo (1821)) and the value concept (Woodruff, 1997) are concepts that are used within the field of digital servitisation. Even though these concepts are a significant part of general business and management studies, their origin lies in economic theory. We argue that it is necessary to include these theories in this chapter for two reasons. First, we understand digitisation as a technological progress that enables an increase in output per unit of input (productivity) comparable to other revolutionary inventions like for example the steam engine, which helped spark the Industrial Revolution. Second, we assume that the digitisation of goods has the possibility of offering a higher utility for consumers.

Because of its heritage from management, strategy, and business research, digital servitisation often refers to the concept of ‘value’, but it fails to deliver a comparable and specific definition. According to different researchers, value for customers and suppliers can be created by using and employing data, shorter product cycles, new business opportunities, customer support, or analytics to achieve a higher return on investment (Porter & Heppelmann, 2015; Rymaszewska, et al., 2017). Even though almost every contribution in the research stream of digital servitisation refers to (additional) ‘value creation’, a clear definition that makes quantification of a value definition has not been adequately addressed so far. In this application, for pinpointing the value of digital servitisation we apply the economic understanding of utility as proposed within the NIE, in which the classical utility maximising behaviour of economic agents is influenced by individual or institutional context (e.g. preferences, transaction costs or information asymmetry) (Coase, 1937, p. 390).

For the valuation of the consumer utility of digital servitisation, we employ a DCE similar to the approach in the preceding chapters of this thesis. This approach allows us to compare different digitised characteristics of electricity supply contracts that may be of high utility for the customer. The theoretical foundations of the DCE approach goes back to the work of authors, such as Lancaster (1966), Thurstone (1927), and McFadden (1974) whose work was already mentioned before in Chapter 2. For our DCE, we selected properties and characteristics for product-service bundles that

- Include different technologies (mobile internet, machine learning, sensors, digital customer interfaces, platforms, etc.),
- Rely on important company capabilities and resources (big data, computing infrastructure, digital processes, communication protocols, etc.), and

- Offer the possibility to increase efficiency and sustainability (energy efficiency, consumption orientation, etc.).

We apply a HB and a CL estimation to the established DCE setup, investigate correlations, and estimate a multivariate regression to estimate and investigate the consumer preferences for a digital perceived product-service bundle.

Based on the assumptions that research postulates for digital servitisation in combination with our expectations from economic theory, we assume that our model estimation and measures show higher perceived utilities of consumers and households for digitised attributes, and hence, we expect to find evidence for the connection of perceived digitisation and higher utility.

This application makes three important contributions: First, it adds to the quantitative body of digital servitisation studies, as comprehensive quantitative research is not often applied in this area. As the concept of servitisation is widely used in practical applications and is a relevant strategy for contemporary management practice, we see this as a major research gap. Therefore, using a quantitative approach is highly recommended in academic research (Suarez, et al., 2013; Visnjic, et al., 2016; Eggert, et al., 2014; Böhm, et al., 2017). Second, by identifying economic models and theory as the foundation for servitisation, we offer evidence for the application of (digital) servitisation on the household level. Lastly, based on economic foundations, we propose an approach to measure the impact of digitisation in the form of digitalised services on the utility of a physical product-service bundle. The implications from these contributions are relevant for managers, policymakers, and researchers alike.

We organise the remainder of Chapter 5 as follows: first we review the theoretical foundations and literature for hybrid value creation and its connection to consumer theory, then we present the state of research for digital servitisation and discuss approaches to evaluate digital utility (section 5.2). Afterwards, we introduce the methodological approach in section 5.3 and the results in section 5.4. The discussion and conclusion follow in section 5.5. This includes the practical and methodological implications of the results with reference to academic theory and to its practical application. Afterwards, limitations and propositions for further research are developed.

5.2 Foundations on digital servitisation, consumer theory and utility-based valuation

5.2.1 Conceptual foundations on hybrid value solutions

Servitisation refers to the shift of manufacturing firm's product portfolios towards a higher degree of integrated service offerings (Vandermerwe & Rada, 1988; Oliva & Kallenberg, 2003) with the objective to provide more utility to suppliers and buyers by combining services with existing product offers. Researchers and practitioners believe that servitisation can lead to an increase of financial performance as well as competitive advantage for the firm (Lightfoot, et al., 2013; Raddats, et al., 2019; Ambroise, et al., 2018; Oliva & Kallenberg, 2003; Gebauer, et al., 2011; Vandermerwe, 2000; Baines, et al., 2017). See also the discussion of servitisation in Chapter 4.2.1 of this thesis, which provides a deeper understanding of the topic and provides the foundation for the discussion in this application.

Within the research field, there are numerous research directions and frequently used concepts (Khanra, et al., 2021; Raddats, et al., 2019). At this point of the thesis, we especially want to highlight the concepts of 'hybrid value solutions' (Velamuri, et al., 2011; Ulaga & Reinartz, 2011; Shankar, et al., 2009) and product-service-systems (Tukker, 2004; Goedkoop, et al., 1999; Mont, 2002a; Zhou & Song, 2021).

Hybrid value solutions can be defined as 'products and services combined into innovative offerings' (Shankar, et al., 2009). However, while 'servitisation' implies additional 'pure' services in addition to physical goods, hybrid offerings do not differentiate between the kind of goods. Service-service combinations are also possible, as well as combinations of product and service (Ulaga & Reinartz, 2011; Grahsl & Velamuri, 2014). The road of hybrid offerings is paved by the resource-based view on the firm (also: resource-advantage theory), which assumes that resource heterogeneity and immobility are the sources for value production and hence competitive advantage (Velamuri, et al., 2011; Ulaga & Reinartz, 2011; Grahsl & Velamuri, 2014; Barney, 1991). Therefore, know-how and suitable capabilities are necessary to integrate, combine, and harmonise offer components thoroughly to create synergetic effects between the different components. Hybrid value creation offers the potential for hard-to-imitate competitive advantage in mature markets where cost leadership is not an option (Velamuri, et al., 2011; Vandermerwe & Rada, 1988). As introduced earlier in this thesis, hybrid value bundles can be divided into additive and synergetic bundles (see Chapter 4.2.2).

Product-service systems (PSS) are a 'marketable set of products and services capable of jointly fulfilling a user's need' (Goedkoop, et al., 1999, p. 3). In contrast to hybrid value solutions, the emphasis for PSS is to reduce environmental impact and increasing efficiency (Velamuri, et al., 2011; Mont, 2002a; Mont, 2002b), e.g., through maintenance services that increase product lifetime ('repair instead of throw-away society') or through pay-per-use models that reduce the total amount of necessary goods (Mont, 2002a; Lightfoot, et al., 2013). It is assumed that PSS leads to new and unique combinations of functions and a decrease of product investment necessities (Goedkoop, et al., 1999).

In the course of this chapter, we base our research framework on the hybrid value approach for consumers and households proposed by Grahsl (2013; Grahsl & Velamuri, 2014), which we already introduced earlier. The framework builds on Vandermerwe and Rada's servitisation model (1988). Based on a PSS understanding, we investigate product-related services that offer possibilities for energy efficiency improvement of households.

5.2.2 The role of digitisation on servitisation

While the connection between digitisation and servitisation has been indirectly preconditioned by earlier servitisation contributions, the direct combination of these two concepts has generated an increasing footprint throughout recent research activities (Kohtamäki, et al., 2021; Paiola, et al., 2021; Coreynen, et al., 2020). Comprehensive literature reviews emphasise that the role of digitisation in the field of servitisation still remains rather unexplored. Nevertheless, it is agreed that digitisation leads to new service offerings, better integration, and the ability to encourage the digital transformation of business models (Raddats, et al., 2019; Khanra, et al., 2021). Khanra et al. (2021) grant the topic of 'digital servitisation' to be an important area for further research and as one of the major aspects to consider when investigating advanced business models for servitisation. Zhou and Song (2021) predict that digitisation will be the catalyst that merges and integrates the different servitisation research streams with each other. From a practical perspective, the progress of digitisation on service and product strategies has been part of managerial narratives since the early 2000s (Kohtamäki, et al., 2021), which clearly shows its importance and practical relevance. This perspective is supported by Porter and Heppelmann (2014) as well as Rymaszewska et al. (2017) who provide further insight into the historic relevance of information technology for products and services by separating three waves of IT: impact of computing, impact of the internet, and impact of sensors, software, and connectivity. Either way, from an economic view this means that these developments had an impact on production or more generally on industrial input-output relations and utilities, as e.g. presented for the British Industrial Revolution by Harley and Crafts (2000) or for the company level by Sklyar et al. (2019a)

Digitisation is often connected to the need to reduce the information asymmetry that is inherent to analogue transactions (Nagle, et al., 2020). Nowadays, customers can compare suppliers and offers more easily than before. This leads to lower average selling prices, to higher variety of offers, and thus to a higher delta towards the utility of the customer for that product (Brynjolfsson, et al., 2003). Therefore, we argue that the customer's WTP for digital product bundles is higher than the combined WTP of separate bundle components. This means, ceteris paribus, digitisation of product bundles increases the delta between purchase price and WTP, hence leading to a consumer surplus (Collis, 2020), which we investigated for our DCE in the second application (Chapter 3) of this thesis.

At its core, digitisation or, synonymously, digital transformation has always meant the accumulation of different concepts interacting with each other. In one of the earlier contributions on digitisation as a lever for service quality and productivity, Hsu and Spohrer (2009) summarise elements of digital connections. They developed a framework for digital connections consisting of 'person' (user and provider), 'processes' (software resources for the digital representation of production factors) and 'data/knowledge, computing ability and 'infrastructure' (network or protocols). About 10 years later, Davenport and Redman (2020) postulate that organisations need to master and coordinate talents (human resources, expertise) in four domains: technology, data, processes and change management. In this framework, technology addresses emerging technical applications as well as IT infrastructure. However, the idea of networks and intercorporate connections is not addressed by this approach, as it is, e.g., proposed by Porter and Heppelmann (2014) or by Hsu and Spohrer (2009).

For the remainder of this application, our definition of digitisation originates from the definition that is widely used in the field: "Digitisation refers to the increasing use of digital technologies for connecting people, systems, companies, products and services" (Coreynen, et al., 2016, p. 3; Paiola, et al., 2021, p. 508; Hsu & Spohrer, 2009). However, we would like to include the aspect of data in this understanding, e.g. as addressed by Porter & Heppelmann (2015) or Vendrell-Herrero, et al. (2021). This leads to the following adjusted definition: *Digitisation is the increasing application of technology for connecting people, systems, data, companies, products and services*.

The understanding of the relationship between digitisation and servitisation can be divided into the firm's internal (1) and the external customer (2) perspective: (1) the application of digital resources and capabilities to foster servitisation (Coreynen, et al., 2016; Sklyar, et al., 2019a; Kowalkowski, et al., 2021; Paschou, et al., 2020; Sjödin, et al., 2020; Tronvoll, et al., 2020; Holmström & Partanen, 2014) and (2) the understanding of digitised service offers (Kohtamäki, et al., 2021; Porter & Heppelmann, 2014; 2015; Aas, et al., 2021; Rymaszewska, et al., 2017; Vendrell-Herrero, et al., 2017; Frank, et al., 2019; Cimini, et al., 2021). We take into account both perspectives and define digital servitisation as *the integration of digital services and applications within a product-service combination that is created by suitable resources and capabilities on the supplier's side* (based on the understanding composed by Porter and Heppelmann (2014; 2015) as well as Vendrell-Herrero, et al. (2017)).

Different motivations for digital servitisation are mentioned in the literature: (1) utilisation of available (big) data, (2) reduction of time to market, (3) new sources of revenue, (4) efficiency of service, and (5) anticipation of risks (Favoretto, et al., 2022; Paschou, et al., 2020; Sjödin, et al., 2020). Additional motivations for offering digitised services are the ability for remote monitoring, data collection, shared insights with customers, reduced costs, providence of self-service, or customers' business processes improvement (Naik, et al., 2020). At the level of the firm, exploitational (improvement of existing products and offers) and explorational capabilities (identification of new value streams and business models) are drivers for digital servitisation (Coreynen, et al., 2020). With regard to external drivers, exploitative companies are more likely to invest in digital capabilities and assets in the case of markets characterised by fast technological changes. Explorative firms, however, are more likely to invest in servitisation when active in markets that are characterised by an intense competitive situation (Coreynen, et al., 2020).

One widely cited foundation of the concept of digital servitisation is Porter and Heppelmann's (2014; 2015) framework on smart and connected products. It is argued that smart products consist of three core elements (Porter & Heppelmann, 2014):

- Physical components (mechanical and electrical parts of the product),
- 'Smart' components (sensors, processors, software, data, customer interface) and
- Connectivity components (protocols, wireless connections with the product; three interaction forms: 1:1; 1:n; n:n).

The concepts of servitisation or hybrid value creation are not directly mentioned in Porter and Heppelmann's contributions – even if underlying and indirect assumptions of these concepts are evident (Porter & Heppelmann, 2015; Kohtamäki, et al., 2021). The capabilities of smart products can be clustered into four areas (Porter & Heppelmann, 2014; Kohtamäki, et al., 2021; Vendrell-Herrero, et al., 2021; Thomson, et al., 2021; Cimini, et al., 2021):

(1) Monitoring: sensors and external data sources enable monitoring of product condition, environment, usage, as well as alerts and notifications.

(2) Control: Enables control of product features and personalisation of user experience through integration of software into the product.
(3) Optimisation: Algorithms enabled by monitoring and control capabilities that optimise product operations, enhance performance, and allow for predictive diagnostics.
(4) Autonomy: All of the other areas combined, as these offer autonomous product operation, connection with other products/systems, autonomous enhancement, personalisation, and self-diagnosis.

Concrete digital and technological applications that are part of a digital service offer are, for example, 3D printing, artificial intelligence, cloud computing, virtual reality, augmented reality, the Internet of Things (IoT), IT capabilities, blockchain, sensors, data warehouses, big data analytics as well as digital user interfaces (Paschou, et al., 2020; Schwab, 2016). A structured and widely cited approach for the combination of servitisation and digitisation is based on the degree of technology that is used for service offerings (Favoretto, et al., 2022; Frank, et al., 2019). According to this approach, there are three levels of digital servitisation: low, moderate and high digital levels of services (Frank, et al., 2019):

- Low digital level: low usage levels of digital technologies for service offerings. Digital technologies are used only as a support and do not provide the service itself; services are manually delivered.
- Moderate digital level: moderate usage levels of digital technologies. Use of digital tools to deliver distinct service offerings to the customer. Digital technologies (mobile apps, cloud, etc.) are used to provide the service itself, adding value that customers are receiving.
- High digital level: high-tech services that can provide value for both customers and the companies' internal processes (‘Industry 4.0’).

Most of the influencing contributions on digital servitisation are of a conceptual or qualitative nature and lack quantitative approaches. However, it is assumed that a high number of contributions is still to come, as the number of published articles in this area has significantly increased since 2016 (Favoretto, et al., 2022; Paschou, et al., 2020; Coreynen, et al., 2020). Nevertheless, there is some quantitative evidence: for example, based on an investigation of manufacturing firms, a study revealed a nonlinear, U-shaped effect of digitised servitisation on financial performance (Kohtamäki, et al., 2020). The results show that a high degree of digitisation and a high focus on servitisation leads to a positive impact on financial performance, while a low maturity of digitisation in combination with a high degree of servitisation leads to a negative impact on performance. These results might be explained best through the concept of the 'digitisation paradox', which postulates that investments in digital capabilities and assets have rarely paid off yet. Approaches to overcome this paradox include offering digital services, product connectivity and the establishment of IoT platforms (Gebauer, et al., 2020; Sjödin, et al., 2020). This paradox is also well-known in the research area of servitisation ('servitisation paradox'), including similar return-on-investment risks or effects (Gebauer, et al., 2005). We discussed the concept already in Chapter 4.2.2 of this thesis.

Digital servitisation is characterised by low marginal costs in comparison to the initial services (Favoretto, et al., 2022; Brynjolfsson, et al., 2019). In addition, traditional services, which complement the product offering, are often replaced or cannibalised by digital services (Rymaszewska, et al., 2017). Nevertheless, digital servitisation is assumed to offer an increasing degree of sustainability within the corresponding business models, e.g., by optimising resource utilisation (Paiola, et al., 2021; Paschou, et al., 2020; Parida & Wincent, 2019; George, et al., 2021).

One of the objectives of the present thesis is the investigation of the utility of digitised product-service bundles. Based on the presented literature, we constructed attribute levels for product-service bundles that include different technologies (mobile internet, machine learning, sensors, digital customer interfaces, platforms, etc.), rely on important company capabilities and resources (big data, computing infrastructure, digital processes, communication protocols, etc.), and offer the possibility to increase efficiency and sustainability (energy efficiency, consumption-oriented, etc.). These characteristics are part of the attributes that we presented throughout the thesis and constructed based on classical servitisation, including service (e.g.

support, communication) and physical product components (e.g. additional devices within the bundle) with reference to the work and model from Grahsl (2013). As we try to investigate the impact of digitisation on the utility of products and services, we focused on direct or indirect digital, technological, or IoT applications within the assigned products and services for the development of the attribute levels. The attribute level, the respective digital considerations, and the links to literature are presented throughout Table 19, Table 20, Table 21, and Table 22. The cost attribute (six attribute levels: 0.00 €, 4.99 €, 9.99 €, 14.99 €, 19.99 €, 24.99 €) is based on market prices for smart plugs (see Chapter 2.4.1).

Table 19: Digital considerations for attribute level PRICECALC

Attribute	Attribute Level	Digital and technical applications within value delivery (examples)	Necessary digital capabilities of the supplier	Keywords and references to literature
Source of price calculation per kWh	Fixed Price per kWh – prices are defined for the contractual time (PRICECALC0)	• Minimal digital capability necessary on the supplier or consumer side • Remote metering data transfer (if applicable to the customer metering device)	No special digital capabilities	• Low digital level (Frank, et al., 2019)
	Changing of prices based on a pre-defined plan (e.g. different prices on weekdays) (PRICECALC1)	• Metering device needs to capture the consumption volumes for scheduled time frames • Supplier needs to store and combine consumption data with the pricing schedule • Data needs to be transferred at least from the consumer to the supplier	Medium digital capabilities	• 'Smart' components, e.g., sensors, processors, software, data, and customer interface (Porter & Heppelmann, 2014) • Energy efficiency (Velamuri, et al., 2011; Mont, 2002a; Mont, 2002b) • Medium digital level (Frank, et al., 2019)
	Decreasing prices per kWh each month with an increase or decrease in overall consumption (PRICECALC2)	• Intensive digital application on front- and backend necessary • Metering device constantly needs to capture the consumption volumes • Supplier needs to store and combine consumption data with the pricing algorithm • Data needs to be transferred back and forth between supplier and consumer	High digital capabilities	• 'Smart' components, e.g., sensors, processors, software, data, and customer interface (Porter & Heppelmann, 2014) • Energy efficiency (Velamuri, et al., 2011; Mont, 2002a; Mont, 2002b) • High digital level (Frank, et al., 2019)

Table 20: Digital considerations for attribute level PRICE_

Attribute	Attribute Level	Digital and technical applications within value delivery (examples)	Necessary digital capabilities of the supplier	Keywords and references to literature (examples)
Price communication and access to bills	Prices are itemised within the initial contract documents; bills are sent via mail (default)	• Minimal digital application in the back- or frontend of the service and product delivery process • Digital processing (and printing) of contractual documents • Storage of customer data in CRM application	No special digital capabilities	• Data/knowledge (Hsu & Spohrer, 2009) • Low digital level (Frank, et al., 2019)
	Prices and monthly bills are sent via email (PRICEMAIL)	• Corporate email infrastructure • Customer database with contact, contractual and consumption information • Connection to ERP applications (for prices) • Process automation for bulk emails • Customers need to be able to receive email communication	Low digital capabilities	• Big data (Paschou, et al., 2020) • Infrastructure, network or protocols (Hsu & Spohrer, 2009) • Low digital level (Frank, et al., 2019)
	Prices and monthly bills are made available through an online portal (login necessary) (PRICEPORTAL)	• Website infrastructure • Web service/hosting infrastructure • Content management system • Customer database with contact, contractual and consumption information necessary • Connection to ERP applications (for prices) • Customers need to access the portal via suitable devices (computers, mobile phones, etc.)	Medium digital capabilities	• Cyber security, cloud computing (Paschou, et al., 2020) • Infrastructure, network or protocols (Hsu & Spohrer, 2009) • Data/knowledge (Hsu & Spohrer, 2009) • Platforms (Gebauer, et al., 2021) • Medium digital level (Frank, et al., 2019)

Prices and monthly bills are made available through a mobile app (PRICEAPP)	• Application infrastructure (parallel to website infrastructure) • Web service/hosting infrastructure • Content management system • Customer database with contact, contractual and consumption information • Connection to ERP applications (for prices) • Customers need to install applications on their (mobile) devices	Medium digital capabilities	• Mobile internet (Schwab, 2016, pp. 11-12; Holmström & Partanen, 2014). • Big data (Paschou, et al., 2020) • Data/knowledge (Hsu & Spohrer, 2009) • Platforms (Gebauer, et al., 2021) • Medium digital level (Frank, et al., 2019)

Table 21: Digital considerations for attribute level SERV_

Attribute	Attribute Level	Digital and technical applications within value delivery (examples)	Necessary digital capabilities of the supplier	Keywords and references to literature (examples)
Service infrastructure	Call Centre (default)	• Customer database with contact, contractual, and consumption information	Low digital capabilities	• Big data (Paschou, et al., 2020) • Low digital level (Frank, et al., 2019)
	Email (SERVEMAIL)	• Corporate email infrastructure • Customer data in CRM application • Customers need to be able to receive and send email communication	Low digital capabilities	• Digital processes, i.e. software resources for the digital representation of production factors (Hsu & Spohrer, 2009) • Low digital level (Frank, et al., 2019)
	Chat Agent (also video Chat) (SERVCHAT)	• Website infrastructure • Web service/hosting infrastructure • Content management system with chat module • Customer database with contact, contractual and consumption information • Customers need to access chat via suitable devices (computers, mobile phones, etc.)	Medium digital capabilities	• Infrastructure, network, or protocols (Hsu & Spohrer, 2009) • Digital Processes, i.e., software resources for the digital representation of production factors (Hsu & Spohrer, 2009) • Medium digital level (Frank, et al., 2019)
	Message service within the smartphone app (SERVAPP)	• Application infrastructure (parallel to website infrastructure) • Web service/hosting infrastructure • Content management system, optional: video chat infrastructure • Customer database with contact, contractual and consumption information • Customers need to install applications on their (mobile) devices	High digital capabilities	• Mobile Internet (Schwab, 2016, pp. 11-12; Holmström & Partanen, 2014). • Infrastructure, network, or protocols (Hsu & Spohrer, 2009) • Platforms (Gebauer, et al., 2021) • Medium digital level (Frank, et al., 2019)

Table 22: Digital considerations for attribute level DEVICE

Attribute	Attribute Level	Digital and technical applications within value delivery (examples)	Necessary digital capabilities of the supplier	Keywords and references to literature (examples)
Additional device included in the contract	No electric plug adapter is included (DEVICE0)	• No digital capability necessary on the supplier or consumer side	No special digital capabilities	• Low digital level (Frank, et al., 2019)
	Manually adjustable electric plug adapter (DEVICE1)	• No digital capability necessary on the supplier or consumer side	No special digital capabilities	• Control (Porter & Heppelmann, 2014) • Low digital level (Frank, et al., 2019)
	Local connected electric plug adapter (DEVICE2)	• Connectivity features of the plug adapters (proprietary or standard communication protocols)	Low digital capabilities	• Control (Porter & Heppelmann, 2014) • Connectivity components (Porter & Heppelmann, 2014) • Low digital level (Frank, et al., 2019)
	Smart plug adapter incl. smartphone app (DEVICE3)	• Connectivity features of the plug adapter (standard communication protocols) with household infrastructure (e.g. telecommunication/ internet infrastructure) • Gateway to connect to the mobile phone app (either locally or via web application) • Customers need to install applications on their (mobile) devices	Medium digital capabilities	• Optimisation (Porter & Heppelmann, 2014) • Infrastructure, network, or protocols (Hsu & Spohrer, 2009) • Connectivity components (protocols, wireless connections) (Porter & Heppelmann, 2014) • Medium digital level (Frank, et al., 2019)

Smart plug adapter incl. smartphone app, and algorithm (DEVICE4)	• Connectivity features of the plug adapter (standard communication protocols) with household infrastructure (e.g. telecommunication/ internet infrastructure) • Web gateway to connect to the mobile phone app and to algorithm infrastructure • Data connection between plug, app and provider • Customers need to install applications on their (mobile) devices • Integration of either artificial intelligence or business intelligence capabilities at the front and back end	High digital capabilities	• Optimisation, autonomy (Porter & Heppelmann, 2014) • Machine learning, artificial intelligence (Schwab, 2016, pp. 11-12; Holmström & Partanen, 2014). • Infrastructure, network or protocols (Hsu & Spohrer, 2009) • Connectivity components (Porter & Heppelmann, 2014) • Energy efficiency (Velamuri, et al., 2011; Mont, 2002a; Mont, 2002b) • High digital level (Frank, et al., 2019)

5.2.3 Economic classification of digital product-service bundles

The concept of servitisation is based on the understanding that the consumer perceives and realises additional utility from a bundled combination of goods and services, as we introduced in Chapter 4. Therefore, the single goods and services within that combination do not need to be owned by the consumer; pay-per-use can also be subsumed within that field, as covered by the concept of PSS. As defined earlier, digitisation is the accumulation of different concepts interacting with each other. We see at least ‘people’, ‘systems’, ‘data’, ‘companies’, ‘products’ and ‘services’ as parts within this definition. Furthermore, a configuration and combination of these concepts might be one component of a product-service bundle. This makes it difficult to apply the traditional fourfold framework for classifying goods according to their rivalry and excludability[13] to a digitised product-service combination. Therefore, we must investigate each attribute of our product-service bundle separately.

In this thesis, we focus on digitised energy bundles that consist of (A) electricity, (B) variable pricing modules, (C) service and communication components, and (D) a physical component (specifically an electricity plug adapter). Electricity is a product from which customers can be excluded if they are not paying for electricity consumption. It can only be used once (Lohse & Künzel, 2011, p. 384; Kempener & de Vivero, 2015). The classification holds true specifically for non-renewable electricity, as it reduces fossil resources for all electricity customers, e.g., oil or gas, even if it is barely noticeable on the global level. We claim that renewable electricity sources are also rival products, as only the source of electricity (e.g., wind, water, photovoltaic) and not the electricity itself can be regarded as non-rival. Hence, we assign electricity (A) to the realm of private goods (rival and excludable), which is also the classical example for this classification.

We can assign a variable price mechanism to the field of excludable and non-rival goods, as access needs to be paid for, but ‘consuming’ does not influence the ability of consumption by other customers (B).

[13] See, for example, Nikander, et al. (2020).

From our perspective, the service and communication components cannot be assigned to one field only (C). There is an exclusion as only paying customers can access goods or services. Within the frame of excludability, the total of the components can be seen as having some rival as well as non-rival characteristics. Nevertheless, for the sake of the argumentation, we assign the service and communication components to the non-rivalry characteristics, and hence, we see those goods as low-congestion goods. For these goods, suppliers can increase output while reducing the average per-unit cost of production to a certain level (e.g., until the level when an additional service agent is needed to handle the expected support calls).

Lastly, the assignment of the physical component is straightforward (D). The device (electricity plug adapter) is strictly excludable and rival for one specific device. Therefore, we see this component as a private good.

Besides the classical understanding of rival and non-rival, with reference to the applied models of digital servitisation and bundling, Nikander et al. (2020) see a third column called ‘anti-rival’ to the goods classification. They propose ‘network goods’ for the combination of excludable and anti-rival as well as ‘symbiotic goods’ and non-excludable and anti-rival. In their understanding of those goods, the subtractability is negative, i.e., if elements are taken away from the good, the overall utility is reduced disproportionally (Nikander, et al., 2020). This taxonomy is very close to the aspect of having synergetic bundles, as introduced earlier and described by Shankar (2009) as well as Grahsl & Velamuri (2014). Examples of network goods are controlled sales platforms and, for symbiotic goods, blockchain technology or, in general, the internet. The three-column classification of goods based on Nikander, et al. (2020) is presented in Table 23.

Table 23: Expansion of the fourfold goods model

	Rival	**Non-rival**	**Anti-rival**
Excludable	Private goods, e.g., food, clothing, electricity	Club/toll or monopoly gods, e.g., movie streaming services	Network goods, e.g., auction platforms, social networks
Non-excludable	Common goods,	Public goods, e.g., the law, search engines	Symbiotic goods, e.g., Wikipedia, blockchain

	Rival	Non-rival	Anti-rival
	e.g., atmosphere, Fish in the open sea		

Source: Nikander, et al. (2020).

Moreover, apart from the anti-rival column, technological innovation might also be assigned to different fields. Initially, the knowledge of the invention is a public good. However, inventors or creators may opt to pursue a patent for an invention at a later time. This would then lead to exclusion and private good characteristics.

5.2.4 Value assessment and perceived utility of digital servitisation

"Customer value is a customer's perceived preference for and evaluation of those product attributes, attribute performances, and consequences arising from use that facilitate (or block) achieving the customer's goals and purposes in use situations." (Woodruff, 1997, p. 142).

The understanding of 'value' within current business and management studies is based on the utility concept from neoclassical economics, where the core assumption is that the buyer always wants to maximise his or her utility. This utility understanding is defined to be directly dependent on the price (Woll, 1993, p. 121; Varian, 1999, p. 33; Coase, 1937, p. 387). With the development of the NIE, impacts on the buyer's preferences (e.g., transaction costs or information asymmetry) have been discussed, which led to an adjusted understanding of the utility concept (Coase, 1937, p. 390).

Academic contributions to digital servitisation often refer to the concept of value, but they fail to deliver a comparable and specific definition for that concept. Even though almost every contribution in the research stream of digital servitisation mentions (additional) 'value creation', a clear definition, hence quantification, of 'value is missing. According to different researchers, value for customers and suppliers might be data (and analytics), shorter product cycles, new business opportunities or customer support (Porter & Heppelmann, 2015; Rymaszewska, et al., 2017). Other studies have named cost reduction, flexibility, or time savings as benefits for customers (Paschou, et al., 2020; Foubert, 1999, p. 17).

In the present application that aims to evaluate the 'value' of digital servitisation, we apply the economic understanding of utility as proposed within the NIE, in which the classical utility maximising behaviour of economic agents is influenced by individual or institutional context (e.g., preferences, transaction costs or information asymmetry) (Coase, 1937, p. 390). This means that in the remainder of this contribution, we apply – if not stated otherwise – the terms customer value and the concept of utility with the same meaning.

Researchers contextualise the topic of digital servitisation within the understanding of relational service-oriented engagements (in contrast to a transactional product-centric framework). This approach emphasises the change in the customers' role and the relation with the firm as well as the emerging value/utility of that relationship (Kamalaldin, et al., 2020). The change of value or utility for customers is highlighted in various contributions to digital servitisation (Simonsson & Agarwal, 2021; Favoretto, et al., 2022; Paschou, et al., 2020; Kuijken, et al., 2017). As a matter of fact, we see the digitisation paradox as a direct indicator of that change in value. If the firm fails to deliver the desired output (utility) to the customer, all investments in capabilities and assets also fail to return on investment (Kuijken, et al., 2017).

Research finds evidence that the value of digital servitisation depends to a certain degree on individuals' perception (e.g., tested based on the individuals' entrepreneurial orientation in a B2B context) and not mainly on the manifestation of it on an institutional level (Simonsson & Agarwal, 2021). Other studies find evidence that value in the case of digital servitisation is created through the involvement of customers (or partners) in the value creation and delivery process ('co-creation) (Tronvoll, et al., 2020; Sjödin, et al., 2020; Coreynen, et al., 2016; Thomson, et al., 2021; Gallouj & Weinstein, 1997; de Vries, 2006). It is assumed that the traditional idea of long R&D innovation processes fails to deliver the desired outcome for the customer, while agile and interactive so-called 'micro-services' serve as the new goal for innovation procedures and, therefore, for value creation (Sjödin, et al., 2020). Coreynen, et al. (2016) built on this value creation argumentation and differentiated between a back-end perspective (digital-enabled improvement of capabilities to create solutions), a front-end perspective (digitally enabled customers to reach their own goals and better understand customer's value creation process) and a customer value perspective (radical change of customer processes and provider-customer relations) for digital servitisation.

There are only a few studies that take an investigative approach to the economic impact of digital servitisation. Comparable to the impact of the industrial revolutions (Schwab, 2016), it might be feasible that the digital-induced change of goods has an impact on individual demand as well as on the production function. Based on this assumption, Vendrell-Herrero et al. (2021) compare consumers' demand functions and WTP of eBooks in contrast to physical books. Results show a shift in consumer valuation of these goods based on third-degree price demand functions (or third-degree price discrimination) and highlight switching points from physical to digital books (Vendrell-Herrero, et al., 2021). Within these results, there is one major insight for our contribution: even though the same customer need is present and the same result (storyline of the book) is provided, different demand curves for digitised and non-digital products can be observed.

There are macroeconomic approaches that try to measure the impact of digitisation on business by investigating the GDP development as a proxy or index for the national production performance and welfare level (Brynjolfsson, et al., 2019; Mammadli & Klivak, 2020; Katz & Koutroumpis, 2013). Other contributions focus on the household level using stated preference methods for measuring the value consumers assign to digital services (Jamison & Wang, 2021; Brynjolfsson & Collis, 2019; Brynjolfsson, et al., 2019). They apply the WTA to identify the customer's reserve price for digital services. This approach follows the idea of utility-based valuation, which relies on the present value of expected future benefits (Ruan, 2019). Even though this method is used mostly for financial assets, e.g., long-term financial bonds or leases, it offers a suitable frame for our valuation approach. In contrast to cost-based evaluation (based on acquisition cost) or market-based value evaluation (based on replacement costs), utility-based evaluation is a subjective assessment, which might be different for each individual. This means that it can offer a 'true' approximation of the value of an asset for each individual and is not based on external paternalism (Ruan, 2019).

5.3 Methodological approach

We estimated part-worth utilities from the observed choices using the HB routine, which is implemented in Sawtooth CBC/HB 5.6 (see Sawtooth Software (2021)). The set-up is hierarchical in the sense that it comprises two levels. On the individual or lower level, the choice data is explained by an MNL model. In addition, there is an aggregate or upper level comprising the prior for the individual-level part-worth utilities. For computational ease, the HB approach relies on the multivariate normal and the inverse Wishart distribution. The software runs a robust iterative process with initial values of zero to estimate unknown parameters. An important property of the HB model is the incorporation of shrinkage, implying that the individual-level estimates become more efficient because they inform each other via the upper level (Sawtooth Software, 2021). See Chapter 2.2.4 of this thesis for further details on the HB estimation procedure.

We ran 10,000 burn-in iterations of the Markov chain (number of iterations before using the results) and 10,000 post-convergence iterations (draws used for each respondent, i.e., 8.0 million draws in total) for the subsequent sampling of the posterior distributions. We excluded the “fixed” task (the choice task with the attribute combination that was the same for all respondents and all blocks) from the estimation. We used effect coding, which means that the last level within each attribute is omitted to avoid linear dependency and is estimated as the negative sum of the other levels within the attribute. Part-worths estimated using effects coding are generally easier to interpret than dummy-coded estimates, especially for models that include interaction terms, as the main effects and interactions are orthogonal (Sawtooth Software, 2021). We did not use interaction effects nor constraints (i.e., forcing one attribute level to always be superior over another attribute level) for the estimation in this application. For the prior covariance matrix, we set the number of prior degrees of freedom to 5, which is the suggested value for the size of our sample (Sawtooth Software, 2021). The prior variance is set to 1. A high prior variance puts a higher weight on fitting each individual's data and less emphasis on using information from the population parameters. In this case, the resulting posterior estimates are rather insensitive to the prior variance, except when there is little information available within the unit of analysis (with reference to the estimated parameters), and the prior degrees of freedom for the covariance matrix are relatively large (Sawtooth Software, 2021). The graphical progress of the estimation is presented in Figure 20.

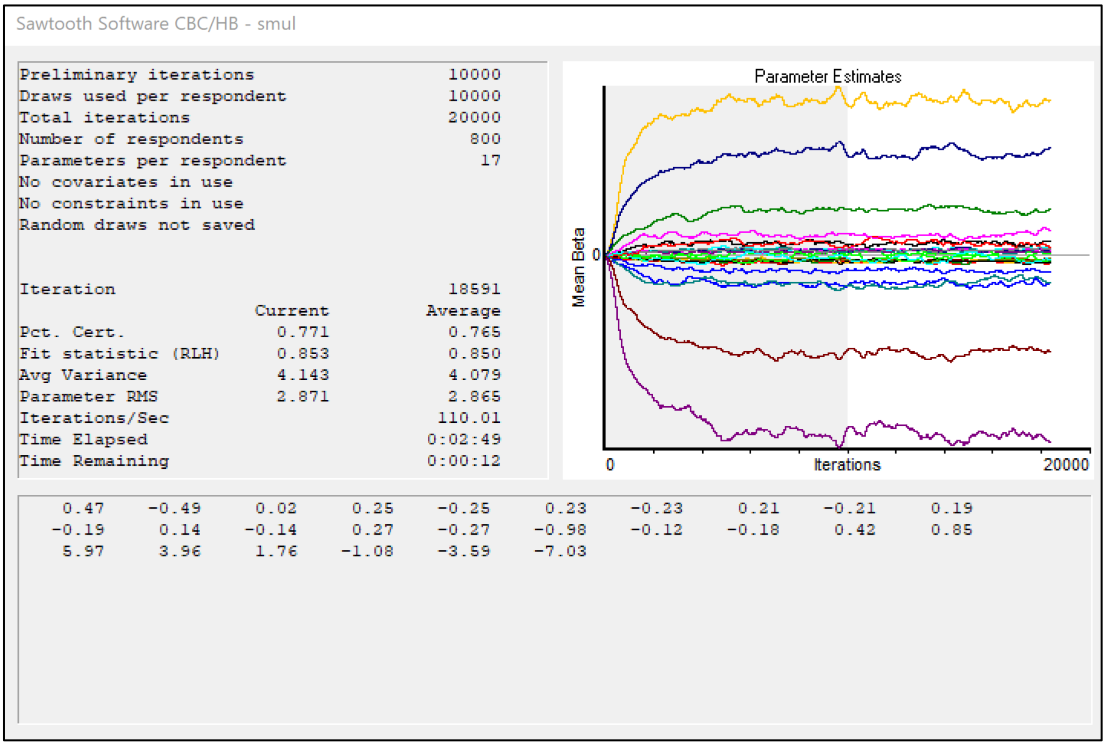


Figure 20: Estimation progress of the CBC/HB estimation.

After the estimation process, we gain the average utilities for each attribute level, the average importance for the different attribute levels, and each of the respondents' individual utility estimates for the different attribute levels.

In the next process, we investigate the correlation between the utility differences of the attributes and the differences of the DM values. The differences between the two values reflect the relative utility contribution of the selected alternatives. Also, we apply a multiple regression analysis to investigate the impact of the DM perception on the individual utilities. This means that the utility difference between the presented alternatives is used as a dependent variable, while the attributes related to the perceived DM differences, as well as demographic and other factors are used as independent variables. As the correlation and regression analysis can be seen as an explorative nature based only on one other academic contribution (Molin, et al., 2001), to double check we also estimate a CL model that includes the DM values for each attribute of each respondent as interaction effects.

5.4 Results

5.4.1 Results from the HB estimation

The estimation results of the HB model are presented below in Table 24. Here, the part-worth utilities are shown for all choice categories. As raw HB utilities are potentially on different scales for different respondents depending on the consistency with which they answer the conjoint questions, we are using so called "zero-centered differences" (ZCD) version of these utilities, as these are normalised per person (Islam, et al., 2009, p. 293). To obtain a ZCD scaling, the raw utilities have been multiplied by a constant so that the range of utilities for attributes averages 100 across attributes for each respondent. This rescaling procedure gives each respondent nearly equivalent weight when computing average utilities across the sample, thus it can be the foundation for a correlation or cluster analysis (Sawtooth Software, 2025).

Table 24: Results from the HB estimation (ZCD)

Label	Utility	Std Deviation	Lower 95% CI	Upper 95% CI
PRICECALC				
PRICECALC0	24.257	70.709	19.357	29.157
PRICECALC1	-25.995	54.330	-29.759	-22.230
PRICECALC2	1.737	53.476	-1.968	5.443
PRICEMAIL	10.589	18.806	9.285	11.892
PRICEPORTAL	9.538	13.855	8.578	10.498
PRICEAPP	8.492	15.651	7.408	9.577
SERVEMAIL	8.514	18.012	7.266	9.762
SERVCHAT	6.822	13.826	5.864	7.780
SERVAPP	8.923	18.333	7.652	10.193
DEVICE				
DEVICE0	-43.555	55.910	-47.430	-39.681
DEVICE1	-0.227	25.369	-1.985	1.530
DEVICE2	-8.031	23.947	-9.691	-6.372
DEVICE3	19.450	29.511	17.405	21.495
DEVICE4	32.364	43.556	29.345	35.382
CHARGE				
0.00 €	203.062	155.794	192.266	213.858
4.99 €	143.828	74.842	138.642	149.014
9.99 €	70.411	30.036	68.330	72.493
14.99 €	-33.891	41.091	-36.738	-31.043
19.99 €	-134.898	70.773	-139.802	-129.994
24.99 €	-248.513	138.291	-258.096	-238.930

Source: Author's own analysis with data from Sawtooth Software.

The part-worth utilities values for PRICECALC show that a negative utility is experienced for the attribute level of having a pre-defined price plan. In contrast, both, the fixed price (PRICECALC0), and the consumption-based calculation attribute level (PRICECALC2) are associated with a positive utility. Which differs for the case of PRICECALC2 from the findings and estimations given in Application 1, Table 7, where this specific attribute is associated with a negative utility. The discrepancy can be explained when taking the confidence interval (-1.968 <> 5.443) into account. It suggests that the ‘true value’ might be zero, which indicates no effect at all. Hence, we do not have enough evidence to identify a statistically significant difference to H0 for that specific attribute.

Price communication and service infrastructure items also show positive part-worth utilities. These are also very similar in terms of their numerical value. However, for price communication, email is preferred as it shows the highest part-worth utility. This implies that other options, including price communication via an online portal or via a mobile app, are comparatively less preferred by the survey participants.

Part-worth utilities for the different device options show large differences in terms of their numerical values. It is also evident that devices with more functionality (or, in some cases, a higher degree of digitalisation)[14] are associated with a higher utility. Furthermore, it must be pointed out that negative utilities have been estimated for all devices except for the two variants of the smart plug adapter (either without or with an algorithm). Moreover, for DEVICE1 (manual plug), the confidence interval includes 0 (-1.985 <> 1.530), which suggests that the difference could also be zero (indicating no effect).

This result provides evidence for a pronounced preference for devices with high digital functionalities – at least in the scope of our investigation. Companies that combine smart devices with services and other products accordingly might generate a higher degree of expected utility.

[14] This particularly refers to the difference in utility for the smart plug adapter incl. smartphone app and algorithm vs. the smart plug adapter incl. smartphone app (without an algorithm). Here, the device with the additional digital feature (algorithm) shows a higher utility.

Finally, the part-worth utilities of the prices show plausible values for the commodity character of electricity. That is because lower prices are associated with a higher utility and vice versa. Also, prices up to 9.99 Euro are associated with a positive utility, while prices starting from 14.99 Euro lead to a decrease of the utility for the product bundle (see Table 24 for the attribute CHARGE).

In addition to the utility point estimate values which have been calculated and shown above in Table 24 (see Chapter 2.2.4.1 for details on the calculation approach), the average importance of the attributes was also determined (see Chapter 2.2.4 for details on average relative importance) and are shown below in Table 25.

Table 25: Average relative importance of the attributes

Average Importances

Attribute	Importance	Std Deviation	Lower 95% CI	Upper 95% CI
PRICECALC	13.038	10.140	12.335	13.740
PRICEMAIL	3.456	3.324	3.225	3.686
PRICEPORTAL	2.901	2.357	2.737	3.064
PRICEAPP	2.994	2.586	2.814	3.173
SERVEMAIL	3.095	3.165	2.876	3.314
SERVCHAT	2.642	2.180	2.491	2.793
SERVAPP	3.366	3.032	3.156	3.576
DEVICE	12.036	7.901	11.489	12.584
CHARGE	56.474	21.304	54.997	57.950

Source: Own analysis with data from Sawtooth Software.

The average importance of the attributes as depicted above in Table 25 shows the importance of a single attribute as a percentage of the importance of all attributes when considered together. It also shows how important an attribute is in relation to another attribute. Consequently, relative comparisons are possible. This comparison allows to derive valuable insights for servitisation strategies. For example, the results clearly show that the price (CHARGE) is the single most important attribute. This is plausible and it implies that servitisation strategies in the energy sector have a limited scope due to the dominance of the price attribute. This finding corresponds with the results from Chapter 4, where we found evidence that the product-service bundle of this investigation is characterised by synergetic effects for some price related attributes (PRICEMAIL, PRICEPORTAL, PRICECALC).

Furthermore, the source of price calculation and the device are relatively more important than the attributes related to price communication and service infrastructure. It must particularly be emphasised that digital servitisation strategies related to price communication and service infrastructure are limited in their impact as they are deemed as relatively unimportant items.

5.4.2 Correlation and multivariate regression analysis

One of the advantages of calculating an HB estimation is that it gives individual part-worth utility estimates for all respondents. This means that we have, on the one hand, the individual utility estimates (revealed preference, part-worth utilities) for each attribute level from the HB procedure, and on the other hand, we have the stated individual digital maturity assessment of each respondent for each attribute level. Besides the utility results from the previous chapter, where we saw a dominant role of the charge, price calculation and device attributes, we also want to find out if a high digital maturity perception comes along with higher utility estimates. In a next step first a correlation analysis and then a multivariate regression are applied to investigate whether the individual digital maturity perception influences the utility estimates for each respondent and for each attribute level.

The correlation and the regression analyses are based on the HB estimations and the corresponding DM values for each attribute and each respondent. To align with the foundational principles of RUMs, which emphasise utility differences rather than absolute utility levels as the primary determinant of choice behaviour, this analysis incorporates utility differences into the correlation and regression models. Specifically, for each respondent, the differences between the HB utility estimations (ΔHB, HB_Diff) and the corresponding perceived DM scores (ΔDM, DM_Diff) were calculated for each attribute. These differences were derived from the pairwise choice sets presented in the DCE, reflecting the relative utility contribution of selected alternatives. This approach better captures the decision-making process, as the selection of an alternative is driven by the utility contrast between options, consistent with the theoretical underpinnings of RUMs (Train, 2009, p. 19).

For the correlation, we used the Spearman correlation, which evaluates the strength and direction of the association between two ranked variables. It is a non-parametric test, suitable for ordinal, interval, or ratio data that may not follow a normal distribution. The results of the correlation are shown below in Table 26.

Table 26: Correlation of HB and DM[15]

Correlation parameter (Δ HB, Δ DM)	Correlation (rho)	p Value
PRICECALC	-8.769e-02	7.457e-18
PRICE_	5.518e-01	0.000e+00
SERV_	4.759e-01	0.000e+00
DEVICE	3.369e-01	2.006e-253

Note: Δ = Difference between alternatives; HB = Hierarchical Bayes estimation; DM = Digital Maturity

Source: Author's own analysis.

From the results shown in Table 26, it can be stated that the categories of price communication (PRICE_), service infrastructure (SERV_), and device (DEVICE) exhibit statistically significant positive correlations between ΔDM and ΔHB. This indicates that the perceived digital maturity of these attributes is associated with corresponding changes in consumer utility. In contrast, price calculation (PRICECALC) demonstrates a weak negative correlation (-0.0877, $p < 7.457e-18$), which, despite its statistical significance, holds little practical relevance. This result aligns with prior findings in the servitisation literature, suggesting that consumers often perceive pricing mechanisms as secondary in their evaluation of digital maturity when compared to service or device enhancements (Coreynen, et al., 2016; Porter & Heppelmann, 2015).

The strongest positive correlation is observed for the PRICE_ attributes (0.5518, $p < 0.001$), underlining a substantial and positive relationship between enhanced digital maturity in price communication features, such as mobile apps or online portals, and consumer utility changes. This finding is consistent with previous research emphasising the critical role of transparent and user-friendly digital communication platforms in improving customer satisfaction and fostering loyalty (Kohtamäki, et al., 2021; Vendrell-Herrero, et al., 2021).

[15] PRICE_ is a vector of all HB estimates and DM evaluations for PRICEMAIL, PRICEAPP and PRICEPORTAL; SERV_ is a vector of all HB estimates and DM evaluations for SERVEMAIL, SERVCHAT and SERVPORTAL.

These tools not only simplify access to billing and pricing information but also align with broader trends in digital transformation that prioritise customer-centricity.

The SERV_ attributes also show a significant positive correlation (0.4759, $p < 0.001$) between ΔDM and ΔHB, though slightly weaker compared to PRICE_. This confirms that digital enhancements to service infrastructure, such as in-app messaging and chat agents, are valued by consumers. However, their relative importance might be lower because such features have become increasingly ubiquitous, reducing their differentiation value. Similar findings were reported in studies on digital service standardisation, which argue that while these features improve operational efficiency, their impact on consumer perception may diminish over time (Tukker, 2004; Oliva & Kallenberg, 2003).

The relationship between ΔHB and ΔDM for DEVICE_ (0.3369, $p < 2.006e\text{-}253$) demonstrates a moderate yet statistically significant positive correlation, reaffirming its importance in digital servitisation strategies. This aligns with research highlighting the increasing consumer preference for smart, connected devices in product-service bundles (Raddats, et al., 2019). These findings emphasise the strategic need for energy firms to have smart devices as part of their digital servitisation offerings, particularly as they provide tangible utility improvements and are often perceived as essential components of modern digital solutions.

In summary, the correlation results highlight the significant roles of price communication and service infrastructure in enhancing consumer utility through digital maturity improvements. The weaker and negative correlation for price calculation suggests limited strategic potential in focusing on this area for digital maturity enhancements. This aligns with the broader literature, which often identifies price mechanisms as enablers rather than drivers of perceived digital transformation value (Coreynen, et al., 2016; Vendrell-Herrero, et al., 2021).

In addition to the correlation, we also wanted to investigate if the digital maturity perception explains a share of the part-worth utility estimation for each respondent and for each attribute level. For that, and in addition to the correlation analysis between ΔHB and ΔDM

, we perform a multivariate regression analysis, using again the difference of the part-worth utilities sums for the two alternatives (ΔHB, HB_Diff) as dependent variable. Independent variables include items that relate to the perceived DM difference (ΔDM, _rDM_Diff) of the attributes as well as demographic and other factors (age, gender, income, attitude towards innovation, etc.). We treat these ordinal variables as continuous, as we only want to investigate if there is a significant relationship between these and towards the dependent Variable (HB_Diff). We use these factors as control variables. The results from the multiple regression analysis are shown below in Table 27.

Table 27: Multivariate regression with control variables

```
Call:
lm(formula = HB_Diff ~ P_rDM_Diff + A1_rDM_Diff + A2_rDM_Diff +
    A3_rDM_Diff + S1_rDM_Diff + S2_rDM_Diff + S3_rDM_Diff + D_rDM_Diff +
    DM_Group + Age + Sex + Innov_Rol + eco + econ + edu + hh_income,
    data = database)

Residuals:
    Min      1Q  Median      3Q     Max
-565.86  -53.82   -0.79   56.23  557.15

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -13.42849    8.52527  -1.575   0.1153
P_rDM_Diff   -8.12625    0.90006  -9.029  < 2e-16 ***
A1_rDM_Diff   4.33102    0.49973   8.667  < 2e-16 ***
A2_rDM_Diff   2.63637    0.44440   5.932 3.09e-09 ***
A3_rDM_Diff   2.38207    0.38482   6.190 6.26e-10 ***
S1_rDM_Diff   2.70358    0.49997   5.408 6.54e-08 ***
S2_rDM_Diff   2.10440    0.43635   4.823 1.44e-06 ***
S3_rDM_Diff   3.01202    0.38846   7.754 9.83e-15 ***
D_rDM_Diff    4.65776    0.54906   8.483  < 2e-16 ***
DM_Group      2.72469    2.38992   1.140   0.2543
Age           0.02366    0.08496   0.279   0.7806
Sex           4.43074    2.45022   1.808   0.0706 .
Innov_Rol    -0.19697    1.12596  -0.175   0.8611
eco           0.77885    0.60447   1.288   0.1976
econ          1.48883    1.09932   1.354   0.1757
edu           1.37575    0.81141   1.696   0.0900 .
hh_income    -1.26960    0.80666  -1.574   0.1155
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 116.2 on 9583 degrees of freedom
Multiple R-squared:  0.04254,	Adjusted R-squared:  0.04094
F-statistic: 26.61 on 16 and 9583 DF,  p-value: < 2.2e-16
```

Source: Author’s own analysis.

Given the methodological challenges associated with using utility estimates derived from an HB model (see Chapter 2.7.3), a bootstrapping approach was employed to address the limitations of the standard errors in the initial regression analysis. This approach involved resampling the dataset with replacement and re-estimating the regression coefficients across 1,000 bootstrap iterations. To ensure robust results, the resampled datasets were checked to confirm that all factor variables retained at least two levels in each iteration. The bootstrapping process captures the variability inherent in the HB estimates, providing empirical standard errors that account for the uncertainty and dependency structure introduced by the Bayesian estimation process. The updated regression results, presented in Table 28, include these bootstrapped standard errors, which improve the reliability of the statistical inference while preserving the original coefficient estimates.

Table 28: Regression results with bootstrapped std. errors

Regression parameter (~ ΔHB)	Coefficients	Std. Error (Bootstrapped)	t Values	p Values	
(Intercept)	-13.4285	8.4598	-1.5873	0.1125	
P_rDM_Diff	-8.1263	0.9555	-8.5050	0.0000	***
A1_rDM_Diff	4.3310	0.5162	8.3898	0.0000	***
A2_rDM_Diff	2.6364	0.4506	5.8505	0.0000	***
A3_rDM_Diff	2.3821	0.3731	6.3850	0.0000	***
S1_rDM_Diff	2.7036	0.5023	5.3822	0.0000	***
S2_rDM_Diff	2.1044	0.4431	4.7496	0.0000	***
S3_rDM_Diff	3.0120	0.3925	7.6745	0.0000	***
D_rDM_Diff	4.6578	0.5381	8.6565	0.0000	***
DM_Group	2.7247	2.4065	1.1322	0.2576	
Age	0.0237	0.0842	0.2811	0.7786	
Sex	4.4307	2.2918	1.9333	0.0532	.
Innov_RoI	-0.1970	1.1524	-0.1709	0.8643	
eco	0.7788	0.6022	1.2933	0.1960	
econ	1.4888	1.0808	1.3776	0.1684	
edu	1.3757	0.8361	1.6454	0.0999	.
hh_income	-1.2696	0.7686	-1.6517	0.0986	.

Note: DM = Digital Maturity; Signif. codes: '***' < 0.001; '**' < 0.01; '*' < 0.05; '.' < 0.01

Source: Author’s own analysis.

Based on the results in Table 27 and Table 28, the analysis reveals several critical insights regarding the relationship between changes in digital maturity perceptions and the dependent variable, HB_Diff. The estimated intercept (-13.429) is not statistically significant, indicating no strong baseline effect for HB_Diff when all independent variables are held constant. This aligns with the model's relatively low explanatory power (R^2 = 4.25%), suggesting that additional factors may be needed to fully capture the variations in consumer utility. Nevertheless, these results are very much comparable to similar approaches from different research fields (Molin, et al., 2001).

Most attribute coefficients related to digital maturity differences demonstrate statistically significant relationships with HB_Diff. For example, A1_rDM_Diff (PRICEMAIL; 4.331), A2_rDM_Diff (PRICEPORTAL; 2.636), A3_rDM_Diff (PRICEAPP; 2.382), S1_rDM_Diff (SERVEMAIL; 2.704), S2_rDM_Diff (SERVCHAT; 2.104), S3_rDM_Diff (SERVAPP; 3.012), and D_rDM_Diff (DEVICE; 4.658) exhibit positive coefficients, indicating that greater perceived differences in the digital maturity of these attributes correspond to higher utility changes. These findings are consistent with the correlation results, which demonstrate significant positive relationships between ΔDM and ΔHB for price communication, service infrastructure, and device attributes. The strong correlation for PRICE_ (ρ = 0.5518, $p < 0.001$) supports the notion that enhancements in digital tools like email notifications, online portals, and mobile apps significantly improve consumer utility by making interactions more transparent and customer-focused (Kohtamäki et al., 2021; Vendrell-Herrero et al., 2021).

Among these attributes, DEVICE (4.658) stands out with the largest positive impact on HB_Diff, a result that aligns with its moderate but statistically significant correlation (ρ = 0.3369, $p < 2.006e\text{-}253$). This finding underscores the critical role of smart devices in influencing consumer utility, consistent with prior studies highlighting the value of smart, connected devices in product-service bundles (Porter & Heppelmann, 2015; Raddats et al., 2019). These devices are perceived as essential enablers of modern digital solutions, providing tangible improvements to functionality and efficiency.

Conversely, P_rDM_Diff (PRICECALC; -8.126) shows a highly significant negative relationship with HB_Diff, suggesting that higher perceived digital maturity for price calculation methods reduces consumer utility. This finding, supported by the weak negative correlation (-0.0877, $p < 7.457e-18$), may reflect consumer discomfort with complex or non-intuitive pricing mechanisms. Such systems can create a sense of reduced control or transparency, which negatively impacts consumer perceptions. Research supports this interpretation, emphasising the importance of simplicity and clarity in pricing strategies to maintain trust and satisfaction (Coreynen et al., 2016; Oliva & Kallenberg, 2003). Given its significance and magnitude, PRICECAL stands out as a key attribute that could be a focal point for further analysis or strategic considerations. For instance, if this analysis is being used to inform product development, marketing strategies, or customer segmentation, pricing mechanisms could be considered a critical element to emphasise or improve upon.

Demographic factors show mixed and less pronounced effects in the updated model. DM_Group (2.725) and Age (0.024) are not statistically significant, suggesting that pre-information campaigns and age differences do not substantially influence HB_Diff. However, Sex (4.431, $p = 0.0532$) approaches significance, indicating a potential trend of higher HB_Diff for male respondents, though this remains inconclusive. Similarly, the education level (Edu; 1.376) and household income (HH_Income; -1.270) exhibit marginal significance, hinting at the nuanced effects of socio-economic factors on consumer utility. These findings suggest that while demographic factors play a secondary role, they may still influence specific subgroups, aligning with broader research on the interplay between socioeconomic variables and consumer behaviour (Coreynen et al., 2016).

Strategically, the findings highlight the importance of enhancing the digital maturity of service infrastructure and device attributes, as these consistently exhibit positive and significant effects. The unexpected negative relationship with price-related digital maturity differences, however, underscores the need for a careful reassessment of strategies in this domain. Simplifying price calculation tools and making them more intuitive could help mitigate consumer concerns and improve utility. Given the reduced influence of demographic factors, efforts should focus on universal improvements to product-service bundles rather than tailored approaches based on pre-information campaigns or age-based segmentation. Nonetheless, the emerging signals from education and income-related variables suggest opportunities for targeted interventions, particularly in designing offerings that address varying levels of digital literacy and financial preferences.

Overall, while the model explains only 4.25% of the variance in HB_Diff, its high statistical significance ($p < 2.2e\text{-}16$) confirms the relevance of digital maturity perceptions in influencing consumer utility.

5.4.3 Direct integration of rDM into a choice-behavioural model

In addition to analysing individual-level utility changes through the regression on HB estimates, we additionally employ a CL model to check on the regression results with an integrated approach and to acknowledge that the regression analysis follows only one example in literature and might seem rather explorative (Molin, et al., 2001).

We decided to estimate a model that includes interactions between the attributes and their respective rDM values. The CL model offers a direct and behaviourally consistent view of how respondents' perceptions of digital maturity influence their likelihood of choosing specific configurations. Compared to more complex models such as MLM, a standard CL model provides a straightforward baseline that clearly illustrates the main effects and interactions without introducing additional random distributions or correlations across parameters. This helps maintain interpretability and transparency, especially when our primary motivation is to identify whether digital perceptions shift attribute preferences. As a result, the CL approach adds to the results from the regression analysis. While the HB-based regression focuses on the connection between rDM perceptions and HB utility differences, the CL model demonstrates how perceived digital maturity interacts with the attributes to drive probabilities of selection. Employing this design offers a methodologically sound yet accessible means of capturing how consumers weigh and compare alternatives in real decision-making scenarios.

The CL model follows the standard random utility framework introduced in Chapter 2.2 in which individual i choosing alternative j in choice situation t obtains utility:

$$U_{ijt} = \beta_0 + \beta_1 X_{ijt} + \beta_2(\mathrm{rDM}_i \times X_{ijt}) + \epsilon_{ijt} \quad (23),$$

where X_{ijt} represents the attributes of alternative j, rDM_i captures the individual i 's perceived digital maturity for those attributes. As already established, $\epsilon_{ijt}$is an i.i.d. error term typically assumed to follow a Type I Extreme Value distribution. By including the interaction term $\mathrm{rDM}_i \times X_{ijt}$the model explicitly accounts for how the valuation of each attribute changes with the individual's perceived digital maturity. The estimation results are presented in Table 29.

Table 29: CL estimation with interaction effects (rDM)

Name	Parameter	WTP	pVal	Rob.s.e.	Sign.
	ASC_alt1	0.9997	0.0001	0.2560	***
Changing of prices based on a pre-defined plan (P1)	PRICECALC1	-2.0057	0.1036	1.2324	
Decreasing prices per kWh each month with consumption change (P2)	PRICECALC2	-4.2759	0.0016	1.3542	**
Prices and monthly bills are sent via email (A1)	PRICEEMAIL	1.8866	0.0200	0.8108	*
Prices and monthly bills made available through an online portal (A2)	PRICEPORTAL	0.1309	0.8594	0.7392	
Price communication and access to bills through mobile app (A3)	PRICEAPP	1.6527	0.0319	0.7704	*
Service infrastructure: E-Mail (S1)	SERVEEMAIL	1.8350	0.0108	0.7196	*
Service infrastructure: Chat Agent (also video Chat) (S2)	SERVCHAT	-0.3220	0.7043	0.8483	
Service infrastructure: Message service within smart phone app (S3)	SERVAPP	0.5438	0.5357	0.8781	
Manually adjustable electric plug adapter (D1)	DEVICE1	3.1975	0.0002	0.8475	***
Local connected electric plug adapter (D2)	DEVICE2	0.2277	0.8211	1.0069	
Smart plug adapter incl. smart phone app (D3)	DEVICE3	2.6450	0.0685	1.4518	
Smart plug adapter incl. smart phone app and analysis (D4)	DEVICE4	2.4759	0.1318	1.6431	
P1_rDM	PRICECALC1_rDM	-0.5249	0.3370	0.5467	
P2_rDM	PRICECALC2_rDM	1.3434	0.0115	0.5318	*
A1_rDM	PRICEEMAIL_rDM	-0.2407	0.4275	0.3033	
A2_rDM	PRICEPORTAL_rDM	0.2955	0.2675	0.2665	
A3_rDM	PRICEAPP_rDM	-0.1583	0.4871	0.2278	
S1_rDM	SERVEEMAIL_rDM	-0.2248	0.4098	0.2728	
S2_rDM	SERVCHAT_rDM	0.3250	0.2605	0.2888	
S3_rDM	SERVAPP_rDM	0.1822	0.4867	0.2620	
D1_rDM	DEVICE1_rDM	-0.2966	0.4538	0.3960	
D2_rDM	DEVICE2_rDM	0.9620	0.0297	0.4424	*
D3_rDM	DEVICE3_rDM	0.3579	0.4554	0.4794	
D4_rDM	DEVICE4_rDM	0.5923	0.1897	0.4517	
Log Likelihood (final)	-5064.42				
Observations	9600				
n	800				

Note: WTP = Willingness to pay; ***p < 0.001; **p < 0.01; *p < 0.05

The results show that certain digital attributes, such as DEVICE2 (D2_rDM) and PRICECALC2 (P2_rDM), show significant interactions with rDM, suggesting that a higher perceived digital maturity positively influences respondents' likelihood of choosing these features. In contrast, some attribute interactions remain non-significant, implying that perceptions of digital maturity do not influence choice behaviour across all attributes. For instance, while PRICECALC2 shows a large negative main effect (indicating initial reluctance toward more dynamic pricing), the positive rDM interaction coefficient suggests that when consumers perceive this pricing mechanism to be digitally advanced, they become more receptive to it. These results support the evidence that the impact of digital maturity is attribute-specific and may offset or reinforce baseline preferences depending on how 'digitally mature' respondents consider the feature to be.

Taken together, the CL model and the regression on HB utility differences provide a perspective of how digital maturity perceptions drive consumer utility. The regression results offer a specific perspective on how much changes in rDM correlate with changes in derived utility differences (HB_Diff). This reveals strong negative perceptions for price calculation features and positive associations, e.g. for devices included in the service bundle. Meanwhile, the CL model confirms and refines these findings in a formal choice-based setting, showing that the effect of digital maturity is indeed attribute-specific and operates via respondents' likelihood of selecting those attributes. Notably, the negative main effect on price calculation in the CL model aligns with the regression's observation that consumers tend to view sophisticated pricing methods with caution (negative correlation and negative regression coefficient of PRICECALC), yet the positive rDM interaction implies that promoting the digital maturity of pricing tools can meaningfully reduce this scepticism. In both approaches, device-related attributes consistently show strong, positive effects when perceived as digitally mature. Thus, while the HB-based regression underscores broad correlations between rDM and utility, the CL analysis verifies these relationships within a formal discrete choice framework.

5.5 Discussion and Conclusion

5.5.1 Summary

One key aim of this third application was to offer a quantitative approach for evaluating the impact of digitisation on product-service bundles (1). Furthermore, we wanted to investigate possible connections between perceived consumer utility and the perceived digital maturity of the goods (2). In addition, we wanted to show that digital servitisation has a solid grounding in economic theory (3).

Using an HB estimation, part-worth utilities were estimated and analysed. The results demonstrated that devices with higher digital functionality (e.g., smart plugs with app integration) yield high utility, with a particularly notable positive impact on device attributes (HB utility: 4.66). In contrast, price calculation methods exhibited negative utility (-8.12), particularly for complex pricing mechanisms such as dynamic pricing. This suggests that consumers view such features sceptically, even if they represent advanced technological capabilities. Therefore, we found that the overall importance of the attributes shows visible differences. Here, the price dimension clearly dominates the average importance while, for example, the price communication and the service infrastructure are characterised as having a relatively minor importance.

The correlation analysis confirmed statistically significant positive relationships between digital maturity (ΔDM) and utility differences (ΔHB) for price communication, service infrastructure and device attributes. For instance, price communication exhibited the strongest correlation ($\rho = 0.5518$, $p < 0.001$), indicating that consumers perceive enhanced digital communication channels as valuable parts of a product-service bundle. Thus, price communication tools, such as apps and portals, significantly enhance consumer utility by offering transparency and ease of use. Service infrastructure and smart devices also play critical roles, with devices particularly standing out as key enablers of increased utility and consumer satisfaction. Conversely, the weak negative correlation for the price calculation attributes (-0.0877, $p < 7.457e-18$) highlights the limited strategic potential of digitalisation efforts in pricing mechanisms.

The regression analysis further validated these relationships, showing that attributes like DEVICE (4.658) and PRICEMAIL (4.331) positively influence utility changes, while price calculation (-8.126) negatively impacts consumer utility. Hence, the regression analysis confirms that most attributes with higher perceived digital maturity contribute positively to consumer utility. However, the negative relationship observed for price calculation highlights the need for firms to simplify pricing mechanisms to avoid consumer dissatisfaction. These findings suggest that enhancing the digital maturity of service infrastructure and devices should remain a strategic priority for firms aiming to maximise consumer utility through digital servitisation.

The estimation of the CL model provided an additional, more formal and behaviourally grounded view of the impact of digital maturity perceptions and choice-making. Interaction terms revealed that perceived digital maturity positively moderates the likelihood of selecting certain features, such as dynamic pricing and smart devices. These results support the impact of DM, which varies across attributes and can offset or reinforce baseline preferences.

Demographic factors play a secondary role, with subtle trends suggesting potential opportunities for targeted strategies based on education or gender. The results reinforce the value of focusing on digital transformation efforts in areas that provide clear and tangible benefits to consumers while addressing potential barriers in complex pricing strategies. The findings demonstrate that digital servitisation strategies must prioritise attributes like devices and service infrastructure while simplifying complex pricing mechanisms. The integration of multiple analytical approaches (HB, correlation, regression, and CL) and their results highlight the critical role of perceived digital maturity in shaping consumer preferences.

5.5.2 Theoretical and managerial implications

The results provide a contribution to the theoretical literature of digital servitisation. We found evidence that the application of digital servitisation is not only relevant for business and management studies but can also be applied in microeconomic environments. We offered economic theories and foundations that incorporate the aspects of utility (Chapter 5.2.4), utilities from product-service bundles and the economic influence of technology on preferences (Chapter 5.2.3). We presented literature that shows that the core idea of the combined elements is not new to economic theories but applied it in a way that we did not find in similar research publications.

We have shown that for research, merely concentrating on investigating the digitisation of the firm's capabilities is only one side of the coin. Our results show that customers tend to value services and products not based on production input but rather based on subjective perception. We can see that especially in the part-worth utilities from PRICECALC, where more digital capabilities from the supplier are necessary to provide the options PRICECALC1 compared to PRICECALC0. Here, there is a higher preference for the static price attribute (PRICECALC0). The same effect can be observed when comparing the utility of PRICEMAIL to PRICEPORTAL and to PRICEAPP, as well as the two attributes SERVMAIL and SERVCHAT. Even though we see an increase in necessary digital capabilities for the suppliers to offer the latter ones (e.g. PRICEAPP and SERVCHAT) compared to the first ones (PRICEMAIL, SERVAIL), the utilities do not necessarily reflect this order. Therefore, in our case, the findings do not support the notion of purely rational or utility-maximising buyer behaviour, where higher investment from the seller in digital services would automatically yield a correspondingly higher utility for the customer. Instead, our estimates suggest that buyers' preferences are influenced by subjective factors, such as perceived ease of use, trust, or familiarity, which may overshadow the expected benefits of more digitally advanced solutions.

This could be an observation that helps to explain the phenomenon of the earlier mentioned digitalisation paradox, which refers to the issue that investments in digital capabilities do not pay off in many cases (Gebauer, et al., 2020; Sjödin, et al., 2020). In our case this paradox is particularly evident in the price-related attributes, where digital communication tools like mobile apps and online portals provide moderate utility improvements. Although technological advanced service infrastructure and price communication tools were positively associated with utility, their contributions were relatively smaller compared to more "basic" attributes. This reinforces the notion that consumers value attributes differently, even when they reflect higher supplier capabilities, and that technological investments must be carefully aligned with consumer expectations to avoid inefficiencies. Therefore, we present findings from which it can be argued that the servitisation and digitisation paradox is indeed valid on the product level (Gebauer, et al., 2020).

The argumentation regarding the servitisation or digitalisation paradox can be extended with respect to their implications to the area of overall firm value generation as well. It can be argued that the generation of product-service combinations with high perceived utility by consumers can have a positive contribution on a firm's financial performance. However, engaging into servitisation strategies without having a clear understanding on the overall impact of the unique utility contributions of the digital maturity of selected attributes might lead to efficiency lost in providing benefits. This issue is already addressed in the literature, as the causal pathways from servitisation to the firm's performance is not well understood (Fang, et al., 2008; Salonen, et al., 2021; Worm, et al., 2017). Hence, if companies invest in digital services, they should do it with enough focus und understanding of the customer demands and their unique preferences. Customer segmentation attempts are useful to employ in this sense, especially in the context of digital business models. Here, value propositions can be offered to specific customer segments. These offers can be presented with a specific product and service design (Wirtz, 2019, p. 38).

Some of the theoretical implications are also relevant for other practical purposes as well. First, we showed that there is value and utility in providing digital servitisation as a measure to differentiate from competitors. We find evidence that digital servitisation attempts lead to higher perceived utility but that the magnitude differs heavily across the different dimensions. There is also a strong relevance of the price to be mentioned, which in turn shows that servitisation attempts need not only focus service characteristics on but also on price value. However, practitioners are advised to concentrate their efforts on the most promising area, where digital services can be implemented. Here, the role of the smart versions of the plug adapter (DEVICE) needs to be emphasised as this was shown to provide a comparatively high utility. Such a smart device might also cater best to ecologically oriented consumers and to consumers with more interest in innovative solutions.

In contrast, the negative utility associated with dynamic pricing mechanisms highlights the need for simplified and transparent pricing strategies. While our CL model revealed that higher perceptions of digital maturity could mitigate scepticism towards complex pricing, the baseline negative utility indicates that such features should be carefully framed to emphasise their benefits and usability. Firms must balance innovation with simplicity to ensure that pricing mechanisms do not alienate consumers. Additionally, the positive utilities associated with digital communication tools, such as mobile apps and portals, underscore their value in fostering transparency and improving customer engagement. These tools can enhance customer loyalty by making interactions more user-friendly and accessible.

Another key managerial implication is the importance of tailoring digital servitisation strategies to specific attributes rather than adopting a one-size-fits-all approach. For instance, while smart devices can serve as key differentiators, pricing innovations require greater attention to consumer perceptions and communication strategies. This attribute-specific approach allows firms to allocate resources more effectively and focus on areas with the highest potential for consumer utility gains. Finally, the correlations between perceived digital maturity and utility changes highlight the importance of aligning marketing and product development efforts with consumer perceptions. Firms should actively promote the sophistication and benefits of their digital features, especially for attributes like dynamic pricing and service infrastructure, to reduce scepticism and encourage adoption.

5.5.3 Further research

The application presents avenues for further research. First, we call for additional economic groundwork in the research field of (digital) servitisation. From our perspective, there is a major gap between these two areas, as servitisation has been one of the dominant market and sales strategies for some decades now, and only a few researchers have made the connection to economic models. While this application has demonstrated the relevance of microeconomic principles in explaining consumer preferences for digitally enhanced product-service bundles, further work is needed to deepen the integration of economic theories into this domain. For example, models that account for behavioural and cognitive biases in decision-making, such as bounded rationality or loss aversion, could provide richer insights into consumer responses to digital offerings. Future research is also required that is directly connected to the field of digital servitisation in the realm of marketing retail electricity contracts.

In line with the need to construct the economic foundation for servitisation, we call for more quantitative work on (digital) servitisation, as measurable effects for product-service bundles are still not widely researched. This is a major blind spot, as the concept is widely used in practical applications and is especially valuable as the impact of servitisation through different indicators on the firm's performance does not seem to be linear (Suarez, et al., 2013; Visnjic, et al., 2016; Eggert, et al., 2014; Böhm, et al., 2017).

Future research should also explore the complex relationships between digital maturity and consumer utility at a more granular level. The mixed results observed for pricing mechanisms, such as the negative utility for dynamic pricing (esp. PRICECALC1), suggest that consumers may struggle with the complexity of these features. Investigating the psychological and behavioural factors underlying this scepticism and testing interventions to improve consumer understanding or trust could yield valuable insights. For instance, experimental studies could assess whether simplified pricing interfaces or targeted educational campaigns reduce resistance to dynamic pricing tools.

Quantitative research remains essential to measure the broader effects of digital servitisation on firm performance and market dynamics. While this application highlighted the attribute-specific impacts of digital maturity on utility, further research is needed to link these findings to business outcomes such as customer retention, revenue growth, and operational efficiency. This is particularly important given the observed 'digitalisation paradox', where technological investments do not always translate into proportional consumer or financial benefits. Longitudinal studies could help identify the conditions under which digital servitisation creates sustainable value for both consumers and firms.

The role of demographic and contextual factors also warrants further investigation. While our application found limited overall influence of demographics, subtle trends in variables such as education and income suggest opportunities for targeted strategies. Research could explore how digital skills, cultural factors, or socio-economic conditions shape consumer responses to digital servitisation, particularly in emerging markets or underrepresented contexts.

Finally, industry-specific approaches are needed to understand the broader applicability of our findings. While this application focused on retail electricity contracts, future work could examine digital servitisation in other sectors, such as healthcare, mobility, or consumer electronics. Cross-industry comparisons could reveal whether the observed attribute-specific impacts and strategic challenges are consistent across different markets or whether unique dynamics emerge in specific industries.

In summary, further research should prioritise the development of economic and behavioural frameworks for digital servitisation, quantitative studies linking digital maturity to firm performance, and advanced modelling approaches that capture consumer heterogeneity. By addressing these gaps, future studies can build on the findings of this research to advance both theoretical understanding and practical applications in the rapidly evolving field of digital servitisation.

6 Conclusion

6.1 Main contributions of the thesis

This thesis has sought to answer the question if potential synergies and perceived DM have an impact on the buying decision for product-service bundles in the consumer energy market. To answer this question, the thesis presents novel contributions in three core applications drawing on appropriate economic models and different quantitative methods to analyse revealed preferences from economic agents (buyers). Unlike contributions elsewhere, especially in the managerial field of servitisation, this thesis adds to the quantitative body of this research area via an economics-based approach. It offers a new perspective involving the economic evaluation of product-service bundles on the basis of customer utility. Thus, for the first time, the utility of consumers is used to evaluate the combined effect of servitisation and digitisation in contrast to previous studies that have focused more on the sellers' firm performance or macroeconomic indicators. The motivation for that is the fact that servitisation is foremost customer-centric, suggesting that a consumer-focused evaluation by suppliers is beneficial. The approach of the thesis is to identify a number of economic issues and, building on appropriate economic concepts and models, to offer guidelines for the practical application of digitised product-service bundles. Before summarising the contributions of each chapter in turn, we begin this concluding chapter by highlighting some core insights that reflect both the academic contributions and potential managerial usefulness of this work:

1. Our findings underscore the resilience of traditional models of consumer preferences despite the integration of digital elements, which could imply that consumers do not easily shift their expectations for service quality and product performance. This insight challenges the common assumption that digital enhancement will automatically lead to higher consumer satisfaction and suggests that consumers may only be willing to pay more if the digital attributes are directly tied to clear benefits.
2. The research indicates that some service combinations can create added value and increase WTP. It is important for companies to understand how to balance the addition of

services to avoid overwhelming consumers, which can result in a mismatch between the services offered and the consumer's expectations for the device's core functionality.

3. In assessing the value of digital features, the thesis recognises the consumers' prioritisation of cost over advanced digital features, which may reflect a practical approach to purchase decisions. Companies should, therefore, consider pricing strategies that reflect the added value of digital features without overshadowing the crucial factor of cost competitiveness.
4. The regression and interaction between digital servitisation attributes and digital maturity suggest that consumers become more accustomed to and capable of using variable pricing mechanisms and digital technologies. They place greater value on certain attributes that offer advanced digital features and benefits. This finding may guide companies in targeting market segments that are more technologically savvy and willing to invest in higher-end, digitally mature products.
5. While acknowledging the attractiveness of investing in digital innovation, our applications advise caution to ensure that corporate investments are purposeful and directly contribute to the utility perceived by the consumer. This approach requires companies to recognise which digital capabilities actually resonate with consumers and drive purchasing decisions, as opposed to pursuing technology for its own sake.
6. Our research emphasises the importance of strategic decision-making in digital servitisation, where firms are encouraged to identify and focus on those digital features that will have the most substantial impact on consumer utility and satisfaction. By doing so, firms can more effectively differentiate their products and services in the marketplace and enhance their competitive position.

In the remainder of this concluding chapter, the theoretical and managerial insights of each contribution of this thesis, set in the context of three core applied chapters (3, 4 and 5), are presented one by one.

6.2 Contributions of Chapter 3

In the first application, we set out to examine the influence of context effects on the selection behaviours consumers display when considering economic goods, particularly energy product-service bundles. Central to this examination was the query of whether consumer preferences and perceived utilities are reliable, as postulated by traditional economic theories, or if they are indeed dynamic, subject to fluctuation due to changing conditions or the situational contexts in which choices are made. We tested this by conducting DCE analysis and utilising a CL model estimation, focusing on the reliability of consumer preferences when presented with contextual attitudinal prompts.

Our findings revealed that consumer preferences within the realms of service, communication, and product attributes remained consistent, as no significant differences were observed between the treatment group (DM1) and the control group (DM2). This outcome suggests that the introduction of digital maturity attitudinal questions did not significantly alter the perceived utility of these attributes among the participants. However, a distinct contrast was detected concerning price-related attributes. The treatment group, which had been exposed to digital context through attitudinal questions beforehand, demonstrated a different WTP for price calculation attributes with a tendency to favour options that incorporated more advanced digital technologies. This indicates that while digital context does influence consumer preferences in the application, its effect is confined to pricing attributes and does not span to other service or product-related attributes.

Nonetheless, the absence of a broad context effect suggests that simply engaging with digital attitudes prior to making choices may not meaningfully enhance WTP for digital attributes, with the exception of price-related factors. As a result, such a treatment may not be as effective as hoped in promoting innovative electricity contracts.

We acknowledge that the application has certain limitations that could be addressed in future research. We did not explore the long-term reliability of context effects, neglecting to assess whether these effects would persist over time, particularly in procedural selection contexts. We also did not explore the possibility of the gap between perceived and experienced utility in both sample groups. Additionally, endogenous contexts were not controlled for in the survey, which might have offered further insights into how such effects could be quantified. Lastly, the method we used to pose attitudinal questions deviated from other studies where respondents evaluated statements based on their personal agreement or approval, which could have influenced our results (Liebe, et al., 2016; Pouta, 2002).

For managers and marketing professionals, our research suggests that treatments focusing on digital attitudes in a pre-decision context may not be universally beneficial. The implication for practice is that such treatments may need to be more narrowly focused on price-related elements where an effect was discernible. Methodologically, we contribute to the limited body of research on context effects in choice experiments that target homogeneous and intangible economic goods. Our research echoes the calls made by Pouta (2002) and Liebe et al. (2016) for an expanded investigation into this domain with different economic goods, offering a refined perspective on consumer behaviour in the digital era, especially within the energy sector. This opens pathways for future research that could delve into the lasting impacts of context effects.

6.3 Contributions of Chapter 4

In this application, we aimed to assess whether servitisation enhances customer value in the retail electricity market, building on established frameworks such as Grahsl's (2013) servitisation model as well as Vandermerwe and Rada's (1988) servitisation stages. We employed a DCE design to specifically investigate synergistic interactions between various service elements (Grahsl & Velamuri, 2014). We found statistical evidence supporting positive synergies, particularly evident in the transition from service provision to support. For example, the interaction between online price availability (PRICEPORTAL) and service infrastructure through email (SERVEMAIL) significantly increased WTP when bundled with a price calculation service based on pre-defined plans (Vandermerwe & Rada, 1988; Grahsl & Velamuri, 2014).

Conversely, our findings also revealed that antagonisms may manifest when emails are solely used for service provision, resulting in a reduced WTP for smart devices, especially those with advanced functionalities. This aligns with the servitisation paradox, where the addition of features to a product bundle does not necessarily enhance its value (Gebauer et al., 2005; 2020). This observation was important in our research, as it underscores the complexities involved in digital transformation within traditional markets.

We extended our analysis to consider barriers to digital engagement, such as the use of apps and online pricing portals. Our results indicate that while transparency in pricing positively impacts WTP, it might concurrently lower revenue per unit of electricity sold, illustrating a classic trade-off between enhancing consumer utility and achieving profit objectives (Fischer, 2021; Noth & Tonzer, 2022; Wallis & Loy, 2021). This aspect of our research connects servitisation to broader societal goals like energy efficiency and climate change mitigation, where we observed a manifestation of the energy-efficiency paradox, a discrepancy between potential and actual energy savings (Jaffe & Stavins, 1994; Gerarden et al., 2017).

From a managerial perspective, our findings are instructive. They suggest that while servitisation can increase customer value and foster loyalty, potentially differentiating offerings in a commoditised market, the configuration of service-product bundles must be handled with precision to avoid generating antagonisms. This necessitates a thorough selection of service touchpoints and an evaluation of the suitability of interaction channels (Sorrell, 2009; Turner, 2013).

Theoretically, our research enriches the quantitative dialogue on servitisation by providing new perspectives on the economic implications of hybrid value creation, rooted in foundational economic theories by Becker (1965), Adams and Yellen (1976), and Lancaster (1966). It highlights the importance of understanding how different attributes interact and jointly influence individuals' decision-making processes, particularly in terms of WTP for hybrid product-service bundles.

Despite its strengths, we acknowledge several limitations to our second application, such as the omission of the energy source attribute from our choice experiment, which could have provided deeper insights into synergies across different servitisation stages (Kim et al., 2013). Looking ahead, we recommend further research into quantifying synergies throughout product lifecycles and exploring physical product-based servitisation models. Moreover, linking servitisation strategies to long-term financial performance in both B2C and B2B contexts could significantly advance the field (Jain & Bala, 2018).

In conclusion, this application not only offers various theoretical propositions within the servitisation literature but also suggests actionable insights for managers in the energy sector, emphasising the strategic integration of services with core products to enhance customer satisfaction and achieve sustainable business growth.

6.4 Contributions of Chapter 5

In Chapter 5, we investigated the quantitative effects of digital servitisation on product-service bundles, focusing on how digitisation influences consumer perceptions and utility. By employing a DCE combined with an HB estimation, we analysed part-worth utilities and the perceived digital maturity of various attributes. This approach offered robust empirical insights into the impact of digital features on consumer utility, addressing a significant gap in the existing literature.

Our analysis revealed that advanced digital features in devices are highly favoured by consumers, as indicated by positive part-worth utilities in price communication, service infrastructure, and the digitalisation of the device (Gebauer et al., 2020; Sjödin et al., 2020). However, we also found that while price remains a dominant factor in consumer decisions, features such as price communication and service infrastructure, despite their positive utility contributions, are considered less crucial by consumers. This understanding suggests that while consumers recognise the benefits of digital enhancements, they prioritise cost above these features.

In examining the correlations, we discovered that attributes related to digital servitisation, particularly service infrastructure and devices, positively correlate with digital maturity, indicating that digitally advanced devices align with higher consumer utility (Worm et al., 2017; Salonen et al., 2021). Nevertheless, the weak negative correlation for price calculation attributes points to the limited potential of digitising this aspect without addressing consumer concerns about complexity. These insights are critical for firms considering where to allocate resources in digital enhancements to maximise consumer satisfaction and utility.

From a theoretical standpoint, our research enriches the economic discourse by linking digital servitisation to consumer utility theories and microeconomic principles. We applied traditional economic models by integrating digital transformation elements within the framework of DCE, particularly in settings like retail electricity pricing (Eggert et al., 2014; Böhm et al., 2017). This approach not only broadens the application of economic theories but also offers a new lens through which to view consumer decision-making in technologically advanced environments.

On the managerial front, the application delineates clear implications for business strategy. The validation of the digitalisation paradox, where investments in digital capabilities do not always yield proportional benefits, advises cautious investment in digital technologies (Gebauer et al., 2020; Sjödin et al., 2020). The negative utility linked to complex pricing mechanisms underscores the importance of simplicity and transparency in pricing strategies. Firms should ensure that digital tools in this domain are intuitive and user-friendly to avoid alienating consumers. Moreover, the moderate utility contributions of price communication and service infrastructure highlight their potential as complementary features that enhance overall consumer satisfaction. As a result, we suggest that companies should focus their digitalisation efforts on aspects that directly enhance perceived utility, particularly in market segments where consumers value innovative and ecologically friendly products.

Our research provides actionable insights for firms looking to leverage digital servitisation as a competitive strategy. By focusing on elements like the digital maturity of devices that significantly impact consumer utility, firms can better tailor their offerings to meet market demands and preferences, particularly among younger and more innovation-oriented demographics (Fang et al., 2008; Suarez et al., 2013).

In conclusion, we advocate for a deeper exploration into the economic underpinnings of digital servitisation and call for more quantitative research to further delineate its impact on consumer behaviour and firm performance. This expanded inquiry is necessary to bridge the existing gaps between theoretical models and practical applications of servitisation and digital transformation in the business landscape.

6.5 Managerial conclusions – a route to impact in a practitioner context

In our discourse, we address several managerial and methodological implications that offer considerations for both practitioners and scholars alike. For this purpose, we are navigating especially in the field of digital servitisation and discrete choice experiments within the context of energy products and services. Taking the combined insight emerging from the analyses and results presented in this thesis, some suggestions are forthcoming.

Our first application reveals that specific treatments in sales scenarios, such as those executed before decision-making, can influence customer decisions with respect to price-related items. This implies that preferences can be altered when it comes to price calculation attributes. Therefore, the use of attitude items prior to the choice task leads to a different WTP for the price calculation items, particularly in favour of the more digitalised or technologically advanced variations. However, they appear to have hardly any effect on service levels, communications, or physical device choices. This insight is crucial for sales and marketing professionals who are aiming to optimise engagement strategies in energy services. Within an online shopping environment, a favourable effect might be achieved through blocks of questions or small games that the customer interacts with prior to the buying situation. The interaction with such pre-purchase activities might be incentivised through offering a discount for the upcoming purchase. This approach offers the possibility of setting the desired context for the buying decision. In addition, information about the desired added value can be offered through interaction, which gives the customer the necessary knowledge to select the intended offer.

By integrating different economic models from the literature, such as from Saviotti et al. (1982), Rothschild (1987), Adams and Yellen (1976), and Becker (1965), we delineate how product-service bundles offer distinct utility to consumers, which is critical in designing practical offerings that align closely with consumer preferences. We find evidence that there are indeed synergetic effects of product-service bundles, even if these are ‘created’ post-purchase within the household environment. For product managers facing the challenge of commoditisation, bundling involving additional services or physical products might offer a route to avoiding intense price competition, high switching rates, situations of low customer profitability/loyalty, and the challenge of highly competitive homogeneity.

Our findings also suggest that the anticipated utility increases or WTP enhancements through servitisation might not always materialise. This has been predicted by earlier studies like Gebauer et al. (2005, 2020) and poses a critical reflection point for energy managers regarding the structuring of service bundles to maximise value without antagonisms. In this matter, we found that customers tend to show a preference for a ‘no-frills’ service interface. This implies that the parts of a digitised bundle should carefully be curated according to customers’ preferences. Specifically, this shows that the hypothesis of ‘more is better’ does not apply in the case of digitised services. On the other hand, in the case of non-service components, it seems that offering physical (non-complex) products with a high digital maturity also leads to high utility. To identify the relevant thresholds of perceived utility or WTP, a DCE with certain (potential) customer segments might offer valuable insights. This may even enable sellers to include competitive product-service configurations in order to gain insights concerning other market participants. Our research supports the notion that consumers value product-service bundles not merely on objective characteristics but based on subjective perceptions of utility. This finding is particularly important in explaining phenomena such as the digitalisation paradox, where digital enhancements do not necessarily equate to higher returns (Gebauer et al., 2020; Sjödin et al., 2020). Thus, companies should tailor their digital servitisation strategies with an understanding of customer preferences and segmentations, potentially leveraging digital capabilities to forge competitive advantages while avoiding the pitfalls of underappreciated digital utilities.

In general, the results of this thesis provide evidence for the digitisation and servitisation paradox on the product level. When sellers decide to invest in the digital transformation of value-generating and/or service capabilities, it is necessary to evaluate possible returns on investments based on customer preferences. If the returns do not cover the required investments, sellers should assess customer reactions and possibly engage in alternative approaches involving, for example, collaboration or joint ventures to split investment risks and foster a change in market or customer behaviour through interaction or information.

In conclusion, our collective insights furnish a comprehensive blueprint for both the strategic orientation and practical implementation of servitisation in the energy sector. By examining the nuanced interplays between product attributes and consumer preferences, we lay a foundation for more informed managerial decisions that could foster sustainable competitive advantages and long-term customer loyalty in a rapidly evolving market landscape. This synthesis of theoretical and practical implications serves not only as a capstone of our research endeavours but also as a guiding framework for future investigations and applications in the realm of energy services.

7 Bibliography

Aas, T. H., Breunig, K. J., Hellström, M. & Hydle, K. M., 2021. Product-Service Systems in the Digital Era: Deconstructing Servitisation Business Model Typologies. In: M. Kohtamäki, et al. eds. *The Palgrave Handbook of Servitization.* Cham: Palgrave Macmillan, pp. 73-87.

Abate, T. G., Mørkbak, M. R. & Olsen, S. B., 2018. Inducing value and institutional learning effects in stated choice experiments using advanced disclosure and instructional choice set treatments. *Agricultural Economics ,* Issue 49, pp. 339 - 351.

Abou-Zeid, M. & Ben-Akiva, M., 2014. Hybrid choice models. In: S. Hess & A. Daly, eds. *Handbook of Choice Modelling.* Cheltenham: Edward Elgar Publishing Limited, pp. 383-412.

Accenture, 2022. *New Energy Consumer,* s.l.: Accenture.

ACER, 2021. *ACER Annual Report on the Results of Monitoring the Internal Electricity and Natural Gas Markets in 2020 - Energy Retail Markets and Consumer Protection Volum,* Brussels: European Union Agency for the Cooperation of Energy Regulators.

Adams, W. J. & Yellen, J. L., 1976. Commodity Bundling and the Burden of Monopoly. *The Quarterly Journal of Economics,* 3(90), pp. 475-498.

Ahmad, N. A. et al., 2022. *Willingness, perceived barriers and motivators in adopting mobile applications for health-related interventions among older adults: A scoping review..* [Online]
Available at: https://bmjopen.bmj.com/content/12/3/e054561
[Accessed 29 02 2024].

Ali, A., Kalatian, A. & Choudhury, C. F., 2023. Comparing and contrasting choice model and machine learning techniques in the context of vehicle ownership decisions. *Transportation Research Part A,* Issue 173.

Allenby, G. M. & Ginter, J. L., 1995. Using Extremes to Design Products and Segment Markets. *Journal of Marketing Researc,* 4(32), pp. 392-403.

Allenby, G. M. & Rossi, P. E., 1999. Marketing models of consumer heterogeneity. *Journal of Econometrics,* Issue 89, pp. 57-78.

Allenby, G. M., Rossi, P. E. & McCulloch, R. E., 2005. *Hierarchical Bayes Models: A Practitioners Guide,* Ohio, Los Angeles, Chicago: s.n.

Ambroise, L., Prim-Allaz, I. & Teyssier, C., 2018. Financial performance of servitized manufacturing firms: A configuration issue between servitization strategies and customer-oriented organizational design. *Industrial Marketing Management,* pp. 54-68.

Amenta, C., Aronica, M. & Stagnaro, C., 2022. Is more competition better? Retail electricity prices and switching rates in the European Union. *Utilities Policy,* Issue 78.

Andrews, R. L., Ainslie, A. & Currim, I. S., 2002. An empirical comparison of logit choice models with discrete versus continuous representations of heterogeneity. *Journal of Marketing Research,* Volume XXXIX, pp. 479 - 487.

Andrews, R. L. & Currim, I. S., 2003. A Comparison of Segment Retention Criteria for Finite Mixture Logit Models. *Journal of Marketing Research,* Volume XL, pp. 235 - 243.

Apps, P. & Rees, R., 2009. *Public Economics and the Household.* Cambridge : Cambridge University Press.

Ashok, S. et al., 2022. Using cognitive interviewing to bridge the intent-interpretation gap for nutrition coverage survey questions in India. *Maternal & Child Nutrition,* pp. 1-14.

Auguste, B. G., Harmon, E. P. & Pandit, V., 2006. The right service strategies for product companies. *McKinsey Quarterly,* Volume 1, pp. 41-51.

Auspurg, K. & Liebe, U., 2011. Choice-experiments and the measurement of behavioral decisions in sociology. *Kölner Zeitschrift für Soziologie und Sozialpsychologie,* Issue 63, pp. 301 - 314.

Aznar, E. T. & Vindel, J. M., 2023. Energy Efficiency, Productivity and the Jevons Paradox. In: E. T. Aznar & F. L. Castellano, eds. *Science, Technology and Innovation in the History of Economic Thought.* Cham, Switzerland: Palgrave Macmillan, p. 109–137.

Baik, S. et al., 2020. Estimating what US residential customers are willing to pay for resilience to large electricity outages of long duration. *Nature Energy,* pp. 250-258.

Baines, T. et al., 2017. Servitization: Revisiting the state-of-the-art and research priorities. *International Journal of Operations and Production Management,* Issue 37, p. 256–278.

Baines, T. S., Lightfoot, H., Benedettini, O. & Kay, J., 2009. The Servitization of manufacturing: A review of literature and reflection on future challenges.. *Journal of Manufacturing Technology Management,* Issue 20, p. 547–567.

Barney, J., 1991. Firm Ressources and Sustained Competitive Advantage. *Journal of Management,* 17(1), pp. 99-120.

Bateman, I. J. et al., 2008. Choice Set Awareness and Ordering Effects in Discrete Choice Experiments. *CSERGE Working Paper EDM 08-01,* pp. 1 - 42.

Bateman, I. J. et al., 2002. *Economic Valuation With Stated Preference Techniques: A Manual.* Cheltenham, UK; Northampton, MA, USA: Edward Elgar Publishing.

Baum, M. A., Dietrich, B. J., Goldstein, R. & Sen, M., 2022. Sensitive Questions, Spillover Effects, and Asking about Citizenship on the US Census. *The Journal of Politics,* 3(84), pp. 1869-1873.

Bayes, T., 1763. LII. An essay towards solving a problem in the doctrine of chances. By the late Rev. Mr. Bayes, F. R. S. communicated by Mr. Price, in a letter to John Canton, A. M. F. R. S. *Philosophical Transactions Royal Society,* Issue 53, p. 370–418.

BDEW, 2022. *Wechselverhalten im Energiemarkt 2022,* Berlin: BDEW Bundesverband der Energie- und Wasserwirtschaft e.V..

Becker, G. S., 1965. A Theory of the Allocation of Time. *The Economic Journal,* 75(299), pp. 493-517.

Bekker-Grob, E. W. d., Ryan, M. & Gerard, K., 2012. Discrete Choice Experiments in Health Economics: A review of the literature. *Health Economics,* Volume 21, pp. 145-172.

Ben-Akiva, M. & Bierlaire, M., 1999. Discrete Choice Methods and their applications to short term travel decisions. In: *Transportation Science Handbook.* Cambridge: MIT, pp. 1-43.

Ben-Akiva, M. et al., 2002. Hybrid Choice Models: Progress and Challenges. *Marketing Letters,* 3(13), p. 163–175.

Ben-Akiva, M. & Morikawa, T., 1990. Estimation of switching models from revealed preferences and stated intentions. *Transportation Research,* 6(24A), p. 485–495.

Bennett, J. & Blamey, R., 2001. *The Choice Modelling Approach to Environmental Valuation.* Cheltenham: Edward Elgar Publishing Limited.

Berg-Schlosser, D., DeMeur, G., Rihoux, B. & C.Ragin, C., 2009. Qualitative Comparative Analysis (QCA) as an Aproach. In: B. Rihoux & C. C.Ragin, eds. *Configurational Comparative Methods: Qualitative Comparative Analysis QCA) and Related Techniques.* Thousand Oaks: SAGE Publications, Inc.

Bhat, C. R., Eluru, N. & Copperman, R. B., 2000. Flexible Model Structures for Discrete Choice Analysis. In: D. A. Hensher & K. J. Button, eds. *Handbook of Transport Modelling.* Leeds: Emerald Group Publishing Limited, pp. 75-104.

Biglieri, E., 2022. *Dimensions of Uncertainty in Communication Engineering.* London, San Diego,: Elsevier Inc..

Bishop, R. C. & Boyle, K. J., 2018. Reliability and Validity in Nonmarket Valuation. *Environmental and Resource Economics,* Issue 72, p. 559–582.

Boardman, A. E., Greenberg, D. H., Vining, A. R. & Weimer, D. L., 2018. *Cost–Benefit Analysis.* 5 ed. Cambridge : Cambridge University Press.

Bodnar, T., Mazurb, S. & Podgórski, K., 2016. Singular inverse Wishart distribution and its application to portfolio theory. *Journal of Multivariate Analysis,* Issue 134, pp. 314-326.

Böhm, E., A. E. & Thiesbrummel, C., 2017. Service transition: A viable option for manufacturing companies with deteriorating financial performance?. *Industrial Marketing Management,* Volume 60, p. 101–111.

Booth, A., Mohr, N. & Peters, P., 2016. *The digital utility: New opportunities and challenges,* San Fransisco, Düsseldorf: McKinsey & Company.

Bossert, O. & Laartz, J., 2017. *Rethinking the technology foundation for digital transformations: The McKinsey Perpetual Evolution approach will help established companies keep pace with digital innovation,* Frankfurt, Berlin: McKinsey & Company.

Brax, S. A. et al., 2021. Explaining the servitization paradox: a configurational theory and a performance measurement framework. *International Journal of Operations & Production Management,* 5(41), pp. 517-546.

Bruhn, M. & Zimmermann, A., 2022. Commodities in the Service Sector: Particularities and Implications for Marketing. In: M. Enke, A. Geigenmüller & A. Leischnig, eds. *Commodity Marketing.* Wiesbaden: Springer Gabler, pp. 43-72.

Brynjolfsson, E. & Collis, A., 2019. How Should we measure the Digital Economy?. *Harvard Business Review,* Issue 6, pp. 1-10.

Brynjolfsson, E. et al., 2019. *GDP-B: Accounting for the Value of New and Free Goods,* Cambridge, MA: National Bureau of Economic Research (NBER).

Brynjolfsson, E., Hu, Y. & Smith, M. D., 2003. Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers. *Management Science,* 11(49), pp. 1580-1596.

Cadwalladr, C. & Graham-Harrison, E., 2018. *Revealed: 50 million Facebook profiles harvested for Cambridge Analytica in major data breach.* [Online]
Available at: https://www.theguardian.com/news/2018/mar/17/cambridge-analytica-facebook-influence-us-election
[Accessed 02 03 2024].

Calle, R. d. A., Cascón, J. & González-Arteaga, T., 2020. Preferences stability: A measure of preferences changes over time. *Decision Support Systems,* Issue 129.

Canitez, F., 2019. Urban public transport systems from new institutional economics perspective: a literature review. *Transport Reviews,* 4(39), p. 511–530.

Carlsson, F., 2010. Design of Stated Preference Surveys: Is There More to Learn from Behavioral Economics?. *Environmental and Ressource Economics,* Issue 46, pp. 167-177.

Carlsson, F., Mørkbak, M. R. & Olsen, S. B., 2012. The first time is the hardest: A test of ordering effects in choice experiments. *Journal of Choice Modelling,* 5(2), pp. 19 - 37.

Casella, G. & George, E. I., 1992. Explaining the Gibbs Sampler. *The American Statistician,* 46(3), pp. 167-174.

Cassini, L. & Robert, V., 2020. Services as drivers of economic growth. Is there an opportunity for Latin America countries?. *Economics of Innovation and New Technolog,* 29(7), pp. 762-783.

Ceci, F. & Masini, A., 2011. Balancing specialized and generic capabilities in the provision of integrated solutions. *Industrial and Corporate Change,* pp. 1-41.

Chamberlin, E., 1933. The Theory of Monopolistic Competition. *The Economic Journal,* 43(172), pp. 661-666 .

Chib, S. & Greenberg, E., 1995. Understanding the Metropolis-Hastings Algorithm. *The American Statistician,* Volume 4, pp. 327-335.

ChoiceMetrics, 2024. *Ngene 1.4 User Manual & Refrence Guide,* s.l.: ChoiceMetrics.

Chrzan, K. & Orme, B., 2000. An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis. *Sawtooth Software - Reserach Paper Series,* pp. 1 - 19.

Chrzan, K. & Orme, B., 2000. *An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis,* Sequim, WA : Sawtooth Software.

Cimini, C. et al., 2021. Digital servitization and competence development: A case-study research. *CIRP Journal of Manufacturing Science and Technology,* Issue 32, p. 447–460.

Clastres, C., 2011. Smart Grids: Another step towards competition, energy security and climate change objectives. *Energy Policy*, 23 June, pp. 5399-5408.

CMA, 2017. *Guidelines for market investigations: Their role, procedures, assessment and remedies (CC3),* London: Competition and Markets Authority.

Coase, R. H., 1937. The Nature of the Firm. *Economica*, 11, pp. 386-405.

Collis, A., 2020. Consumer Welfare in the Digital Economy. In: *The Global Antitrust Institute Report on the Digital Economy 14.* s.l.:Global Antitrust Institute.

Connor, P. M. et al., 2014. Policy and regulation for smart grids in the United Kingdom. *Renewable and Sustainable Energy Reviews*, 13 August, pp. 269-286.

Coreynen, W., Matthyssens, P. & van Bockhaven, W., 2016. Boosting servitization through digitization: Pathways and dynamic resource configurations for manufacturers. *Industrial Marketing Management*, 23 April, pp. 1-12.

Coreynen, W., Matthyssens, P., Vanderstraeten, J. & Witteloostuijn, A. v., 2020. Unravelling the internal and external drivers of digital servitization: A dynamic capabilities and contingency perspective on firm strategy. *Industrial Marketing Management,* 63(3), p. 265–277.

CranenburghI, S. v., Wang, S., Vij, A. & PereiraI, F., 2022. Choice modelling in the age of machine learning - Discussion paper. *Journal of Choice Modelling,* Issue 42.

Cusumano, M. A., Kahl, S. J. & Suarez, F. F., 2015. Services, industry evolution, and the competitive strategies of product firms. *Strategic Management Journal,* 4(36), p. 559–575.

Czajkowski, M., Giergiczy, M. & Greene, W. H., 2014. Learning and Fatigue Effects Revisited: Investigating the Effects of Accounting for Unobservable Preference and Scale Heterogeneity. *Land Economics,* 90(2), pp. 323-350.

Davenport, T. H. & Redman, T. C., 2020. *Digital Transformation Comes down to Talent in 4 Key Areas.* [Online]
Available at: https://hbr.org/2020/05/digital-transformation-comes-down-to-talent-in-4-key-areas
[Accessed 19 03 2021].

De la Casa, L. G. & Timberlake, W., 2006. Effects of preexposure and retention interval placement on latent inhibition and perceptual learning in a choice-maze discrimination task. *Learning & Behavior,* 34(2), pp. 193-201.

de Vries, E. J., 2006. Innovation in services in networks of organizations and in the distribution of services. *Research Policy,* Issue 35, p. 1037–1051.

DESTATIS, 2024. *Households by types of households - Germany.* [Online]
Available at: https://www.destatis.de/EN/Themes/Society-Environment/Population/Households-Families/Tables/households.html
[Accessed 29 5 2024].

Dhar, R. & Simonson, I., 2003. The Effect of Forced Choice on Choice. *Journal of Marketing Research,* Volume XL, p. 146–160.

Diewert, W., 1974. Applications of dualty Theory. In: M. D. I. a. D. A. Kendrick, ed. *Frontiers of Quatitative Economics.* North-Holland: Amsterdam, London, pp. 106-171.

Dmitrijeva, J., Schroeder, A., Bigdeli, A. Z. & Baines, T., 2022. Paradoxes in servitization: A processual perspective. *Industrial Marketing Management,* Issue 101, p. 141–152.

Eakin, K. & Faruqui, A., 2000. Pricing Retail Electricity: Making Money Selling a Commodity. In: A. E. K. Faruqui, ed. *Pricing in Competitive Electricity Markets.* Boston, MA. : Springer.

Easton, F. F. & Pullman, M. E., 2001. Optimizing Service Attributes: The Seller's Utility Problem. *Decision Sciences,* 2(32), pp. 251-275.

Edgeworth, F. Y., 1881. *Mathematical Psychics: An Essay on the Application of Mathematics to the Moral Sciences.* London: C. Kegan Paul & Co.

Eggert, A., Hogreve, J., Ulaga, W. & Muenkhoff, E., 2011. Industrial services, product innovations, and firm profitability: A multiple-group latent growth curve analysis. *Industrial Marketing Management,* Issue 40, pp. 661-670.

Eggert, A., Hogreve, J., Ulaga, W. & Muenkhoff, E., 2014. Revenue and Profit Implications of Industrial Service Strategies. *Journal of Service Research,* 17(1), pp. 23-39.

Enke, M., Geigenmüller, A. & Leischnig, A., 2010. Commodity Marketing - Eine Einführung. In: M. Enke & A. Geigenmüller, eds. *Commodity Marketing. Grundlagen - Besonderheiten - Erfahrungen.* Wiesbaden: Gabler Verlag, pp. 5-29.

European Commission, 2008. *Memo on the Renewable Energy and Climate Change Package.* [Online]
Available at: https://ec.europa.eu/commission/presscorner/detail/en/MEMO_08_33
[Accessed 20 07 2022].

European Commission, 2012. *Overview: Liberalisation of the electricity and gas markets.* [Online]
Available at: http://ec.europa.eu/competition/sectors/energy/overview_en.html
[Accessed 4 January 2015].

European Commission, 2021. *European Green Deal: Commission proposes transformation of EU economy and society to meet climate ambitions.* [Online]
Available at: https://ec.europa.eu/commission/presscorner/detail/en/IP_21_3541
[Accessed 20 07 2022].

Fang, E., Palmatier, R. W. & Steenkamp, J.-B. E., 2008. Effect of Service Transition Strategies on Firm Value. *Journal of Marketing,* Issue 72, pp. 1-14.

Favoretto, C. et al., 2022. From servitization to digital servitization: How digitalization transforms companies' transition towards services. *Industrial Marketing Management,* Issue 102, p. 104–121.

Feick, L. & Higie, R. A., 1992. The Effects of Preference Heterogeneity and Source Characteristics on Ad Processing and Judgements about Endorsers. *Journal of Advertising,* 21(2), pp. 9-24.

Feldmann, A. M. & Serrano, R., 2006. *Walfare Economics and Social Choice Theory.* 2 ed. New York: Springer.

Felser, G., 2015. *Werbe- und Konsumentenpsychologie.* 4 ed. Wiesbaden: Springer .

Fiebig, D. G., Keane, M. P., Louviere, J. & Wasi, N., 2009. The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity. *Marketing Science,* pp. 1-29.

Fine, B. & Milonakis, D., 2009. *From Economics Imperialism to Freakonomics.* London, New York: Routledge.

Fischer, A., 2021. *How Energy Efficiency Will Power Net-Zero Climate Goals,* Paris: IEA.

Forkmann, S., Henneberg, S. C., Witell, L. & Kindström, D., 2017. Driver Configurations for Successful Service Infusion. *Journal of Service Research,* 3(20), pp. 275-291.

Foubert, B., 1999. *Product Bundling: Theory and Application,* Antwerp: University of Antwerp, Faculty of Business and Economics.

Frank, A. G., Mendes, G. H., Ayalac, N. F. & Ghezzid, A., 2019. Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. *Technological Forecasting & Social Change*, 18 January, pp. 341-351.

Frantz, R., 2020. It didn't just happen overnight. In: R. Frantz, ed. *The Beginnings of Behavioral Economics.* London: Academic Press, pp. 47-70.

Frischknecht, B., Eckert, C., Louviere, J. & Ribeiro, T., 2014. Simple ways to estimate choice models for single consumers. In: A. D. Stephane Hess, ed. *Handbook of Choice Modelling.* s.l.:Edward Elgar Publishing Limited, pp. 498-517.

Gallouj, F. & Weinstein, O., 1997. Innovation in services. *Research Policy,* Volume 26, pp. 537-556.

Ganesh, S. & Cave, V., 2018. P-values, p-values everywhere!. *New Zealand Veterinary Journal,* 66(2), pp. 55-56.

Gebauer, H., 2008. Identifying service strategies in product manufacturing companies by exploring environment–strategy configurations. *Industrial Marketing Management,* Issue 37, p. 278–291.

Gebauer, H., Fleisch, E. & Friedli, T., 2005. Overcoming the Service Paradox in Manufacturing Companies. *European Management Journal,* 23(1), pp. 14-26.

Gebauer, H., Fleisch, E., Lamprecht, C. & Wortmann, F., 2020. Growth paths for overcoming the digitalization paradox. *Business Horizons,* Issue 63, pp. 313 - 323.

Gebauer, H., Gustafsson, A. & Witell, L., 2011. Competitive advantage through service differentiation by manufacturing companies. *Journal of Business Research,* Issue 64, p. 1270–1280.

Gebauer, H., Paiola, M., Saccani, N. & Rapaccini, M., 2021. Digital servitization: Crossing the perspectives of digitization and servitization. *Industrial Marketing Management,* Issue 93, p. 382–388.

Gelman, A. et al., 2013. *Bayesian Data Analysis.* 3 ed. Boca Raton, FL: Chapman & Hall.

Geman, S. & Geman, D., 1984. Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Issue 2, pp. 609-628.

George, G., Merrill, R. K. & Schillebeeckx, a. S. J. D., 2021. Digital Sustainability and Entrepreneurship: How Digital Innovations Are Helping Tackle Climate Change and Sustainable Development. *Entrepreneurship Theory and Practice,* 5(45), p. 999–1027.

Gerarden, T. D., Newell, R. G. & Stavins, R. N., 2017. Assessing the Energy-Efficiency Gap. *Journal of Economic Literature,* 4(55), p. 1486–1525.

Giebel, G. et al., 2022. Problems and Barriers Related to the Use of Digital Health Applications: Protocol for a Scoping Review. *JMIR Research Protokolls,* 4(11).

Gilleran, M. et al., 2021. Impact of electric vehicle charging on the power demand of retail buildings. *Advances in Applied Energy,* Issue 4.

Giordano, V. & Fulli, G., 2011. A business case for Smart Grid technologies: A systemic perspective. *Energy Policy*, 3 November, pp. 252-259.

Glimcher, P. W., Camerer, C. F., Fehr, E. & Poldrack, R. A., 2009. Introduction: A Brief History of Neuroeconomics. In: P. W. Glimcher, C. F. Camerer, E. Fehr & R. A. Poldrack, eds. *Neuroeconomics.* London, San Diego, Burlington: Elsevier Inc., pp. 1-11.

Goedkoop, M. J., Halen, C. J. v., Riele, H. R. t. & Rommens, P. J., 1999. *Product service systems, ecological and economic basics,* The Hague: Dutch Ministries of Environment and Economic Affairs.

Golsteyn, B. & Schildberg-Hörisch, H., 2017. Challenges in research on preferences and personality traits: Measurement, stability, and inference. *Journal of Economic Psychology*, 6 03, pp. 1-6.

Goodman, A. C., 1998. Andrew Court and the Invention of Hedonic Price Analysis. *Journal of urban Economics,* Issue 44, pp. 291- 298.

Grahsl, I., 2013. *Identifikation und Erschließung innovativer Wachstumspotenziale von Energieversorgungsunternehmen im Provatkundenmanagement.* 1. ed. Göttingen: Cuvillier Verlag.

Grahsl, I. & Velamuri, V. K., 2014. *Servitization Logics for Utilities: A Systematic Approach to Develop B2C-Offerings.* Dublin, XXV ISPIM Conference - Innovation for Sustainable Economy & Society.

Grebitus, C., Lusk, J. L. & Nayga, R. M. J., 2013. Explaining differences in real and hypothetical experimental auctions and choice experiments with personality. *Journal of Economic Psychology,* Issue 36, pp. 11 - 26.

Greene, W. H., 2016. *NLOGIT Version 6 Reference Guide,* Plainview, NY, USA: Econometric Software, Inc..

Greene, W. H. & Hensher, D. A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B,* Issue 37, p. 681–698.

Griliches, Z., 1991. Hedonic Price Indexes and the Measurement of Capital and Productivity. In: Ernst R. Berndt and Jack E. Triplett, ed. *Fifty Years of Economic Measurement: The Jubilee of the Conference on Research in Income and Wealth.* Chicago: University of Chicago Press, pp. 185-206.

Grüne-Yanoff, T. & Hansson, S. O., 2009. Preference Change: An Introduction. In: T. Grüne-Yanoff & S. O. Hansson, eds. *Preference Change: Approaches from Philosophy, Economics and Psychology.* Dordrecht Heidelberg London New York: Springer, p. 1–26.

Guthridge, G. S., Burns, A. V. & Pelotti, P., 2012. *Actionable Insights for the New Energy Consumer,* Vancuver, Milan: Accenture Innovation Center for Energy and Utilities.

Hainmueller, J., Hopkins, D. J. & Yamamoto, T., 2014. Causal Inference in Conjoint Analysis: Understanding Multidimensional Choices via Stated Preference Experiments. *Political Analysis,* Volume 22, p. 1–30.

Haller, T., Kässer, M. & Trukenmüller, M., 2022. *Consumer perception of price development and the associated behavioural adjustment,* München: Simon Kucher.

Hanemann, W. M., 1984. Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses. *American Journal of Agricultural Economics,* 66(3), pp. 332-341.

Hanemann, W. M., 1991. Willingness to Pay and Willingness to Accept: How Much Can They Differ?. *The American Economic Review,* 81(3), pp. 635-647.

Harley, C. K. & Crafts, N. F. R., 2000. Simulating the Two Views of the British Industrial Revolution. *The Journal of Economic History,* 60(3), pp. 819-841.

Harnois, C. E., 2022. What do we measure when we measure perceptions of everyday discrimination?. *Social Science & Medicine,* Issue 292.

Hein, M., Goeken, N., Kurz, P. & Steiner, W. J., 2022. Using Hierarchical Bayes draws for improving shares of choice predictions in conjoint simulations: A study based on conjoint choice data. *European Journal of Operational Research,* Issue 297, p. 630–651.

Helm, R., Steiner, M., Scholl, A. & Manthey, L., 2004. A Comparative Empirical Study on Common Methods for Measuring Preferences. *Jenaer Schriften zur Wirtschaftswissenschaft*, pp. 1-26.

Hensher, D. A., 2009. Hypothetical bias, choice experiments and willingness to pay. *Transportation Research,* Part B(44), pp. 735 - 752.

Hensher, D. A. & Greene, W. H., 2002. Specification and estimation of the nested logit model: alternative normalisations. *Transportation Research Part B ,* Issue 36, pp. 1-17.

Hensher, D. A. & Greene, W. H., 2002. *The Mixed Logit Model: The State of Practice,* Sydney: Institute of Transport Studies (Sydney & Monash), The Australian Key Centre in Transport Management, C37, The University of Sydney NSW 2006, Australia.

Hensher, D. A., Rose, J. M. & Greene, W. H., 2005. *Applied Choice Analysis.* 1. ed. Cambridge, New York, Melbourne, Madrid, Cape Town, Singapore, São Paulo: Cambridge University Press.

Herfindahl, O., 1950. *Concentration In The Steel Industry.* New York, USA: Columbia University.

Hess, S. & Beharry-Borg, N., 2012. Accounting for Latent Attitudes in Willingness-to-PayStudies: The Case of Coastal Water QualityImprovements in Tobago. *Environmental and Resource Economics volume,* Volume 52, pp. 109-131.

Hess, S. & Palma, D., 2019. Apollo: A flexible, powerful and customisable freeware package for choice model estimation and application. *Journal of Choice Modelling,* 23(2019), pp. 1-26.

Hess, S. & Palma, D., 2022. *Apollo Choice Modelling Manual.* [Online] Available at: http://www.apollochoicemodelling.com/files/manual/Apollo.pdf [Accessed 12 01 2022].

Hess, S., Rose, J. M. & Polak, J., 2010. Non-trading, lexicographic and inconsistent behaviour in stated choice data. *Transportation Research Part D,* Volume 15, pp. 405 - 417.

Hess, S., Train, K. E. & Polak, J. W., 2006. On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice. *Transportation Research Part B,* Volume 40, pp. 147-163.

Hicks, J. R., 1943. The Four Consumer's Surpluses. *The Review of Economic Studies,* 11(1), pp. 31-41.

Hirschman, A. O., 1964. The Paternity of an Index. *The American Economic Review,* 54(5), p. 761.

Hodgson, G. M., 2009. Institutional Economics into the Twenty-First Century. *Studi e Note di Economia,* 1(2009), pp. 03-26.

Hoffman, S. D. & Duncan, G. J., 1988. Multinomial and Conditional Logit Discrete-Choice Models in Demography. *Demography,* 25(3), pp. 415-427.

Holmström, J. & Partanen, J., 2014. Digital manufacturing-driven transformations of service supply chains for complex products. *Supply Chain Management: An International Journal,* 4(19), p. 421–430 .

Houle, S., 2015. An Introduction to the Fundamentals of Randomized Controlled Trials in Pharmacy Research. *CJHP Research Primer Series,* 1(68), pp. 28-32.

Hsu, C. & Spohrer, J. C., 2009. Improving service quality and productivity: exploring the digital connections scaling model. *Int. J. Services Technology and Management*, pp. 272-292.

Huber, J. & Train, K., 2001. On the Similarity of Classical and Bayesian Estimates of Individual Mean Partworths. *Marketing Letters,* 12(3), pp. 259 - 269.

Huber, J. & Zwerina, K., 1996. The Importance of Utility Balance in Efficient Choice Designs. *Journal of Marketing Research,* 3(33), pp. 307-317.

IEA, 2013. *World Energy Outlook 2013.* Paris: International Energy Agency.

Islam, T., Louviere, J. & Pihlens, D., 2009. *Aggregate choice and individual models: a comparison of top-down and bottom-up approaches.* Delray Beach, Florida, Sawtooth Software Conference.

Jaeger, S. R. & Cardello, A. V., 2022. Factors affecting data quality of online questionnaires: Issues and metrics for sensory and consumer research. *Food Quality and Preference,* Issue 102.

Jaffe, A. B. & Stavins, R. N., 1994. The energy-efficiency gap. *Energy Policy,* 10(22), pp. 804-810.

Jain, A. & Bala, R., 2018. Differentiated or integrated: Capacity and service level choice for differentiated products. *European Journal of Operational Research,* Issue 266, pp. 1025-1037.

James, G., Witten, D., Hastie, T. & Tibshirani, R., 2021. *An Introduction to Statistical Learning with Applications in R.* 2. ed. New York : Springer, New York, NY.

Jamison, M. A. & Wang, P., 2021. Valuation of digital goods during the coronavirus outbreak in the United States. *Telecommunications Policy,* Issue 45, pp. 1-10.

Jen-Yi, L., Krishnasamy, M. & Der-Thanq, C., 2015. Research with persons with intellectual disabilities: An inclusive adaptation of Tourangeau’s model. *ALTER, European Journal of Disability Research,* Issue 9, p. 304–316.

Johnson, R. M., 2000. *Understanding HB: An Intuitive Approach,* Sequim, WA 98382: Sawtooth Software.

Johnston, R. J. et al., 2017. Contemporary Guidance for Stated Preference Studies. *Journal of the Association of Environmental and Resource Economists*, 6, pp. 319 - 40.

Jun, S. Y., Kim, K. H. & Par, H. K., 2019. The effect of the preorder strategy on consumers' product choice: The moderating role of product experience and payment timing. *Journal of Business Research,* Issue 99, pp. 80-86.

Kaastra, W. et al., 2020. *New Energy Customer: Delivering new energy experiences for future growth,* s.l.: Accenture Research.

Kaczor, S., Kryvinska, N. & Strauss, C., 2017. *Pitfalls in Servitization and Managerial Implications.* Volterra, Italy, Global Conference on Services Management (GLOSERV 2017).

Kadıoglu, B. et al., 2022. Sample Complexity of Rank Regression Using Pairwise Comparisons. *Pattern Recognition,* pp. 1-47.

Kahneman, D., 2003. Maps of Bounded Rationality: Psychology for Behavioral Economics. *The American Economic Review,* 93(5), pp. 1449-1475.

Kahneman, D. & Tversky, A., 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica,* 2(47), pp. 263-292.

Kamakura, W. A. & Russell, G. J., 1989. A Probabilistic Choice Model for Market Segmentation and Elasticity Structure. *Journal of Marketing Research,* 4(26), pp. 379-390.

Kamalaldin, A., Linde, L., Sjödin, D. & Parida, V., 2020. Transforming provider-customer relationships in digital servitization: A relational view on digitalization. *Industrial Marketing Management,* Issue 89, p. 306–325.

Kanninen, B. J., 2002. Optimal Design for Multinomial Choice Experiments. *Journal of Marketing Research,* 2(39), pp. 214-227.

Katz, R. & Koutroumpis, P., 2013. Measuring digitization: A growth and welfare multiplier. *Technovation,* Issue 33, pp. 314-319.

Kempener, R. & de Vivero, G., 2015. *Renewables and Electricity Storage - A technology roadmap for REmap 2030,* Abu Dhabi, Bonn: International Renewable Energy Agency (IRENA).

Khanra, S., Dhir, A., Parida, V. & Kohtamäki, M., 2021. Servitization research: A review and bibliometric analysis of past achievements and future promises. *Journal of Business Research,* Issue 131, pp. 151-166.

Kim, D. & Park, B.-J. R., 2017. The moderating role of context in the effects of choice attributes on hotel choice: A discrete choice experiment. *Tourism Management,* Issue 63, pp. 439 - 451.

Kim, J., Park, J., Kim, J. & Heo, E., 2013. Renewable electricity as a differentiated good? The case of the Republic of Korea. *Energy Policy,* Issue 54, pp. 327-334.

Kløjgaard, M. E., Bech, M. & Søgaard, R., 2012. Designing a Stated Choice Experiment: The Value of a Qualitative Process. *Journal of Choice Modelling,* 5(2), pp. 1-18.

Kohtamäki, M., Parida, V., Patel, P. C. & Gebauer, H., 2020. The relationship between digitalization and servitization: The role of servitization in capturing the financial potential of digitalization. *Technological Forecasting & Social Change,* Issue 151, pp. 1-9.

Kohtamäki, M., Partanen, J., Parida, V. & Wincent, J., 2013. Non-linear relationship between industrial service offering and sales growth: The moderating role of network capabilities. *Industrial Marketing Management,* Issue 42, p. 1374–1385.

Kohtamäki, M. et al., 2021. Unfolding the digital servitization path from products to product-service-software systems: Practicing change through intentional narratives. *Journal of Business Research,* Issue 137, p. 379–392.

Kowalkowski, C., Sörhammar, D. & Tronvoll, B., 2021. Digital Servitization: HowManufacturing Firms Can Enhance Resource Integration and Drive Ecosystem Transformation. In: M. Kohtamäki, et al. eds. *The Palgrave Handbook of Servitization.* Cham: Palgrave Macmillan, pp. 27-39.

Kreye, M. E. & Donk, D. P. v., 2021. Servitization for consumer products: an empirical exploration of challenges and benefits for supply chain partners. *International Journal of Operations & Production Management,* 41(5), pp. 494-516.

Kuijken, B., Gemser, G. & Wijnberg, N. M., 2017. Effective product-service systems: A value-based framework. *Industrial Marketing Management,* Issue 60, pp. 33-41.

Lancaster, K. J., 1966. A New Approach to Consumer Theory. *The Journal of Political Economy*, 4, pp. 132-157.

Lehrke, S., Lewis, M., Bliznakov, K. & Weber, J., 2018. *The Digital Energy Retailer.* [Online] Available at: https://www.bcg.com/publications/2018/digital-energy-retailer [Accessed 16 07 2022].

Lenk, P., 2014. Bayesian estimation of random utility models. In: S. H. &. A. Daly, ed. *Handbook of Choice Modelling.* s.l.:Edward Elgar Publishing, pp. 457-497.

Lenk, P. J., DeSarbo, W. S., Green, P. E. & Young, M. R., 1996. Hierarchical Bayes Conjoint Analysis: Recovery of Partworth Heterogeneity from Reduced Experimental Designs. *Marketing Science,* 2(15), pp. 173-191.

Levitt, S. D. & List, J. A., 2007. What Do Laboratory Experiments Measuring Social Preferences Reveal about the Real World?. *The Journal of Economic Perspectives,* 21(2), pp. 153-174.

Lexutt, E., 2020. Different roads to servitization success – A configurational analysis of financial and non-financial service performance. *Industrial Marketing Management,* Issue 84, pp. 105-125.

Liebe, U., Hundeshagen, C., Beyer, H. & von Cramon-Taubadel, S., 2016. Context effects and the temporal stability of stated preferences. *Social Science Research,* pp. 1 - 13.

Lightfoot, H., Baines, T. & Smart, P., 2013. The servitization of manufacturing: A systematic literature review of interdependent trends. *International Journal of Operations & Production Management,* 33(11/12), pp. 1408-1434.

Littlechild, S., 2018. Competition, regulation and price controls in the GB retail energy market. *Utilities Policy,* Issue 52, pp. 59-69.

Loewenstein, G. & Lerner, J. S., 2003. Making, The Role of Affect in Decision. In: R. J. Davidson, K. R. Scherer & H. H. Goldsmith, eds. *Handbook of Affective Sciences.* Oxford: Oxford University Press, pp. 619-642.

Lohse, L. & Künzel, M., 2011. Customer Relationship Management im Energiemarkt - CRM in Commodity Industrien am Beispiel eines Energiedienstleisters. In: M. Enke & A. Geigenmüller, eds. *Commodity Marketing.* Wiesbaden: Gabler Verlag, Springer Fachmedien Wiesbaden GmbH, pp. 381-401.

Long Jr., J. B., 1984. Gaussian Demand and Commodity Bundling. *The Journal of Business,* 1(57), pp. 235-246.

Long, J. S. & Freese, J., 2001. *Regression Models for categorical dependent varibales using STATA.* 10 ed. Texas : Stata Corporation.

Louviere, J. J., Flynn, T. N. & Carson, R. T., 2010. Discrete Choice Experiments Are Not Conjoint Analysis. *Journal of Choice Modelling,* 3(3), pp. 57-72.

Louviere, J. J. & Hensher, D. A., 1982. Design and Analysis of Simulated Choice or Allocation Experiments in Travel Choice Modeling. *Transportation Research Record,* Issue 890, pp. 11-17.

Louviere, J. J., Hensher, D. A. & Swait, J. D., 2000. *Stated Choice Methods: Analysis and Applications.* Cambridge, United Kingdom: Cambride University Press.

Louviere, J. J. & Woodworth, G., 1983. Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. *Journal of Marketing Research,* 20(4), pp. 350-367.

Lubow, R. E., Rifkin, B. & Alek, M., 1967. The context effect: The relationship between stimulus preexposure and environmental preexposure determines subsequent learning. *Journal of Experimental Psychology Animal Behavior Processes*, 1, pp. 38 - 47.

Luce, R. D., 1959. *A theory of individual choice behavior.* New York: Columbia University.

Mammadli, E. & Klivak, V., 2020. *Measuring the effect of the Digitalization,* Tartu: University of Tartu, Faculty of Economics and Business Administration.

Mangham, L. J., Hanson, K. & McPake, B., 2009. How to do (or not to do) ... Designing a discrete choice experiment for application in a low-income country. *Health Policy and Planning,* Issue 24, p. 151–158.

Mankiw, G., 2018. *Principles of Microeconomics.* 8 ed. Boston, MA: Cengage Learning..

Mariel, P. et al., 2021. *Environmental Valuation with Discrete Choice Experiments.* Cham: Springer Nature Switzerland AG.

Marshall, A., 1890. *Principles of Economics.* 8 ed. London: Macmillan and Co.

Marshall, D., Chan, S.-S. & Curry, J., 2010. *A head-to-head comparison of the traditional (top-down) approach to choice modeling with a proposed bottom-up approach..* Newport Beach, California, Sawtooth Software Conference.

Mas-Colell, A., Whinston, M. D. & & Green, J. R., 1995. *Microeconomic Theory.* Oexford: Oxford University Press.

Matthyssens, P. & Vandenbempt, K., 2008. Moving from basic offerings to value-added solutions: Strategies, barriers and alignment. *Industrial Marketing Management*, 21 2, pp. 316-328.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In: P. Zarembka, ed. *Frontiers in econometrics.* New York: Academic Press, pp. 105-142.

McFadden, D., 1981. Econometric models of probabilistic choice. In: C. F. Manski & D. L. McFadden, eds. *Structural Analysis of Discrete Data.* Cambridge, MA: MIT Press, pp. 198-271.

McFadden, D., 2014. The new science of pleasure: consumer choice behavior and the measurement of well-being. In: S. Hess & A. Daly, eds. *The Handbook of Choice Modeling.* Cheltenham, UK; Northampton, USA: Edward Elgar Publishing Limited, pp. 7-48.

McFadden, D. & Train, K., 2000. Mixed MNL Models for Discrete Response. *Journal of Applied Econometrics,* 15(5), pp. 447-470.

McIntosh, E., 2006. Using Discrete Choice Experiments within a Cost-Benefit Analysis Framework. *Pharmacoeconomics,* 9(24), pp. 855 - 868.

Menger, C., 1871. *Principles of Economics.* Auburn, Ala. : Ludwig von Mises Institute.

Meyerhoff, J. & Glenk, K., 2013. Learning how to choose – effects of instructional choice sets in discrete choice experiments. *Working Paper on Management in Environmental Planning,* pp. 1 - 26.

Michaud, C., Joly, I., Llerena, D. & Lobasenko, V., 2017. Consumers' willingness to pay for sustainable and innovative products: a choice experiment with upgradeable products. *International Journal of Sustainable Development ·,* 20(1/2), pp. 8-32.

Mishan, E. J., 1976. The Use of Compensating and Equivalent Variations in Cost-Benefit Analysis. *Economica,* 43(170), pp. 185-197.

Molin, E. J., Oppewal, H. & Timmermans, H. J., 2001. Analyzing heterogeneity in conjoint estimates of residential preference. *Journal of Housing and the Built Environment,* 16(3/4), pp. 267-284.

Mont, O., 2002a. Clarifying the concept of product–service system. *Journal of Cleaner Production,* Issue 10, p. 237–245.

Mont, O., 2002b. Drivers and barriers for shifting towards more service-oriented businesses: Analysis of the PSS field and contributions from Sweden. *The Journal of Sustainable Product Design,* Issue 2, p. 89–103.

Murphy, E. R., Illes, J. & Reiner, P. B., 2008. Neuroethics of Neuromarketing. *Journal of Consumer Behaviour,* 7(4-5), pp. 293-302.

Nadel, L. & Willner, J., 1980. Context and conditioning: A place for space. *Physiological Psychology,* 2(8), pp. 218-228.

Nagle, F., Seamans, R. & Tadelis, S., 2020. *Transaction Cost Economics in the Digital Economy: A Research Agenda,* Boston: Harvard Business School.

Naik, P. et al., 2020. Behind the scenes of digital servitization: Actualising IoT-enabled affordances. *Industrial Marketing Management,* Issue 89, p. 232–244.

Nauen, A. & Enke, M., 2022. Customer Engagement as an Approach to De-Commoditisation. In: M. Enke, A. Geigenmüller & A. Leischnig, eds. *Commodity Marketing.* Wiesbaden: Springer Gabler, pp. 237-254.

Ndebele, T., Marsh, D. & Scarpa, R., 2019. Consumer switching in retail electricity markets: Is price all that matters?. *Energy Economics,* Issue 83, pp. 88-103.

Nicholson, W. & Snyder, C., 2007. *Microeconomic Theory Basic Principles and Extensions.* 10 ed. Mason, OH, USA: Thomson Higher Education.

Nikander, P., Eloranta, V., Karhu, K. & Hiekkanen, K., 2020. *Digitalisation, anti-rival compensation and governance: Need for experiments. Abstract from Nordic Workshop on Digital Foundations of Business,,* Espoo, Finland.: Aalto University.

North, D. C., 1990. *Institutions, Institutional Change and Economic Performance.* Cambridge, UK: Cambridge University Press.

Noth, F. & Tonzer, L., 2022. Understanding climate activism: Who participates in climate marches such as ‘‘Fridays for Future’’ and what can we learn from it?. *Energy Research & Social Science,* Issue 84, pp. 1-7.

Nylund, K. L., Asparouhov, T. & Muthén, B. O., 2007. Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study. *Structural Equation Modeling,* 14(4), pp. 535-569.

OFGEM, 2019. *State of the Energy Market 2019,* London, UK: Office of Gas and Electricity Markets (Ofgem).

Oliva, R. & Kallenberg, R., 2003. Managing the transition from products to services. *International Journal of Service Industry Management*, pp. 160-172.

Ordanini, A., Parasuraman, A. & Rubera, G., 2014. When the Recipe Is More Important Than the Ingredients: A Qualitative Comparative Analysis (QCA) of Service Innovation Configurations. *Journal of Service Research,* 2(17), pp. 134-149.

Orme, 2010. Sample Size Issues for Conjoint Analysis. In: *Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research.* Madison, Wisconsin: Research Publishers LLC, pp. 57-65.

Orme, B., 2014. Including Holdout Choice Tasks in Conjoint Studies. *Sawtooth Software: Research Paper Series,* pp. 1 - 7.

Orme, B., 2025. *Sawtooth Community.* [Online]
Available at: https://community.sawtoothsoftware.com/lighthouse-studio/post/standard-errors-in-the-advanced-design-test-JRXF9NzRQYlMvit
[Accessed 24 January 2025].

Orme, B. K., 2020. *Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research.* 4 ed. Manhattan Beach, CA: Research Publishers LLC.

Paiola, M., Schiavone, F., Grandinetti, R. & Chen, J., 2021. Digital servitization and sustainability through networking: Some evidences from IoT-based business models. *Journal of Business Research,* Issue 132, p. 507–516.

Pareto, V., 1906. *Manual of Political Economy.* Oxfort: Oxford University Press.

Parida, V., Sjödin, D. R., Wincent, J. & Kohtamäki, M., 2014. Mastering the Transition to Product-Service Provision. *Research-Technology Management,* pp. 44-52.

Parida, V. & Wincent, J., 2019. Why and how to compete through sustainability: a review and outline of trends influencing firm and network-level transformation. *International Entrepreneurship and Management Journal,* Issue 15, pp. 1-19.

Paschou, T., M. R., Adrodegari, F. & Saccani, N., 2020. Digital servitization in manufacturing: A systematic literature review and research agenda. *Industrial Marketing Management,* Issue 89, p. 278–292.

Phaneuf, D. J. & Requate, T., 2017. *A Course in Envirnmental Economics.* Cambridge, UK: Cambridge University Press .

Pigou, A. C., 1920. *The Economics of Welfare.* 4 ed. London: Macmillan.

Poe, G. L., Severance-Lossin, E. K. & Welsh, M. P., 1994. Measuring the Difference (X — Y) of Simulated Distributions: A Convolutions Approach. *American Journal of Agricultural Economics,* 76(4), pp. 904-915.

Porst, R., 2013. *Fragebogen - Ein Arbeitsbuch.* 4 ed. Wiesbaden: Springer.

Porter, M. E., 1987. From Competititve Advantage to Corporate Strategy. *Harvard Business Review,* Volume 3, pp. 2-22.

Porter, M. E. & Heppelmann, J. E., 2014. How Smart, Connected Products Are Transforming Competition. *Harvard Business Review,* Issue 11, pp. 3-23.

Porter, M. E. & Heppelmann, J. E., 2015. How Smart, Connected Products Are Transforming Companies. *Harvard Business Review,* Issue 10, pp. 2-19.

Pouta, E., 2002. Attitude and belief questions as a source of context effect in a contingent valuation survey. *Journal of Economic Psychology,* Issue 25, pp. 229 - 242.

Pullman, M. E., Verma, R. & Goodale, J. C., 2001. Service Design and Operations Strategy Formulation in Multicultural Markets. *Journal of Operations Management,* 19(2), pp. 239-254.

Raddats, C. et al., 2019. Servitization: A contemporary thematic review of four major research streams. *Industrial Marketing Management,* Issue 83, p. 207–223.

Rangan, V. K. & Bowmann, G. T., 1992. Beating the Commodity Magnet. *Industrial Marketing Management*, 8, pp. 215-224.

Ratcliffe, J. & Longworth, L., 2002. Investigating the structural reliability of a discrete choice experiment within health technology assessment. *International Journal of Technology Assessment in Health Care,* 1(18), p. 139–144.

Revelt, D. & Train, K., 1998. Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level. *The Review of Economics and Statistics,* 4(80), pp. 647-657.

Ricardo, D., 1821. *On the Principles of Political Economy and Taxation.* 3. ed. Kitchener, Ontariop: Batoche Books.

Rombouts, S., 2019. *Towards a better understanding of consumer acceptance and valuation of product-service systems - A discrete choice experiment on laundry solution,* Utrecht: Utrecht University, ABN-AMRO.

Rooderkerk, R. P., Van Heerde, Harald J. & Bijmolt, T. H., 2011. Incorporating Context Effects into a Choice Model. *Journal of Marketing Research,* 8, 48(4), pp. 767-780.

Rose, J. M. & Bliemer, M. C., 2004. *The Design of Stated Choice Experiments: The State of Practice and Future Challenges,* Sydney: Institute of Transport Studies .

Rossi, P. E. & Allenby, G. M., 2003. Bayesian Statistics and Marketing. *Marketing Science,* 22(3), pp. 304-328.

Rossi, P. E., Allenby, G. M. & McCulloch, R., 2005. *Bayesian Statistics and Marketing.* West Sussex: John Wiley & Sons Ltd.

Rossmann, A., 2018. *Digital Maturity: Conceptualization and Measurement Model.* San Fransico, Thirty Ninth International Conference on Information Systems.

Rothschild, R., 1987. The Theory of Monopolistic Competition: E.H. Chamberlin's Influence on Industrial Organisation Theory over Sixty Years. *Journal of Economic Studies,* pp. 34-54.

Rousseau, S., 2020. Millennials' acceptance of product-service systems: Leasing smartphones in Flanders (Belgium). *Journal of Cleaner Production,* pp. 1-9.

Ruan, K., 2019. Digital Assets as Economic Goods. In: C. Janco, ed. *Digital Asset Valuation and Cyber Risk Measurement: Principles of Cybernomics.* London, San Diego, Cambridge; Oxford: Elsevier Academic Press, pp. 1-28.

Ruiz-Martín, A. & Díaz-Garrido, E., 2021. A Review of Servitization Theoretical Foundations. *Journal of Industrial Engineering and Management,* 3(14), pp. 496-519.

Ryan, M. & Gerard, K., 2003. Using discrete choice experiments to value health care programmes: current practice and future research reflections. *Applied Health Economics and Health Policy,* 2(1), pp. 55-64.

Rymaszewska, A., Helo, P. & Gunasekaran, A., 2017. IoT powered servitization of manufacturing – an exploratory case study. *International Journal of Production Economics,* Issue 192, p. 92–105.

Saaty, T. L., 2008. Relative Measurement and Its Generalization in Decision Making - Why Pairwise Comparisons are Central in Mathematics for the Measurement of Intangible Factors The Analytic Hierarchy/Network Process. *Revista de la Real Academia de Ciencias Exactas, Físicas y Naturales. Serie A. Matemáticas,* 2(102), pp. 251-318.

Sagebiel, J., Glenk, K. & Meyerhoff, J., 2017. Spatially explicit demand for afforestation. *Forest Policy and Economics,* 12 02, Issue 78, pp. 190-199.

Sagebiel, J. & Rommel, K., 2014. Preferences for electricity supply attributes in emerging megacities — Policy implications from a discrete choice experiment of private households in Hyderabad, India. *Energy for Sustainable Development*, pp. 89-99.

Salonen, A. et al., 2020. Engaging a product-focused sales force in solution selling: interplay of individual- and organizational-level conditions. *Journal of the Academy of Marketing Science,* pp. 1-26.

Salonen, A., Zimmer, M. & Keränen, J., 2021. Theory development in servitization through the application of fsQCA and experiments. *International Journal of Operations & Production Management,* 41(5), pp. 746-769.

Sammer, K., 2007. *Der Einfluss von Ökolabelling auf die Kaufentscheidung -- Evaluation der Schweizer Energieetikette mittels Discrete-Choice-Experimenten.* 1. ed. Graz: Universität St.Gallen Hochschule für Wirtschafts-, Rechts- und Sozialwissenschaften (HSG).

Samuelson, P. A., 1938. A Note on the Pure Theory of Consumer's Behaviour. *Economica,* 5(17), pp. 61-71.

Samuelson, P. A., 1948. Consumption Theory in Terms of Revealed Preference. *Economica,* 15(60), pp. 243-253.

Samuelson, P. A., 1956. Social Indifference Curves. *The Quarterly Journal of Economics,* 2, LXX(1), pp. 1-22.

Santamaria, L., Nieto, M. J. & Miles, I., 2011. Service innovation in manufacturing firms: Evidence from Spain. *Technovation,* pp. 144-155.

Sarrias, M. & Daziano, R. A., 2017. Multinomial Logit Models with Continuous and Discrete Individual Heterogeneity in R: The gmnl Package. *Journal of Statistical Software,* 79(2), pp. 1-46.

Saunders, M. N. K., Lewis, P. & Thornhill, A., 2019. *Research Methods For Business Stundents.* 8 ed. Harlow, UK: Pearson Education Limited.

Savage, L. J., 1972. *The Foundations otf Statistics.* 2 ed. New York: Dover Publications, Inc.

Saviotti, P., Stubbs, P., Coombs, R. & Gibbons, M., 1982. An Approach to the Construction of Indexes of Technological Change and of Technological Sophistication. *Technological forecasting and scocial change ,* Issue 21, pp. 133-147.

Sawtooth Software, 2017. *The CBC System for Choice-Based Conjoint Analysis,* Orem, Utah USA: Sawtooth Software, Inc..

Sawtooth Software, 2021. *The CBC/HB System Technical Paper V5.6,* Provo, Utah: Sawtooth Software, Inc..

Sawtooth Software, 2024a. *Testing the CBC Design.* [Online]
Available at: https://sawtoothsoftware.com/help/lighthouse-studio/manual/cbc-test-design.html
[Accessed 30 03 2024].

Sawtooth Software, 2024. *Specifying Fixed or Holdout Tasks.* [Online]
Available at: https://sawtoothsoftware.com/help/lighthouse-studio/manual/cbc-fixed-tasks.html
[Accessed 30 3 2024].

Sawtooth Software, 2025. *CBC utilities.* [Online]
Available at: https://sawtoothsoftware.com/help/discover/analysis/cbc/cbc-utilities#
[Accessed 08 02 2025].

Scarpa, R., Ferrini, S. & Willis, K., 2005. Performance of error component models for status-quo effects in choice experiments. In: R. Scarpa & A. Alberini, eds. *Environmental and Resource Valuation in the UK.* Dordrecht, The Netherlands: Springer, pp. 247-273.

Scarpa, R. & Thiene, M., 2005. Destination Choice Models for Rock Climbing in the Northeastern Alps: A Latent-Class Approach Based on Intensity of Preferences. *Land Economics,* 81(3), pp. 426-444.

Schleich, J., Faure, C., Guetlein, M.-C. & Tu, G., 2020. Household preferences for new heating systems: Insights from a multi-country discrete choice experiment. *Working Paper Sustainability and Innovation,* Issue No. S 05/2020, pp. 1-21.

Schwab, K., 2016. *The Fourth Industrial Revolution.* Cologny/Geneva: World Economic Forum.

Sen, A., 1979. Utilitarianism and Welfarism. *The Journal of Philosophy ,* 76(9), pp. 463-489.

Sent, E.-M., 2018. Rationality and bounded rationality: you can't have one without the other. *The European Journal of the History of Economic Thought,* 25(6), pp. 1370-1386.

Shankar, V., Berry, L. L. & Dotzel, T., 2009. A Practical Guide to Combining Products and Services. *Harvard Business Review*, November, pp. 94-99.

Simon, H. A., 1955. A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics,* 1(69), pp. 99-118.

Simon, H. A., 1956. Rational Choice and the Structure of the Environment. *Psychological Review,* 63(2), pp. 129-138.

Simonsson, J. & Agarwal, G., 2021. Perception of value delivered in digital servitization. *Industrial Marketing Management,* Issue 99, p. 167–174.

Sjödin, D., Parida, V. & Kohtamäki, M., 2019. Relational governance strategies for advanced service provision: Multiple paths to superior financial performance in servitization. *Journal of Business Research,* p. 906–915.

Sjödin, D., Parida, V., Kohtamäki, M. & Wincent, J., 2020. An agile co-creation process for digital servitization: A micro-service innovation approach. *Journal of Business Research,* Issue 112, p. 478–491.

Sjödin, D. R., Parida, V. & Kohtamäki, M., 2016. Capability configurations for advanced service offerings in manufacturing firms: Using fuzzy set qualitative comparative analysis. *Journal of Business Research,* Issue 69, p. 5330–5335.

Sklyar, A., Kowalkowski, C., Sörhammar, D. & Tronvoll, B., 2019a. Resource integration through digitalisation: a service ecosystem perspective. *Journal of Marketing Management,* Issue 35, pp. 974-991.

Sorrell, S., 2009. Jevons' Paradox revisited: The evidence for backfire from improved energy efficiency. *Energy Policy*, 19 January, pp. 1456-1469.

StataCorp, 2023. *Stata Choice Models Reference Manual Release 18,* College Station, Texas: Stata Press .

Steiner, M., 2007. *Nachfrageorientierte Präferenzmessung.* Jena: Deutscher Universitäts-Verlag | GWV Fachverlage GmbH, Wiesbaden.

Steiner, M., Eggert, A., Ulaga, W. & Backhaus, K., 2014. Do customized service packages impede value capture in industrial markets?. *Journal of the Academy of Marketing Science,* pp. 1-16.

Stigler, G. J., 1950a. The Development of Utility Theory. II. *Journal of Political Economy,* 5(58), pp. 373-396.

Suarez, F. F., Cusumano, M. A. & Kahl, S. J., 2013. Services and the Business Models of Product Firms: An Empirical Analysis of the Software Industry. *Management Science,* 2(59), pp. 420-435.

Sunstein, C. R., 2016. *The Ethics of Influence: Government in the Age of Behavioral Science.* [Online]
Available at: https://archive.org/details/ethicsofinfluenc0000suns/page/n7/mode/2up
[Accessed 02 03 2024].

Swait, J. & Louviere, J., 1993. The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models. *Journal of Marketing Research,* 3(30), pp. 305-314.

Szinay, D. et al., 2021. Understanding Uptake of Digital Health Products: Methodology Tutorial for a Discrete Choice Experiment Using the Bayesian Efficient Design. *Journal of Medical Internet Research.*

Tekle, F. B., Gudicha, D. W. & Vermunt, J. K., 2016. Power analysis for the bootstrap likelihood ratio test for the number of classes in latent class models. *Advances in Data Analysis and Classification,* Volume 10, p. 209–224.

Temme, J., 2009. Discrete-Choice-Modelle. In: S. Albers, et al. eds. *Methodik der empirischen Forschung.* Wiesbaden: Gabler | GWV Fachverlage GmbH, pp. 299 - 314.

Thaler, R. H. & Sunstein, C. R., 2008. *Nudge: Improving Decisions About Health, Wealth, and Happiness..* New Haven, CT: Yale University Press.

The Economist, 2022a. *How to fix the world's energy emergency without wrecking the environment.* [Online]
Available at: https://www.economist.com/leaders/2022/06/23/how-to-fix-the-worlds-energy-emergency-without-wrecking-the-environment
[Accessed 29 07 2022].

The Economist, 2022b. *Electrifying everything does not solve the climate crisis, but it is a great start.* [Online]
Available at: https://www.economist.com/technology-quarterly/2022/06/23/electrifying-everything-does-not-solve-the-climate-crisis-but-it-is-a-great-start
[Accessed 30 07 2022].

Thomadsen, R. et al., 2017. How Context Affects Choice. *Customer Needs and Solutions,* 5(1), p. 3–14.

Thomadsen, R. et al., 2017. How Context Affects Choice. *Customer Needs and Solutions.*

Thomson, L., Kamalaldin, A., Sjödin, D. & Parida, V., 2021. A maturity framework for autonomous solutions in manufacturing firms: The interplay oftechnology, ecosystem, and business model. *International Entrepreneurship and Management Journal,* pp. 1-28.

Thurstone, L. L., 1927. A law of comparative judgment.. *Psychological Review,* p. 273–286.

Tourangeau, R., 2021. Survey Reliability: Models, Methods, and Findings. *Journal of Survey Statistics and Methodology ,* Issue 9, pp. 961-991.

Tourangeau, R. & Rasinski, K. A., 1988. Cognitive Processes Underlying Context Effects in Attitude Measurement. *Psychological Bulletin,* 103(3), pp. 299 - 314.

Tourangeau, R., Rips, L. J. & Rasinski, K., 2000. *The Psychology of Survey Response.* Cambridge: Cambridge University Press.

Train, K., 2001. *A Comparison of Hierarchical Bayes and Maximum Simulated Likelihood for Mixed Logit,* s.l.: Department of Economics, University of California, Berkeley..

Train, K. E., 2009. *Discrete Choice Methods with Simulation.* 2 ed. Cambridge, New York, Melbourne, Madrid, Cape Town, Singapore, São Paulo, Delhi: Cambridge University Press.

Tronvoll, B., Sklyar, A., Sörhammar, D. & Kowalkowski, C., 2020. Transformational shifts through digital servitization. *Industrial Marketing Management,* Issue 89, p. 293–305.

Tukker, A., 2004. Eight types of product–service system: Eight ways to sustainability?. *Business Strategy and the Environment*, pp. 246-260.

Turner, K., 2013. 'Rebound' effects from increased energy efficiency: a time to pause and reflect. *The Energy Journal 34 (4)*, Oct., pp. 25-42.

Tversky, A. & Kahneman, D., 1981. The Framing of Decisions and the Psychology of Choice. *Science,* 211(4481), pp. 453-458.

Tyers, R., Sweeney, M. & Moon, B., 2019. Harnessing behavioural insights to encourage consumer engagement in the British energy market: Results from a field trial. *Journal of Behavioral and Experimental Economics,* Issue 80, p. 162–176.

Ulaga, W. & Reinartz, W. J., 2011. Hybrid Offerings: How Manufacturing Firms Combine Goods and Services Successfully. *Journal of Marketing*, 11, pp. 5-23.

Vandermerwe, S., 2000. How Increasing Value to Customers Improves Business Results. *MIT Sloan Management Review*, 15 10, p. 27–37.

Vandermerwe, S. & Rada, J., 1988. Servitization of business: Adding value by adding services. *European Management Journal*, pp. 314-324.

Varian, H. R., 1999. *Grundzüge der Mikroökonomik (Intermediate Microeconomics - Fourth Editions).* 4. ed. Munich, Vienna, oldenbourg: R. Oldenbourgh Verlag.

Varian, H. R., 2014. *Intermediate Microeconomics - A Modern Approach.* 9 ed. New York, London: W. W. Norton & Company.

Velamuri, V. K., 2011. *Hybrid Value Creation.* Erlangen-Nürnberg: Springer Gabler.

Velamuri, V. K., Neyer, A.-K. & Möslein, K. M., 2010. *Hybrid Value Creation - Understanding the Value Creating Attributes.* Göttingen, MKWI 2010 – Integration von Produkt und Dienstleistung - Hybride Wertschöpfung.

Velamuri, V. K., Neyer, A.-K. & Möslein, K. M., 2011. Hybrid value creation: a systematic review of an evolving research area. *Journal für Betriebswirtschaft,* Issue 61, pp. 3 - 35.

Vendrell-Herrero, F., Bustinza, O. F., Parry, G. & Georgantzis, N., 2017. Servitization, digitization and supply chain interdependency. *Industrial Marketing Management,* Issue 60, p. 69–81.

Vendrell-Herrero, F., Bustinza, O. F. & Vaillant, Y., 2021. Adoption and optimal configuration of smart products: The role of firm internationalization and offer hybridization. *Industrial Marketing Management,* Issue 95, p. 41–53.

Verma, R., Iqbal, Z. & Plaschka, G., 2004. Understanding Customer Choices in E-Financial Services. *California Management Review,* 46-67(4), p. 43.

Verma, R., Thompson, G. M. & Louviere, J. J., 1999. Configuring Service Operations in Accordance With Customer Needs and Preferences. *Journal of Service Research,* 1(3), pp. 262-274.

Verma, R., Thompson, G. M., Moore, W. L. & Louviere, J. J., 2001. Effective Design of Products/Services: An Approach Based on Integration of Marketing and Operations Management Decisions. *Decision Sciences,* 32(1), pp. 165-193.

Vij, A. & Walker, J. L., 2014. Hybrid choice models: the identification problem. In: S. Hess & A. Daly, eds. *Handbook of choice modelling.* Cheltenham: Edward Elgar Publishing Limited, pp. 519-564.

Visnjic, I., Wiengarten, F. & Neely, A., 2016. Only the Brave: Product Innovation, Service Business Model Innovation, and Their Impact on Performance. *Product Development & Management Association,* 1(33), pp. 36-52.

Vogel, V., Evanschitzky, H. & Ramaseshan, B., 2008. Customer Equity Drivers and Future Sales. *Journal of Marketing,* Issue 72, pp. 98-108.

von Neumann, J. & Morgenstern, O., 1944. *Theory of Games and Economic Behaviour.* Princeton: Princeton University Press.

Wagstaff, S., Burton, J. & Zolkiewski, J., 2021. Should We Cooperate? Game Theory Insights for Servitization.. *Journal of Service Management,* pp. 1-78.

Wallis, H. & Loy, L. S., 2021. What drives pro-environmental activism of young people? A survey study on the Fridays For Future movement. *Journal of Environmental Psychology,* Issue 74, pp. 1-10.

Wang, H., Rowen, D. L., Brazier, J. E. & Jiang, L., 2023. Discrete Choice Experiments in Health State Valuation: A Systematic Review of Progress and New Trends. *Applied Health Economics and Health Policy,* Issue 21, p. 405–418.

Wang, S., Mo, B. & Zhao, J., 2020. Deep neural networks for choice analysis: Architecture design with alternative-specific utility functions. *Transportation Research Part C,* Issue 112, pp. 234-251.

Westerman, G., Bonnet, D. & McAfee, A., 2014. *Leading Digital: Turning Technology into Business Transformation.* s.l.:Harvard Business Review Press.

Wierenga, B., 1984. Empirical test of the Lancaster characteristics model. *International Journal of Research in Marketing,* Issue 1, pp. 263-293.

Williamson, O. E., 2000. The New Institutional Economics: Taking Stock, Looking Ahead. *Journal of Economic Literature,* 3(38), pp. 595-613.

Williams, R., 2006. Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *The Stata Journal ,* Issue 1, p. 58–82.

Willig, R. D., 1976. Consumer's Surplus Without Apology. *The American Economic Review,* 4(66), pp. 589-597.

Wirtz, B. W., 2019. *Digital Business Models.* Cham, Switzerland: Springer Nature Switzerland AG.

Woldeab, S., 2014. *Leistungsdifferenzierung im Energieversorgungswettbewerb.* 1. ed. Munich, Mering: Rainer Hampp Verlag.

Woll, A., 1993. *Allgemeine Volkswirtschaftslehre.* 11 ed. Munich: Verlag Franz Vahlen GmbH.

Woo, C. et al., 2014. A review of electricity product differentiation. *Applied Energy,* Issue 114, pp. 262-272.

Woodruff, R. B., 1997. Customer Value: The Next Source for Competitive Advantage. *Journal of the Academy of Marketing Science,* 2(25), pp. 139-153.

Worm, S., Bharadwaj, S. G., Ulaga, W. & Reinartz, W. J., 2017. When and why do customer solutions pay off in business markets?. *Journal of the Academic Marketing Science,* Issue 45, p. 490–512.

Yang, C.-C. & Yang, C.-C., 2007. Separating Latent Classes by Information Criteria. *Journal of Classification,* Volume 24, pp. 183-203.

Yang, J.-C.et al., 2021. Is Easier Better Than Harder? An Experiment on Choice Experiments for Benefit-Risk Tradeoff Preferences. *Medical Decision Making,* 41(2), pp. 222-232.

Zamrudi, Z. et al., 2019. Smart meter adoption: the role of consumer experience in using smart device. *IOP Conf. Series: Journal of Physics: Conf. Series ,* Issue 1175.

Zhou, C. & Song, W., 2021. Digitalization as a way forward: A bibliometric analysis of 20 Years of servitization research. *Journal of Cleaner Production,* Issue 300, pp. 1-14.

8 Appendices

8.1 Choice design efficiency test (Sawtooth)

```
CBC Design Efficiency Test
Copyright Sawtooth Software
11/23/2020 9:00:02 AM

Task generation method is 'Balanced Overlap' using a seed of 43.
Based on 400 version(s).
Includes 4800 total choice tasks (12 per version).
Each choice task includes 2 concepts and 9 attributes.


A Priori Estimates of Standard Errors for Attribute Levels
-------------------------------------------------------------
Att/Lev   Freq.   Actual    Ideal      Effic.
 1    1      3200 (this level has been deleted) fixed price
 1    2      3200   0.0313   0.0312   0.9895    pre def plan
 1    3      3200   0.0310   0.0312   1.0112    consumption based

 2    1      4800 (this level has been deleted) yes
 2    2      4800   0.0224   0.0224   0.9995    no

 3    1      4800 (this level has been deleted) yes
 3    2      4800   0.0222   0.0222   0.9996    no

 4    1      4801 (this level has been deleted) yes
 4    2      4799   0.0222   0.0222   0.9995    no

 5    1      4800 (this level has been deleted) yes
 5    2      4800   0.0224   0.0224   0.9998    no

 6    1      4800 (this level has been deleted) yes
 6    2      4800   0.0224   0.0223   0.9996    no

 7    1      4800 (this level has been deleted) yes
 7    2      4800   0.0225   0.0225   0.9996    no

 8    1      1920 (this level has been deleted) no socket
 8    2      1921   0.0421   0.0424   1.0136    manually
 8    3      1920   0.0424   0.0424   1.0000    local
 8    4      1919   0.0424   0.0424   0.9971    smart app only
 8    5      1920   0.0424   0.0424   1.0005    smart app analysis

 9    1      1601 (this level has been deleted) 0
 9    2      1600   0.0467   0.0470   1.0117    5
 9    3      1599   0.0470   0.0470   0.9984    10
 9    4      1600   0.0471   0.0470   0.9941    15
 9    5      1600   0.0470   0.0470   0.9988    20
 9    6      1600   0.0472   0.0470   0.9938    25

Note: The efficiencies reported above for this design assume an equal number of respondents complete each
version.
```

Two-Way Frequencies

Att/ Lev	1/1	1/2	1/3	2/1	2/2	3/1	3/2	4/1	4/2	5/1	5/2	6/1	6/2	7/1	7/2	8/1	8/2	8/3	8/4	8/5	9/1	9/2	9/3	9/4	9/5	9/6
1/1	3200	0	0	1601	1599	1599	1601	1601	1599	1599	1601	1600	1600	1599	1601	640	640	640	640	640	535	534	531	534	533	533
1/2	0	3200	0	1599	1601	1601	1599	1601	1599	1601	1599	1601	1599	1600	1600	642	640	639	639	640	532	533	534	535	534	532
1/3	0	0	3200	1600	1600	1600	1600	1599	1601	1600	1600	1599	1601	1601	1599	638	641	641	640	640	534	533	534	531	533	535
2/1	1601	1599	1600	4800	0	2399	2401	2400	2400	2399	2401	2399	2401	2400	2400	959	961	961	960	959	798	800	799	800	801	802
2/2	1599	1601	1600	0	4800	2401	2399	2401	2399	2401	2399	2401	2399	2400	2400	961	960	959	959	961	803	800	800	800	799	798
3/1	1599	1601	1600	2399	2401	4800	0	2399	2401	2400	2400	2401	2399	2402	2398	958	960	958	961	963	803	801	800	797	800	799
3/2	1601	1599	1600	2401	2399	0	4800	2402	2398	2400	2400	2399	2401	2398	2402	962	961	962	958	957	798	799	799	803	800	801
4/1	1601	1601	1599	2400	2401	2399	2402	4801	0	2400	2401	2401	2400	2401	2400	960	961	959	959	962	800	800	799	800	800	802
4/2	1599	1599	1601	2400	2399	2401	2398	0	4799	2400	2399	2399	2400	2399	2400	960	960	961	960	958	801	800	800	800	800	798
5/1	1599	1601	1600	2399	2401	2400	2400	2400	2400	4800	0	2400	2400	2399	2401	960	959	961	961	959	802	800	799	800	800	799
5/2	1601	1599	1600	2401	2399	2400	2400	2401	2399	0	4800	2400	2400	2401	2399	960	962	959	958	961	799	800	800	800	800	801
6/1	1600	1601	1599	2399	2401	2401	2399	2401	2399	2400	2400	4800	0	2400	2400	961	961	959	958	961	800	800	797	801	801	801
6/2	1600	1599	1601	2401	2399	2399	2401	2400	2400	2400	2400	0	4800	2400	2400	959	960	961	961	959	801	800	802	799	799	799
7/1	1599	1600	1601	2400	2400	2402	2398	2401	2399	2399	2401	2400	2400	4800	0	962	960	959	959	960	801	799	801	801	800	798
7/2	1601	1600	1599	2400	2400	2398	2402	2400	2400	2401	2399	2400	2400	0	4800	958	961	961	960	960	800	801	798	799	800	802
8/1	640	642	638	959	961	958	962	960	960	960	960	961	959	962	958	1920	0	0	0	0	320	321	318	319	321	321
8/2	640	640	641	961	960	960	961	961	960	959	962	961	960	960	961	0	1921	0	0	0	321	321	320	320	320	319
8/3	640	639	641	961	959	958	962	959	961	961	959	959	961	959	961	0	0	1920	0	0	323	321	319	319	318	320
8/4	640	639	640	960	959	961	958	959	960	961	958	958	961	959	960	0	0	0	1919	0	318	319	321	322	320	319
8/5	640	640	640	959	961	963	957	962	958	959	961	961	959	960	960	0	0	0	0	1920	319	318	321	320	321	321
9/1	535	532	534	798	803	803	798	800	801	802	799	800	801	801	800	320	321	323	318	319	1601	0	0	0	0	0
9/2	534	533	533	800	800	801	799	800	800	800	800	800	800	799	801	321	321	321	319	318	0	1600	0	0	0	0
9/3	531	534	534	799	800	800	799	799	800	799	800	797	802	801	798	318	320	319	321	321	0	0	1599	0	0	0
9/4	534	535	531	800	800	797	803	800	800	800	800	801	799	801	799	319	320	319	322	320	0	0	0	1600	0	0
9/5	533	534	533	801	799	800	800	800	800	800	800	801	799	800	800	321	320	318	320	321	0	0	0	0	1600	0
9/6	533	532	535	802	798	799	801	802	798	799	801	801	799	798	802	321	319	320	319	321	0	0	0	0	0	1600

8.2 Survey questions and scales

No	Question	Remarks
S1	Are you male or female?	
	Male	
	Female	
	Other	
S2	How old are you?	
	|____| years	
S3	In what area code area do you live?	
S4-1	Who is responsible in your household regarding questions like brand selection and grocery shopping?	
	My own responsibility	
	Shared responsibility	
	Full responsibility of an other person	
S4-2	Who is responsible in your household regarding decisions concerning your car (Buying, Selling, Maintenance, etc.)	
	My own responsibility	
	Shared responsibility	
	Full responsibility of an other person	
S4-3	Who is responsible in your household regarding decisions concerning energy supply?	
	My own responsibility	
	Shared responsibility	
	Full responsibility of an other person	
S4-4	Who is responsible in your household regarding decisions concerning telecommunication and internet?	
	My own responsibility	
	Shared responsibility	
	Full responsibility of an other person	
S5	What is you current ownership or rental status	
	Rented Apartment	
	Rented House	
	Property Apartment	
	Property House	
	Other	
F1G1	Please evaluate, how digital you perceive the following product attributes	
	Very digital	for each attribute level
	Slightly digital	
	Little digital	
	not digital	
	I don't know / no answer	

No	Question	Remarks
F1G2	Please rank the following product attributes. Start with the one that you perceive as the most digital on Number 1 (= most digital, 4 = least digital)	
	most digital	For all attribute level of each attribute
	second most digital	
	third most digital (in the case of three attribute level: least digital)	
	least digital	

DCE "… Please look at the two product alternatives and choose for that one that you perceive as the most favourite."

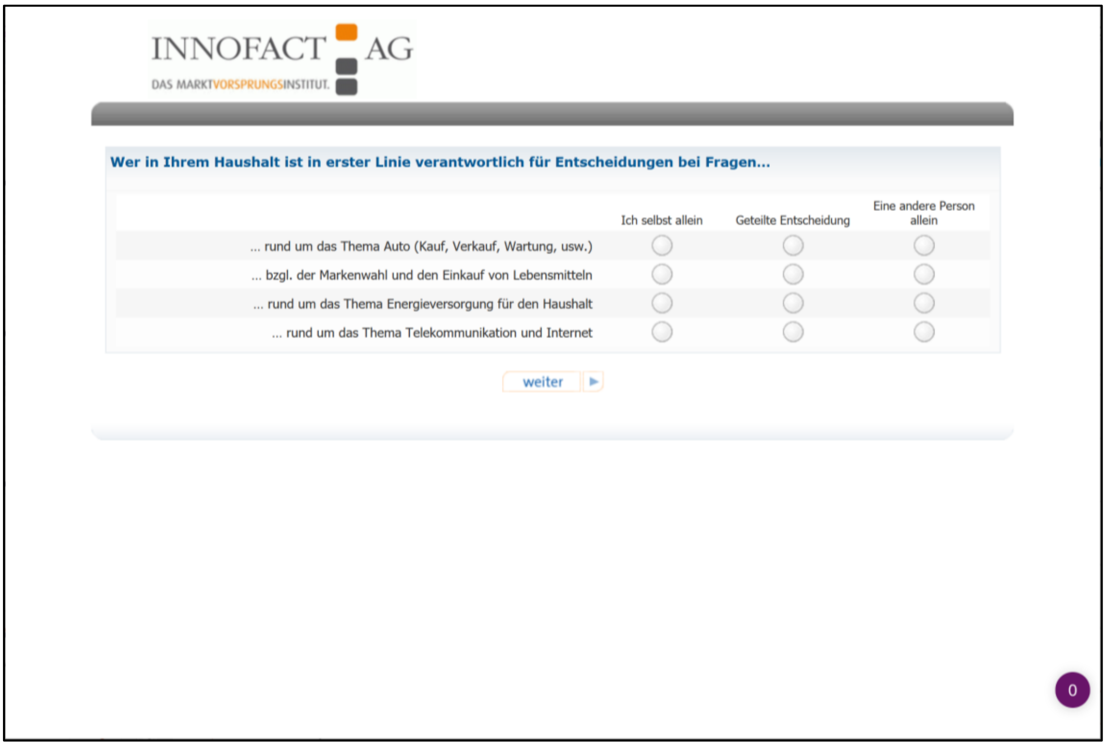
No	Question	Remarks
F3	How certain have you been with the choices of the different product alternatives?	
	absolute certain	
	certain	
	neither/nor	
	little certain	
	absolute not certain	
F4	How easy did you find the choices for the different product alternatives?	
	very easy	
	easy	
	neither/nor	
	hard	
	very hard	
F5	How likely would it be, that you can buy the following attribute combination on the free market? - Source of price calculation: Decreasing prices per kWh each month with increase or decrease of overall consumption - Price communication and access to bills through mobile app - Additional device included in the contract: Smart plug adapter incl. smartphone app and algorithm - Service infrastructure: Message service within smartphone app	
	Most likely	
	likely	
	neither/nor	
	little likely	
	Unlikely	

No	Question	Remarks
F6	In the survey we wanted to know, which product alternative you would prefer and would buy. For us it would be interesting to know, if your decision would have changed in the case of a different payment method, e.g. in the case of a service fee instead of a full purchase. **Description FULL PURCHASE:** After the contract you have the ownership of the devices. You don't need to return them and are able to use them to your own will. This means, the device will fully be financed through the monthly payments. If the device breaks (and now warranty applies), it will not be replaced **Description SERVICE FEE:** The devices will be replaced after the contract with new or better devices. If the device breaks it will be replaced. If the contract is cancelled you have to return the device. You only have the monthly payments to pay Please tell us, which payment methods (based on the descriptions above) are of relevance for you (multi selection possible)	
	Hire purchase	
	Full purchase at the begin of the contract	
	Service or use fee	
	I don't know / no answer	
F7	From the selected payment methods, which one would be your most preferred? (Display dependent from choice of prior question)	
	Hire purchase	
	Full purchase at the begin of the contract	
	Service or use fee	
	I don't know / no answer	
F8	With regards to your attitude to services and products we would like to know the statement that apply most to you:	
	Usually I buy services and products as one of the first	
	I usually wait with buying new products and services until first experiences and tests are available	
	I usually buy new services and products when they reached a certain maturity and have proven useful	
	I usually buy new services and products when I am able to get them as a discount.	
	I usually stick with my services and products and only buy new ones, when there is no alternative left.	
F9	How often did you switch your energy provider in the past 5 years (please so not take switching due to moving into account)	
	None	
	1 time	
	2 times	
	3 times	
	4 times or more	
	I don't know / no answer	

No	Question	Remarks
F10	Do you already use programmable or smart plugs? (multi selection)	
	No (single selection)	
	yes, Manually adjustable electric plug adapter	
	yes, Local connected electric plug adapter	
	yes, Smart plug adapter incl. smartphone app	
	yes, Smart plug adapter incl. smartphone app and algorithm	
	yes, other smart plugs: |________________________| (input)	
	I don't know / no answer (single selection)	
F11	Would you describe yourself rather ecological or economical oriented?	
	Full ecological focus	
	Mostly ecological focus	
	Slightly ecological focus	
	Ecological and economical with same shares	
	Slightly economical focus	
	Mostly economical focus	
	Full economical focus	
F2G1	Please evaluate, how digital you perceive the following product attributes	
	see above	
F2G2	Please rank the following product attributes. Start with the one that you perceive as the most digital on Number 1 (= most digital, 4 = least digital)	
	see above	
SD1	What is your last - or current - educational achievement	
	Secondary school without completed vocational training	
	Secondary school with completed vocational training	
	University entrance qualification with completed vocational training	
	High School without University entrance qualification	
	University entrance qualification without completed university studies	
	Completed university studies	
SD2	What is your current professional situation?	
	Full time job	
	Part time job	
	currently unemployed	
	Retired	
	Househusband/wife	
	Student	

No	Question	Remarks
SD3	What is your current position within your company	
	C-Level	
	Owner	
	Senior Management	
	Middle Management	
	Higher State Officer	
	Medium State Officer	
	Project Management	
	Employee	
	Blue Collar // Worker	
	Trainee	
	Other	
SD4	What is your current household income?	
	under 1.000 €	
	1.000€ - 1.999€	
	2.000€ - 2.999€	
	3.000€ - 3.999€	
	4.000€ - 4.999€	
	5.000€ - 5.999€	
	over 6.000 €	
SD5	What is your family status?	
	Marriage	
	not married, with partner	
	divorced, widowed	
	single	
SD5	How many persons live in your household (over 18 years)?	
	1 Person (only me)	
	2 Persons	
	3 Persons	
	4 Persons	
	5 and more Persons	
SD6	Are there children in your household below the age of 18?	
	No	
	Yes, one child under the age of 18	
	Yes, two children under the age of 18	
	Yes, three or more children under the age of 18	

8.3 Survey example (control group)



INNOFACT AG
DAS MARKTVORSPRUNGSINSTITUT.

Im Folgenden werden wir Ihnen einige Fragen zu verschiedenen Energieprodukten stellen. Stellen Sie sich vor, Sie stehen vor der Entscheidung einen neuen Stromtarif abzuschließen. Sie haben dabei die Möglichkeit aus verschiedenen Produktvarianten zu wählen, die sich in ihren Eigenschaften unterscheiden. Bitte schauen Sie sich jeweils alle möglichen Varianten an und entscheiden sich für die aus Ihrer Sicht beste Alternative.

Diese Ausgangslage gilt für alle Fragen und ändert sich nicht. Lediglich die Zusammensetzung der Produktalternativen wird variiert.

Bitte klicken Sie auf 'weiter' ...

weiter

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Allgemeine Informationen zu den Produktbestandteilen

Grundlage für die Gestaltung des Arbeitspreises
Die Preisermittlung für Strom (kWh) kann inzwischen auch in Abhängigkeit vom Verbrauchsverhalten gestaltet werden. Die technischen Grundlagen dafür (sog. "Smart Meter") werden in Zukunft in jedem Haus verfügbar sein.

Bereitstellung der Preisinformationen und Rechnungen
Es werden Ihnen verschiedene Arten der Bereitstellung angeboten. Gehen Sie davon aus, dass Sie die Regelmäßigkeit dieser Kommunikation nach Vertragsabschluss selber festlegen können.

Service- bzw. Kontaktmöglichkeiten mit dem Anbieter
Für den Kontakt (z.B. für Fragen zur Rechnung) zu Ihrem Stromanbieter werden Ihnen verschiedene Interaktions- und Kontaktkanäle angeboten.

Steckdosen
Ein Produktbestandteil werden Steckdosen bzw. sog. Zwischenstecker für eine Steuerung der angeschlossenen Geräte sein (z.B. via Zeitschaltfunktion). Mit diesen Steckern können Sie je nach Variante automatische An/Aus-Zeiten festlegen, angeschlossene Geräte fernsteuern, den Stromverbrauch einsehen/auswerten oder Einschalt- bzw. Abschalt-Abläufe programmieren. Diese Steckdosen funktionieren wie „normale" Verlängerungskabel; es ist keine bauliche Veränderung notwendig.
Eine Kurzbeschreibung der vier möglichen Steckdosenvarianten wird Ihnen in der Befragung jeweils durch folgendes Symbol angezeigt: ⓘ.

Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis
Jeder Stromtarif enthält einen verbrauchsunabhängigen Preisbestandteil (sog. 'Grundpreis'). Die dargestellten Kosten decken den Grundpreis und zusätzlich alle Aufwände für die Produkt- und Servicebestandteile ab.

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Stellen Sie sich vor, Sie stehen vor der Entscheidung einen neuen Stromtarif abzuschließen. Sie haben dabei die Möglichkeit, aus zwei Produktvarianten zu wählen, die sich lediglich in den unten aufgeführten Bestandteilen unterscheiden. Bitte schauen Sie sich jeweils beide möglichen Produkte an und entscheiden sich dann für die aus Ihrer Sicht beste Alternative.

Wir möchten Sie bitten, diese Entscheidungssituation völlig unabhängig von Ihren vorherigen Entscheidungen und nur auf Basis der unten gezeigten Produkte zu treffen.

	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ	Festpreis pro kWh, gültig für die gesamte Vetragsdauer
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Durch ein Online-Kundenportal • Über eine Smartphone-App	• Per Post • Via E-Mail
Servicekontakt ⓘ	• Über ein Callcenter • Via Chat ⓘ auf Homepage	• Über ein Callcenter • Via E-Mail • In einer Smartphone-App
Im Angebot enthaltene Steckdose ⓘ	Intelligente Steckdose inkl. App ⓘ	Intelligente Steckdose inkl. App und Analyse ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	0,00 €	14,99 €
	○	○

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Vielen Dank für Ihre erste Antwort in diesem Teil des Fragebogens. Im Folgenden wird Ihnen diese Entscheidungssituation erneut mehrere Male mit unterschiedlichen Produkten präsentiert. Auch wenn es auf den ersten Blick nicht so aussieht, variieren dabei alle Produkte in ihren Bestandteilen und weichen voneinander ab.

Wir möchten Sie bitten, diese Entscheidungssituation völlig unabhängig von Ihren vorherigen Entscheidungen und jedes Mal neu zu treffen.

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Stellen Sie sich vor, Sie stehen vor der Entscheidung einen neuen Stromtarif abzuschließen. Sie haben dabei die Möglichkeit, aus zwei Produktvarianten zu wählen, die sich lediglich in den unten aufgeführten Bestandteilen unterscheiden. Bitte schauen Sie sich jeweils beide möglichen Produkte an und entscheiden sich dann für die aus Ihrer Sicht beste Alternative.

Wir möchten Sie bitten, diese Entscheidungssituation völlig unabhängig von Ihren vorherigen Entscheidungen und nur auf Basis der unten gezeigten Produkte zu treffen.

	Produkt 1	Produkt 2
Grundlage für die Preisgestaltung pro kWh ⓘ	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ	Wechselnde kWh-Preise gemäß Verbrauchsverhalten ⓘ
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Durch ein Online-Kundenportal	• Per Post • Via E-Mail • Über eine Smartphone-App
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail • Via Chat ⓘ auf Homepage	• Über ein Callcenter • In einer Smartphone-App
Im Angebot enthaltene Steckdose ⓘ	Intelligente Steckdose inkl. App ⓘ	Manuell programmierbare Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	4,99 €	14,99 €
	○	○

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Stellen Sie sich vor, Sie stehen vor der Entscheidung einen neuen Stromtarif abzuschließen. Sie haben dabei die Möglichkeit, aus zwei Produktvarianten zu wählen, die sich lediglich in den unten aufgeführten Bestandteilen unterscheiden. Bitte schauen Sie sich jeweils beide möglichen Produkte an und entscheiden sich dann für die aus Ihrer Sicht beste Alternative.

Wir möchten Sie bitten, diese Entscheidungssituation völlig unabhängig von Ihren vorherigen Entscheidungen und nur auf Basis der unten gezeigten Produkte zu treffen.

	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Wechselnde kWh-Preise gemäß Verbrauchsverhalten ⓘ	Wechselnde kWh-Preise gemäß Verbrauchsverhalten ⓘ
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Via E-Mail • Durch ein Online-Kundenportal	• Per Post • Über eine Smartphone-App
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail • Via Chat ⓘ auf Homepage • In einer Smartphone-App	• Über ein Callcenter
Im Angebot enthaltene Steckdose ⓘ	Lokal vernetzte Steckdose ⓘ	Intelligente Steckdose inkl. App und Analyse ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	9,99 €	9,99 €
	○	○

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	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Festpreis pro kWh, gültig für die gesamte Vetragsdauer	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Via E-Mail • Durch ein Online-Kundenportal	• Per Post
Servicekontakt ⓘ	• Über ein Callcenter • Via Chat ⓘ auf Homepage	• Über ein Callcenter • Via E-Mail • In einer Smartphone-App
Im Angebot enthaltene Steckdose ⓘ	Lokal vernetzte Steckdose ⓘ	Keine Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	24,99 €	19,99 €
	○	○

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	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Festpreis pro kWh, gültig für die gesamte Vetragsdauer	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Via E-Mail • Über eine Smartphone-App	• Per Post • Via E-Mail • Über eine Smartphone-App
Servicekontakt ⓘ	• Über ein Callcenter	• Über ein Callcenter • Via E-Mail • Via Chat ⓘ auf Homepage
Im Angebot enthaltene Steckdose ⓘ	Lokal vernetzte Steckdose ⓘ	Lokal vernetzte Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	4,99 €	19,99 €
	○	○

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Vielen Dank für Ihre Antworten bisher. Es folgen nun noch **8** weitere Abfragen, bevor wir Ihnen noch einige generelle abschließende Fragen stellen wollen.

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Stellen Sie sich vor, Sie stehen vor der Entscheidung einen neuen Stromtarif abzuschließen. Sie haben dabei die Möglichkeit, aus zwei Produktvarianten zu wählen, die sich lediglich in den unten aufgeführten Bestandteilen unterscheiden. Bitte schauen Sie sich jeweils beide möglichen Produkte an und entscheiden sich dann für die aus Ihrer Sicht beste Alternative.

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	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ	Festpreis pro kWh, gültig für die gesamte Vetragsdauer
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Via E-Mail • Durch ein Online-Kundenportal • Über eine Smartphone-App	• Per Post • Über eine Smartphone-App
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail • Via Chat ⓘ auf Homepage • In einer Smartphone-App	• Über ein Callcenter
Im Angebot enthaltene Steckdose ⓘ	Intelligente Steckdose inkl. App und Analyse ⓘ	Manuell programmierbare Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	14,99 €	4,99 €
	○	○

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	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Festpreis pro kWh, gültig für die gesamte Vetragsdauer	Wechselnde kWh-Preise gemäß Verbrauchsverhalten ⓘ
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Durch ein Online-Kundenportal	• Per Post • Via E-Mail • Durch ein Online-Kundenportal • Über eine Smartphone-App
Servicekontakt ⓘ	• Über ein Callcenter • In einer Smartphone-App	• Über ein Callcenter • Via E-Mail • Via Chat ⓘ auf Homepage
Im Angebot enthaltene Steckdose ⓘ	Intelligente Steckdose inkl. App und Analyse ⓘ	Keine Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	14,99 €	0,00 €
	○	○

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	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Festpreis pro kWh, gültig für die gesamte Vetragsdauer	Festpreis pro kWh, gültig für die gesamte Vetragsdauer
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Über eine Smartphone-App	• Per Post • Via E-Mail • Durch ein Online-Kundenportal
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail • Via Chat ⓘ auf Homepage • In einer Smartphone-App	• Über ein Callcenter
Im Angebot enthaltene Steckdose ⓘ	Intelligente Steckdose inkl. App ⓘ	Keine Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	0,00 €	19,99 €
	○	○

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	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Wechselnde kWh-Preise gemäß Verbrauchsverhalten ⓘ	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Via E-Mail	• Per Post
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail • Via Chat ⓘ auf Homepage	• Über ein Callcenter
Im Angebot enthaltene Steckdose ⓘ	Manuell programmierbare Steckdose ⓘ	Lokal vernetzte Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	4,99 €	4,99 €
	○	○

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Vielen Dank für Ihre Antworten bisher. Es folgen nun noch **4** weitere Abfragen, bevor wir Ihnen noch einige generelle abschließende Fragen stellen wollen.

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Wir möchten Sie bitten, diese Entscheidungssituation völlig unabhängig von Ihren vorherigen Entscheidungen und nur auf Basis der unten gezeigten Produkte zu treffen.

	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Durch ein Online-Kundenportal • Über eine Smartphone-App	• Per Post • Via E-Mail • Über eine Smartphone-App
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail • In einer Smartphone-App	• Über ein Callcenter • Via Chat ⓘ auf Homepage
Im Angebot enthaltene Steckdose ⓘ	Lokal vernetzte Steckdose ⓘ	Intelligente Steckdose inkl. App ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	19,99 €	9,99 €
	○	○

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Wir möchten Sie bitten, diese Entscheidungssituation völlig unabhängig von Ihren vorherigen Entscheidungen und nur auf Basis der unten gezeigten Produkte zu treffen.

	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Wechselnde kWh-Preise gemäß Verbrauchsverhalten ⓘ	Festpreis pro kWh, gültig für die gesamte Vetragsdauer
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Via E-Mail • Durch ein Online-Kundenportal • Über eine Smartphone-App	• Per Post
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail • Via Chat ⓘ auf Homepage • In einer Smartphone-App	• Über ein Callcenter • Via Chat ⓘ auf Homepage • In einer Smartphone-App
Im Angebot enthaltene Steckdose ⓘ	Keine Steckdose ⓘ	Keine Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	24,99 €	14,99 €
	○	○

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Stellen Sie sich vor, Sie stehen vor der Entscheidung einen neuen Stromtarif abzuschließen. Sie haben dabei die Möglichkeit, aus zwei Produktvarianten zu wählen, die sich lediglich in den unten aufgeführten Bestandteilen unterscheiden. Bitte schauen Sie sich jeweils beide möglichen Produkte an und entscheiden sich dann für die aus Ihrer Sicht beste Alternative.

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	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Wechselnde kWh-Preise gemäß Verbrauchsverhalten ⓘ	Festpreis pro kWh, gültig für die gesamte Vetragsdauer
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Via E-Mail • Durch ein Online-Kundenportal	• Per Post • Über eine Smartphone-App
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail	• Über ein Callcenter • Via Chat ⓘ auf Homepage • In einer Smartphone-App
Im Angebot enthaltene Steckdose ⓘ	Intelligente Steckdose inkl. App und Analyse ⓘ	Manuell programmierbare Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	9,99 €	24,99 €
	○	○

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Stellen Sie sich vor, Sie stehen vor der Entscheidung einen neuen Stromtarif abzuschließen. Sie haben dabei die Möglichkeit, aus zwei Produktvarianten zu wählen, die sich lediglich in den unten aufgeführten Bestandteilen unterscheiden. Bitte schauen Sie sich jeweils beide möglichen Produkte an und entscheiden sich dann für die aus Ihrer Sicht beste Alternative.

Wir möchten Sie bitten, diese Entscheidungssituation völlig unabhängig von Ihren vorherigen Entscheidungen und nur auf Basis der unten gezeigten Produkte zu treffen.

	Produkt 1	**Produkt 2**
Grundlage für die Preisgestaltung pro kWh ⓘ	Wechselnde kWh-Preise gemäß Verbrauchsverhalten ⓘ	Unterschiedliche kWh-Preise nach einem vordefinierten Zeitplan ⓘ
Bereitstellung Rechnungen und Preisinformationen ⓘ	• Per Post • Via E-Mail	• Per Post • Durch ein Online-Kundenportal • Über eine Smartphone-App
Servicekontakt ⓘ	• Über ein Callcenter • Via E-Mail • In einer Smartphone-App	• Über ein Callcenter
Im Angebot enthaltene Steckdose ⓘ	Intelligente Steckdose inkl. App ⓘ	Manuell programmierbare Steckdose ⓘ
Verbrauchsunabhängige monatliche Kosten inkl. Grundpreis ⓘ	0,00 €	14,99 €
	○	○

Bitte klicken Sie auf 'weiter' ...

weiter ▶

0

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Danke, dass Sie an diesem Teil der Befragung teilgenommen haben. Sie werden nun zu den weiteren Fragen geleitet.

Bitte klicken Sie auf 'weiter' ...

weiter

0

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Wie sicher waren Sie sich bei Ihren Entscheidungen für die verschiedenen Produktalternativen?

völlig sicher	sicher	weder/noch	unsicher	völlig unsicher
○	○	○	○	○

weiter

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Wie einfach fanden Sie die Entscheidungen für die verschiedenen Produktalternativen?

sehr einfach	einfach	weder/noch	schwer	sehr schwer
○	○	○	○	○

weiter ▶

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Für wie wahrscheinlich halten Sie es, dass die folgende Eigenschaftskombination am Markt verfügbar ist?

Preisgestaltung:
Wechselnde kWh-Preise gemäß Verbrauchsverhalten z.B. günstige Preise bei Verbrauchsreduzierungen

Preisinformationen & Rechnungen:
Bereitstellung der Preisinformationen und Rechnungen durch eine Smartphone-Anwendung (App)

Zusätzliches Gerät:
Intelligente Steckdose inkl. App und Algorithmus

Servicekanäle:
Nachrichtenfunktion in einer Smartphone-Anwendung (App)

Höchst wahrscheinlich	Wahrscheinlich	Neutral	Unwahrscheinlich	Höchst unwahrscheinlich
○	○	○	○	○

weiter ▶

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In der Befragung haben wir Sie gefragt, welches der jeweils dargestellten Angebote Sie kaufen würden.

Es wäre uns noch wichtig zu wissen, wie Ihre Entscheidung im Falle eines anderen Bezahlmodells, z.B. einer monatlichen Servicegebühr anstelle des Kaufes, ausgesehen hätte.

Folgende Rahmenbedingungen sehen wir für die beiden Bezahlmodelle insbesondere in Hinblick auf die im Angebot enthaltenen Steckdosen:

Rahmenbedingungen KAUF:
Die Geräte gehören nach Abschluss der ursprünglichen Vertragslaufzeit Ihnen, Sie können sie weiter ohne Einschränkungen nutzen und müssen diese nicht zurückgeben. Das heißt, dass das Gerät durch die monatlichen Beiträge einmalig bezahlt wird. Bei Defekt werden die Geräte nicht ersetzt.

Rahmenbedingungen GEBÜHR:
Die Geräte werden nach Ablauf der ursprünglichen Vertragslaufzeit durch neue ersetzt. Bei Defekt werden die Geräte auch ersetzt. Bei Vertragsende müssen Sie die Geräte dem Anbieter zurückgeben. Demnach haben Sie für das Gerät regelmäßige Kosten.

Bitte geben Sie an, welche Zahlungsvarianten in dem oben genannten Kontext für Sie grundsätzlich denkbar sind. (Mehrfachnennungen möglich)

- ☐ Service-/ Nutzungsgebühr
- ☐ Kauf komplett
- ☐ Kauf auf Raten
- ☐ Weiß nicht / Keine Angabe

weiter ▶

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Und welche Zahlungsvariante würden Sie favorisieren?

- ○ Kauf auf Raten
- ○ Kauf komplett
- ○ Service-/ Nutzungsgebühr
- ○ Unentschlossen / egal

weiter ▶

0

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In Bezug auf neue Dienstleistungen und Produkte würden wir gern Ihre Haltung kennenlernen. Bitte wählen Sie die Aussage aus, die am ehesten für Sie zutrifft:

- ○ Ich gehöre immer zu den Ersten, die neue Dienstleistungen und Produkte direkt nutzen, sobald sie auf den Markt kommen.
- ○ Ich nutze gerne neue Dienstleistungen und Produkte, warte aber, bis sie von den ersten Nutzern getestet wurden.
- ○ Ich nutze neue Dienstleistungen und Produkte meist erst, wenn sie sich als nützlich am Markt bewährt haben.
- ○ Ich nutze neue Dienstleistungen und Produkte erst, wenn sie auf dem Markt deutlich preisgünstiger angeboten werden.
- ○ Ich bin zufrieden mit den Dienstleistungen und Produkten, die ich bisher nutze und nutze neue Dienstleistungen und Produkte nur, wenn es auf dem Markt keine Alternative mehr gibt.

weiter ▶

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Wie häufig haben Sie in den letzten 5 Jahren Ihren Stromversorger aktiv gewechselt (ohne Berücksichtigung von Umzügen)?

- ○ Gar nicht
- ○ 1 Mal
- ○ 2 Mal
- ○ 3 Mal
- ○ 4 Mal oder noch häufiger
- ○ Weiß nicht / Keine Angabe

weiter ▶

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Nutzen Sie bereits programmierbare, vernetzte bzw. intelligente Steckdosen?

(Mehrfachnennungen möglich)

- ☐ Nein
- ☐ Ja, manuell programmierbare Steckdosen
- ☐ Ja, lokal vernetzte Steckdose
- ☐ Ja, intelligente Steckdose inkl. App
- ☐ Ja, intelligente Steckdose inkl. App und Analyse
- ☐ Ja, sonstige Steckdosen und zwar: ____
- ☐ Weiß nicht / Keine Angabe

weiter ▶

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Würden Sie sich eher als ökologisch oder ökonomisch orientiert einschätzen?

Vollständig ökologisch orientiert	Meist ökologisch orientiert	Eher ökologisch orientiert	Zu gleichen Teilen ökologisch und ökonomisch	Eher ökonomisch orientiert	Meist ökonomisch orientiert	Vollständig ökonomisch orientiert
○	○	○	○	○	○	○

weiter ▶

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Im Folgenden bitten wir Sie, Produkte und Produkteigenschaften zu bewerten. Für die Bewertung wollen wir uns insbesondere auf das Thema Digitalisierung dieser Produkte und Produkteigenschaften konzentrieren. Uns ist dabei wichtig, dass Sie sich darauf konzentrieren, was Sie – ganz persönlich– als digital einschätzen (und was nicht). Es gibt hier kein Richtig oder Falsch!

Wenn Sie Sich bei der Einschätzung nicht sicher sind, überlegen Sie, ob die jeweilige Eigenschaft aus Ihrer Sicht viel oder wenig Technologie/Daten bedingt, benötigt oder enthält.

(Weiter-Button erscheint in Kürze)

0

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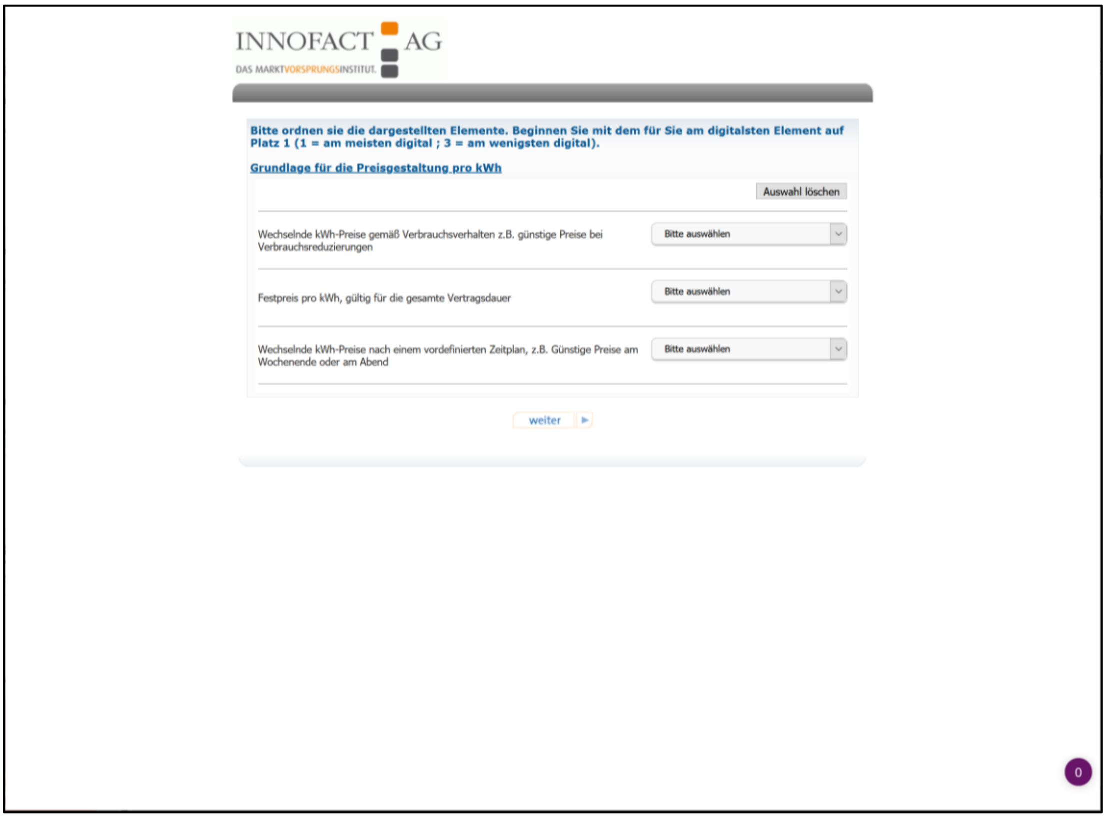
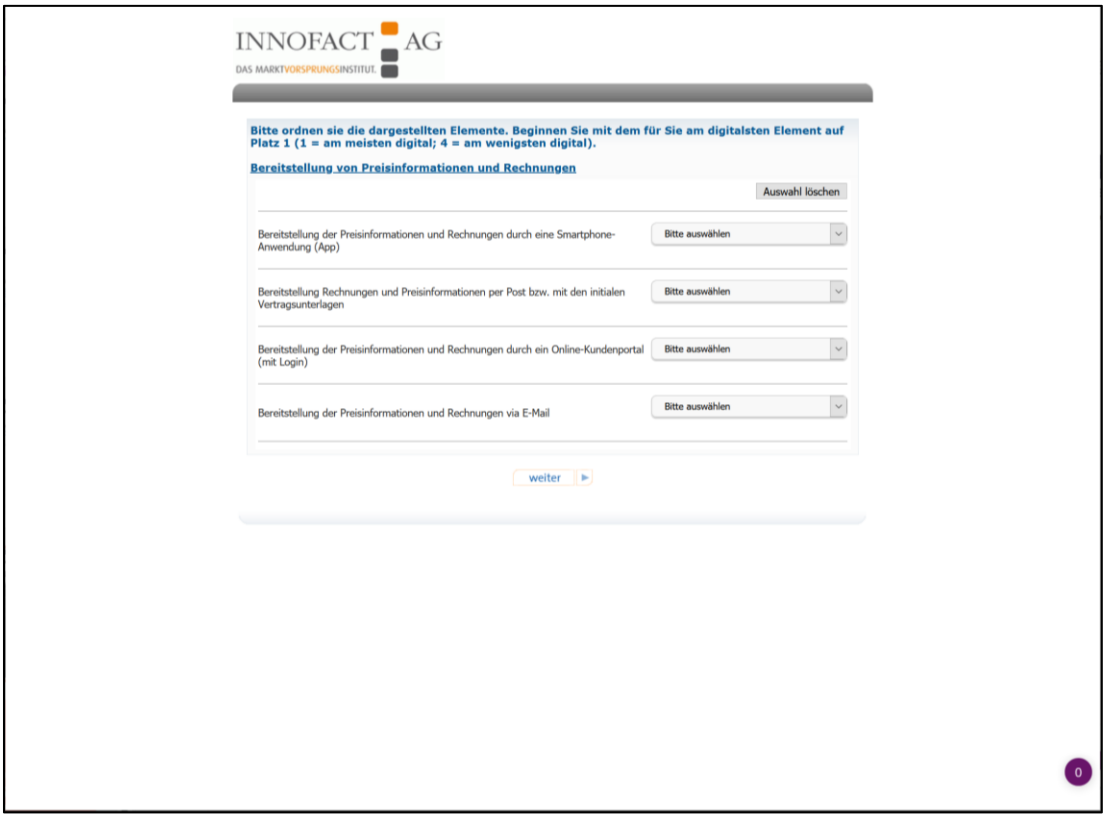
Bitte geben Sie uns Ihre Einschätzung, für wie digital Sie die dargestellten Produktbestandteile einschätzen:

Eine Kurzbeschreibung der Funktionen der jeweiligen Steckdosenvariante wird Ihnen durch folgendes Symbol angezeigt: ℹ

	Sehr digital	Etwas digital	Wenig digital	Gar nicht digital	Weiß nicht / Keine Angabe
Grundlage für die Preisgestaltung pro kWh					
Wechselnde kWh-Preise gemäß Verbrauchsverhalten ℹ	○	○	○	○	○
Festpreis pro kWh, gültig für die gesamte Vetragsdauer	○	○	○	○	○
Wechselnde kWh-Preise nach einem vordefinierten Zeitplan ℹ	○	○	○	○	○
Bereitstellung von Preisinformationen und Rechnungen					
Bereitstellung der Preisinformationen und Rechnungen über eine Smartphone-App	○	○	○	○	○
Bereitstellung Rechnungen und Preisinformationen per Post bzw. mit den initialen Vertragsunterlagen	○	○	○	○	○
Bereitstellung der Preisinformationen und Rechnungen durch ein Online-Kundenportal	○	○	○	○	○
Bereitstellung der Preisinformationen und Rechnungen via E-Mail	○	○	○	○	○
Im Angebot enthaltende Steckdose					
Lokal vernetzte Steckdose ℹ	○	○	○	○	○
Manuell programmierbare Steckdose ℹ	○	○	○	○	○
Intelligente Steckdose inkl. App ℹ	○	○	○	○	○
Intelligente Steckdose inkl. App und Analyse ℹ	○	○	○	○	○
Servicekanäle					
Chat auf Homepage ℹ	○	○	○	○	○
via E-Mail	○	○	○	○	○
über eine Smartphone-App	○	○	○	○	○
über ein Callcenter	○	○	○	○	○

weiter ▸


INNOFACT AG
DAS MARKTVORSPRUNGSINSTITUT.
Bitte ordnen sie die dargestellten Elemente. Beginnen Sie mit dem für Sie am digitalsten Element auf Platz 1 (1 = am meisten digital ; 3 = am wenigsten digital).
Grundlage für die Preisgestaltung pro kWh
Auswahl löschen
Wechselnde kWh-Preise gemäß Verbrauchsverhalten z.B. günstige Preise bei Verbrauchsreduzierungen
Bitte auswählen
Festpreis pro kWh, gültig für die gesamte Vertragsdauer
Bitte auswählen
Wechselnde kWh-Preise nach einem vordefinierten Zeitplan, z.B. Günstige Preise am Wochenende oder am Abend
Bitte auswählen
weiter
0


INNOFACT AG
DAS MARKTVORSPRUNGSINSTITUT.
Bitte ordnen sie die dargestellten Elemente. Beginnen Sie mit dem für Sie am digitalsten Element auf Platz 1 (1 = am meisten digital; 4 = am wenigsten digital).
Bereitstellung von Preisinformationen und Rechnungen
Auswahl löschen
Bereitstellung der Preisinformationen und Rechnungen durch eine Smartphone-Anwendung (App)
Bitte auswählen
Bereitstellung Rechnungen und Preisinformationen per Post bzw. mit den initialen Vertragsunterlagen
Bitte auswählen
Bereitstellung der Preisinformationen und Rechnungen durch ein Online-Kundenportal (mit Login)
Bitte auswählen
Bereitstellung der Preisinformationen und Rechnungen via E-Mail
Bitte auswählen
weiter
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INNOFACT AG
DAS MARKTVORSPRUNGSINSTITUT.

Bitte ordnen sie die dargestellten Elemente. Beginnen Sie mit dem für Sie am digitalsten Element auf Platz 1 (1 = am meisten digital; 4 = am wenigsten digital).

Eine Kurzbeschreibung der Funktionen der jeweiligen Steckdosenvariante wird Ihnen durch folgendes Symbol angezeigt: ⓘ

Im Angebot enthaltende Steckdose

Auswahl löschen

Lokal vernetzte Steckdose ⓘ	Bitte auswählen
Manuell programmierbare Steckdose ⓘ	Bitte auswählen
Intelligente Steckdose inkl. App ⓘ	Bitte auswählen
Intelligente Steckdose inkl. App und Analyse ⓘ	Bitte auswählen

weiter ▸

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INNOFACT AG
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Bitte ordnen sie die dargestellten Elemente. Beginnen Sie mit dem für Sie am digitalsten Element auf Platz 1 (1 = am meisten digital; 4 = am wenigsten digital).

Servicekanäle

Auswahl löschen

Chat, Video-Chat auf der Anbieterwebsite	Bitte auswählen
E-Mail	Bitte auswählen
Nachrichtenfunktion in einer Smartphone-Anwendung (App)	Bitte auswählen
Callcenter	Bitte auswählen

weiter ▸

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Was ist Ihr höchster Bildungsabschluss bzw. welche Schule haben Sie zuletzt besucht oder besuchen Sie derzeit?

- [ ] Volks-/Hauptschule ohne abgeschlossene Berufsausbildung
- [ ] Volks-/Hauptschule mit abgeschlossener Berufsausbildung
- [ ] Abitur, Hochschulreife mit abgeschlossener Berufsausbildung
- [ ] Höhere Schule ohne Abitur
- [x] Abitur, Hochschulreife ohne abgeschlossenes (Fach-) Hochschulstudium
- [ ] Abgeschlossenes (Fach-) Hochschulstudium

weiter

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INNOFACT AG

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Bitte geben Sie Ihre momentane berufliche Situation an.

- [ ] Ich arbeite Vollzeit
- [ ] Ich arbeite Teilzeit
- [ ] Ich bin zurzeit arbeitslos
- [ ] Ich bin Rentner/in bzw. Pensionär/in
- [ ] Ich bin Hausfrau/ -mann
- [ ] Ich bin Student/in, Schüler/in (Vollzeit)

weiter

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Welche Position haben Sie in Ihrem Unternehmen inne?

- ○ Geschäftsführung, Vorstand
- ○ Inhaber/in
- ☑ Senior Management
- ○ Mittleres Management
- ○ Beamter höherer/gehobener Dienst
- ○ Beamter mittlerer/einfacher Dienst
- ○ Projektmanagement
- ○ Angestellter ohne Leitungsfunktion
- ○ Arbeiter
- ○ Auszubildender, Trainee
- ○ Sonstiges

weiter ▸

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Wie hoch ist Ihr monatliches Haushaltsnettoeinkommen (also das gesamte Einkommen Ihres Haushalts nach Steuern und Pflichtabgaben)?

- ○ Unter 1.000€
- ○ 1.000€ - 1.999€
- ○ 2.000€ - 2.999€
- ○ 3.000€ - 3.999€
- ○ 4.000€ - 4.999€
- ○ 5.000€ - 5.999€
- ○ 6.000€ und mehr

weiter ▸

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Wie ist Ihr Familienstand?

- Verheiratet
- Nicht verheiratet, aber in Partnerschaft lebend
- Geschieden oder verwitwet
- Single

weiter

0

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Wie viele Personen ab 18 Jahren leben in Ihrem Haushalt, Sie selbst miteingeschlossen?

- 1 Person (nur ich selbst)
- 2 Personen
- 3 Personen
- 4 Personen
- 5 und mehr Personen

weiter

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Leben in Ihrem Haushalt Kinder unter 18 Jahren?

- Nein
- Ja, ein Kind unter 18 Jahren
- Ja, zwei Kinder unter 18 Jahren
- Ja, drei oder mehr Kinder unter 18 Jahren

weiter

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8.4 R codes and scripts

8.4.1 R Script for Chapter 3: CL model incl. split samples and post processing

```
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="210312_MNL_Mull",
  modelDescr ="Simple MNL model on Preferences for Digital Services",
  indivID    ="ID"
)

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1")

colnames(database) <- c("ID", colnames(database)[-1])

database = subset(database,database$Task!=5,)

database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))



round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}


wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]
```

```
  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(


  ASC_alt1      =     0,
  PRICECALC1    =     0,
  PRICECALC2    =     0,
  PRICEEMAIL    =     0,
  PRICEPORTAL   =     0,
  PRICEAPP      =     0,
  SERVEEMAIL    =     0,
  SERVCHAT      =     0,
  SERVAPP       =     0,
  #DEVICE0       =     0,
  DEVICE1       =     0,
  DEVICE2       =     0,
  DEVICE3       =     0,
  DEVICE4       =     0,
  CHARGE        =     0,
  scale_treat   =     1  # Initial scale parameter for treatment group
)

apollo_fixed = c()

apollo_inputs = apollo_validateInputs()

apollo_probabilities = function(apollo_beta, apollo_inputs, functionality = "estimate") {
  # Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  # Create list of probabilities
  P = list()

  # Create list of utilities
  V = list()

  # Treatment indicator based on DM_Group variable
  treatment_indicator = DM_Group == 1  # 1 for treatment, 2 for control

  # Scale parameter based on group membership
  scale = ifelse(treatment_indicator, scale_treat, 1)  # scale_treat for treatment group, 1 for control
group

  # Define utility functions for alternatives
  V[['alt1']] = scale * ( ASC_alt1 +
                                   PRICECALC1   * (att_P_alt1 == 2) +
                                   PRICECALC2   * (att_P_alt1 == 3) +
                                   PRICEEMAIL   * (att_A1_alt1 == 1) +
                                   PRICEPORTAL  * (att_A2_alt1 == 1) +
                                   PRICEAPP     * (att_A3_alt1 == 1) +
                                   SERVEEMAIL   * (att_S1_alt1 == 1) +
                                   SERVCHAT     * (att_S2_alt1 == 1) +
                                   SERVAPP      * (att_S3_alt1 == 1) +
                                   DEVICE1      * (att_T_alt1 == 1) +
                                   DEVICE2      * (att_T_alt1 == 2) +
                                   DEVICE3      * (att_T_alt1 == 3) +
                                   DEVICE4      * (att_T_alt1 == 4) +
                                   CHARGE       * att_C_alt1
  )

  V[['alt2']] = scale * (
                                   PRICECALC1   * (att_P_alt2 == 2) +
                                   PRICECALC2   * (att_P_alt2 == 3) +
                                   PRICEEMAIL   * (att_A1_alt2 == 1) +
                                   PRICEPORTAL  * (att_A2_alt2 == 1) +
                                   PRICEAPP     * (att_A3_alt2 == 1) +
```

```
                                    SERVEEMAIL   * (att_S1_alt2 == 1) +
                                    SERVCHAT     * (att_S2_alt2 == 1) +
                                    SERVAPP      * (att_S3_alt2 == 1) +
                                    DEVICE1      * (att_T_alt2 == 1) +
                                    DEVICE2      * (att_T_alt2 == 2) +
                                    DEVICE3      * (att_T_alt2 == 3) +
                                    DEVICE4      * (att_T_alt2 == 4) +
                                    CHARGE       * att_C_alt2
  )


  mnl_settings = list(
    alternatives = c(alt1 = 1, alt2 = 2),
    avail = list(alt1 = 1, alt2 = 1),
    choiceVar = choice,
    V = V
  )


  P[['model']] = apollo_mnl(mnl_settings, functionality)

  # Take product across observations for the same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  # Prepare and return outputs
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}

# Estimate the heteroskedastic logit model
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

# Output the model results
apollo_modelOutput(model, modelOutput_settings = list(printPVal = TRUE))

# Save the model results
apollo_saveOutput(model, saveOutput_settings = list(
  printPVal = TRUE,
  saveEst = TRUE,
  saveModeObject = TRUE
))



WTP_Pooled_HLM <- wtp(cost = "CHARGE",names(model$estimate), model = model)
saveRDS(WTP_Pooled_HLM, "WTP_Pooled_HLM.rds")
saveRDS(model, "MNL_Mull_model_HLM.rds")

WTP_Pooled_HLM

########################################################################################


### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="210312_MNL_Mull",
  modelDescr ="Simple MNL model on Preferences for Digital Services",
  indivID    ="ID"
)
```

```
database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1")

colnames(database) <- c("ID", colnames(database)[-1])

database = subset(database,database$Task!=5,)


database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))



database = subset(database,database$DM_Group!=2,) #


round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}


wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(

                ASC_alt1      =     0,
                PRICECALC1    =     0,
                PRICECALC2    =     0,
                PRICEEMAIL    =     0,
                PRICEPORTAL   =     0,
                PRICEAPP      =     0,
                SERVEEMAIL    =     0,
                SERVCHAT      =     0,
                SERVAPP       =     0,
                #DEVICE0       =     0,
                DEVICE1       =     0,
                DEVICE2       =     0,
                DEVICE3       =     0,
```

```
                DEVICE4      =    0,
                CHARGE       =    0
                )
e
apollo_fixed = c()

apollo_inputs = apollo_validateInputs()

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()



  V[['alt1']]  =
    ASC_alt1                        +
    PRICECALC1   * (att_P_alt1==2)  +
    PRICECALC2   * (att_P_alt1==3)  +
    PRICEEMAIL   * (att_A1_alt1==1) +
    PRICEPORTAL  * (att_A2_alt1==1) +
    PRICEAPP     * (att_A3_alt1==1) +
    SERVEEMAIL   * (att_S1_alt1==1) +
    SERVCHAT     * (att_S2_alt1==1) +
    SERVAPP      * (att_S3_alt1==1) +
    #DEVICE0      * (att_T_alt1==0)  +
    DEVICE1      * (att_T_alt1==1)  +
    DEVICE2      * (att_T_alt1==2)  +
    DEVICE3      * (att_T_alt1==3)  +
    DEVICE4      * (att_T_alt1==4)  +
    CHARGE       * att_C_alt1

  V[['alt2']]  =
    PRICECALC1   * (att_P_alt2==2)  +
    PRICECALC2   * (att_P_alt2==3)  +
    PRICEEMAIL   * (att_A1_alt2==1) +
    PRICEPORTAL  * (att_A2_alt2==1) +
    PRICEAPP     * (att_A3_alt2==1) +
    SERVEEMAIL   * (att_S1_alt2==1) +
    SERVCHAT     * (att_S2_alt2==1) +
    SERVAPP      * (att_S3_alt2==1) +
    #DEVICE0      * (att_T_alt2==0)  +
    DEVICE1      * (att_T_alt2==1)  +
    DEVICE2      * (att_T_alt2==2)  +
    DEVICE3      * (att_T_alt2==3)  +
    DEVICE4      * (att_T_alt2==4)  +
    CHARGE       * att_C_alt2


  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V
  )


  ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}


model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)


apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,
                                                    printCovar=FALSE,
```

```
                                                    printCorr=FALSE,
                                                    printOutliers=FALSE,
                                                    printChange=FALSE,
                                                    saveEst=TRUE,
                                                    saveCov=FALSE,
                                                    saveCorr=FALSE,
                                                    saveModeObject=TRUE
))

apollo_saveOutput(model, saveOutput_settings=list(printPVal=TRUE,
                                                  printCovar=FALSE,
                                                  printCorr=FALSE,
                                                  printOutliers=FALSE,
                                                  printChange=FALSE,
                                                  saveEst=TRUE,
                                                  saveCov=FALSE,
                                                  saveCorr=FALSE,
                                                  saveModeObject=TRUE
))

WTP_DM1 <- wtp(cost = "CHARGE",names(model$estimate), model = model) #MOdel Output for DM1
saveRDS(WTP_DM1, "WTP_DM1.rds")
saveRDS(model, "MNL_DM1_Mull_model.rds")

write.csv2(wtp(cost = "CHARGE",names(model$estimate), model = model), "WTP_values_DM1_MNL.csv")


##########################################################################################################
##############################################

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="210312_MNL_Mull",
  modelDescr ="Simple MNL model on Preferences for Digital Services",
  indivID    ="ID"
)

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1")

colnames(database) <- c("ID", colnames(database)[-1])

database = subset(database,database$Task!=5,)


database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
```

```
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


database = subset(database,database$DM_Group!=1,)



round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(



  ASC_alt1      =     0,
  PRICECALC1    =     0,
  PRICECALC2    =     0,
  PRICEEMAIL    =     0,
  PRICEPORTAL   =     0,
  PRICEAPP      =     0,
  SERVEEMAIL    =     0,
  SERVCHAT      =     0,
  SERVAPP       =     0,
  #DEVICE0       =     0,
  DEVICE1       =     0,
  DEVICE2       =     0,
  DEVICE3       =     0,
  DEVICE4       =     0,
  CHARGE        =     0
)

apollo_fixed = c()

apollo_inputs = apollo_validateInputs()

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()
```

```
  #BASIC MNL
MODEL##########################################################################################################
###########################################

  V[['alt1']]  =
    ASC_alt1                        +
    PRICECALC1   * (att_P_alt1==2)  +
    PRICECALC2   * (att_P_alt1==3)  +
    PRICEEMAIL   * (att_A1_alt1==1) +
    PRICEPORTAL  * (att_A2_alt1==1) +
    PRICEAPP     * (att_A3_alt1==1) +
    SERVEEMAIL   * (att_S1_alt1==1) +
    SERVCHAT     * (att_S2_alt1==1) +
    SERVAPP      * (att_S3_alt1==1) +
    #DEVICE0      * (att_T_alt1==0)  +
    DEVICE1      * (att_T_alt1==1)  +
    DEVICE2      * (att_T_alt1==2)  +
    DEVICE3      * (att_T_alt1==3)  +
    DEVICE4      * (att_T_alt1==4)  +
    CHARGE       * att_C_alt1

  V[['alt2']]  =
    PRICECALC1   * (att_P_alt2==2)  +
    PRICECALC2   * (att_P_alt2==3)  +
    PRICEEMAIL   * (att_A1_alt2==1) +
    PRICEPORTAL  * (att_A2_alt2==1) +
    PRICEAPP     * (att_A3_alt2==1) +
    SERVEEMAIL   * (att_S1_alt2==1) +
    SERVCHAT     * (att_S2_alt2==1) +
    SERVAPP      * (att_S3_alt2==1) +
    #DEVICE0      * (att_T_alt2==0)  +
    DEVICE1      * (att_T_alt2==1)  +
    DEVICE2      * (att_T_alt2==2)  +
    DEVICE3      * (att_T_alt2==3)  +
    DEVICE4      * (att_T_alt2==4)  +
    CHARGE       * att_C_alt2


  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V
  )


  ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}


model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)


apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,
                                                    printCovar=FALSE,
                                                    printCorr=FALSE,
                                                    printOutliers=FALSE,
                                                    printChange=FALSE,
                                                    saveEst=TRUE,
                                                    saveCov=FALSE,
                                                    saveCorr=FALSE,
                                                    saveModeObject=TRUE
))

apollo_saveOutput(model, saveOutput_settings=list(printPVal=TRUE,
                                                  printCovar=FALSE,
                                                  printCorr=FALSE,
                                                  printOutliers=FALSE,
                                                  printChange=FALSE,
                                                  saveEst=TRUE,
                                                  saveCov=FALSE,
                                                  saveCorr=FALSE,
```

```
                                                  saveModeObject=TRUE
))


WTP_DM2 <- wtp(cost = "CHARGE",names(model$estimate), model = model) #MOdel Output for DM2
saveRDS(WTP_DM2, "WTP_DM2.rds")
saveRDS(model, "MNL_DM2_Mull_model.rds")
write.csv2(wtp(cost = "beta_c",names(model$estimate), model = model), "WTP_values_DM2_MNL.csv")

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000)

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}


WTP_DM1 <- readRDS("WTP_DM1.rds") #WTP VALUES FOR DM1 (SOURCE FOR T-TEST)
WTP_DM2 <- readRDS("WTP_DM2.rds") #WTP VALUES FOR DM2 (SOURCE FOR T-TEST)
#WTP_Total <- readRDS("WTP_Total.rds") #WTP VALUES FOR DM2 (SOURCE FOR T-TEST)
WTP_HLM <- readRDS("WTP_Pooled_HLM.rds") #WTP VALUES FOR Pooled heteroskedastic logit model

#model_MNL_Total <- readRDS("MNL_Mull_model.rds")
model_MNL_HLM <- readRDS("MNL_Mull_model_HLM.rds")
model_MNL_DM1 <- readRDS("MNL_DM1_Mull_model.rds")
model_MNL_DM2 <- readRDS("MNL_DM2_Mull_model.rds")


coef.names = names(model_MNL_HLM[["estimate"]])
para.descript = data.frame(description = c("","Changing of prices based on a pre-defined plan",
                                              "Decreasing prices per kWh each month with consumption
change",
                                              "Prices and monthly bills are sent via email",
                                              "Prices and monthly bills made available through an online
portal ",
                                              "Price communication and access to bills through mobile
app",
                                              "Service infrastructure: E-Mail",
                                              "Service infrastructure: Chat Agent (also video Chat)",
                                              "Service infrastructure: Message service within smart phone
app",
                                              "Manually adjustable electric plug adapter",
                                              "Local connected electric plug adapter",
                                              "Smart plug adapter incl. smart phone app",
                                              "Smart plug adapter incl. smart phone app and analysis",
                                              "scale_treat"
                                            ))

parameter <-(coef.names[-14]) #


WTP_HLM_pVal_4 <- round_df(WTP_HLM,4)
WTP_DM1_pVal_4   <- round_df(WTP_DM1,4)
WTP_DM2_pVal_4   <- round_df(WTP_DM2,4)


LL_HLM_2 <- round_df(model_MNL_HLM$LLout[1],2)
LL_DM1_2 <-   round_df(model_MNL_DM1$LLout[1],2)
LL_DM2_2 <-   round_df(model_MNL_DM2$LLout[1],2)
```

```r
# Determine the number of rows to add
rows_to_add_DM1 <- 14 - nrow(WTP_DM1_pVal_4)
rows_to_add_DM2 <- 14 - nrow(WTP_DM2_pVal_4)

# Create a matrix with empty strings and matching column names
empty_matrix_DM1 <- matrix("", nrow = rows_to_add_DM1, ncol = ncol(WTP_DM1_pVal_4))
empty_matrix_DM2 <- matrix("", nrow = rows_to_add_DM2, ncol = ncol(WTP_DM2_pVal_4))

colnames(empty_matrix_DM1) <- colnames(WTP_DM1_pVal_4)
colnames(empty_matrix_DM2) <- colnames(WTP_DM2_pVal_4)

# Use rbind to add the empty rows
WTP_DM1_pVal_4 <- rbind(WTP_DM1_pVal_4, empty_matrix_DM1)
WTP_DM2_pVal_4 <- rbind(WTP_DM2_pVal_4, empty_matrix_DM2)

results_MNL_P1 <- data.frame(cbind(parameter,para.descript,
                                   wtp_total=WTP_HLM_pVal_4[,1],
                                   V4=WTP_HLM_pVal_4[,4],
                                   rob.s.e._total=WTP_HLM_pVal_4[,2],
                                   wtp_DM1=WTP_DM1_pVal_4[,1],
                                   V7=WTP_DM1_pVal_4[,4],
                                   rob.s.e._DM1=WTP_DM1_pVal_4[,2],
                                   wtp_DM2=WTP_DM2_pVal_4[,1],
                                   V10=WTP_DM2_pVal_4[,4],
                                   rob.s.e._DM2=WTP_DM2_pVal_4[,2]))

# Create new rows with specific 'parameter' and 'description', and 0s elsewhere
new_row1 <- data.frame(
  parameter = "PRICECALC0",
  description = "Fixed Price per kWh – prices are defined for the contractual time",
  wtp_total = formatC(0, format = "f", digits = 4),
  V4 = formatC(0, format = "f", digits = 4),
  rob.s.e._total = formatC(0, format = "f", digits = 4),
  wtp_DM1 = formatC(0, format = "f", digits = 4),
  V7 = formatC(0, format = "f", digits = 4),
  rob.s.e._DM1 = formatC(0, format = "f", digits = 4),
  wtp_DM2 = formatC(0, format = "f", digits = 4),
  V10 = formatC(0, format = "f", digits = 4),
  rob.s.e._DM2 = formatC(0, format = "f", digits = 4),
  stringsAsFactors = FALSE
)

new_row2 <- data.frame(
  parameter = "(default)",
  description = "Prices are itemized within the initial contract documents, bills are sent via mail",
  wtp_total = formatC(0, format = "f", digits = 4),
  V4 = formatC(0, format = "f", digits = 4),
  rob.s.e._total = formatC(0, format = "f", digits = 4),
  wtp_DM1 = formatC(0, format = "f", digits = 4),
  V7 = formatC(0, format = "f", digits = 4),
  rob.s.e._DM1 = formatC(0, format = "f", digits = 4),
  wtp_DM2 = formatC(0, format = "f", digits = 4),
  V10 = formatC(0, format = "f", digits = 4),
  rob.s.e._DM2 = formatC(0, format = "f", digits = 4),
  stringsAsFactors = FALSE
)

new_row3 <- data.frame(
  parameter = "(default)",
  description = "Service Infrastructure: Call centre",
  wtp_total = formatC(0, format = "f", digits = 4),
  V4 = formatC(0, format = "f", digits = 4),
  rob.s.e._total = formatC(0, format = "f", digits = 4),
  wtp_DM1 = formatC(0, format = "f", digits = 4),
  V7 = formatC(0, format = "f", digits = 4),
  rob.s.e._DM1 = formatC(0, format = "f", digits = 4),
  wtp_DM2 = formatC(0, format = "f", digits = 4),
  V10 = formatC(0, format = "f", digits = 4),
  rob.s.e._DM2 = formatC(0, format = "f", digits = 4),
  stringsAsFactors = FALSE
)

new_row4 <- data.frame(
  parameter = "DEVICE0",
  description = "No electric plug adapter included",
  wtp_total = formatC(0, format = "f", digits = 4),
  V4 = formatC(0, format = "f", digits = 4),
  rob.s.e._total = formatC(0, format = "f", digits = 4),
  wtp_DM1 = formatC(0, format = "f", digits = 4),
  V7 = formatC(0, format = "f", digits = 4),
```

```
  rob.s.e._DM1 = formatC(0, format = "f", digits = 4),
  wtp_DM2 = formatC(0, format = "f", digits = 4),
  V10 = formatC(0, format = "f", digits = 4),
  rob.s.e._DM2 = formatC(0, format = "f", digits = 4),
  stringsAsFactors = FALSE
)

# Insert new_row4 after row 9
results_MNL_P1 <- rbind(
  results_MNL_P1[1:9, ],
  new_row4,
  results_MNL_P1[10:nrow(results_MNL_P1), ]
)

# Insert new_row3 after row 6
results_MNL_P1 <- rbind(
  results_MNL_P1[1:6, ],
  new_row3,
  results_MNL_P1[7:nrow(results_MNL_P1), ]
)

# Insert new_row2 after row 3
results_MNL_P1 <- rbind(
  results_MNL_P1[1:3, ],
  new_row2,
  results_MNL_P1[4:nrow(results_MNL_P1), ]
)

# Insert new_row1 after row 1
results_MNL_P1 <- rbind(
  results_MNL_P1[1:1, ],
  new_row1,
  results_MNL_P1[2:nrow(results_MNL_P1), ]
)

ft <- flextable(results_MNL_P1)

ft <- set_header_labels(ft, parameter = "Parameter",
                        description = "Name",
                        wtp_total = "WTP",
                        V4 = "pVal",
                        rob.s.e._total = "Rob.s.e.",
                        wtp_DM1 ="WTP",
                        V7 = "pVal",
                        rob.s.e._DM1 = "Rob.s.e.",
                        wtp_DM2 = "WTP",
                        V10 = "pVal",
                        rob.s.e._DM2 = "Rob.s.e.") #
#Infozeilen
ft <-
add_footer_row(ft,values=c("n","",model_MNL_HLM$nIndivs[1],"","",model_MNL_DM1$nIndivs[1],"","",model_MNL_
DM2$nIndivs[1],"",""),colwidths=c(1,1,1,1,1,1,1,1,1,1,1)) #Zeile unter Tabelle f?r MOdellinformationen "n"
ft <-
add_footer_row(ft,values=c("Observations","",model_MNL_HLM$nObs[1],"","",model_MNL_DM1$nObs[1],"","",model
_MNL_DM2$nObs[1],"",""),colwidths=c(1,1,1,1,1,1,1,1,1,1,1)) #Zeile unter Tabelle f?r MOdellinformationen
"obsverations"
ft <- add_footer_row(ft,values=c("Log Likelihood (final)","",LL_HLM_2
,"","",LL_DM1_2,"","",LL_DM2_2,"",""),colwidths=c(1,1,1,1,1,1,1,1,1,1,1)) #Zeile unter Tabelle f?r
MOdellinformationen "LogLike..."

ft <- align(ft,j=c(3,5,6,8,9,11),align="right",part="all")
ft <- align(ft,align="right",part="footer")
ft <- align(ft,j=c(1,2,4,7,10),align="left",part="all")

ft <- width(ft, j=c(4,7,10),width = 0.2)
ft <- width(ft, j=c(3,5,6,8,9,11),width = 1.5)
ft <- width(ft, j=1,width = 1.5)
ft <- width(ft, j=2,width = 4.0)


ft <- add_footer_lines(ft, "Note: WTP = Willingness to pay; ***p < 0.001; **p < 0.01; *p < 0.05; DM1 and
DM2 refer to the two different sample groups: Treatment Group (DM1) and Control Group (DM2)")

ft <- add_header_row(ft, colwidths =c(2,3,3,3), values=c("","Total","Treatment Group (DM 1)","Control
Group (DM 2)")) # zus?tzliche ?berschriftenzeile
ft <- align(ft,align="left",part="header")
ft <- align(ft,j=c(1),align="left",part="all")
ft <- valign(ft, valign = "top", part = "body")
ft <- valign(ft, valign = "top", part = "footer")
ft <- align(ft,j=c(2),align="left",part="header")
```

```
my_border <- fp_border(color="black", width=1)
ft <- vline(ft, j = 5, border = my_border)
ft <- vline(ft, j = 8, border = my_border)


ft
save_as_image(ft, path = "Total_results.png")


################################################################################
#Differnece tests


library(dplyr)
library(flextable)
library(magrittr)
library(officer)  # for fp_border

# Function for significance symbols based on p-value
significance_symbol <- function(p) {
  case_when(
    p < 0.001 ~ "***",
    p < 0.01  ~ "**",
    p < 0.05  ~ "*",
    TRUE      ~ ""
  )
}

# Choose z-value for 99.7% CI
z_crit <- 3

df_DM1_vs_DM2 <- results_MNL_P1 %>%
  mutate(
    wtp_DM1       = as.numeric(wtp_DM1),
    rob.s.e._DM1  = as.numeric(rob.s.e._DM1),
    wtp_DM2       = as.numeric(wtp_DM2),
    rob.s.e._DM2  = as.numeric(rob.s.e._DM2)
  ) %>%
  rowwise() %>%
  mutate(
    diff_WTP  = wtp_DM1 - wtp_DM2,
    diff_SE   = sqrt(rob.s.e._DM1^2 + rob.s.e._DM2^2),
    z_value   = diff_WTP / diff_SE,
    p_value   = 2 * (1 - pnorm(abs(z_value))),
    # 99.7% CI for difference
    ci997_low  = diff_WTP - z_crit * diff_SE,
    ci997_high = diff_WTP + z_crit * diff_SE,
    # CI for DM1 and DM2 individually
    dm1_low  = wtp_DM1 - z_crit * rob.s.e._DM1,
    dm1_high = wtp_DM1 + z_crit * rob.s.e._DM1,
    dm2_low  = wtp_DM2 - z_crit * rob.s.e._DM2,
    dm2_high = wtp_DM2 + z_crit * rob.s.e._DM2

  ) %>%
  ungroup() %>%
  # Round key columns to 4 decimals
  mutate(
    diff_SE    = round(diff_SE,    4),
    z_value    = round(z_value,    4),
    p_value    = round(p_value,    4),
    ci997_low  = round(ci997_low,  4),
    ci997_high = round(ci997_high, 4)
  ) %>%
  # Add significance symbols after p_value
  mutate(
    sig_symbol = significance_symbol(p_value)
  ) %>%
  # Keep only relevant columns for the final table
  dplyr::select(
    parameter,
    wtp_DM1,
    rob.s.e._DM1,
    wtp_DM2,
    rob.s.e._DM2,
    diff_WTP,
    diff_SE,
    z_value,
    p_value,
    sig_symbol,
    ci997_low,
    ci997_high
```

```
  )


ft_diff_DM1_DM2 <- flextable(df_DM1_vs_DM2)

ft_diff_DM1_DM2 <- set_header_labels(
  ft_diff_DM1_DM2,
  parameter      = "Parameter",
  wtp_DM1        = "WTP (DM1)",
  rob.s.e._DM1   = "SE (DM1)",
  wtp_DM2        = "WTP (DM2)",
  rob.s.e._DM2   = "SE (DM2)",
  diff_WTP       = "Diff (DM1-DM2)",
  diff_SE        = "SE (Diff)",
  z_value        = "z-Value",
  p_value        = "p-Value",
  sig_symbol     = "*",
  ci997_low      = "CI99.7% (Low)",
  ci997_high     = "CI99.7% (High)"
)

ft_diff_DM1_DM2 <- add_header_row(
  ft_diff_DM1_DM2,
  colwidths = c(1,2,2,8),
  values    = c("", "Treatment Group (DM1)", "Control Group (DM2)", "Difference Statistics")
)

# Basic styling
ft_diff_DM1_DM2 <- align(ft_diff_DM1_DM2, align = "center", part = "header")
ft_diff_DM1_DM2 <- valign(ft_diff_DM1_DM2, valign = "top", part = "body")

my_border <- fp_border(color="black", width=1)
ft_diff_DM1_DM2 <- vline(ft_diff_DM1_DM2, j = 5, border = my_border)

ft_diff_DM1_DM2 <- width(ft_diff_DM1_DM2, j = 6, width = 2.0)

ft_diff_DM1_DM2 <- set_table_properties(ft_diff_DM1_DM2, layout = "fixed")

ft_diff_DM1_DM2 <- add_footer_lines(
  ft_diff_DM1_DM2,
  "Note: ±3 * SE for ~99.7% confidence intervals. p-Value from two-sided z-test. '*' indicates
significance at *p < 0.05, **p < 0.01, ***p < 0.001."
)

ft_diff_DM1_DM2




##################### Post Processing for Bootstrap method and Poe at al test


rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="210312_MNL_Mull",
  modelDescr ="Simple CL model on Preferences for Digital Services",
  indivID    ="ID"
)

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1")
```

```r
colnames(database) <- c("ID", colnames(database)[-1])

database = subset(database,database$Task!=5,)

database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))

database_complete = database

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}


AnzBoot = 1000

database = database_complete

database = subset(database,database$DM_Group!=1,)

apollo_beta = c(


  ASC_alt1      =     0,
  PRICECALC1    =     0,
  PRICECALC2    =     0,
  PRICEEMAIL    =     0,
  PRICEPORTAL   =     0,
  PRICEAPP      =     0,
  SERVEEMAIL    =     0,
  SERVCHAT      =     0,
  SERVAPP       =     0,
  DEVICE1       =     0,
  DEVICE2       =     0,
  DEVICE3       =     0,
```

```
  DEVICE4       =     0,
  CHARGE        =     0
)

apollo_fixed = c()


apollo_inputs = apollo_validateInputs()


apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()

  V[['alt1']]  =
    ASC_alt1                         +
    PRICECALC1   * (att_P_alt1==2)  +
    PRICECALC2   * (att_P_alt1==3)  +
    PRICEEMAIL   * (att_A1_alt1==1) +
    PRICEPORTAL  * (att_A2_alt1==1) +
    PRICEAPP     * (att_A3_alt1==1) +
    SERVEEMAIL   * (att_S1_alt1==1) +
    SERVCHAT     * (att_S2_alt1==1) +
    SERVAPP      * (att_S3_alt1==1) +
    DEVICE1      * (att_T_alt1==1)  +
    DEVICE2      * (att_T_alt1==2)  +
    DEVICE3      * (att_T_alt1==3)  +
    DEVICE4      * (att_T_alt1==4)  +
    CHARGE       * att_C_alt1

  V[['alt2']]  =
    PRICECALC1   * (att_P_alt2==2)  +
    PRICECALC2   * (att_P_alt2==3)  +
    PRICEEMAIL   * (att_A1_alt2==1) +
    PRICEPORTAL  * (att_A2_alt2==1) +
    PRICEAPP     * (att_A3_alt2==1) +
    SERVEEMAIL   * (att_S1_alt2==1) +
    SERVCHAT     * (att_S2_alt2==1) +
    SERVAPP      * (att_S3_alt2==1) +
    DEVICE1      * (att_T_alt2==1)  +
    DEVICE2      * (att_T_alt2==2)  +
    DEVICE3      * (att_T_alt2==3)  +
    DEVICE4      * (att_T_alt2==4)  +
    CHARGE       * att_C_alt2




  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V
  )


  ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}


apollo_beta = c( ASC_alt1      =     0,
                 PRICECALC1    =     0,
                 PRICECALC2    =     0,
                 PRICEEMAIL    =     0,
```

```
                 PRICEPORTAL   =     0,
                 PRICEAPP      =     0,
                 SERVEEMAIL    =     0,
                 SERVCHAT      =     0,
                 SERVAPP       =     0,
                 DEVICE1       =     0,
                 DEVICE2       =     0,
                 DEVICE3       =     0,
                 DEVICE4       =     0,
                 CHARGE        =     0
)

apollo_fixed = c()


apollo_inputs = apollo_validateInputs()

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()


  V[['alt1']]  =
    ASC_alt1                         +
    PRICECALC1   * (att_P_alt1==2)   +
    PRICECALC2   * (att_P_alt1==3)   +
    PRICEEMAIL   * (att_A1_alt1==1)  +
    PRICEPORTAL  * (att_A2_alt1==1)  +
    PRICEAPP     * (att_A3_alt1==1)  +
    SERVEEMAIL   * (att_S1_alt1==1)  +
    SERVCHAT     * (att_S2_alt1==1)  +
    SERVAPP      * (att_S3_alt1==1)  +
    DEVICE1      * (att_T_alt1==1)   +
    DEVICE2      * (att_T_alt1==2)   +
    DEVICE3      * (att_T_alt1==3)   +
    DEVICE4      * (att_T_alt1==4)   +
    CHARGE       * att_C_alt1

  V[['alt2']]  =
    PRICECALC1   * (att_P_alt2==2)   +
    PRICECALC2   * (att_P_alt2==3)   +
    PRICEEMAIL   * (att_A1_alt2==1)  +
    PRICEPORTAL  * (att_A2_alt2==1)  +
    PRICEAPP     * (att_A3_alt2==1)  +
    SERVEEMAIL   * (att_S1_alt2==1)  +
    SERVCHAT     * (att_S2_alt2==1)  +
    SERVAPP      * (att_S3_alt2==1)  +
    DEVICE1      * (att_T_alt2==1)   +
    DEVICE2      * (att_T_alt2==2)   +
    DEVICE3      * (att_T_alt2==3)   +
    DEVICE4      * (att_T_alt2==4)   +
    CHARGE       * att_C_alt2



  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V
  )


  ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
```

```
#SCHAETZER auf allen Daten
model_DM2 = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs,
estimate_settings=list(silent=TRUE,writeIter=FALSE))

#Bootstrapping
model = apollo_bootstrap(apollo_beta, apollo_fixed, apollo_probabilities,
apollo_inputs,bootstrap_settings=list(nRep=AnzBoot,samples=NA,calledByEstimate=FALSE,recycle=FALSE))

m_estimates = data.frame(model$estimates)

WTP_Total_DM2 = -m_estimates[,1:13]/ m_estimates$CHARGE

database = database_complete

database = subset(database,database$DM_Group!=2,)


apollo_beta = c(  ASC_alt1      =     0,
                  PRICECALC1    =     0,
                  PRICECALC2    =     0,
                  PRICEEMAIL    =     0,
                  PRICEPORTAL   =     0,
                  PRICEAPP      =     0,
                  SERVEEMAIL    =     0,
                  SERVCHAT      =     0,
                  SERVAPP       =     0,
                  DEVICE1       =     0,
                  DEVICE2       =     0,
                  DEVICE3       =     0,
                  DEVICE4       =     0,
                  CHARGE        =     0
)

apollo_fixed = c()

apollo_inputs = apollo_validateInputs()

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()


  V[['alt1']]  =
    ASC_alt1                        +
    PRICECALC1   * (att_P_alt1==2)  +
    PRICECALC2   * (att_P_alt1==3)  +
    PRICEEMAIL   * (att_A1_alt1==1) +
    PRICEPORTAL  * (att_A2_alt1==1) +
    PRICEAPP     * (att_A3_alt1==1) +
    SERVEEMAIL   * (att_S1_alt1==1) +
    SERVCHAT     * (att_S2_alt1==1) +
    SERVAPP      * (att_S3_alt1==1) +
    DEVICE1      * (att_T_alt1==1)  +
    DEVICE2      * (att_T_alt1==2)  +
    DEVICE3      * (att_T_alt1==3)  +
    DEVICE4      * (att_T_alt1==4)  +
    CHARGE       * att_C_alt1

  V[['alt2']]  =                                #
    PRICECALC1   * (att_P_alt2==2)  +
    PRICECALC2   * (att_P_alt2==3)  +
    PRICEEMAIL   * (att_A1_alt2==1) +
    PRICEPORTAL  * (att_A2_alt2==1) +
    PRICEAPP     * (att_A3_alt2==1) +
    SERVEEMAIL   * (att_S1_alt2==1) +
    SERVCHAT     * (att_S2_alt2==1) +
    SERVAPP      * (att_S3_alt2==1) +
    DEVICE1      * (att_T_alt2==1)  +
    DEVICE2      * (att_T_alt2==2)  +
    DEVICE3      * (att_T_alt2==3)  +
    DEVICE4      * (att_T_alt2==4)  +
```

```
    CHARGE       * att_C_alt2


  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V
  )


  ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}


#SCHAETZER auf allen Daten
model_DM1 = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs,
estimate_settings=list(silent=TRUE,writeIter=FALSE))

#Bootstrapping
model = apollo_bootstrap(apollo_beta, apollo_fixed, apollo_probabilities,
apollo_inputs,bootstrap_settings=list(nRep=AnzBoot,samples=NA,calledByEstimate=FALSE,recycle=FALSE))

m_estimates = data.frame(model$estimates)

WTP_Total_DM1 = -m_estimates[,1:13]/ m_estimates$CHARGE


#Empirische Dichten fuer DM2 / DM1:

tabelle = data.frame(wtpname=c(),dm1_mw=c(),dm1_se = c(),dm1_p=c(),dm2_mw=c(),dm2_se = c(),dm2_p=c())


library(scales)

par(mfrow=c(5,3))
par(mar = c(2, 2, 2, 2))
for (i in 1:length(WTP_Total_DM1[1,])) {
  werte = c(WTP_Total_DM1[,i],WTP_Total_DM2[,i],0)
  name_spalte = paste("WTP/",names(WTP_Total_DM1)[i],sep="")


  h1 = hist(WTP_Total_DM1[,i],breaks=20,plot=FALSE)
  h2 = hist(WTP_Total_DM2[,i],breaks=20,plot=FALSE)
  ywerte = max(h1$density,h2$density)

hist(WTP_Total_DM1[,i],xlim=c(min(werte),max(werte)),ylim=c(0,max(ywerte)),breaks=20,col=alpha("blue",0.5)
,freq=FALSE,xlab=name_spalte,ylab="density",main=name_spalte)
  lines(density(WTP_Total_DM1[,i]),col="blue")

  hist(WTP_Total_DM2[,i],breaks=20,col=alpha("red",0.5),freq=FALSE,add=TRUE)
  lines(density(WTP_Total_DM2[,i]),col="red")
  #legend("topright",legend=c("DM1","DM2"),fill=c("blue","red"))


  F1 = ecdf(WTP_Total_DM1[,i])
  F2 = ecdf(WTP_Total_DM2[,i])

  zeile =
data.frame(wtpname=names(WTP_Total_DM1)[i],dm1_mw=mean(WTP_Total_DM1[,i]),dm1_se=sd(WTP_Total_DM1[,i]),dm1
_p=2*min(F1(0),1 - F1(0)),dm2_mw=mean(WTP_Total_DM2[,i]),dm2_se=sd(WTP_Total_DM2[,i]),dm2_p=2*min(F2(0),1
- F2(0)))
  tabelle = rbind(tabelle,zeile)
}

plot(c(0),type="n",axes=FALSE,xlab="",ylab="")
legend("topright",legend=c("DM1","DM2"),fill=c("blue","red"))


#Differenz-Verteilungsfunktion gemaess Poe et al. 1994

tabelle = data.frame(wtpname=c(),mw=c(),p=c())
```

```r
integrationsbereich = -1000:1000/100
N = length(integrationsbereich)
Nmitte = (N+1)/2

delta_xy = integrationsbereich[2]-integrationsbereich[1]


par(mfrow=c(5,3))
par(mar = c(2, 2, 2, 2))
for (i in 1:length(WTP_Total_DM1[1,])) {

  #Empirische Dichten (histogramme, linear interpoliert)

  x = WTP_Total_DM1[,i]
  y = WTP_Total_DM2[,i]

  all_v = rep(x,length(y)) - rep(y,each=length(x))
  min_v = min(all_v)
  max_v = max(all_v)

  #Dichten von x,y (Histogramme)
  ergx = hist(x,breaks=integrationsbereich,plot=FALSE)$density
  ergy = hist(y,breaks=integrationsbereich,plot=FALSE)$density


  Fv = rep(0, length(integrationsbereich)-1)
  fv = rep(0,length(integrationsbereich)-1)

  #density
  fv = convolve(ergx,ergy,type="open")
  fv = fv[(Nmitte-1) : (3*(Nmitte-1))]*delta_xy^2

  #empirical distribution function
  Fv = cumsum(fv)

  werte = c(WTP_Total_DM1[,i],WTP_Total_DM2[,i],0)
  name_spalte = paste("Difference WTP/",names(WTP_Total_DM1)[i],sep="")
  plot(integrationsbereich,fv,type="l",xlab=name_spalte,ylab="density",main=name_spalte)
  lines(rep(0,2),c(-10,10),lty=2)


  #empirical 95%-confidence interval
  q0025=integrationsbereich[which(Fv > 0.025)[1]]
  q0975=integrationsbereich[which(Fv > 0.975)[1]]
  lines(rep(q0025,2),c(-10,10),lty=2,col="blue")
  lines(rep(q0975,2),c(-10,10),lty=2,col="blue")


  #Schaetzungen Differenz:

  #Mittelwert
  mittelwert = sum(fv*integrationsbereich)

  #p-Wert
  if (Fv[Nmitte] < 0.5) {
    pwert = 2*Fv[Nmitte]
  } else {
    pwert = 2*(1-Fv[Nmitte])
  }

  #Standardabweichung Bootstrap-Vtlg
  see = sum(fv*integrationsbereich^2) - mittelwert^2

  zeile = data.frame(wtpname=names(WTP_Total_DM1)[i],mw=mittelwert,se=see,p=pwert)
  tabelle = rbind(tabelle,zeile)

}

plot(c(0),type="n",axes=FALSE,xlab="",ylab="")
legend("topright",legend=c("Emp. Δ densities","0.95 CI"),fill=c("black","blue"))


print(tabelle)
```

8.4.2 R Script for Chapter 4: CL model with Interactions

```
### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000)

### Initialise code
apollo_initialise()

### Set core controls
apollo_control = list(
  modelName  ="211208_CL_Interactions",
  modelDescr ="CL_Interactions",
  indivID    ="ID"
)

# ################################################################# #
#### LOAD DATA AND APPLY ANY TRANSFORMATIONS                     ####
# ################################################################# #

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1")

colnames(database) <- c("ID", colnames(database)[-1])

database = subset(database,database$Task!=5,) #Fix task


database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]
```

```
  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

# ################################################################# #
#### DEFINE MODEL PARAMETERS                                     ####
# ################################################################# #

### Vector of parameters, including any that are kept fixed in estimation
apollo_beta = c(

# ################ Basic Model
                ASC_alt1   =     0,
                PRICECALC1 =     0,
                PRICECALC2 =     0,
                PRICEEMAIL =     0,
                PRICEPORTAL=     0,
                PRICEAPP   =     0,
                SERVEMAIL  =     0,
                SERVCHAT   =     0,
                SERVAPP    =     0,
                DEVICE1    =     0,
                DEVICE2    =     0,
                DEVICE3    =     0,
                DEVICE4    =     0,
                CHARGE     =     0
)

### Vector with names (in quotes) of parameters to be kept fixed at their starting value in apollo_beta,
use apollo_beta_fixed = c() if none
apollo_fixed = c()

# ################################################################# #
#### GROUP AND VALIDATE INPUTS                                   ####
# ################################################################# #

apollo_inputs = apollo_validateInputs()

# ################################################################# #
#### DEFINE MODEL AND LIKELIHOOD FUNCTION                        ####
# ################################################################# #

apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){

  ### Attach inputs and detach after function exit
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  ### Create list of probabilities P
  P = list()

  ### List of utilities: these must use the same names as in mnl_settings, order is irrelevant
  V = list()

  V[['alt1']]  =
    ASC_alt1                   +
    PRICECALC1    * (att_P_alt1==2)  +
    PRICECALC2    * (att_P_alt1==3)  +
    PRICEEMAIL    * (att_A1_alt1==1) +
    PRICEPORTAL   * (att_A2_alt1==1) +
    PRICEAPP      * (att_A3_alt1==1) +
    SERVEMAIL     * (att_S1_alt1==1) +
    SERVCHAT      * (att_S2_alt1==1) +
    SERVAPP       * (att_S3_alt1==1) +
    DEVICE1       * (att_T_alt1==1)  +
    DEVICE2       * (att_T_alt1==2)  +
    DEVICE3       * (att_T_alt1==3)  +
    DEVICE4       * (att_T_alt1==4)  +
    CHARGE        * att_C_alt1
```

```
  V[['alt2']]  =                                #Utility function Alternative 2
    PRICECALC1    * (att_P_alt2==2)  +
    PRICECALC2    * (att_P_alt2==3)  +
    PRICEEMAIL    * (att_A1_alt2==1) +
    PRICEPORTAL   * (att_A2_alt2==1) +
    PRICEAPP      * (att_A3_alt2==1) +
    SERVEMAIL     * (att_S1_alt2==1) +
    SERVCHAT      * (att_S2_alt2==1) +
    SERVAPP       * (att_S3_alt2==1) +
    DEVICE1       * (att_T_alt2==1)  +
    DEVICE2       * (att_T_alt2==2)  +
    DEVICE3       * (att_T_alt2==3)  +
    DEVICE4       * (att_T_alt2==4)  +
    CHARGE        * att_C_alt2


  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V
  )

   ### Compute probabilities using MNL model
  P[['model']] = apollo_mnl(mnl_settings, functionality)

  ### Take product across observation for same individual
  P = apollo_panelProd(P, apollo_inputs, functionality)

  ### Prepare and return outputs of function
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}

#View(apollo_probabilities)

# ################################################################# #
#### MODEL ESTIMATION                                            ####
# ################################################################# #

model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

apollo_saveOutput(model, saveOutput_settings=list(printPVal=TRUE,
                                                  printCovar=FALSE,
                                                  printCorr=FALSE,
                                                  printOutliers=FALSE,
                                                  printChange=FALSE,
                                                  saveEst=TRUE,
                                                  saveCov=FALSE,
                                                  saveCorr=FALSE,
                                                  saveModeObject=TRUE
))



# ################################################################# #
#### MODEL OUTPUTS                                               ####
# ################################################################# #

# ----------------------------------------------------------------- #
#---- FORMATTED OUTPUT (TO SCREEN)                               ----
# ----------------------------------------------------------------- #

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,
                                                    printCovar=FALSE,
                                                    printCorr=FALSE,
                                                    printOutliers=FALSE,
                                                    printChange=FALSE,
                                                    saveEst=TRUE,
                                                    saveCov=FALSE,
                                                    saveCorr=FALSE,
                                                    saveModeObject=TRUE
))

WTP_Base <- wtp(cost = "CHARGE",names(model$estimate), model = model)
saveRDS(WTP_Base, "WTP_Base.rds")
saveRDS(model,  "Model_Base.rds")


#P1################################################################################
```

```
### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_p0_CL_Mull",
  modelDescr ="WTP_p0",
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)

database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


round_df <- function(x, digits) {
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}


wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
```

```
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}


apollo_beta = c(

  ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

   PRICEEMAIL_p0     =     0,
  PRICEPORTAL_p0     =     0,
     PRICEAPP_p0     =     0,
    SERVEMAIL_p0     =     0,
     SERVCHAT_p0     =     0,
      SERVAPP_p0     =     0,
      DEVICE1_p0     =     0,
      DEVICE2_p0     =     0,
      DEVICE3_p0     =     0,
      DEVICE4_p0     =     0
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                +
    PRICECALC1                                        * (att_P_alt1==2)     +
    PRICECALC2                                        * (att_P_alt1==3)     +
    (PRICEEMAIL   +  (PRICEEMAIL_p0   * (att_P_alt1==1))) * (att_A1_alt1==1)     +
    (PRICEPORTAL  + (PRICEPORTAL_p0   * (att_P_alt1==1))) * (att_A2_alt1==1)     +
    (PRICEAPP     +    (PRICEAPP_p0   * (att_P_alt1==1))) * (att_A3_alt1==1)     +
    (SERVEMAIL    +   (SERVEMAIL_p0   * (att_P_alt1==1))) * (att_S1_alt1==1)     +
    (SERVCHAT     +    (SERVCHAT_p0   * (att_P_alt1==1))) * (att_S2_alt1==1)     +
    (SERVAPP      +     (SERVAPP_p0   * (att_P_alt1==1))) * (att_S3_alt1==1)     +
    (DEVICE1      +     (DEVICE1_p0   * (att_P_alt1==1))) * (att_T_alt1==1)     +
    (DEVICE2      +     (DEVICE2_p0   * (att_P_alt1==1))) * (att_T_alt1==2)     +
    (DEVICE3      +     (DEVICE3_p0   * (att_P_alt1==1))) * (att_T_alt1==3)     +
    (DEVICE4      +     (DEVICE4_p0   * (att_P_alt1==1))) * (att_T_alt1==4)     +
    CHARGE                                            * (att_C_alt1)

  V[['alt2']]  =
    PRICECALC1                                          * (att_P_alt2==2)     +
    PRICECALC2                                          * (att_P_alt2==3)     +
    (PRICEEMAIL   +  (PRICEEMAIL_p0     * (att_P_alt2==1))) * (att_A1_alt2==1)     +
    (PRICEPORTAL  + (PRICEPORTAL_p0     * (att_P_alt2==1))) * (att_A2_alt2==1)     +
    (PRICEAPP     +    (PRICEAPP_p0     * (att_P_alt2==1))) * (att_A3_alt2==1)     +
    (SERVEMAIL    +   (SERVEMAIL_p0     * (att_P_alt2==1))) * (att_S1_alt2==1)     +
    (SERVCHAT     +    (SERVCHAT_p0     * (att_P_alt2==1))) * (att_S2_alt2==1)     +
    (SERVAPP      +     (SERVAPP_p0     * (att_P_alt2==1))) * (att_S3_alt2==1)     +
    (DEVICE1      +     (DEVICE1_p0     * (att_P_alt2==1))) * (att_T_alt2==1)     +
    (DEVICE2      +     (DEVICE2_p0     * (att_P_alt2==1))) * (att_T_alt2==2)     +
    (DEVICE3      +     (DEVICE3_p0     * (att_P_alt2==1))) * (att_T_alt2==3)     +
    (DEVICE4      +     (DEVICE4_p0     * (att_P_alt2==1))) * (att_T_alt2==4)     +
    CHARGE                                              * (att_C_alt2)

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,
```

```
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_p0 <- wtp(cost = "CHARGE",names(model$estimate), model = model)
saveRDS(WTP_p0, "WTP_p0.rds")
saveRDS(model,"Model_p0.rds")



#P1################################################################################

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_p1_CL_Mull",
  modelDescr ="WTP_p1",
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


# database_DM1 <- subset(database,database$DM_Group!=2,)
# database_DM2 <- subset(database,database$DM_Group!=1,)

################################################

##############################
#Funktion zum Runden von Werten

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
```

```
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

##############################
#WTP-Berechnung auf Basis Apollo_delta_method

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}


apollo_beta = c(

  ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

   PRICEEMAIL_p1     =     0,
  PRICEPORTAL_p1    =     0,
     PRICEAPP_p1       =     0,
    SERVEMAIL_p1      =     0,
     SERVCHAT_p1       =     0,
      SERVAPP_p1        =     0,
      DEVICE1_p1        =     0,
      DEVICE2_p1        =     0,
      DEVICE3_p1        =     0,
      DEVICE4_p1        =     0
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
      ASC_alt1                                                                      +
      PRICECALC1                                        * (att_P_alt1==2)      +
      PRICECALC2                                        * (att_P_alt1==3)      +
     (PRICEEMAIL   +  (PRICEEMAIL_p1   * (att_P_alt1==2))) * (att_A1_alt1==1)     +
     (PRICEPORTAL  + (PRICEPORTAL_p1   * (att_P_alt1==2))) * (att_A2_alt1==1)     +
     (PRICEAPP     +    (PRICEAPP_p1   * (att_P_alt1==2))) * (att_A3_alt1==1)     +
     (SERVEMAIL    +   (SERVEMAIL_p1   * (att_P_alt1==2))) * (att_S1_alt1==1)     +
     (SERVCHAT     +    (SERVCHAT_p1   * (att_P_alt1==2))) * (att_S2_alt1==1)     +
     (SERVAPP      +     (SERVAPP_p1   * (att_P_alt1==2))) * (att_S3_alt1==1)     +
     (DEVICE1      +     (DEVICE1_p1   * (att_P_alt1==2))) * (att_T_alt1==1)      +
     (DEVICE2      +     (DEVICE2_p1   * (att_P_alt1==2))) * (att_T_alt1==2)      +
     (DEVICE3      +     (DEVICE3_p1   * (att_P_alt1==2))) * (att_T_alt1==3)      +
     (DEVICE4      +     (DEVICE4_p1   * (att_P_alt1==2))) * (att_T_alt1==4)      +
      CHARGE                                            * (att_C_alt1)

  V[['alt2']]  =
      PRICECALC1                                          * (att_P_alt2==2)      +
      PRICECALC2                                          * (att_P_alt2==3)      +
     (PRICEEMAIL   +  (PRICEEMAIL_p1     * (att_P_alt2==2))) * (att_A1_alt2==1)     +
     (PRICEPORTAL  + (PRICEPORTAL_p1     * (att_P_alt2==2))) * (att_A2_alt2==1)     +
     (PRICEAPP     +    (PRICEAPP_p1     * (att_P_alt2==2))) * (att_A3_alt2==1)     +
     (SERVEMAIL    +   (SERVEMAIL_p1     * (att_P_alt2==2))) * (att_S1_alt2==1)     +
     (SERVCHAT     +    (SERVCHAT_p1     * (att_P_alt2==2))) * (att_S2_alt2==1)     +
     (SERVAPP      +     (SERVAPP_p1     * (att_P_alt2==2))) * (att_S3_alt2==1)     +
```

```
     (DEVICE1      +     (DEVICE1_p1     * (att_P_alt2==2))) * (att_T_alt2==1)      +
     (DEVICE2      +     (DEVICE2_p1     * (att_P_alt2==2))) * (att_T_alt2==2)      +
     (DEVICE3      +     (DEVICE3_p1     * (att_P_alt2==2))) * (att_T_alt2==3)      +
     (DEVICE4      +     (DEVICE4_p1     * (att_P_alt2==2))) * (att_T_alt2==4)      +
      CHARGE                                                 * (att_C_alt2)

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

                 WTP_p1 <- wtp(cost = "CHARGE",names(model$estimate), model = model)
         saveRDS(WTP_p1, "WTP_p1.rds")
saveRDS(model,"Model_p1.rds")

WTP_p1 <- readRDS("WTP_p1.rds")
Model_p1 <- readRDS("Model_p1.rds")


#####################################################################################################
############


#P2##################################################################################################
##############
#setwd("C:\\Users\\sasch.DESKTOP-LRKJOSB\\OneDrive\\Dropbox\\01_Dissertation\\00_Contributions\\01 DCE
Setup\\15_R-Workingspace\\06_WIP")

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen


apollo_initialise()

apollo_control = list(
  modelName  ="211208_p2_CL_Mull",
  modelDescr    ="WTP_p2",
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
```

```
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


# database_DM1 <- subset(database,database$DM_Group!=2,)
# database_DM2 <- subset(database,database$DM_Group!=1,)

################################################

##############################
#Funktion zum Runden von Werten

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

##############################
#WTP-Berechnung auf Basis Apollo_delta_method

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(

  ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

   PRICEEMAIL_p2     =     0,
  PRICEPORTAL_p2    =     0,
     PRICEAPP_p2       =     0,
    SERVEMAIL_p2      =     0,
     SERVCHAT_p2       =     0,
      SERVAPP_p2        =     0,
      DEVICE1_p2        =     0,
      DEVICE2_p2        =     0,
      DEVICE3_p2        =     0,
      DEVICE4_p2        =     0
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
```

```
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                   +
    PRICECALC1                                            * (att_P_alt1==2)      +
    PRICECALC2                                            * (att_P_alt1==3)      +
    (PRICEEMAIL   +  (PRICEEMAIL_p2   * (att_P_alt1==3))) * (att_A1_alt1==1)     +
    (PRICEPORTAL  + (PRICEPORTAL_p2   * (att_P_alt1==3))) * (att_A2_alt1==1)     +
    (PRICEAPP     +    (PRICEAPP_p2   * (att_P_alt1==3))) * (att_A3_alt1==1)     +
    (SERVEMAIL    +   (SERVEMAIL_p2   * (att_P_alt1==3))) * (att_S1_alt1==1)     +
    (SERVCHAT     +    (SERVCHAT_p2   * (att_P_alt1==3))) * (att_S2_alt1==1)     +
    (SERVAPP      +     (SERVAPP_p2   * (att_P_alt1==3))) * (att_S3_alt1==1)     +
    (DEVICE1      +     (DEVICE1_p2   * (att_P_alt1==3))) * (att_T_alt1==1)      +
    (DEVICE2      +     (DEVICE2_p2   * (att_P_alt1==3))) * (att_T_alt1==2)      +
    (DEVICE3      +     (DEVICE3_p2   * (att_P_alt1==3))) * (att_T_alt1==3)      +
    (DEVICE4      +     (DEVICE4_p2   * (att_P_alt1==3))) * (att_T_alt1==4)      +
    CHARGE                                                * (att_C_alt1)

  V[['alt2']]  =
    PRICECALC1                                              * (att_P_alt2==2)      +
    PRICECALC2                                              * (att_P_alt2==3)      +
    (PRICEEMAIL   +  (PRICEEMAIL_p2     * (att_P_alt2==3))) * (att_A1_alt2==1)     +
    (PRICEPORTAL  + (PRICEPORTAL_p2     * (att_P_alt2==3))) * (att_A2_alt2==1)     +
    (PRICEAPP     +    (PRICEAPP_p2     * (att_P_alt2==3))) * (att_A3_alt2==1)     +
    (SERVEMAIL    +   (SERVEMAIL_p2     * (att_P_alt2==3))) * (att_S1_alt2==1)     +
    (SERVCHAT     +    (SERVCHAT_p2     * (att_P_alt2==3))) * (att_S2_alt2==1)     +
    (SERVAPP      +     (SERVAPP_p2     * (att_P_alt2==3))) * (att_S3_alt2==1)     +
    (DEVICE1      +     (DEVICE1_p2     * (att_P_alt2==3))) * (att_T_alt2==1)      +
    (DEVICE2      +     (DEVICE2_p2     * (att_P_alt2==3))) * (att_T_alt2==2)      +
    (DEVICE3      +     (DEVICE3_p2     * (att_P_alt2==3))) * (att_T_alt2==3)      +
    (DEVICE4      +     (DEVICE4_p2     * (att_P_alt2==3))) * (att_T_alt2==4)      +
    CHARGE                                                 * (att_C_alt2)

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

                 WTP_p2 <- wtp(cost = "CHARGE",names(model$estimate), model = model)
         saveRDS(WTP_p2, "WTP_p2.rds")
saveRDS(model,"Model_p2.rds")
#####################################################################################################
############

#A1###################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000)

apollo_initialise()
```

```
apollo_control = list(
  modelName  ="211208_a1_CL_Mull",                                                         #EINSATZ
  modelDescr    ="WTP_a1",                                                                  #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

   PRICECALC1_a1        =     0,                                                               #EINSATZ
   PRICECALC2_a1        =     0,                                                                #EINSATZ
    SERVEMAIL_a1        =     0,                                                              #EINSATZ
     SERVCHAT_a1        =     0,                                                             #EINSATZ
      SERVAPP_a1        =     0,                                                            #EINSATZ
      DEVICE1_a1        =     0,                                                            #EINSATZ
      DEVICE2_a1        =     0,                                                            #EINSATZ
      DEVICE3_a1        =     0,                                                            #EINSATZ
      DEVICE4_a1        =     0                                                             #EINSATZ
)
```

```
apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                  +          #EINSATZ
    (PRICECALC1  + (PRICECALC1_a1 * (att_A1_alt1==1)))     * ( att_P_alt1==2)     +          #EINSATZ
    (PRICECALC2  + (PRICECALC2_a1 * (att_A1_alt1==1)))     * ( att_P_alt1==3)     +          #EINSATZ
    PRICEEMAIL                                             * (att_A1_alt1==1)     +          #EINSATZ
    PRICEPORTAL                                            * (att_A2_alt1==1)     +          #EINSATZ
    PRICEAPP                                               * (att_A3_alt1==1)     +          #EINSATZ
    (SERVEMAIL    +   (SERVEMAIL_a1   * (att_A1_alt1==1))) * (att_S1_alt1==1)     +          #EINSATZ
    (SERVCHAT     +    (SERVCHAT_a1   * (att_A1_alt1==1))) * (att_S2_alt1==1)     +          #EINSATZ
    (SERVAPP      +     (SERVAPP_a1   * (att_A1_alt1==1))) * (att_S3_alt1==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_a1   * (att_A1_alt1==1))) * (att_T_alt1==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_a1   * (att_A1_alt1==1))) * (att_T_alt1==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_a1   * (att_A1_alt1==1))) * (att_T_alt1==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_a1   * (att_A1_alt1==1))) * (att_T_alt1==4)      +          #EINSATZ
    CHARGE                                                 * (att_C_alt1)                    #EINSATZ

  V[['alt2']]  =
    (PRICECALC1  + (PRICECALC1_a1 * (att_A1_alt2==1)))     * ( att_P_alt2==2)     +          #EINSATZ
    (PRICECALC2  + (PRICECALC2_a1 * (att_A1_alt2==1)))     * ( att_P_alt2==3)     +          #EINSATZ
    PRICEEMAIL                                             * (att_A1_alt2==1)     +          #EINSATZ
    PRICEPORTAL                                            * (att_A2_alt2==1)     +          #EINSATZ
    PRICEAPP                                               * (att_A3_alt2==1)     +          #EINSATZ
    (SERVEMAIL    +   (SERVEMAIL_a1   * (att_A1_alt2==1))) * (att_S1_alt2==1)     +          #EINSATZ
    (SERVCHAT     +    (SERVCHAT_a1   * (att_A1_alt2==1))) * (att_S2_alt2==1)     +          #EINSATZ
    (SERVAPP      +     (SERVAPP_a1   * (att_A1_alt2==1))) * (att_S3_alt2==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_a1   * (att_A1_alt2==1))) * (att_T_alt2==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_a1   * (att_A1_alt2==1))) * (att_T_alt2==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_a1   * (att_A1_alt2==1))) * (att_T_alt2==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_a1   * (att_A1_alt2==1))) * (att_T_alt2==4)      +          #EINSATZ
    CHARGE                                                 * (att_C_alt2)                    #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_a1 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_a1, "WTP_a1.rds")                                                           #EINSATZ
saveRDS(model,"Model_a1.rds")                                                           #EINSATZ
#####################################################################################################
############

#A2##################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)
```

```
options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_a2_CL_Mull",                                                          #EINSATZ
  modelDescr    ="WTP_a2",                                                                  #EINSATZ
  indivID    ="ID")


database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                PRICECALC1_a2        =     0,
#EINSATZ
                PRICECALC2_a2        =     0,
#EINSATZ
```

```
                 SERVEMAIL_a2        =     0,
#EINSATZ
                  SERVCHAT_a2        =     0,
#EINSATZ
                   SERVAPP_a2        =     0,
#EINSATZ
                   DEVICE1_a2        =     0,
#EINSATZ
                   DEVICE2_a2        =     0,
#EINSATZ
                   DEVICE3_a2        =     0,
#EINSATZ
                   DEVICE4_a2        =     0
#EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                   +          #EINSATZ
    (PRICECALC1  + (PRICECALC1_a2 * (att_A2_alt1==1)))     * ( att_P_alt1==2)     +          #EINSATZ
    (PRICECALC2  + (PRICECALC2_a2 * (att_A2_alt1==1)))     * ( att_P_alt1==3)     +          #EINSATZ
    PRICEEMAIL                                             * (att_A1_alt1==1)     +          #EINSATZ
    PRICEPORTAL                                            * (att_A2_alt1==1)     +          #EINSATZ
    PRICEAPP                                               * (att_A3_alt1==1)     +          #EINSATZ
    (SERVEMAIL    +   (SERVEMAIL_a2   * (att_A2_alt1==1))) * (att_S1_alt1==1)     +          #EINSATZ
    (SERVCHAT     +    (SERVCHAT_a2   * (att_A2_alt1==1))) * (att_S2_alt1==1)     +          #EINSATZ
    (SERVAPP      +     (SERVAPP_a2   * (att_A2_alt1==1))) * (att_S3_alt1==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_a2   * (att_A2_alt1==1))) * (att_T_alt1==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_a2   * (att_A2_alt1==1))) * (att_T_alt1==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_a2   * (att_A2_alt1==1))) * (att_T_alt1==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_a2   * (att_A2_alt1==1))) * (att_T_alt1==4)      +          #EINSATZ
    CHARGE                                                 * (att_C_alt1)                    #EINSATZ

  V[['alt2']]  =
    (PRICECALC1  + (PRICECALC1_a2 * (att_A2_alt2==1)))     * ( att_P_alt2==2)     +          #EINSATZ
    (PRICECALC2  + (PRICECALC2_a2 * (att_A2_alt2==1)))     * ( att_P_alt2==3)     +          #EINSATZ
    PRICEEMAIL                                             * (att_A1_alt2==1)     +          #EINSATZ
    PRICEPORTAL                                            * (att_A2_alt2==1)     +          #EINSATZ
    PRICEAPP                                               * (att_A3_alt2==1)     +          #EINSATZ
    (SERVEMAIL    +   (SERVEMAIL_a2   * (att_A2_alt2==1))) * (att_S1_alt2==1)     +          #EINSATZ
    (SERVCHAT     +    (SERVCHAT_a2   * (att_A2_alt2==1))) * (att_S2_alt2==1)     +          #EINSATZ
    (SERVAPP      +     (SERVAPP_a2   * (att_A2_alt2==1))) * (att_S3_alt2==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_a2   * (att_A2_alt2==1))) * (att_T_alt2==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_a2   * (att_A2_alt2==1))) * (att_T_alt2==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_a2   * (att_A2_alt2==1))) * (att_T_alt2==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_a2   * (att_A2_alt2==1))) * (att_T_alt2==4)      +          #EINSATZ
    CHARGE                                                 * (att_C_alt2)                    #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_a2 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_a2, "WTP_a2.rds")                                                            #EINSATZ
saveRDS(model,"Model_a2.rds")                                                            #EINSATZ
#####################################################################################################
############

#A3##################################################################################################
##############
### Clear memory
```

```
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_a3_CL_Mull",                                                    #EINSATZ
  modelDescr    ="WTP_a3",                                                              #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2
```

```
  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                PRICECALC1_a3        =     0,
#EINSATZ
                PRICECALC2_a3        =     0,
#EINSATZ
                 SERVEMAIL_a3        =     0,
#EINSATZ
                  SERVCHAT_a3        =     0,
#EINSATZ
                   SERVAPP_a3        =     0,
#EINSATZ
                   DEVICE1_a3        =     0,
#EINSATZ
                   DEVICE2_a3        =     0,
#EINSATZ
                   DEVICE3_a3        =     0,
#EINSATZ
                   DEVICE4_a3        =     0
#EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                  +          #EINSATZ
    (PRICECALC1  + (PRICECALC1_a3 * (att_A3_alt1==1)))     * ( att_P_alt1==2)      +          #EINSATZ
    (PRICECALC2  + (PRICECALC2_a3 * (att_A3_alt1==1)))     * ( att_P_alt1==3)      +          #EINSATZ
    PRICEEMAIL                                             * (att_A1_alt1==1)      +          #EINSATZ
    PRICEPORTAL                                            * (att_A2_alt1==1)      +          #EINSATZ
    PRICEAPP                                               * (att_A3_alt1==1)      +          #EINSATZ
    (SERVEMAIL    +   (SERVEMAIL_a3   * (att_A3_alt1==1))) * (att_S1_alt1==1)     +          #EINSATZ
    (SERVCHAT     +    (SERVCHAT_a3   * (att_A3_alt1==1))) * (att_S2_alt1==1)     +          #EINSATZ
    (SERVAPP      +     (SERVAPP_a3   * (att_A3_alt1==1))) * (att_S3_alt1==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_a3   * (att_A3_alt1==1))) * (att_T_alt1==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_a3   * (att_A3_alt1==1))) * (att_T_alt1==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_a3   * (att_A3_alt1==1))) * (att_T_alt1==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_a3   * (att_A3_alt1==1))) * (att_T_alt1==4)      +          #EINSATZ
    CHARGE                                                 * (att_C_alt1)                     #EINSATZ

  V[['alt2']]  =
    (PRICECALC1  + (PRICECALC1_a3 * (att_A3_alt2==1)))     * ( att_P_alt2==2)      +          #EINSATZ
    (PRICECALC2  + (PRICECALC2_a3 * (att_A3_alt2==1)))     * ( att_P_alt2==3)      +          #EINSATZ
    PRICEEMAIL                                             * (att_A1_alt2==1)      +          #EINSATZ
    PRICEPORTAL                                            * (att_A2_alt2==1)      +          #EINSATZ
    PRICEAPP                                               * (att_A3_alt2==1)      +          #EINSATZ
    (SERVEMAIL    +   (SERVEMAIL_a3   * (att_A3_alt2==1))) * (att_S1_alt2==1)     +          #EINSATZ
    (SERVCHAT     +    (SERVCHAT_a3   * (att_A3_alt2==1))) * (att_S2_alt2==1)     +          #EINSATZ
    (SERVAPP      +     (SERVAPP_a3   * (att_A3_alt2==1))) * (att_S3_alt2==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_a3   * (att_A3_alt2==1))) * (att_T_alt2==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_a3   * (att_A3_alt2==1))) * (att_T_alt2==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_a3   * (att_A3_alt2==1))) * (att_T_alt2==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_a3   * (att_A3_alt2==1))) * (att_T_alt2==4)      +          #EINSATZ
    CHARGE                                                 * (att_C_alt2)                     #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,
```

```
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_a3 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_a3,"WTP_a3.rds")                                                                #EINSATZ
saveRDS(model,"Model_a3.rds")                                                                #EINSATZ

##########################################################################################################
############

#S1########################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_s1_CL_Mull",                                                     #EINSATZ
  modelDescr    ="WTP_s1",                                                              #EINSATZ
  indivID    ="ID")


database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}
```

```
wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                PRICECALC1_s1       =    0,
#EINSATZ
                PRICECALC2_s1       =    0,
#EINSATZ
                PRICEEMAIL_s1       =    0,
#EINSATZ
               PRICEPORTAL_s1       =    0,
#EINSATZ
                  PRICEAPP_s1       =    0,
#EINSATZ
                   DEVICE1_s1       =    0,
#EINSATZ
                   DEVICE2_s1       =    0,
#EINSATZ
                   DEVICE3_s1       =    0,
#EINSATZ
                   DEVICE4_s1       =    0
#EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                  +          #EINSATZ
    (PRICECALC1   +  (PRICECALC1_s1   * (att_S1_alt1==1)))  * ( att_P_alt1==2)     +          #EINSATZ
    (PRICECALC2   +  (PRICECALC2_s1   * (att_S1_alt1==1)))  * ( att_P_alt1==3)     +          #EINSATZ
    (PRICEEMAIL   + (PRICEEMAIL_s1    * (att_S1_alt1==1)))  * (att_A1_alt1==1)     +          #EINSATZ
    (PRICEPORTAL  + (PRICEPORTAL_s1   * (att_S1_alt1==1)))  * (att_A2_alt1==1)     +          #EINSATZ
    (PRICEAPP     + (PRICEAPP_s1      * (att_S1_alt1==1)))  * (att_A3_alt1==1)     +          #EINSATZ
    SERVEMAIL                                               * (att_S1_alt1==1)     +          #EINSATZ
    SERVCHAT                                                * (att_S2_alt1==1)     +          #EINSATZ
    SERVAPP                                                 * (att_S3_alt1==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_s1   * (att_S1_alt1==1)))  * (att_T_alt1==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_s1   * (att_S1_alt1==1)))  * (att_T_alt1==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_s1   * (att_S1_alt1==1)))  * (att_T_alt1==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_s1   * (att_S1_alt1==1)))  * (att_T_alt1==4)      +          #EINSATZ
    CHARGE                                                  * (att_C_alt1)                    #EINSATZ

  V[['alt2']]  =
    (PRICECALC1   +  (PRICECALC1_s1   * (att_S1_alt2==1)))  * ( att_P_alt2==2)     +          #EINSATZ
    (PRICECALC2   +  (PRICECALC2_s1   * (att_S1_alt2==1)))  * ( att_P_alt2==3)     +          #EINSATZ
    (PRICEEMAIL   + (PRICEEMAIL_s1    * (att_S1_alt2==1)))  * (att_A1_alt2==1)     +          #EINSATZ
    (PRICEPORTAL  + (PRICEPORTAL_s1   * (att_S1_alt2==1)))  * (att_A2_alt2==1)     +          #EINSATZ
    (PRICEAPP     + (PRICEAPP_s1      * (att_S1_alt2==1)))  * (att_A3_alt2==1)     +          #EINSATZ
    SERVEMAIL                                               * (att_S1_alt2==1)     +          #EINSATZ
    SERVCHAT                                                * (att_S2_alt2==1)     +          #EINSATZ
    SERVAPP                                                 * (att_S3_alt2==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_s1   * (att_S1_alt2==1)))  * (att_T_alt2==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_s1   * (att_S1_alt2==1)))  * (att_T_alt2==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_s1   * (att_S1_alt2==1)))  * (att_T_alt2==3)      +          #EINSATZ
```

```
    (DEVICE4      +     (DEVICE4_s1   * (att_S1_alt2==1)))  * (att_T_alt2==4)      +          #EINSATZ
    CHARGE                                                  * (att_C_alt2)                    #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_s1 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_s1,"WTP_s1.rds")                                                                #EINSATZ
saveRDS(model,"Model_s1.rds")                                                                #EINSATZ

##########################################################################################################
############

#S2########################################################################################################
##############
### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_s2_CL_Mull",                                                         #EINSATZ
  modelDescr    ="WTP_s2",                                                                  #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
```

```
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                 PRICECALC1_s2        =     0,
#EINSATZ
                 PRICECALC2_s2        =     0,
#EINSATZ
                 PRICEEMAIL_s2        =     0,
#EINSATZ
                PRICEPORTAL_s2        =     0,
#EINSATZ
                   PRICEAPP_s2        =     0,
#EINSATZ
                    DEVICE1_s2        =     0,
#EINSATZ
                    DEVICE2_s2        =     0,
#EINSATZ
                    DEVICE3_s2        =     0,
#EINSATZ
                    DEVICE4_s2        =     0
#EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                 +           #EINSATZ
    (PRICECALC1   +  (PRICECALC1_s2   * (att_S2_alt1==1)))   * ( att_P_alt1==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_s2   * (att_S2_alt1==1)))   * ( att_P_alt1==3)     +           #EINSATZ
    (PRICEEMAIL   + (PRICEEMAIL_s2    * (att_S2_alt1==1)))   * (att_A1_alt1==1)     +           #EINSATZ
    (PRICEPORTAL  + (PRICEPORTAL_s2   * (att_S2_alt1==1)))   * (att_A2_alt1==1)     +           #EINSATZ
    (PRICEAPP     + (PRICEAPP_s2      * (att_S2_alt1==1)))   * (att_A3_alt1==1)     +           #EINSATZ
    SERVEMAIL                                                * (att_S1_alt1==1)     +           #EINSATZ
    SERVCHAT                                                 * (att_S2_alt1==1)     +           #EINSATZ
    SERVAPP                                                  * (att_S3_alt1==1)     +           #EINSATZ
    (DEVICE1      +     (DEVICE1_s2   * (att_S2_alt1==1)))   * (att_T_alt1==1)      +           #EINSATZ
    (DEVICE2      +     (DEVICE2_s2   * (att_S2_alt1==1)))   * (att_T_alt1==2)      +           #EINSATZ
    (DEVICE3      +     (DEVICE3_s2   * (att_S2_alt1==1)))   * (att_T_alt1==3)      +           #EINSATZ
    (DEVICE4      +     (DEVICE4_s2   * (att_S2_alt1==1)))   * (att_T_alt1==4)      +           #EINSATZ
```

```
    CHARGE                                                   * (att_C_alt1)                    #EINSATZ

  V[['alt2']]  =
    (PRICECALC1   +  (PRICECALC1_s2   * (att_S2_alt2==1)))  * ( att_P_alt2==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_s2   * (att_S2_alt2==1)))  * ( att_P_alt2==3)     +           #EINSATZ
    (PRICEEMAIL   + (PRICEEMAIL_s2    * (att_S2_alt2==1)))  * (att_A1_alt2==1)     +           #EINSATZ
    (PRICEPORTAL  + (PRICEPORTAL_s2   * (att_S2_alt2==1)))  * (att_A2_alt2==1)     +           #EINSATZ
    (PRICEAPP     + (PRICEAPP_s2      * (att_S2_alt2==1)))  * (att_A3_alt2==1)     +           #EINSATZ
    SERVEMAIL                                               * (att_S1_alt2==1)     +           #EINSATZ
    SERVCHAT                                                * (att_S2_alt2==1)     +           #EINSATZ
    SERVAPP                                                 * (att_S3_alt2==1)     +           #EINSATZ
    (DEVICE1      +     (DEVICE1_s2   * (att_S2_alt2==1)))  * (att_T_alt2==1)      +           #EINSATZ
    (DEVICE2      +     (DEVICE2_s2   * (att_S2_alt2==1)))  * (att_T_alt2==2)      +           #EINSATZ
    (DEVICE3      +     (DEVICE3_s2   * (att_S2_alt2==1)))  * (att_T_alt2==3)      +           #EINSATZ
    (DEVICE4      +     (DEVICE4_s2   * (att_S2_alt2==1)))  * (att_T_alt2==4)      +           #EINSATZ
    CHARGE                                                  * (att_C_alt2)                     #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_s2 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_s2,"WTP_s2.rds")                                                                #EINSATZ
saveRDS(model,"Model_s2.rds")                                                                #EINSATZ

#####################################################################################################
############

#S3##################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_s3_CL_Mull",                                                        #EINSATZ
  modelDescr    ="WTP_s3",                                                                 #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
```

```
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                 PRICECALC1_s3        =     0,
#EINSATZ
                 PRICECALC2_s3        =     0,
#EINSATZ
                 PRICEEMAIL_s3        =     0,
#EINSATZ
                PRICEPORTAL_s3        =     0,
#EINSATZ
                   PRICEAPP_s3        =     0,
#EINSATZ
                    DEVICE1_s3        =     0,
#EINSATZ
                    DEVICE2_s3        =     0,
#EINSATZ
                    DEVICE3_s3        =     0,
#EINSATZ
                    DEVICE4_s3        =     0
#EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
```

```
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                       +          #EINSATZ
    (PRICECALC1   +  (PRICECALC1_s3   * (att_S3_alt1==1)))   * ( att_P_alt1==2)     +          #EINSATZ
    (PRICECALC2   +  (PRICECALC2_s3   * (att_S3_alt1==1)))   * ( att_P_alt1==3)     +          #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_s3   * (att_S3_alt1==1)))   * (att_A1_alt1==1)     +          #EINSATZ
    (PRICEPORTAL  + (PRICEPORTAL_s3   * (att_S3_alt1==1)))   * (att_A2_alt1==1)     +          #EINSATZ
    (PRICEAPP     +    (PRICEAPP_s3   * (att_S3_alt1==1)))   * (att_A3_alt1==1)     +          #EINSATZ
    SERVEMAIL                                                * (att_S1_alt1==1)     +          #EINSATZ
    SERVCHAT                                                 * (att_S2_alt1==1)     +          #EINSATZ
    SERVAPP                                                  * (att_S3_alt1==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_s3   * (att_S3_alt1==1)))   * (att_T_alt1==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_s3   * (att_S3_alt1==1)))   * (att_T_alt1==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_s3   * (att_S3_alt1==1)))   * (att_T_alt1==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_s3   * (att_S3_alt1==1)))   * (att_T_alt1==4)      +          #EINSATZ
    CHARGE                                                   * (att_C_alt1)                    #EINSATZ

  V[['alt2']]  =
    (PRICECALC1   +  (PRICECALC1_s3   * (att_S3_alt2==1)))   * ( att_P_alt2==2)     +          #EINSATZ
    (PRICECALC2   +  (PRICECALC2_s3   * (att_S3_alt2==1)))   * ( att_P_alt2==3)     +          #EINSATZ
    (PRICEEMAIL   + (PRICEEMAIL_s3    * (att_S3_alt2==1)))   * (att_A1_alt2==1)     +          #EINSATZ
    (PRICEPORTAL  + (PRICEPORTAL_s3   * (att_S3_alt2==1)))   * (att_A2_alt2==1)     +          #EINSATZ
    (PRICEAPP     + (PRICEAPP_s3      * (att_S3_alt2==1)))   * (att_A3_alt2==1)     +          #EINSATZ
    SERVEMAIL                                                * (att_S1_alt2==1)     +          #EINSATZ
    SERVCHAT                                                 * (att_S2_alt2==1)     +          #EINSATZ
    SERVAPP                                                  * (att_S3_alt2==1)     +          #EINSATZ
    (DEVICE1      +     (DEVICE1_s3   * (att_S3_alt2==1)))   * (att_T_alt2==1)      +          #EINSATZ
    (DEVICE2      +     (DEVICE2_s3   * (att_S3_alt2==1)))   * (att_T_alt2==2)      +          #EINSATZ
    (DEVICE3      +     (DEVICE3_s3   * (att_S3_alt2==1)))   * (att_T_alt2==3)      +          #EINSATZ
    (DEVICE4      +     (DEVICE4_s3   * (att_S3_alt2==1)))   * (att_T_alt2==4)      +          #EINSATZ
    CHARGE                                                   * (att_C_alt2)                    #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_s3 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_s3,"WTP_s3.rds")                                                                #EINSATZ
saveRDS(model,"Model_s3.rds")                                                                #EINSATZ

#####################################################################################################################
############

#d1##################################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()
```

```
apollo_control = list(
  modelName  ="211208_d1_CL_Mull",                                                          #EINSATZ
  modelDescr    ="WTP_d1",                                                                   #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}


wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                 PRICECALC1_d1       =     0,
#EINSATZ
                 PRICECALC2_d1       =     0,
#EINSATZ
                 PRICEEMAIL_d1       =     0,
#EINSATZ
                PRICEPORTAL_d1       =     0,
#EINSATZ
                   PRICEAPP_d1       =     0,
#EINSATZ
```

```
                  SERVEMAIL_d1       =     0,
                   SERVCHAT_d1       =     0,
                    SERVAPP_d1       =     0
#EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                   +          #EINSATZ
    (PRICECALC1    +  (PRICECALC1_d1   * (att_T_alt1==1)))    * ( att_P_alt1==2)     +          #EINSATZ
    (PRICECALC2    +  (PRICECALC2_d1   * (att_T_alt1==1)))    * ( att_P_alt1==3)     +          #EINSATZ
    (PRICEEMAIL    +  (PRICEEMAIL_d1   * (att_T_alt1==1)))    * (att_A1_alt1==1)     +          #EINSATZ
    (PRICEPORTAL   +  (PRICEPORTAL_d1  * (att_T_alt1==1)))    * (att_A2_alt1==1)     +          #EINSATZ
    (PRICEAPP      +  (PRICEAPP_d1     * (att_T_alt1==1)))    * (att_A3_alt1==1)     +          #EINSATZ
    (SERVEMAIL     +  (SERVEMAIL_d1    * (att_T_alt1==1)))    * (att_S1_alt1==1)     +          #EINSATZ
    (SERVCHAT      +  (SERVCHAT_d1     * (att_T_alt1==1)))    * (att_S2_alt1==1)     +          #EINSATZ
    (SERVAPP       +  (SERVAPP_d1      * (att_T_alt1==1)))    * (att_S3_alt1==1)     +          #EINSATZ
    DEVICE1                                                   * (att_T_alt1==1)      +          #EINSATZ
    DEVICE2                                                   * (att_T_alt1==2)      +          #EINSATZ
    DEVICE3                                                   * (att_T_alt1==3)      +          #EINSATZ
    DEVICE4                                                   * (att_T_alt1==4)      +          #EINSATZ
    CHARGE                                                    * (att_C_alt1)                    #EINSATZ

  V[['alt2']]  =
    (PRICECALC1   +  (PRICECALC1_d1   * (att_T_alt2==1)))    * ( att_P_alt2==2)     +          #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d1   * (att_T_alt2==1)))    * ( att_P_alt2==3)     +          #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_d1   * (att_T_alt2==1)))    * (att_A1_alt2==1)     +          #EINSATZ
    (PRICEPORTAL  +  (PRICEPORTAL_d1  * (att_T_alt2==1)))    * (att_A2_alt2==1)     +          #EINSATZ
    (PRICEAPP     +  (PRICEAPP_d1     * (att_T_alt2==1)))    * (att_A3_alt2==1)     +          #EINSATZ
    (SERVEMAIL    +  (SERVEMAIL_d1    * (att_T_alt2==1)))    * (att_S1_alt2==1)     +          #EINSATZ
    (SERVCHAT     +  (SERVCHAT_d1     * (att_T_alt2==1)))    * (att_S2_alt2==1)     +          #EINSATZ
    (SERVAPP      +  (SERVAPP_d1      * (att_T_alt2==1)))    * (att_S3_alt2==1)     +          #EINSATZ
    DEVICE1                                                  * (att_T_alt2==1)      +          #EINSATZ
    DEVICE2                                                  * (att_T_alt2==2)      +          #EINSATZ
    DEVICE3                                                  * (att_T_alt2==3)      +          #EINSATZ
    DEVICE4                                                  * (att_T_alt2==4)      +          #EINSATZ
    CHARGE                                                   * (att_C_alt2)                    #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_d1 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_d1,"WTP_d1.rds")                                                           #EINSATZ
saveRDS(model,"Model_d1.rds")                                                           #EINSATZ

#####################################################################################################
############

#d2##################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
```

```
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_d2_CL_Mull",                                                           #EINSATZ
  modelDescr    ="WTP_d2",                                                                    #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}
```

```
apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                 PRICECALC1_d2     =     0,
#EINSATZ
                 PRICECALC2_d2     =     0,
#EINSATZ
                 PRICEEMAIL_d2     =     0,
#EINSATZ
                PRICEPORTAL_d2     =     0,
#EINSATZ
                   PRICEAPP_d2     =     0,
#EINSATZ
                  SERVEMAIL_d2     =     0,
                   SERVCHAT_d2     =     0,
                    SERVAPP_d2     =     0                                                      #EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                  +           #EINSATZ
    (PRICECALC1   +  (PRICECALC1_d2   * (att_T_alt1==2)))    * ( att_P_alt1==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d2   * (att_T_alt1==2)))    * ( att_P_alt1==3)     +           #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_d2   * (att_T_alt1==2)))    * (att_A1_alt1==1)     +           #EINSATZ
    (PRICEPORTAL  +  (PRICEPORTAL_d2  * (att_T_alt1==2)))    * (att_A2_alt1==1)     +           #EINSATZ
    (PRICEAPP     +  (PRICEAPP_d2     * (att_T_alt1==2)))    * (att_A3_alt1==1)     +           #EINSATZ
    (SERVEMAIL    +  (SERVEMAIL_d2    * (att_T_alt1==2)))    * (att_S1_alt1==1)     +           #EINSATZ
    (SERVCHAT     +  (SERVCHAT_d2     * (att_T_alt1==2)))    * (att_S2_alt1==1)     +           #EINSATZ
    (SERVAPP      +  (SERVAPP_d2      * (att_T_alt1==2)))    * (att_S3_alt1==1)     +           #EINSATZ
    DEVICE1                                                  * (att_T_alt1==1)      +           #EINSATZ
    DEVICE2                                                  * (att_T_alt1==2)      +           #EINSATZ
    DEVICE3                                                  * (att_T_alt1==3)      +           #EINSATZ
    DEVICE4                                                  * (att_T_alt1==4)      +           #EINSATZ
    CHARGE                                                   * (att_C_alt1)                     #EINSATZ

  V[['alt2']]  =
    (PRICECALC1   +  (PRICECALC1_d2   * (att_T_alt2==2)))    * ( att_P_alt2==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d2   * (att_T_alt2==2)))    * ( att_P_alt2==3)     +           #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_d2   * (att_T_alt2==2)))    * (att_A1_alt2==1)     +           #EINSATZ
    (PRICEPORTAL  +  (PRICEPORTAL_d2  * (att_T_alt2==2)))    * (att_A2_alt2==1)     +           #EINSATZ
    (PRICEAPP     +  (PRICEAPP_d2     * (att_T_alt2==2)))    * (att_A3_alt2==1)     +           #EINSATZ
    (SERVEMAIL    +  (SERVEMAIL_d2    * (att_T_alt2==2)))    * (att_S1_alt2==1)     +           #EINSATZ
    (SERVCHAT     +  (SERVCHAT_d2     * (att_T_alt2==2)))    * (att_S2_alt2==1)     +           #EINSATZ
    (SERVAPP      +  (SERVAPP_d2      * (att_T_alt2==2)))    * (att_S3_alt2==1)     +           #EINSATZ
    DEVICE1                                                  * (att_T_alt2==1)      +           #EINSATZ
    DEVICE2                                                  * (att_T_alt2==2)      +           #EINSATZ
    DEVICE3                                                  * (att_T_alt2==3)      +           #EINSATZ
    DEVICE4                                                  * (att_T_alt2==4)      +           #EINSATZ
    CHARGE                                                   * (att_C_alt2)                     #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_d2 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_d2, "WTP_d2.rds")                                                            #EINSATZ
saveRDS(model,"Model_d2.rds")                                                            #EINSATZ

##########################################################################################################
############
```

```
#d3############################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_d3_CL_Mull",                                                        #EINSATZ
  modelDescr    ="WTP_d3",                                                                 #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
```

```
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                 PRICECALC1_d3     =     0,
#EINSATZ
                 PRICECALC2_d3     =     0,
#EINSATZ
                 PRICEEMAIL_d3     =     0,
#EINSATZ
                PRICEPORTAL_d3     =     0,
#EINSATZ
                   PRICEAPP_d3     =     0,
#EINSATZ
                  SERVEMAIL_d3     =     0,
                   SERVCHAT_d3     =     0,
                    SERVAPP_d3     =     0                                                     #EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                 +            #EINSATZ
    (PRICECALC1   +  (PRICECALC1_d3   * (att_T_alt1==3)))    * ( att_P_alt1==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d3   * (att_T_alt1==3)))    * ( att_P_alt1==3)     +           #EINSATZ
    (PRICEEMAIL   + (PRICEEMAIL_d3    * (att_T_alt1==3)))    * (att_A1_alt1==1)     +           #EINSATZ
    (PRICEPORTAL  + (PRICEPORTAL_d3   * (att_T_alt1==3)))    * (att_A2_alt1==1)     +           #EINSATZ
    (PRICEAPP     + (PRICEAPP_d3      * (att_T_alt1==3)))    * (att_A3_alt1==1)     +           #EINSATZ
    (SERVEMAIL    +(SERVEMAIL_d3      * (att_T_alt1==3)))    * (att_S1_alt1==1)     +           #EINSATZ
    (SERVCHAT     +(SERVCHAT_d3       * (att_T_alt1==3)))    * (att_S2_alt1==1)     +           #EINSATZ
    (SERVAPP       +(SERVAPP_d3       * (att_T_alt1==3)))    * (att_S3_alt1==1)     +           #EINSATZ
    DEVICE1                                                  * (att_T_alt1==1)      +           #EINSATZ
    DEVICE2                                                  * (att_T_alt1==2)      +           #EINSATZ
    DEVICE3                                                  * (att_T_alt1==3)      +           #EINSATZ
    DEVICE4                                                  * (att_T_alt1==4)      +           #EINSATZ
    CHARGE                                                   * (att_C_alt1)                     #EINSATZ

  V[['alt2']]  =
    (PRICECALC1   +  (PRICECALC1_d3   * (att_T_alt2==3)))    * ( att_P_alt2==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d3   * (att_T_alt2==3)))    * ( att_P_alt2==3)     +           #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_d3   * (att_T_alt2==3)))    * (att_A1_alt2==1)     +           #EINSATZ
    (PRICEPORTAL  +  (PRICEPORTAL_d3  * (att_T_alt2==3)))    * (att_A2_alt2==1)     +           #EINSATZ
    (PRICEAPP     +  (PRICEAPP_d3     * (att_T_alt2==3)))    * (att_A3_alt2==1)     +           #EINSATZ
    (SERVEMAIL    +  (SERVEMAIL_d3    * (att_T_alt2==3)))    * (att_S1_alt2==1)     +           #EINSATZ
    (SERVCHAT     +  (SERVCHAT_d3     * (att_T_alt2==3)))    * (att_S2_alt2==1)     +           #EINSATZ
    (SERVAPP      +  (SERVAPP_d3      * (att_T_alt2==3)))    * (att_S3_alt2==1)     +           #EINSATZ
    DEVICE1                                                  * (att_T_alt2==1)      +           #EINSATZ
    DEVICE2                                                  * (att_T_alt2==2)      +           #EINSATZ
    DEVICE3                                                  * (att_T_alt2==3)      +           #EINSATZ
    DEVICE4                                                  * (att_T_alt2==4)      +           #EINSATZ
    CHARGE                                                   * (att_C_alt2)                     #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,
```

```
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_d3 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_d3,"WTP_d3.rds")                                                                #EINSATZ
saveRDS(model,"Model_d3.rds")                                                                #EINSATZ

#############################################################################################################
############

#d4#########################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_d4_CL_Mull",                                                         #EINSATZ
  modelDescr    ="WTP_d4",                                                                  #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))

round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}
```

```
wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                PRICECALC1_d4     =     0,
#EINSATZ
                PRICECALC2_d4     =     0,
#EINSATZ
                PRICEEMAIL_d4     =     0,
#EINSATZ
               PRICEPORTAL_d4     =     0,
#EINSATZ
                  PRICEAPP_d4     =     0,
#EINSATZ
                 SERVEMAIL_d4     =     0,
                  SERVCHAT_d4     =     0,
                   SERVAPP_d4     =     0                                                        #EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                        +           #EINSATZ
    (PRICECALC1   +  (PRICECALC1_d4   * (att_T_alt1==4)))    * ( att_P_alt1==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d4   * (att_T_alt1==4)))    * ( att_P_alt1==3)     +           #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_d4   * (att_T_alt1==4)))    * (att_A1_alt1==1)     +           #EINSATZ
    (PRICEPORTAL  +  (PRICEPORTAL_d4  * (att_T_alt1==4)))    * (att_A2_alt1==1)     +           #EINSATZ
    (PRICEAPP     +  (PRICEAPP_d4     * (att_T_alt1==4)))    * (att_A3_alt1==1)     +           #EINSATZ
    (SERVEMAIL    +  (SERVEMAIL_d4    * (att_T_alt1==4)))    * (att_S1_alt1==1)     +           #EINSATZ
    (SERVCHAT     +  (SERVCHAT_d4     * (att_T_alt1==4)))    * (att_S2_alt1==1)     +           #EINSATZ
    (SERVAPP      +  (SERVAPP_d4      * (att_T_alt1==4)))    * (att_S3_alt1==1)     +           #EINSATZ
    DEVICE1                                                  * (att_T_alt1==1)      +           #EINSATZ
    DEVICE2                                                  * (att_T_alt1==2)      +           #EINSATZ
    DEVICE3                                                  * (att_T_alt1==3)      +           #EINSATZ
    DEVICE4                                                  * (att_T_alt1==4)      +           #EINSATZ
    CHARGE                                                   * (att_C_alt1)                     #EINSATZ

  V[['alt2']]  =
    (PRICECALC1   +  (PRICECALC1_d4   * (att_T_alt2==4)))    * ( att_P_alt2==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d4   * (att_T_alt2==4)))    * ( att_P_alt2==3)     +           #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_d4   * (att_T_alt2==4)))    * (att_A1_alt2==1)     +           #EINSATZ
    (PRICEPORTAL  +  (PRICEPORTAL_d4  * (att_T_alt2==4)))    * (att_A2_alt2==1)     +           #EINSATZ
    (PRICEAPP     +  (PRICEAPP_d4     * (att_T_alt2==4)))    * (att_A3_alt2==1)     +           #EINSATZ
    (SERVEMAIL    +  (SERVEMAIL_d4    * (att_T_alt2==4)))    * (att_S1_alt2==1)     +           #EINSATZ
    (SERVCHAT     +  (SERVCHAT_d4     * (att_T_alt2==4)))    * (att_S2_alt2==1)     +           #EINSATZ
    (SERVAPP      +  (SERVAPP_d4      * (att_T_alt2==4)))    * (att_S3_alt2==1)     +           #EINSATZ
    DEVICE1                                                  * (att_T_alt2==1)      +           #EINSATZ
    DEVICE2                                                  * (att_T_alt2==2)      +           #EINSATZ
    DEVICE3                                                  * (att_T_alt2==3)      +           #EINSATZ
    DEVICE4                                                  * (att_T_alt2==4)      +           #EINSATZ
    CHARGE                                                   * (att_C_alt2)                     #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
```

```
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_d4 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_d4,"WTP_d4.rds")                                                                #EINSATZ
saveRDS(model,"Model_d4.rds")                                                                #EINSATZ

#####################################################################################################
############

#d0#################################################################################################
##############

### Clear memory
rm(list = ls())

### Load libraries
library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #Maxprint option hochgestzt, um correlationmatrix f?r den einfluss vom "T" auf
die anderen Attribute vollst?ndnig darzustellen

apollo_initialise()

apollo_control = list(
  modelName  ="211208_d0_CL_Mull",                                                       #EINSATZ
  modelDescr    ="WTP_d0",                                                                  #EINSATZ
  indivID    ="ID")

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #Datensatz MIT DM-Scores

colnames(database) <- c("ID", colnames(database)[-1]) #Umbenennung der ID-Spalte aufgrund von Format

database = subset(database,database$Task!=5,) #werte f?r Fixtask entfernen

#IM DATENSATZ SIND NOCH DIE GANZEN EUR-WERTE (5,10,15,20 & 25) ANSTELLE DER GRENZWERTE (xx.99)
database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1), #Attribute Level "no plug" has value =1 in
Raw Data, For estimation of interaction effects (Paper 2) relabel necessary
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))
```

```
round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(ASC_alt1 =
0,PRICECALC1=0,PRICECALC2=0,PRICEEMAIL=0,PRICEPORTAL=0,PRICEAPP=0,SERVEMAIL=0,SERVCHAT=0,SERVAPP=0,DEVICE1
=0,DEVICE2=0,DEVICE3=0,DEVICE4=0,CHARGE=0,

                PRICECALC1_d0     =     0,
#EINSATZ
                PRICECALC2_d0     =     0,
#EINSATZ
                PRICEEMAIL_d0     =     0,
#EINSATZ
               PRICEPORTAL_d0     =     0,
#EINSATZ
                  PRICEAPP_d0     =     0,
#EINSATZ
                 SERVEMAIL_d0     =     0,
                  SERVCHAT_d0     =     0,
                   SERVAPP_d0     =     0                                                        #EINSATZ
)

apollo_fixed = c()
apollo_inputs = apollo_validateInputs()
apollo_probabilities=function(apollo_beta, apollo_inputs, functionality="estimate"){
  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))
  P = list()
  V = list()

  V[['alt1']]  =
    ASC_alt1                                                                    +           #EINSATZ
    (PRICECALC1   +  (PRICECALC1_d0   * (att_T_alt1==0)))    * ( att_P_alt1==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d0   * (att_T_alt1==0)))    * ( att_P_alt1==3)     +           #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_d0   * (att_T_alt1==0)))    * (att_A1_alt1==1)     +           #EINSATZ
    (PRICEPORTAL  +  (PRICEPORTAL_d0  * (att_T_alt1==0)))    * (att_A2_alt1==1)     +           #EINSATZ
    (PRICEAPP     +  (PRICEAPP_d0     * (att_T_alt1==0)))    * (att_A3_alt1==1)     +           #EINSATZ
    (SERVEMAIL    +  (SERVEMAIL_d0    * (att_T_alt1==0)))    * (att_S1_alt1==1)     +           #EINSATZ
    (SERVCHAT     +  (SERVCHAT_d0     * (att_T_alt1==0)))    * (att_S2_alt1==1)     +           #EINSATZ
    (SERVAPP      +  (SERVAPP_d0      * (att_T_alt1==0)))    * (att_S3_alt1==1)     +           #EINSATZ
    DEVICE1                                                  * (att_T_alt1==1)      +           #EINSATZ
    DEVICE2                                                  * (att_T_alt1==2)      +           #EINSATZ
    DEVICE3                                                  * (att_T_alt1==3)      +           #EINSATZ
    DEVICE4                                                  * (att_T_alt1==4)      +           #EINSATZ
    CHARGE                                                   * (att_C_alt1)                     #EINSATZ

  V[['alt2']]  =
    (PRICECALC1   +  (PRICECALC1_d0   * (att_T_alt2==0)))    * ( att_P_alt2==2)     +           #EINSATZ
    (PRICECALC2   +  (PRICECALC2_d0   * (att_T_alt2==0)))    * ( att_P_alt2==3)     +           #EINSATZ
    (PRICEEMAIL   +  (PRICEEMAIL_d0   * (att_T_alt2==0)))    * (att_A1_alt2==1)     +           #EINSATZ
    (PRICEPORTAL  +  (PRICEPORTAL_d0  * (att_T_alt2==0)))    * (att_A2_alt2==1)     +           #EINSATZ
    (PRICEAPP     +  (PRICEAPP_d0     * (att_T_alt2==0)))    * (att_A3_alt2==1)     +           #EINSATZ
    (SERVEMAIL    +  (SERVEMAIL_d0    * (att_T_alt2==0)))    * (att_S1_alt2==1)     +           #EINSATZ
    (SERVCHAT     +  (SERVCHAT_d0     * (att_T_alt2==0)))    * (att_S2_alt2==1)     +           #EINSATZ
```

```
    (SERVAPP      +  (SERVAPP_d0      * (att_T_alt2==0)))    * (att_S3_alt2==1)     +          #EINSATZ
    DEVICE1                                                  * (att_T_alt2==1)      +          #EINSATZ
    DEVICE2                                                  * (att_T_alt2==2)      +          #EINSATZ
    DEVICE3                                                  * (att_T_alt2==3)      +          #EINSATZ
    DEVICE4                                                  * (att_T_alt2==4)      +          #EINSATZ
    CHARGE                                                   * (att_C_alt2)                    #EINSATZ

  mnl_settings = list(
    alternatives = c(alt1=1, alt2=2),
    avail        = list(alt1=1, alt2=1),
    choiceVar    = choice,
    V             = V)

  P[['model']] = apollo_mnl(mnl_settings, functionality)
  P = apollo_panelProd(P, apollo_inputs, functionality)
  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}
model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)#
apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE,

apollo_modelOutput(model, modelOutput_settings=list(printPVal=TRUE, printCovar=FALSE, printCorr=FALSE,
printOutliers=FALSE,printChange=FALSE, saveEst=TRUE, saveCov=FALSE, saveCorr=FALSE, saveModeObject=TRUE))

WTP_d0 <- wtp(cost = "CHARGE",names(model$estimate), model = model)        #EINSATZ
saveRDS(WTP_d0,"WTP_d0.rds")                                                            #EINSATZ
saveRDS(model,"Model_d0.rds")                                                            #EINSATZ

##########################################################################################################
############

library(knitr)
library(kableExtra)

get_asterisks <- function(p_value) {
  if (p_value < 0.001) return("***")
  else if (p_value < 0.01) return("**")
  else if (p_value < 0.05) return("*")
  else return("")
}

      WTP_Base <- readRDS ("WTP_Base.rds")
    Model_Base <- readRDS("Model_Base.rds")

      WTP_p0 <- readRDS ("WTP_p0.rds")
    Model_p0 <- readRDS ("Model_p0.rds")

      WTP_p1 <- readRDS ("WTP_p1.rds")
    Model_p1 <- readRDS ("Model_p1.rds")

      WTP_p2 <- readRDS ("WTP_p2.rds")
    Model_p2 <- readRDS("Model_p2.rds")

      WTP_a1 <- readRDS("WTP_a1.rds")
    Model_a1 <- readRDS("Model_a1.rds")

      WTP_a2 <- readRDS("WTP_a2.rds")
    Model_a2 <- readRDS("Model_a2.rds")

      WTP_a3 <- readRDS("WTP_a3.rds")
    Model_a3 <- readRDS("Model_a3.rds")

      WTP_s1 <- readRDS("WTP_s1.rds")
    Model_s1 <- readRDS("Model_s1.rds")

      WTP_s2 <- readRDS("WTP_s2.rds")
    Model_s2 <- readRDS("Model_s2.rds")

      WTP_s3 <- readRDS ("WTP_s3.rds")
    Model_s3 <- readRDS("Model_s3.rds")

      WTP_d0 <- readRDS("WTP_d0.rds")
    Model_d0 <- readRDS ("Model_d0.rds")

      WTP_d1 <- readRDS("WTP_d1.rds")
    Model_d1 <- readRDS ("Model_d1.rds")

      WTP_d2 <- readRDS("WTP_d2.rds")
    Model_d2 <- readRDS("Model_d2.rds")

      WTP_d3 <- readRDS("WTP_d3.rds")
```

```
    Model_d3 <- readRDS("Model_d3.rds")

      WTP_d4 <- readRDS("WTP_d4.rds")
    Model_d4 <- readRDS("Model_d4.rds")


# Extracting the LL values from the models

    LL_Base <- round_df(Model_Base$LLout[1],2)
    LL_p0 <- round_df(Model_p0$LLout[1],2)
    LL_p1 <- round_df(Model_p1$LLout[1],2)
    LL_p2 <- round_df(Model_p2$LLout[1],2)
    LL_a1 <- round_df(Model_a1$LLout[1],2)
    LL_a2 <- round_df(Model_a2$LLout[1],2)
    LL_a3 <- round_df(Model_a3$LLout[1],2)
    LL_s1 <- round_df(Model_s1$LLout[1],2)
    LL_s2 <- round_df(Model_s2$LLout[1],2)
    LL_s3 <- round_df(Model_s3$LLout[1],2)
    LL_d0 <- round_df(Model_d0$LLout[1],2)
    LL_d1 <- round_df(Model_d1$LLout[1],2)
    LL_d2 <- round_df(Model_d2$LLout[1],2)
    LL_d3 <- round_df(Model_d3$LLout[1],2)
    LL_d4 <- round_df(Model_d4$LLout[1],2)


    #creating a data frame for model comparison, Step 1: Modelnames
    model.names = data.frame(Model = c("Base Model",
                                       "IMo_PRICECALC0",
                                       "IMo_PRICECALC1",
                                       "IMo_PRICECALC2",
                                       "IMo_PRICEEMAIL",
                                       "IMo_PRICEPORTAL",
                                       "IMo_PRICEAPP",
                                       "IMo_SERVEMAIL",
                                       "IMo_SERVCHAT",
                                       "IMo_SERVAPP",
                                       "IMo_DEVICE0",
                                       "IMo_DEVICE1",
                                       "IMo_DEVICE2",
                                       "IMo_DEVICE3",
                                       "IMo_DEVICE4"))

    #creating a data frame for model comparison, Step 2: LL Values for each model
    LL.Values = data.frame(LL = c(LL_Base,
                                  LL_p0,
                                  LL_p1,
                                  LL_p2,
                                  LL_a1,
                                  LL_a2,
                                  LL_a3,
                                  LL_s1,
                                  LL_s2,
                                  LL_s3,
                                  LL_d0,
                                  LL_d1,
                                  LL_d2,
                                  LL_d3,
                                  LL_d4))

    #creating a data frame for model comparison, Step 3: Degrees of Freedom for each model
    DoF.Values =data.frame(DoF=c(9588,
                                 9578,
                                 9578,
                                 9578,
                                 9579,
                                 9579,
                                 9579,
                                 9579,
                                 9579,
                                 9579,
                                 9580,
                                 9580,
                                 9580,
                                 9580,
                                 9580))


     #creating a data frame for model comparison
     LL.Results = data.frame(c(model.names,LL.Values,DoF.Values))

     # Set LL_base as the log-likelihood of the base model
```

```
    LL_base <- LL.Results$LL[1]

    # Calculate Chi-Squared Statistic using log-likelihoods directly
    LL.Results$Chi <- -2 * (LL_base - LL.Results$LL)

    # Calculate Degrees of Freedom
    LL.Results$DoF <- LL.Results$DoF[1] - LL.Results$DoF

    # Calculate P-Values using log-likelihood values and degrees of freedom
    LL.Results$p_value <- round(pchisq(LL.Results$Chi, df = LL.Results$DoF, lower.tail = FALSE), digits =
4)


    #LL.Results$p_value <- round(LL.Results$p_value, digits = 4)
    LL.Results$p_sig <- sapply(LL.Results$p_value, get_asterisks)

table_comparison <- kable(
  LL.Results,
  format = "html",
  escape = FALSE,
  align = c("l", "c", "c", "c", "c", "c"),
  caption = ""
) %>%
  kable_styling(full_width = FALSE)

footnote <- "LL = Log Likelihood; DoF = Degrees of Freedom; Chi = Chi-Squared Statistic; ***p < 0.001; **p
< 0.01; *p < 0.05"
table_comparison <- add_footnote(table_comparison, footnote)

# Print the table
print(table_comparison)

#A1########
WTP_a1$p_sig <- sapply(WTP_a1$pVal, get_asterisks)

WTP_a1 <- WTP_a1 %>%
  mutate(New_Column = 1 - (pVal / 2),Other_Column = pVal / 2)

table_PRICEEMAIL <- kable(
  WTP_a1,
  col.names = c("Paramter", "WTP", "Rob. s.e.", "Rob. t-ratio", "p Value (2-sided)", "", "pVal WTP > 0",
"pVal WTP < 0"),
  format = "html",
  escape = FALSE,
  align = c("l", "c", "c", "c","l","c","c","c"),
  caption = "Estimation results IMo_PRICEEMAIL",
  digits = 4
) %>%
  kable_styling(full_width = FALSE, bootstrap_options = "condensed")
footnote <- "WTP = Willingness to pay; LL = Log Likelihood; ***p < 0.001; **p < 0.01; *p < 0.05"
table_PRICEEMAIL <- add_footnote(table_PRICEEMAIL, footnote)


#S1########
WTP_s1$p_sig <- sapply(WTP_s1$pVal, get_asterisks)

WTP_s1 <- WTP_s1 %>%
  mutate(New_Column = 1 - (pVal / 2),Other_Column = pVal / 2)

table_SERVEMAIL <- kable(
  WTP_s1,
  col.names = c("Paramter", "WTP", "Rob. s.e.", "Rob. t-ratio", "p Value (2-sided)", "", "pVal WTP > 0",
"pVal WTP < 0"),
  format = "html",
  escape = FALSE,
  align = c("l", "c", "c", "c","l","c","c","c"),
  caption = "Estimation results IMo_SERVEMAIL",
  digits = 4
) %>%
  kable_styling(full_width = FALSE, bootstrap_options = "condensed")
footnote <- "WTP = Willingness to pay; LL = Log Likelihood; ***p < 0.001; **p < 0.01; *p < 0.05"
table_SERVEMAIL <- add_footnote(table_SERVEMAIL, footnote)


#D0########
WTP_d0$p_sig <- sapply(WTP_d0$pVal, get_asterisks)

WTP_d0 <- WTP_d0 %>%
  mutate(New_Column = 1 - (pVal / 2),Other_Column = pVal / 2)

table_DEVICE0 <- kable(
```

```
  WTP_d0,
  col.names = c("Paramter", "WTP", "Rob. s.e.", "Rob. t-ratio", "p Value (2-sided)", "", "pVal WTP > 0",
"pVal WTP < 0"),
  format = "html",
  escape = FALSE,
  align = c("l", "c", "c", "c","l","c","c","c"),
  caption = "Estimation results IMo_DEVICE0",
  digits = 4
) %>%
  kable_styling(full_width = FALSE, bootstrap_options = "condensed")
footnote <- "WTP = Willingness to pay; LL = Log Likelihood; ***p < 0.001; **p < 0.01; *p < 0.05"
table_DEVICE0 <- add_footnote(table_DEVICE0, footnote)


#Results for Thesis
print(table_comparison)
print(table_SERVEMAIL)
print(table_PRICEEMAIL)
print(table_DEVICE0)
```

8.4.3 R Script for Chapter 5: Post processing of HB model, CL model

```
rm(list = ls())

### Load libraries

library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(openxlsx)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)
library(car)
library(openxlsx)
library(stargazer)
library(boot)

options(max.print=1000000)
database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1") #
colnames(database) <- c("ID", colnames(database)[-1])
database = subset(database,database$Task!=5,)


round_df <- function(x, digits) {
  # round all numeric variables
  # x: data frame
  # digits: number of digits to round
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}

database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


####Recoding of DM attributes#############

#Coding raw data for aDM:
#1,00           #Very digital
#2,00           #Slightly digital
#3,00           #Little digital
#4,00           #not digital
#5,00           #I don't know / no answer
#99,00        Skipped

#Coding raw data for rDM (3 Attributes)
# 1        #most digital
# 2        #second most digital
# 3        #least digital
#Coding raw data for rDM (4 Attributes)
# 1        #most digital
# 2        #second most digital
# 3        #third most digital
# 4        #least digital
```

```
#Recoding of RELATIVE digital Maturity evaluations. Before: 1 = highest, After 3/4 = highest

database$rDM_P0_adj <- car::recode(database$rDM_P0,"1=3; 2=2; 3=1")
database$rDM_P1_adj <- car::recode(database$rDM_P1,"1=3; 2=2; 3=1")
database$rDM_P2_adj <- car::recode(database$rDM_P2,"1=3; 2=2; 3=1")
database$rDM_A0_adj <- car::recode(database$rDM_A0,"1=4; 2=3; 3=2; 4=1")
database$rDM_A1_adj <- car::recode(database$rDM_A1,"1=4; 2=3; 3=2; 4=1")
database$rDM_A2_adj <- car::recode(database$rDM_A2,"1=4; 2=3; 3=2; 4=1")
database$rDM_A3_adj <- car::recode(database$rDM_A3,"1=4; 2=3; 3=2; 4=1")
database$rDM_S0_adj <- car::recode(database$rDM_S0,"1=4; 2=3; 3=2; 4=1")
database$rDM_S1_adj <- car::recode(database$rDM_S1,"1=4; 2=3; 3=2; 4=1")
database$rDM_S2_adj <- car::recode(database$rDM_S2,"1=4; 2=3; 3=2; 4=1")
database$rDM_S3_adj <- car::recode(database$rDM_S3,"1=4; 2=3; 3=2; 4=1")
database$rDM_D1_adj <- car::recode(database$rDM_D1,"1=4; 2=3; 3=2; 4=1")
database$rDM_D2_adj <- car::recode(database$rDM_D2,"1=4; 2=3; 3=2; 4=1")
database$rDM_D3_adj <- car::recode(database$rDM_D3,"1=4; 2=3; 3=2; 4=1")
database$rDM_D4_adj <- car::recode(database$rDM_D4,"1=4; 2=3; 3=2; 4=1")


#Recoding of Attributes A and S

#Alternative 1
database$att_A1_alt1_adj <- car::recode(database$att_A1_alt1,"1=0; 2=1")
database$att_A2_alt1_adj <- car::recode(database$att_A2_alt1,"1=0; 2=1")
database$att_A3_alt1_adj <- car::recode(database$att_A3_alt1,"1=0; 2=1")

database$att_S1_alt1_adj <- car::recode(database$att_S1_alt1,"1=0; 2=1")
database$att_S2_alt1_adj <- car::recode(database$att_S2_alt1,"1=0; 2=1")
database$att_S3_alt1_adj <- car::recode(database$att_S3_alt1,"1=0; 2=1")

#Alternative 2
database$att_A1_alt2_adj <- car::recode(database$att_A1_alt2,"1=0; 2=1")
database$att_A2_alt2_adj <- car::recode(database$att_A2_alt2,"1=0; 2=1")
database$att_A3_alt2_adj <- car::recode(database$att_A3_alt2,"1=0; 2=1")

database$att_S1_alt2_adj <- car::recode(database$att_S1_alt2,"1=0; 2=1")
database$att_S2_alt2_adj <- car::recode(database$att_S2_alt2,"1=0; 2=1")
database$att_S3_alt2_adj <- car::recode(database$att_S3_alt2,"1=0; 2=1")


#Recoding of Eco_econ

#eco: 4=0, 3=1, 2=2, 1=3
#econ: 4=0, 5=1, 6=2, 7=3

database$eco <- car::recode(database$eco_econ,"4=0; 3=1; 2=2; 1=3")
database$econ <- car::recode(database$eco_econ,"4=0; 5=1; 6=2; 7=3")


##############################

#Creation of new attribute codings based on DM scores (e.g. when respondent A values Beta_a1 with 4 (high
digital), the original attribut value of 1 will be replaced with 4)

#ALTERNATIVE 1

database$att_P_rDM_alt1 <-  with(database, ifelse(att_P_alt1==1, rDM_P0_adj,
                            with(database, ifelse(att_P_alt1==2, rDM_P1_adj,
                            with(database, ifelse(att_P_alt1==3, rDM_P2_adj,0))))))

database$att_A1_rDM_alt1 <- with(database, ifelse(att_A1_alt1==1, rDM_A1_adj,0))
database$att_A2_rDM_alt1 <- with(database, ifelse(att_A2_alt1==1, rDM_A2_adj,0))
database$att_A3_rDM_alt1 <- with(database, ifelse(att_A3_alt1==1, rDM_A3_adj,0))

database$att_S1_rDM_alt1 <- with(database, ifelse(att_S1_alt1==1, rDM_S1_adj,0))
database$att_S2_rDM_alt1 <- with(database, ifelse(att_S2_alt1==1, rDM_S2_adj,0))
database$att_S3_rDM_alt1 <- with(database, ifelse(att_S3_alt1==1, rDM_S3_adj,0))

database$att_D_rDM_alt1 <-  with(database, ifelse(att_T_alt1==0, 0,
                            with(database, ifelse(att_T_alt1==1, rDM_D1_adj,
                            with(database, ifelse(att_T_alt1==2, rDM_D2_adj,
                            with(database, ifelse(att_T_alt1==3, rDM_D3_adj,
                            with(database, ifelse(att_T_alt1==4, rDM_D4_adj,99))))))))))

#ALTERNATIVE 2

database$att_P_rDM_alt2 <-  with(database, ifelse(att_P_alt2==1, rDM_P0_adj,
                            with(database, ifelse(att_P_alt2==2, rDM_P1_adj,
                            with(database, ifelse(att_P_alt2==3, rDM_P2_adj,0))))))
```

```
database$att_A1_rDM_alt2 <- with(database, ifelse(att_A1_alt2==1, rDM_A1_adj,0))
database$att_A2_rDM_alt2 <- with(database, ifelse(att_A2_alt2==1, rDM_A2_adj,0))
database$att_A3_rDM_alt2 <- with(database, ifelse(att_A3_alt2==1, rDM_A3_adj,0))

database$att_S1_rDM_alt2 <- with(database, ifelse(att_S1_alt2==1, rDM_S1_adj,0))
database$att_S2_rDM_alt2 <- with(database, ifelse(att_S2_alt2==1, rDM_S2_adj,0))
database$att_S3_rDM_alt2 <- with(database, ifelse(att_S3_alt2==1, rDM_S3_adj,0))

database$att_D_rDM_alt2 <-  with(database, ifelse(att_T_alt2==0, 0,
                            with(database, ifelse(att_T_alt2==1, rDM_D1_adj,
                            with(database, ifelse(att_T_alt2==2, rDM_D2_adj,
                            with(database, ifelse(att_T_alt2==3, rDM_D3_adj,
                            with(database, ifelse(att_T_alt2==4, rDM_D4_adj,99))))))))))


#Creation of a DM score for each alternative

database$DM_value_rDM_Alt1 <- rowSums(sapply(database[ ,c("att_P_rDM_alt1",
                                                          "att_A1_rDM_alt1",
                                                          "att_A2_rDM_alt1",
                                                          "att_A3_rDM_alt1",
                                                          "att_S1_rDM_alt1",
                                                          "att_S2_rDM_alt1",
                                                          "att_S3_rDM_alt1",
                                                          "att_D_rDM_alt1")],function(x)
as.numeric(as.character(x))), na.rm=TRUE)

database$DM_value_rDM_Alt2 <- rowSums(sapply(database[ ,c("att_P_rDM_alt2",
                                                          "att_A1_rDM_alt2",
                                                          "att_A2_rDM_alt2",
                                                          "att_A3_rDM_alt2",
                                                          "att_S1_rDM_alt2",
                                                          "att_S2_rDM_alt2",
                                                          "att_S3_rDM_alt2",
                                                          "att_D_rDM_alt2")],function(x)
as.numeric(as.character(x))), na.rm=TRUE)


#Creation of differences between rDM_Alt1 and rDM_alt2, difference based on the choice column
database$DM_Diff <- ifelse(database$choice == 1,
                                 database$DM_value_rDM_Alt1 - database$DM_value_rDM_Alt2,
                                 database$DM_value_rDM_Alt2 - database$DM_value_rDM_Alt1)



#Integration of Respodent IDs to match  HB Utilities

sawtooth_data <- read.csv("expall.csv")
colnames(sawtooth_data) <- c("sys_RespNum", colnames(sawtooth_data)[-1])

sawtooth_data <- sawtooth_data%>%
  rename(ID = sys_SequentialRespNum)

database <- merge(database, sawtooth_data, by = "ID")


#import of utilities from HBestimation from Sawtooth

#sheet_name <- "Individual Utilities"
sheet_name <- "Individual Utilities"
#excel_file <- "Utility Report.xlsx"
excel_file <- "Utility Report_COR.xlsx"
# #rename IDs and merge of dataset with HB estimations for each attribute
HB_Utilities <- read_excel(excel_file, sheet = sheet_name)
#
HB_Utilities <- HB_Utilities %>%
rename(sys_RespNum = ID)
#
# HB_Utilities <- merge(HB_Utilities, Sawtooth_Filter, by = "sys_RespNum")
#
# HB_Utilities <- HB_Utilities %>%
#   rename(ID.1 = id)

database <- merge (database,HB_Utilities, by = "sys_RespNum")

database <- database %>%
  rename(P0_HB = `fixed price`,
         P1_HB = `pre def plan`,
         P2_HB = `consumption based`,
```

```
         A1_HB = A1,
         A2_HB = A2,
         A3_HB = A3,
         S1_HB = S1,
         S2_HB = S2,
         S3_HB = S3,
         D0_HB =`no socket`,
         D1_HB =`manually`,
         D2_HB =`local`,
         D3_HB =`smart app only`,
         D4_HB =`smart app analysis`)


#####Data Mutation, Generation of HB-Values for each Alternative

#ALTERNATIVE 1

database$P_HB_alt1 <-  with(database, ifelse(att_P_alt1==1, P0_HB,
                       with(database, ifelse(att_P_alt1==2, P1_HB,
                       with(database, ifelse(att_P_alt1==3, P2_HB,0))))))

database$A1_HB_alt1 <- with(database, ifelse(att_A1_alt1==1, A1_HB,0))
database$A2_HB_alt1 <- with(database, ifelse(att_A2_alt1==1, A2_HB,0))
database$A3_HB_alt1 <- with(database, ifelse(att_A3_alt1==1, A3_HB,0))

database$S1_HB_alt1 <- with(database, ifelse(att_S1_alt1==1, S1_HB,0))
database$S2_HB_alt1 <- with(database, ifelse(att_S2_alt1==1, S2_HB,0))
database$S3_HB_alt1 <- with(database, ifelse(att_S3_alt1==1, S3_HB,0))

database$D_HB_alt1 <-  with(database, ifelse(att_T_alt1==0, 0,
                       with(database, ifelse(att_T_alt1==1, D1_HB,
                       with(database, ifelse(att_T_alt1==2, D2_HB,
                       with(database, ifelse(att_T_alt1==3, D3_HB,
                       with(database, ifelse(att_T_alt1==4, D4_HB,99))))))))))

#ALTERNATIVE 2

database$P_HB_alt2 <-  with(database, ifelse(att_P_alt2==1, P0_HB,
                       with(database, ifelse(att_P_alt2==2, P1_HB,
                       with(database, ifelse(att_P_alt2==3, P2_HB,0))))))

database$A1_HB_alt2 <- with(database, ifelse(att_A1_alt2==1, A1_HB,0))
database$A2_HB_alt2 <- with(database, ifelse(att_A2_alt2==1, A2_HB,0))
database$A3_HB_alt2 <- with(database, ifelse(att_A3_alt2==1, A3_HB,0))

database$S1_HB_alt2 <- with(database, ifelse(att_S1_alt2==1, S1_HB,0))
database$S2_HB_alt2 <- with(database, ifelse(att_S2_alt2==1, S2_HB,0))
database$S3_HB_alt2 <- with(database, ifelse(att_S3_alt2==1, S3_HB,0))

database$D_HB_alt2 <-  with(database, ifelse(att_T_alt2==0, 0,
                       with(database, ifelse(att_T_alt2==1, D1_HB,
                       with(database, ifelse(att_T_alt2==2, D2_HB,
                       with(database, ifelse(att_T_alt2==3, D3_HB,
                       with(database, ifelse(att_T_alt2==4, D4_HB,99))))))))))


#Sum of HB for each Alternative

database$HB_Alt1 <- rowSums(sapply(database[ ,c("P_HB_alt1",
                                                "A1_HB_alt1",
                                                "A2_HB_alt1",
                                                "A3_HB_alt1",
                                                "S1_HB_alt1",
                                                "S2_HB_alt1",
                                                "S3_HB_alt1",
                                                "D_HB_alt1")],function(x) as.numeric(as.character(x))),
na.rm=TRUE)

database$HB_Alt2 <- rowSums(sapply(database[ ,c("P_HB_alt2",
                                                "A1_HB_alt2",
                                                "A2_HB_alt2",
                                                "A3_HB_alt2",
                                                "S1_HB_alt2",
                                                "S2_HB_alt2",
                                                "S3_HB_alt2",
                                                "D_HB_alt2")],function(x) as.numeric(as.character(x))),
na.rm=TRUE)


#Creation of differences between HB_Alt1 and HB_alt2, difference based on the choice column
```

```
database$HB_Diff <- ifelse(database$choice == 1,
                                 database$HB_Alt1 - database$HB_Alt2,
                                 database$HB_Alt2 - database$HB_Alt1)


#Generation of HB Differences for each attribute/choice

database$P_HB_Diff <- ifelse(database$choice == 1,
                              database$P_HB_alt1 - database$P_HB_alt2,
                              database$P_HB_alt2 - database$P_HB_alt1)

database$A1_HB_Diff <- ifelse(database$choice == 1,
                              database$A1_HB_alt1 - database$A1_HB_alt2,
                              database$A1_HB_alt2 - database$A1_HB_alt1)
database$A2_HB_Diff <- ifelse(database$choice == 1,
                              database$A2_HB_alt1 - database$A2_HB_alt2,
                              database$A2_HB_alt2 - database$A2_HB_alt1)
database$A3_HB_Diff <- ifelse(database$choice == 1,
                              database$A3_HB_alt1 - database$A3_HB_alt2,
                              database$A3_HB_alt2 - database$A3_HB_alt1)

database$S1_HB_Diff <- ifelse(database$choice == 1,
                              database$S1_HB_alt1 - database$S1_HB_alt2,
                              database$S1_HB_alt2 - database$S1_HB_alt1)
database$S2_HB_Diff <- ifelse(database$choice == 1,
                              database$S2_HB_alt1 - database$S2_HB_alt2,
                              database$S2_HB_alt2 - database$S2_HB_alt1)
database$S3_HB_Diff <- ifelse(database$choice == 1,
                              database$S3_HB_alt1 - database$S3_HB_alt2,
                              database$S3_HB_alt2 - database$S3_HB_alt1)

database$D_HB_Diff <- ifelse(database$choice == 1,
                              database$D_HB_alt1 - database$D_HB_alt2,
                              database$D_HB_alt2 - database$D_HB_alt1)


database$P_rDM_Diff <- ifelse(database$choice == 1,
                              database$att_P_rDM_alt1 - database$att_P_rDM_alt2,
                              database$att_P_rDM_alt2 - database$att_P_rDM_alt1)
database$A1_rDM_Diff <- ifelse(database$choice == 1,
                              database$att_A1_rDM_alt1 - database$att_A1_rDM_alt2,
                              database$att_A1_rDM_alt2 - database$att_A1_rDM_alt1)
database$A2_rDM_Diff <- ifelse(database$choice == 1,
                              database$att_A2_rDM_alt1 - database$att_A2_rDM_alt2,
                              database$att_A2_rDM_alt2 - database$att_A2_rDM_alt1)
database$A3_rDM_Diff <- ifelse(database$choice == 1,
                              database$att_A3_rDM_alt1 - database$att_A3_rDM_alt2,
                              database$att_A3_rDM_alt2 - database$att_A3_rDM_alt1)
database$S1_rDM_Diff <- ifelse(database$choice == 1,
                              database$att_S1_rDM_alt1 - database$att_S1_rDM_alt2,
                              database$att_S1_rDM_alt2 - database$att_S1_rDM_alt1)
database$S2_rDM_Diff <- ifelse(database$choice == 1,
                              database$att_S2_rDM_alt1 - database$att_S2_rDM_alt2,
                              database$att_S2_rDM_alt2 - database$att_S2_rDM_alt1)
database$S3_rDM_Diff <- ifelse(database$choice == 1,
                              database$att_S3_rDM_alt1 - database$att_S3_rDM_alt2,
                              database$att_S3_rDM_alt2 - database$att_S3_rDM_alt1)
database$D_rDM_Diff <- ifelse(database$choice == 1,
                              database$att_D_rDM_alt1 - database$att_D_rDM_alt2,
                              database$att_D_rDM_alt2 - database$att_D_rDM_alt1)

############Auxiliary regression

reg_model_ctrl <- lm(HB_Diff~
                       P_rDM_Diff   +
                       A1_rDM_Diff  +
                       A2_rDM_Diff  +
                       A3_rDM_Diff  +
                       S1_rDM_Diff  +
                       S2_rDM_Diff  +
                       S3_rDM_Diff  +
                       D_rDM_Diff   +

                       DM_Group   +
                       #att_CHARGE +
                       Age        +
                       Sex        +
                       Innov_Rol  +
```

```
                       eco        +
                       econ       +
                       edu        +
                       hh_income, data = database)

summary(reg_model_ctrl)



#Correlation

Diff_cor.test <-  cor.test(database$HB_Diff, database$DM_Diff, method="spearman", exact = FALSE)


p_diff_ds  <- database[, c("sys_RespNum", "ID", "P_rDM_Diff",  "P_HB_Diff")]
a1_diff_ds <- database[, c("sys_RespNum", "ID", "A1_rDM_Diff", "A1_HB_Diff")]
a2_diff_ds <- database[, c("sys_RespNum", "ID", "A2_rDM_Diff", "A2_HB_Diff")]
a3_diff_ds <- database[, c("sys_RespNum", "ID", "A3_rDM_Diff", "A3_HB_Diff")]
s1_diff_ds <- database[, c("sys_RespNum", "ID", "S1_rDM_Diff", "S1_HB_Diff")]
s2_diff_ds <- database[, c("sys_RespNum", "ID", "S2_rDM_Diff", "S2_HB_Diff")]
s3_diff_ds <- database[, c("sys_RespNum", "ID", "S3_rDM_Diff", "S3_HB_Diff")]
d_diff_ds  <- database[, c("sys_RespNum", "ID", "D_rDM_Diff",  "D_HB_Diff")]

# Rename columns in order to merge them
colnames(p_diff_ds)[colnames(p_diff_ds)   == "P_rDM_Diff"]  <- "rDM_diff"
colnames(a1_diff_ds)[colnames(a1_diff_ds) == "A1_rDM_Diff"] <- "rDM_diff"
colnames(a2_diff_ds)[colnames(a2_diff_ds) == "A2_rDM_Diff"] <- "rDM_diff"
colnames(a3_diff_ds)[colnames(a3_diff_ds) == "A3_rDM_Diff"] <- "rDM_diff"
colnames(s1_diff_ds)[colnames(s1_diff_ds) == "S1_rDM_Diff"] <- "rDM_diff"
colnames(s2_diff_ds)[colnames(s2_diff_ds) == "S2_rDM_Diff"] <- "rDM_diff"
colnames(s3_diff_ds)[colnames(s3_diff_ds) == "S3_rDM_Diff"] <- "rDM_diff"
colnames(d_diff_ds)[colnames(d_diff_ds)   == "D_rDM_Diff"]  <- "rDM_diff"


colnames(p_diff_ds)[colnames(p_diff_ds) == "P_HB_Diff"] <- "HB_diff"
colnames(a1_diff_ds)[colnames(a1_diff_ds) == "A1_HB_Diff"] <- "HB_diff"
colnames(a2_diff_ds)[colnames(a2_diff_ds) == "A2_HB_Diff"] <- "HB_diff"
colnames(a3_diff_ds)[colnames(a3_diff_ds) == "A3_HB_Diff"] <- "HB_diff"
colnames(s1_diff_ds)[colnames(s1_diff_ds) == "S1_HB_Diff"] <- "HB_diff"
colnames(s2_diff_ds)[colnames(s2_diff_ds) == "S2_HB_Diff"] <- "HB_diff"
colnames(s3_diff_ds)[colnames(s3_diff_ds) == "S3_HB_Diff"] <- "HB_diff"
colnames(d_diff_ds)[colnames(d_diff_ds) == "D_HB_Diff"] <- "HB_diff"



P_diff_cor_ds <- rbind(p_diff_ds)
A_diff_cor_ds <- rbind(a1_diff_ds, a2_diff_ds, a3_diff_ds)
S_diff_cor_ds <- rbind(s1_diff_ds, s2_diff_ds, s3_diff_ds)
D_diff_cor_ds <- rbind(d_diff_ds)


P_diff_cor.test <-  cor.test(P_diff_cor_ds$HB_diff, P_diff_cor_ds$rDM_diff, method="spearman", exact =
FALSE)
A_diff_cor.test <-  cor.test(A_diff_cor_ds$HB_diff, A_diff_cor_ds$rDM_diff, method="spearman", exact =
FALSE)
S_diff_cor.test <-  cor.test(S_diff_cor_ds$HB_diff, S_diff_cor_ds$rDM_diff, method="spearman", exact =
FALSE)
D_diff_cor.test <-  cor.test(D_diff_cor_ds$HB_diff, D_diff_cor_ds$rDM_diff, method="spearman", exact =
FALSE)


P_diff_cor.test
A_diff_cor.test
S_diff_cor.test
D_diff_cor.test


Attr_diff_cor <- rbind(cbind(data.frame(HB_DM_corr    = "PRICECALC",
                                         corr_t      =  P_diff_cor.test$estimate[1],
                                         p.value     =  as.numeric(P_diff_cor.test$p.value[1]))),

                        cbind(data.frame(HB_DM_corr  = "PRICE_",
                                         corr_t      =  A_diff_cor.test$estimate[1],
                                         p.value     =  as.numeric(A_diff_cor.test$p.value[1]))),

                        cbind(data.frame(HB_DM_corr  = "SERV_",
                                         corr_t      =  S_diff_cor.test$estimate[1],
                                         p.value     =  as.numeric(S_diff_cor.test$p.value[1]))),

                        cbind(data.frame(HB_DM_corr  = "DEVICE",
                                         corr_t      =  D_diff_cor.test$estimate[1],
```

```
                                         p.value     =  as.numeric(D_diff_cor.test$p.value[1]))))


Attr_diff_cor$p.value = formatC(Attr_diff_cor$p.value, format = "e", digits = 3)
Attr_diff_cor$corr_t = formatC(Attr_diff_cor$corr_t, format = "e", digits = 3)


Attr_diff_cor


ft_attr_diff_cor <- flextable(Attr_diff_cor)
ft_attr_diff_cor <- set_header_labels(ft_attr_diff_cor,HB_DM_corr = "Correlation parameter (Δ HB, Δ DM)",corr_t = "Correlation (rho)",p.value = "p Value")
ft_attr_diff_cor <- add_footer_lines(ft_attr_diff_cor, "Note: Δ = Difference between alternatives; HB = Hierarchical Bayes estimation; DM = Digital Maturity")

ft_attr_diff_cor <- set_formatter(ft_attr_diff_cor, columns = c("corr_t", "p.value"), value = function(x) sprintf("%.4e", x))
ft_attr_diff_cor <- width(ft_attr_diff_cor, width = 2.5)


ft_attr_diff_cor



#Bootstrapping Method for robust Standard errors

# Define the regression function for bootstrapping
regression_function <- function(database, indices) {
  # Resample the data
  boot_data <- database[indices, ]

  # Ensure factors have at least two levels
  if (any(sapply(boot_data, function(x) is.factor(x) && length(unique(x)) < 2))) {
    return(rep(NA, length(coef(lm(HB_Diff ~ ., data = database)))))  # Return NA for invalid samples
  }

  # Fit the regression model
  model <- lm(HB_Diff ~ P_rDM_Diff + A1_rDM_Diff + A2_rDM_Diff + A3_rDM_Diff +
                S1_rDM_Diff + S2_rDM_Diff + S3_rDM_Diff + D_rDM_Diff +
                DM_Group + Age + Sex + Innov_Rol + eco + econ + edu + hh_income,
              data = boot_data)
  # Return the coefficients
  return(coef(model))
}

# Perform bootstrapping with the correct dataset name
set.seed(123)  # For reproducibility
bootstrap_results <- boot(database, regression_function, R = 1000)

# Extract bootstrapped standard errors
boot_se <- apply(bootstrap_results$t, 2, sd, na.rm = TRUE)

# Combine results into a summary table
boot_results <- data.frame(
  Coefficients = coef(lm(HB_Diff ~ P_rDM_Diff + A1_rDM_Diff + A2_rDM_Diff + A3_rDM_Diff +
                           S1_rDM_Diff + S2_rDM_Diff + S3_rDM_Diff + D_rDM_Diff +
                           DM_Group + Age + Sex + Innov_Rol + eco + econ + edu + hh_income,
                         data = database)),
  Bootstrapped_SE = boot_se
)

# Display the results
print(boot_results)


# Extract coefficients from the original regression model
model <- lm(HB_Diff ~ P_rDM_Diff + A1_rDM_Diff + A2_rDM_Diff + A3_rDM_Diff +
              S1_rDM_Diff + S2_rDM_Diff + S3_rDM_Diff + D_rDM_Diff +
              DM_Group + Age + Sex + Innov_Rol + eco + econ + edu + hh_income,
            data = database)
coefficients <- coef(model)

# Extract bootstrapped standard errors
boot_se <- apply(bootstrap_results$t, 2, sd, na.rm = TRUE)

# Calculate degrees of freedom from the regression model
degrees_of_freedom <- df.residual(model)

# Calculate t-values and p-values
t_values <- coefficients / boot_se
```

```
p_values <- 2 * pt(-abs(t_values), df = degrees_of_freedom)

#Addition of siginificance codes
significance_codes <- ifelse(p_values < 0.001, "***",
                      ifelse(p_values < 0.01, "**",
                      ifelse(p_values < 0.05, "*",
                      ifelse(p_values < 0.1, ".", " "))))


# Combine results into a data frame
updated_results <- data.frame(
  Parameters = names(coefficients),
  Coefficients = round(coefficients, 4),
  Bootstrapped_SE = round(boot_se, 4),
  t_values = round(t_values, 4),
  p_values = round(p_values, 4),
  Significance = significance_codes
)



ft_reg.bs <- flextable(updated_results)
ft_reg.bs <- set_header_labels(ft_reg.bs,Parameters = "Regression parameter (~ ΔHB)",Coefficients =
"Coefficients",Bootstrapped_SE = "Std. Error (Bootstrapped)",t_values = "t Values",p_values = "p Values",
Significance = "")
ft_reg.bs <- width(ft_reg.bs, width = 2.5)
ft_reg.bs <- add_footer_lines(ft_reg.bs, "Note: DM = Digital Maturity; Signif. codes: '***' < 0.001; '**'
< 0.01; '*' < 0.05; '.' < 0.01")


ft_reg.bs

# Print updated results
print(updated_results)



########Conditional logit with interactions#################

rm(list = ls())

library(apollo)
library(tidyverse)
library(rlang)
library(mded)
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(flextable)
library(rstatix)
library(webshot)

options(max.print=1000000) #
apollo_initialise()

apollo_control = list(
  modelName  ="210312_CL_rDM",
  modelDescr ="CL with rDM interactions",
  indivID    ="ID"
)

database <- read.csv2("DATA_US_v07.csv",header=TRUE, encoding="latin1")

colnames(database) <- c("ID", colnames(database)[-1]) #

database = subset(database,database$Task!=5,)

database <- database%>%
  mutate(att_C_alt1 = ifelse(att_C_alt1 == 25, 24.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 20, 19.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 15, 14.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 10, 9.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 5, 4.99, att_C_alt1),
         att_C_alt1 = ifelse(att_C_alt1 == 0, 0, att_C_alt1))%>%
  mutate(att_C_alt2 = ifelse(att_C_alt2 == 25, 24.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 20, 19.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 15, 14.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 10, 9.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 5, 4.99, att_C_alt2),
         att_C_alt2 = ifelse(att_C_alt2 == 0, 0, att_C_alt2))%>%
```

```
  mutate(att_T_alt1 = ifelse(att_T_alt1 == 1, 0, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 2, 1, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 3, 2, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 4, 3, att_T_alt1),
         att_T_alt1 = ifelse(att_T_alt1 == 5, 4, att_T_alt1))%>%
  mutate(att_T_alt2 = ifelse(att_T_alt2 == 1, 0, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 2, 1, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 3, 2, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 4, 3, att_T_alt2),
         att_T_alt2 = ifelse(att_T_alt2 == 5, 4, att_T_alt2))


database$rDM_P0_adj <- car::recode(database$rDM_P0,"1=3; 2=2; 3=1")
database$rDM_P1_adj <- car::recode(database$rDM_P1,"1=3; 2=2; 3=1")
database$rDM_P2_adj <- car::recode(database$rDM_P2,"1=3; 2=2; 3=1")
database$rDM_A0_adj <- car::recode(database$rDM_A0,"1=4; 2=3; 3=2; 4=1")
database$rDM_A1_adj <- car::recode(database$rDM_A1,"1=4; 2=3; 3=2; 4=1")
database$rDM_A2_adj <- car::recode(database$rDM_A2,"1=4; 2=3; 3=2; 4=1")
database$rDM_A3_adj <- car::recode(database$rDM_A3,"1=4; 2=3; 3=2; 4=1")
database$rDM_S0_adj <- car::recode(database$rDM_S0,"1=4; 2=3; 3=2; 4=1")
database$rDM_S1_adj <- car::recode(database$rDM_S1,"1=4; 2=3; 3=2; 4=1")
database$rDM_S2_adj <- car::recode(database$rDM_S2,"1=4; 2=3; 3=2; 4=1")
database$rDM_S3_adj <- car::recode(database$rDM_S3,"1=4; 2=3; 3=2; 4=1")
database$rDM_D1_adj <- car::recode(database$rDM_D1,"1=4; 2=3; 3=2; 4=1")
database$rDM_D2_adj <- car::recode(database$rDM_D2,"1=4; 2=3; 3=2; 4=1")
database$rDM_D3_adj <- car::recode(database$rDM_D3,"1=4; 2=3; 3=2; 4=1")
database$rDM_D4_adj <- car::recode(database$rDM_D4,"1=4; 2=3; 3=2; 4=1")

#ALTERNATIVE 1

database$att_P_rDM_alt1 <-  with(database, ifelse(att_P_alt1==1, rDM_P0_adj,
                            with(database, ifelse(att_P_alt1==2, rDM_P1_adj,
                            with(database, ifelse(att_P_alt1==3, rDM_P2_adj,0))))))

database$att_A1_rDM_alt1 <- with(database, ifelse(att_A1_alt1==1, rDM_A1_adj,0))
database$att_A2_rDM_alt1 <- with(database, ifelse(att_A2_alt1==1, rDM_A2_adj,0))
database$att_A3_rDM_alt1 <- with(database, ifelse(att_A3_alt1==1, rDM_A3_adj,0))

database$att_S1_rDM_alt1 <- with(database, ifelse(att_S1_alt1==1, rDM_S1_adj,0))
database$att_S2_rDM_alt1 <- with(database, ifelse(att_S2_alt1==1, rDM_S2_adj,0))
database$att_S3_rDM_alt1 <- with(database, ifelse(att_S3_alt1==1, rDM_S3_adj,0))

database$att_D_rDM_alt1 <-  with(database, ifelse(att_T_alt1==0, 0,
                            with(database, ifelse(att_T_alt1==1, rDM_D1_adj,
                            with(database, ifelse(att_T_alt1==2, rDM_D2_adj,
                            with(database, ifelse(att_T_alt1==3, rDM_D3_adj,
                            with(database, ifelse(att_T_alt1==4, rDM_D4_adj,99))))))))))

#ALTERNATIVE 2

database$att_P_rDM_alt2 <-  with(database, ifelse(att_P_alt2==1, rDM_P0_adj,
                            with(database, ifelse(att_P_alt2==2, rDM_P1_adj,
                            with(database, ifelse(att_P_alt2==3, rDM_P2_adj,0))))))

database$att_A1_rDM_alt2 <- with(database, ifelse(att_A1_alt2==1, rDM_A1_adj,0))
database$att_A2_rDM_alt2 <- with(database, ifelse(att_A2_alt2==1, rDM_A2_adj,0))
database$att_A3_rDM_alt2 <- with(database, ifelse(att_A3_alt2==1, rDM_A3_adj,0))

database$att_S1_rDM_alt2 <- with(database, ifelse(att_S1_alt2==1, rDM_S1_adj,0))
database$att_S2_rDM_alt2 <- with(database, ifelse(att_S2_alt2==1, rDM_S2_adj,0))
database$att_S3_rDM_alt2 <- with(database, ifelse(att_S3_alt2==1, rDM_S3_adj,0))

database$att_D_rDM_alt2 <-  with(database, ifelse(att_T_alt2==0, 0,
                            with(database, ifelse(att_T_alt2==1, rDM_D1_adj,
                            with(database, ifelse(att_T_alt2==2, rDM_D2_adj,
                            with(database, ifelse(att_T_alt2==3, rDM_D3_adj,
                            with(database, ifelse(att_T_alt2==4, rDM_D4_adj,99))))))))))


#Creation of a DM score for each alternative

database$DM_value_rDM_Alt1 <- rowSums(sapply(database[ ,c("att_P_rDM_alt1",
                                                          "att_A1_rDM_alt1",
                                                          "att_A2_rDM_alt1",
                                                          "att_A3_rDM_alt1",
                                                          "att_S1_rDM_alt1",
                                                          "att_S2_rDM_alt1",
                                                          "att_S3_rDM_alt1",
```

```
                                                           "att_D_rDM_alt1")],function(x)
as.numeric(as.character(x))), na.rm=TRUE)

database$DM_value_rDM_Alt2 <- rowSums(sapply(database[ ,c("att_P_rDM_alt2",
                                                           "att_A1_rDM_alt2",
                                                           "att_A2_rDM_alt2",
                                                           "att_A3_rDM_alt2",
                                                           "att_S1_rDM_alt2",
                                                           "att_S2_rDM_alt2",
                                                           "att_S3_rDM_alt2",
                                                           "att_D_rDM_alt2")],function(x)
as.numeric(as.character(x))), na.rm=TRUE)


round_df <- function(x, digits) {
  numeric_columns <- sapply(x, mode) == 'numeric'
  x[numeric_columns] <-  round(x[numeric_columns], digits)
  x
}


significance_codes <- function(pval) {
  if (is.na(pval)) {
    return("")
  } else if (pval < 0.001) {
    return("***")
  } else if (pval < 0.01) {
    return("**")
  } else if (pval < 0.05) {
    return("*")
  } else {
    return("")
  }
}



wtp <- function(cost, attr, model) {

  wtp_values =data.frame(wtp =numeric(), robse=numeric() , robt= numeric() )
  attr <- attr[-which(attr==cost)]

  for (a in attr) {
    deltaMethod_settings=list(operation="ratio", parName1=a, parName2=cost)
    wtp_values[which(attr==a),]<- apollo_deltaMethod(model, deltaMethod_settings)

  }
  wtp_values$wtp <- wtp_values$wtp*-1
  wtp_values$robse <- wtp_values$robse*1
  wtp_values$robt <- wtp_values$robt*-1
  wtp_values$pVal <- (1-pnorm((abs(wtp_values$robt))))*2

  rownames(wtp_values) <- attr
  return(wtp_values)

}

apollo_beta = c(
  ASC_alt1           =     0,
  PRICECALC1         =     0,
  PRICECALC2         =     0,
  PRICEEMAIL         =     0,
  PRICEPORTAL        =     0,
  PRICEAPP           =     0,
  SERVEEMAIL         =     0,
  SERVCHAT           =     0,
  SERVAPP            =     0,
  DEVICE1            =     0,
  DEVICE2            =     0,
  DEVICE3            =     0,
  DEVICE4            =     0,
  CHARGE             =     0,


  PRICECALC1_rDM     =     0,
  PRICECALC2_rDM     =     0,
  PRICEEMAIL_rDM     =     0,
  PRICEPORTAL_rDM    =     0,
  PRICEAPP_rDM       =     0,
  SERVEEMAIL_rDM     =     0,
  SERVCHAT_rDM       =     0,
```

```
  SERVAPP_rDM        =     0,
  DEVICE1_rDM        =     0,
  DEVICE2_rDM        =     0,
  DEVICE3_rDM        =     0,
  DEVICE4_rDM        =     0
  #CHARGE_rDM         =     0

)

apollo_fixed = c()

apollo_inputs = apollo_validateInputs()

apollo_probabilities = function(apollo_beta, apollo_inputs, functionality = "estimate") {

  apollo_attach(apollo_beta, apollo_inputs)
  on.exit(apollo_detach(apollo_beta, apollo_inputs))

  P = list()

  V = list()


  V[['alt1']] = ( ASC_alt1 +
                   PRICECALC1   * (att_P_alt1 == 2) +
                   PRICECALC2   * (att_P_alt1 == 3) +
                   PRICEEMAIL   * (att_A1_alt1 == 1) +
                   PRICEPORTAL  * (att_A2_alt1 == 1) +
                   PRICEAPP     * (att_A3_alt1 == 1) +
                   SERVEEMAIL   * (att_S1_alt1 == 1) +
                   SERVCHAT     * (att_S2_alt1 == 1) +
                   SERVAPP      * (att_S3_alt1 == 1) +
                   DEVICE1      * (att_T_alt1 == 1) +
                   DEVICE2      * (att_T_alt1 == 2) +
                   DEVICE3      * (att_T_alt1 == 3) +
                   DEVICE4      * (att_T_alt1 == 4) +
                   CHARGE       * att_C_alt1 +

                   PRICECALC1_rDM  * (att_P_alt1 == 2)  * att_P_rDM_alt1  +
                   PRICECALC2_rDM  * (att_P_alt1 == 3)  * att_P_rDM_alt1  +
                   PRICEEMAIL_rDM  * (att_A1_alt1 == 1) * att_A1_rDM_alt1 +
                   PRICEPORTAL_rDM * (att_A2_alt1 == 1) * att_A2_rDM_alt1 +
                   PRICEAPP_rDM    * (att_A3_alt1 == 1) * att_A3_rDM_alt1 +
                   SERVEEMAIL_rDM  * (att_S1_alt1 == 1) * att_S1_rDM_alt1 +
                   SERVCHAT_rDM    * (att_S2_alt1 == 1) * att_S2_rDM_alt1 +
                   SERVAPP_rDM     * (att_S3_alt1 == 1) * att_S3_rDM_alt1 +
                   DEVICE1_rDM     * (att_T_alt1 == 1)  * att_D_rDM_alt1  +
                   DEVICE2_rDM     * (att_T_alt1 == 2)  * att_D_rDM_alt1  +
                   DEVICE3_rDM     * (att_T_alt1 == 3)  * att_D_rDM_alt1  +
                   DEVICE4_rDM     * (att_T_alt1 == 4)  * att_D_rDM_alt1
  )

  V[['alt2']] = (
    PRICECALC1   * (att_P_alt2 == 2) +
      PRICECALC2   * (att_P_alt2 == 3) +
      PRICEEMAIL   * (att_A1_alt2 == 1) +
      PRICEPORTAL  * (att_A2_alt2 == 1) +
      PRICEAPP     * (att_A3_alt2 == 1) +
      SERVEEMAIL   * (att_S1_alt2 == 1) +
      SERVCHAT     * (att_S2_alt2 == 1) +
      SERVAPP      * (att_S3_alt2 == 1) +
      DEVICE1      * (att_T_alt2 == 1) +
      DEVICE2      * (att_T_alt2 == 2) +
      DEVICE3      * (att_T_alt2 == 3) +
      DEVICE4      * (att_T_alt2 == 4) +
      CHARGE       * att_C_alt2 +

      PRICECALC1_rDM  * (att_P_alt2 == 2) * att_P_rDM_alt2 +
      PRICECALC2_rDM  * (att_P_alt2 == 3) * att_P_rDM_alt2 +
      PRICEEMAIL_rDM  * (att_A1_alt2 == 1) * att_A1_rDM_alt2 +
      PRICEPORTAL_rDM * (att_A2_alt2 == 1) * att_A2_rDM_alt2 +
      PRICEAPP_rDM    * (att_A3_alt2 == 1) * att_A3_rDM_alt2 +
      SERVEEMAIL_rDM  * (att_S1_alt2 == 1) * att_S1_rDM_alt2 +
      SERVCHAT_rDM    * (att_S2_alt2 == 1) * att_S2_rDM_alt2 +
      SERVAPP_rDM     * (att_S3_alt2 == 1) * att_S3_rDM_alt2 +
      DEVICE1_rDM     * (att_T_alt2 == 1) * att_D_rDM_alt2 +
      DEVICE2_rDM     * (att_T_alt2 == 2) * att_D_rDM_alt2 +
      DEVICE3_rDM     * (att_T_alt2 == 3) * att_D_rDM_alt2 +
      DEVICE4_rDM     * (att_T_alt2 == 4) * att_D_rDM_alt2
  )
```

```
  mnl_settings = list(
    alternatives = c(alt1 = 1, alt2 = 2),
    avail = list(alt1 = 1, alt2 = 1),
    choiceVar = choice,
    V = V
  )


  P[['model']] = apollo_mnl(mnl_settings, functionality)

  P = apollo_panelProd(P, apollo_inputs, functionality)

  P = apollo_prepareProb(P, apollo_inputs, functionality)
  return(P)
}

model = apollo_estimate(apollo_beta, apollo_fixed, apollo_probabilities, apollo_inputs)

apollo_modelOutput(model, modelOutput_settings = list(printPVal = TRUE))

# Save the model results
apollo_saveOutput(model, saveOutput_settings = list(
  printPVal = TRUE,
  saveEst = TRUE,
  saveModeObject = TRUE
))


WTP_CL_rDM <- wtp(cost = "CHARGE",names(model$estimate), model = model)
saveRDS(WTP_CL_rDM, "WTP_CL_rDM.rds")
saveRDS(model, "model_CL_rDM.rds")

WTP_CL_rDM

WTP_CL_rDM <- readRDS("WTP_CL_rDM.rds")
Model_CL_rDM <- readRDS("model_CL_rDM.rds")


coef.names = names(Model_CL_rDM[["estimate"]])
para.descript = data.frame(description = c("","Changing of prices based on a pre-defined plan (P1)",
                                           "Decreasing prices per kWh each month with consumption change
(P2)",
                                           "Prices and monthly bills are sent via email (A1)",
                                           "Prices and monthly bills made available through an online
portal (A2)",
                                           "Price communication and access to bills through mobile app
(A3)",
                                           "Service infrastructure: E-Mail (S1)",
                                           "Service infrastructure: Chat Agent (also video Chat) (S2)",
                                           "Service infrastructure: Message service within smart phone app
(S3)",
                                           "Manually adjustable electric plug adapter (D1)",
                                           "Local connected electric plug adapter (D2)",
                                           "Smart plug adapter incl. smart phone app (D3)",
                                           "Smart plug adapter incl. smart phone app and analysis (D4)",
                                           "P1_rDM",
                                           "P2_rDM",
                                           "A1_rDM",
                                           "A2_rDM",
                                           "A3_rDM",
                                           "S1_rDM",
                                           "S2_rDM",
                                           "S3_rDM",
                                           "D1_rDM",
                                           "D2_rDM",
                                           "D3_rDM",
                                           "D4_rDM"

))

parameter <-(coef.names[-14])

WTP_CL_pVal_4 <- round_df(WTP_CL_rDM,4)
LL_CL_2 <- round_df(Model_CL_rDM$LLout[1],2)


results_CL_rDM <- data.frame(cbind(para.descript,parameter,
                                   wtp_total=WTP_CL_pVal_4[,1],
                                   V4=WTP_CL_pVal_4[,4],
                                   rob.s.e._total=WTP_CL_pVal_4[,2]))
```

```
results_CL_rDM$SignCode <- sapply(results_CL_rDM$V4, significance_codes)


results_CL_rDM

ft <- flextable(results_CL_rDM)

ft <- set_header_labels(ft, description = "Name", parameter = "Parameter", wtp_total = "WTP", V4 = "pVal",
rob.s.e._total = "Rob.s.e.", SignCode = "Sign.")

ft <- add_footer_row(ft,values=c("n",Model_CL_rDM$nIndivs[1],"","","",""),colwidths=c(1,1,1,1,1,1))
ft <-
add_footer_row(ft,values=c("Observations",Model_CL_rDM$nObs[1],"","","",""),colwidths=c(1,1,1,1,1,1))
ft <- add_footer_row(ft,values=c("Log Likelihood (final)",LL_CL_2,"","","",""),colwidths=c(1,1,1,1,1,1))
ft <- add_footer_lines(ft, "Note: WTP = Willingness to pay; ***p < 0.001; **p < 0.01; *p < 0.05")
ft <- width(ft, j=1,width = 5.0)


ft
save_as_image(ft, path = "Results_CL_rDM.png")

results_CL_rDM
```

That's all Folks!