Department of Marketing

Measuring Customer Experience in The Age of Artificial Intelligence

by

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Acknowledgments

﴿وَآخِرُ دَعْوَاهُمْ أَنِ الْحَمْدُ لِلَّهِ رَبِّ الْعَالَمِينَ﴾

(يونس: ١٠)

"And their closing prayer will be, all praise is for Allah—Lord of all worlds!"

(Yunus: 10)

I begin these acknowledgements with this verse from the Holy Qur'an as a humble expression of gratitude. All praise is truly due to Allah, the Lord of the worlds, who granted me the strength, patience, and opportunity to begin and complete this thesis. I am deeply thankful for the countless blessings that have sustained me both seen and unseen throughout this PhD journey. From the gift of knowledge and the ability to pursue it, to the people He placed in my life to support and guide me, I recognize His mercy at every step. I pray that the knowledge I've gained, and the person I've become through this journey, serve a greater purpose. May Allah use me in His service and never turn me away.

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To my heart and soul, my mum and dad, Mohammad and Basma.
To my backbones and source of strength, my brothers, Sanad and Saif.
And to my better half, my calm and constant, Tareq, my husband.
For your love, your patience, and every sacrifice you made along the way, I see it all.
I know how heavy the distance was, and how much you quietly carried with me.

This PhD is for all of you. It's your achievement as much as it is mine.

To my grandparents, To my Teta who is here, and to my other Teta and both Jeddos in heaven hopefully watching proudly from above.
You always said you wanted to see a "certificate as large as the door" on the wall.
Well, this one might not be quite that size, but it's the biggest they offer and definitely wall-worthy!

And so, I’ll end with the words of a wise man:

“It only has to make sense on the day you submit it”
Dr. Matthew Alexander

That day has come, so here’s hoping it makes sense.

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Abstract

The emergence of artificial intelligence-enabled technologies (AI-ETs) has revolutionized customer experiences (CX), where AI-ETs play increasingly prominent roles, customers interact more actively, new touchpoints are introduced and existing ones and reconfigured. Despite acknowledged importance on both academic and practical levels, the impact of artificial intelligence (AI) on CX is underexplored, reflecting a novel and developing phenomena. Previous literature typically views AI as contextual, fails to acknowledge its transformative potential, and frequently adopts a conceptual focus or addresses individual touchpoints rather than AI's holistic impact. To address this gap, this thesis aims to explore customer experiences enabled by AI and measure their impact on associated behavioural outcomes through two research objectives. The first objective is to understand and map the research landscape on the role of AI in shaping customer experiences. The second objective is to develop a scale for measuring the AICX.

This thesis begins with a systematic literature review (SLR) to explore AI-enabled customer experiences (AICX) and identify knowledge gaps. This informed a sequential exploratory mixed methods study conducted in two phases. Phase one involved qualitative conceptualisation of AICX and item generation, drawing on literature and netnography, followed by expert review. Phase two focused on quantitative validation of the scale, conducted through a pilot and three surveys with customers who had prior interactions with AI-ETs.

This thesis makes three key contributions to CX theory and the broader services marketing literature. First, it introduces the AICX as a unified and novel construct, conceptualised with a framework of diverse AI-ETs. Second, it presents the AI-ET Cube, offering a systematic approach to categorising and analysing AI-ETs based on their roles within the customer journey, shifting the focus from technological characteristics to their functional and experiential impact. Finally, it develops a measurement scale—a robust tool to measure, manage, and adapt AICX. These contributions address key theoretical and empirical gaps by providing a structured lens to study AICX dynamics and enabling businesses to assess and optimise its implementation.

Chapter 1 . Introduction

"In fact, it seems possible that within the next three years, anything not connected to AI will be considered obsolete or ineffective".

(McKinsey and Company, 2024)

Customer experience (CX) is a key marketing construct that has attracted extensive scholarly attention due to its theoretical significance and managerial relevance (Ostrom et al., 2021; Verma et al., 2021). From a managerial perspective, CX management is widely regarded as a critical mechanism for strategic differentiation, enabling firms to distinguish themselves in increasingly competitive and saturated markets (Arkadan, Macdonald and Wilson, 2024; Gerea, Gonzalez-Lopez and Herskovic, 2021; Homburg, Jozić and Kuehnl, 2017; Palmer, 2010). As a result, CX has been elevated to a top organizational priority across industries (Caruelle et al., 2024; Larivière et al., 2025). Practitioner research reinforces this emphasis, revealing that 85% of 1,500 executives identify CX enhancement as a critical or high-priority business objective (Adobe, 2023). From a theoretical standpoint, prior research consistently demonstrates that effectively understanding and optimizing CX strengthens customer relationships, enhances satisfaction, and drives competitive advantage in increasingly dynamic and complex markets (Bolton et al., 2018; De Keyser et al., 2020; Kranzbühler et al., 2018). Empirical evidence further confirms CX's pivotal role in shaping consumer behaviour and driving business success (Le, Wu and Hyun, 2024).

Despite this significance in both research and practice, the CX literature remains nascent, fragmented, and developmentally unsettled (Arkadan, Macdonald and Wilson, 2024). While the expanding body of CX research has contributed to a deeper understanding of experiential phenomena, it has also intensified debates concerning CX's conceptual foundations, reinforcing a lack of consensus within the field (Becker and Jaakkola, 2020). Divergent perspectives persist regarding how CX should be defined, conceptualized, and operationalized, particularly with respect to its dimensionality and boundaries (Becker and Jaakkola, 2020; Brakus, Schmitt and Zarantonello, 2009; Lemon and Verhoef, 2016). These debates extend further to CX's nomological network and theoretical origins, highlighting ongoing tensions regarding its relationship with adjacent constructs such as satisfaction, value, and engagement (Godovykh and Tasci, 2020; Lemon and Verhoef, 2016; Waqas, Hamzah and Salleh, 2021). Rather than converging toward a unified understanding, the field continues to evolve in parallel and sometimes competing directions, limiting theoretical integration and cumulative knowledge development.

Extending these debates, recent research increasingly positions technology as a key factor in reshaping how customer experience is formed and understood. Technological developments do not merely influence CX outcomes; they alter the processes, interactions, and conditions through which experiences emerge (Larivière et al., 2017). In this regard, research highlights how technological disruptions give rise to new experiential forms, including extra-sensory experiences, hyper-personalized experiences, and beyond-automation experiences, phenomena that challenge assumptions embedded in traditional CX frameworks and require renewed scholarly attention (Buhalis et al., 2019; Larivière et al., 2017). As digital technologies become more deeply embedded in customer journeys, they add a critical layer of complexity to already fragmented CX debates, raising questions about whether existing conceptualizations remain sufficient to capture contemporary experiential realities.

Within this broader technological landscape, artificial intelligence (AI) occupies a particularly significant position. In 2023, the global AI market was valued at over €130 billion and is projected to approach €1.9 trillion by 2030 (Statista, 2023). A recent McKinsey report (2024) further indicates that organizations are incorporating AI across more business functions than ever before. Over the past decade, advances in AI have expanded commercial applications, creating transformative business opportunities (Furman and Seamans, 2019). In parallel, the growing consumer adoption of AI-based tools underscores the evolving landscape of CX. The success of these applications has driven increasing interest in AI adoption (Pan, 2016), prompting a growing body of research on customer acceptance of AI technologies (Kelly, Kaye and Oviedo-Trespalacios, 2023; Kim, Giroux and Lee, 2021).

Beyond its scale and diffusion, the literature increasingly emphasizes the distinct role of AI in redefining customer interactions and perceptions of experience (Ameen et al., 2021; Bolton et al., 2018; Chen and Prentice, 2024; Flavián, Ibáñez-Sánchez and Orús, 2019; Foroudi et al., 2018; Hoyer et al., 2020; Lv, Qiu and Cho, 2024; Peruchini, da Silva and Teixeira, 2024; Verma et al., 2021). AI-enabled technologies introduce adaptive, autonomous, and often opaque modes of interaction that differ qualitatively from earlier forms of digital mediation. For instance, Hoyer et al. (2020) highlight the disruptive potential of AI-powered technologies, arguing that "these technologies will result in an entirely new concept of customer experience" (p. 58). Collectively, this body of work positions AI-enabled technologies (AI-ETs) as a primary factor in the reconfiguration of CX, intensifying existing conceptual challenges and raising new questions regarding how customer experience should be understood through the AI lens.

Further advancements are expected to deepen AI's influence through increasing levels of autonomy, embodiment, and experiential richness (Doğan and Niyet, 2024; Ivanov et al., 2019; Knani, Echchakoui and Ladhari, 2022; Tussyadiah, 2020). While the literature suggests that AI's full potential remains unrealized, its current impact on customer experience is already substantial, warranting continued scholarly and managerial attention. From AI-based innovations such as intelligent voice assistants to the enhancement of existing technologies such as augmented reality, AI-ETs play an increasingly prominent and visible role in shaping customer experiences. Their capacity to deliver context-driven, real-time, and customizable interactions exemplifies this shift (Ostrom, Fotheringham and Bitner, 2019; Alimamy and Jung, 2024).

At the same time, customers' roles within service experiences continue to evolve, as interactions increasingly involve intelligent systems alongside or in place of human actors (Larivière et al., 2017). New touchpoints emerge, while existing ones are reconfigured to accommodate AI-enabled functionalities (Larivière et al., 2025). Under these conditions, traditional CX frameworks largely developed in contexts characterized by relatively stable, human-centric interactions are limited in their ability to fully capture the depth, dynamicity, and emergent nature of AI-enabled customer experiences.

AI-ETs are embedded throughout the customer journey and serve diverse purposes, ranging from visible to non-visible applications within service encounters (Ostrom, Fotheringham and Bitner, 2019). While behind-the-scenes AI-ETs primarily support managerial functions such as: optimizing operations, forecasting demand, or improving decision-making (Marinchak, 2018; Nguyen, 2023; Sidaoui, Jaakkola and Burton, 2020)customer-facing AI-enabled technologies play a particularly consequential role for CX, as they directly engage customers and mediate experiential responses in real time. These technologies, including chatbots, virtual assistants, service robots, and extended reality applications such as augmented, virtual, and mixed reality, are now embedded across the customer journey and actively transform customer experiences (Doborjeh et al., 2022; Chi, Chi and Gursoy, 2024; Grundner and Neuhofer, 2021; Knani, Echchakoui and Ladhari, 2022; Lee, Wu and Hyun, 2024; Liu et al., 2024; Pillai and Sivathanu, 2020; Saputra et al., 2024).

Through automated social presence, customer-facing AI-enabled technologies create a sense of human-like interaction that can enhance social engagement and perceived service quality (Van Doorn et al., 2017). Moreover, they extend the concept of peripheral service evidence by acting as digital counterparts that bridge physical and digital interactions within service encounters (Lee and Lee, 2024). As such, customer-facing AI-ETs are characterized by higher levels of technological embodiment, reflecting their capacity to simulate social and interactive qualities typically associated with human service providers (Tussyadiah, Jung and Tom Dieck, 2018). Consequently, these technologies function as experience-relevant touchpoints, shaping customer experience across cognitive, emotional, behavioural, sensorial, and social dimensions, reinforcing the need to examine CX as it emerges through AI-enabled interactions.

However, existing CX research has yet to offer a coherent conceptualization that explicitly accounts for how customer experience emerges when AI-enabled technologies actively shape the structure, dynamics, and conditions of the customer journey. In combination, these developments point to a clear need for a more precise conceptual lens through which to examine customer experience in contexts where experiential processes are being fundamentally reconfigured by AI-enabled technologies. Addressing this gap requires moving beyond treating AI as a contextual variable and toward conceptualizing how customer experience emerges when customer journeys are shaped by AI-ETs. In response to this theoretical challenge, this thesis introduces AI-enabled Customer Experience (AICX) as a construct designed to capture the experiential journey formed through the integration of AI-enabled technologies.

Within this conceptual context, the services sector provides a particularly compelling context in which to examine AICX. Services are inherently experiential and interaction-intensive, with value creation rooted in ongoing exchanges between customers and service providers (Ostrom, Fotheringham and Bitner, 2019; Kozinets and Gretzel, 2024). This reliance on interaction renders service experiences especially susceptible to technological mediation and disruption, as AI-ETs reshape service delivery and redefine customer engagement (Huang and Rust, 2018; Gursoy and Cai, 2025). Within the service domain, tourism represents a theoretically and empirically powerful setting: customer experiences are immersive, emotionally charged, multi-sensory, and unfold across extended, technology-mediated journeys (Godovykh and Tasci, 2020; Pratisto et al., 2022; Park, Lee and Back, 2023; Buhalis et al., 2024). These characteristics amplify the experiential implications of AI-enabled technologies, making tourism a critical context in which to observe and analyse AICX.

Accordingly, this thesis begins by investigating AI-enabled customer experience in the tourism sector, with a focus on customer-facing AI-enabled technologies such as chatbots, virtual assistants, service robots, and immersive applications. By examining how these technologies shape customers' experiential responses across the customer journey, the study advances conceptual understanding of AICX and contributes to the broader customer experience literature by addressing a timely and theoretically significant gap. The thesis then proceeds to develop and validate a scale of AI-enabled customer experience.

1.1. Thesis Aim and Objectives

The overall aim of this research is to **explore customer experiences enabled by AI and measure their impact on associated behavioural outcomes**. This aim is driven by the need to: understand the transformative impacts of AI-ETs on CX (Hoyer *et al*., 2020); investigate new emerging forms of experience resulting from integration of AI-ETs (Buhalis *et al*., 2019; Ghesh, Alexander and Davis, 2024; Hoyer *et al*., 2020) and how changes in broader consumer behaviour have been reshaped and derived (Ameen *et al*., 2021; Lv *et al*., 2024).

The importance of advancing service research through the lens of AI has been widely recognised (Bock *et al*., 2020, Verma *et al*., 2021, Vlačić *et al*., 2021). Despite significant scholarly response, much remains fragmented, often examining AI at the touchpoint level rather than comprehensively (Alimamy and Jung, 2024, Dandotiya *et al*., 2024, Liu *et al*., 2024). Recognition of AI as a unified framework is mostly conceptual (Ameen *et al*., 2021; Chintalapati and Pandey, 2022; Hoyer *et al*., 2020; Jabeen, Zaidi and Al Dhaheri, 2022; Peruchini, da Silva and Teixeira, 2024; Verma *et al*., 2021; Vlačić *et al*., 2021), with empirical research on AI remaining limited, often focusing on its influence rather than its transformative potential (Ghesh, Alexander and Davis, 2024). The growing body of literature lacks a unified framework to capture the transformative impact of AI-ETs, perpetuating fragmentation. This underscores the need to explore AICX as an emerging phenomenon within the broader CX framework, providing a foundation for future research. As a hypernym, AI encompasses diverse, interconnected technologies with evolving, far-reaching impacts. An exploratory phase is essential to address these complexities and deepen the conceptual understanding of AICX.

Accordingly, the thesis aim is addressed, through the following research objective:
Research Objective 1: To understand and map the research landscape on the role of AI in shaping customer experiences.

This objective is addressed through a SLR, which is presented in Chapter 3. The SLR is designed to critically examine existing literature to provide a comprehensive overview of the current state of knowledge. By introducing AICX as an emerging phenomenon, mapping its research landscape, and identifying key gaps, it establishes a foundation for further investigation and conceptual development.

The SLR plays a central role in justifying the research aim, informing the specific objectives, and shaping the overall research design to ensure alignment with the identified gaps. It highlights the lack of an established scale to assess AICX and the limited understanding of its outcomes, reinforcing the need for the scale development study that follows. Accordingly, a second research objective is proposed as follows:

Research Objective 2: To develop a scale for measuring the AICX.

This research objective is addressed through a scale development study, which constitutes the empirical component of this thesis. The study is designed in two phases: a qualitative phase (Chapter 5) and a quantitative phase (Chapter 6).

AICX is conceptualised in this study as arising from the integration of AI-ETs across the customer journey. This integration not only redefines traditional service touchpoints but also introduces novel ones, thereby reshaping the customer's role in the experience. Given this shift, there is a critical need to understand and manage AICX effectively. However, the service literature currently lacks robust, validated tools capable of measuring this redefined concept comprehensively (Bueno *et al.*, 2019, Ghesh, Alexander and Davis, 2024). Existing scales fall short of capturing its complexity and scope.

This thesis responds to this gap by grounding the scale development process in established CX and technology-related literature, with a focus on the service sector. It positions AICX as an emergent construct that extends existing CX theories and frameworks and argues for the necessity of a new measurement tool tailored to this evolving landscape.

1.2. Research Design

Following an initial review of the literature on CX and the introduction of AICX as an emerging phenomenon, the necessity of beginning with an exploratory phase and approaching the literature systematically was recognized. Accordingly, a SLR was conducted in March 2022. The SLR facilitated a comprehensive exploration of this under researched area, identified critical knowledge gaps, and informed the thesis's aim, objectives, and overall design. Using the SLR as the first step in this thesis ensured it could stand alone as a significant academic contribution. In fact, the SLR was submitted and published in *Tourism Review* (Ghesh, Alexander and Davis, 2024).

The empirical part of this thesis, informed by the SLR findings, employs a mixed-methods approach using a sequential exploratory design for scale development. It began with a qualitative phase (Chapter 5), conducted between March 2023 and November 2023, which provided the foundation for the subsequent quantitative phase (Chapter 6) undertaken from November 2023 to June 2024. The developed scale was presented at an academic conference in July 2024, with a journal submission planned for 2025. **Error! Reference source not found.** provides a visual summary of the research approach, highlighting its key components and overall structure.

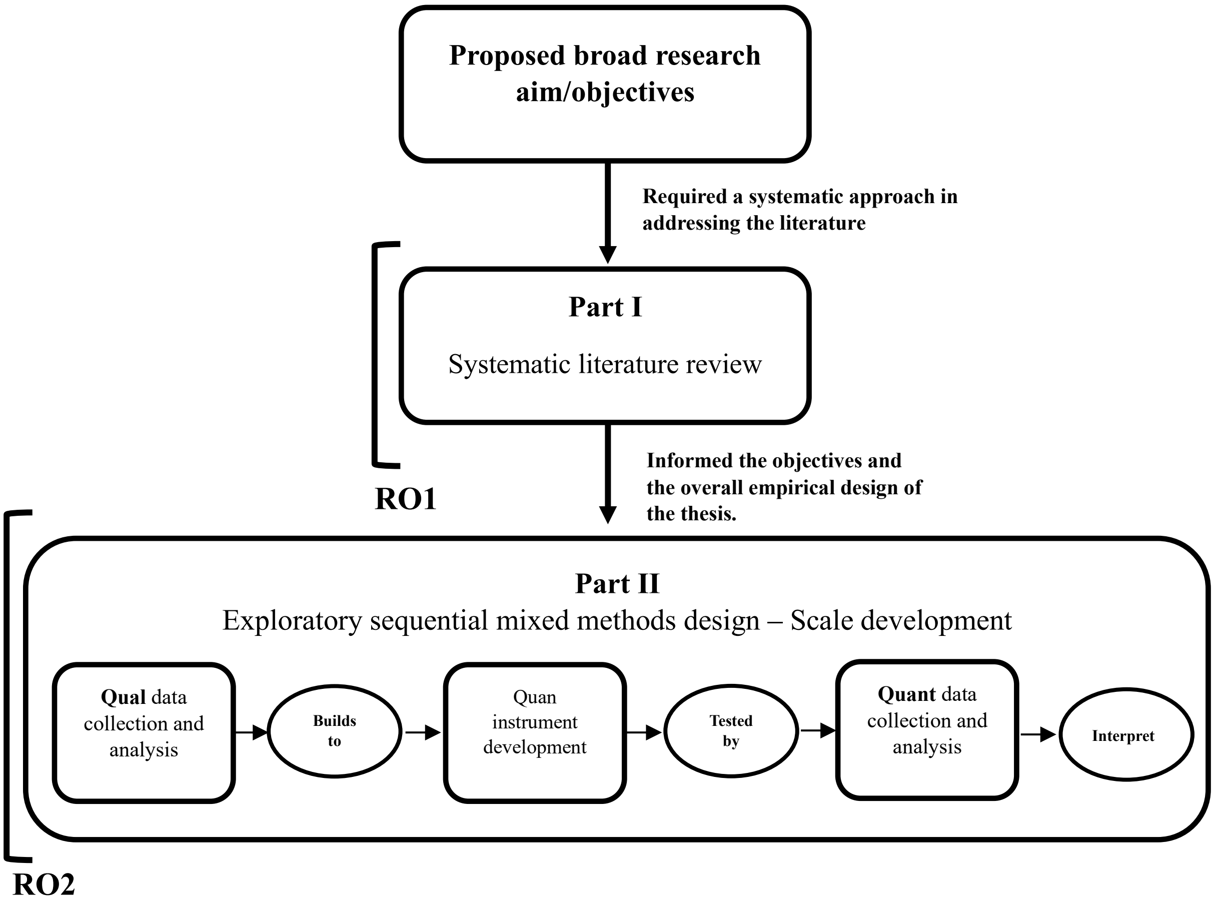


Figure 1-1 Research approach

1.3. Thesis Overview

The thesis structure is carefully designed to align with the subject area, philosophical approach, and research design. It begins with an initial literature overview (Chapter 2) that addresses the theoretical foundations of CX and traces its evolution, culminating in the introduction of AICX as an emerging phenomenon. This is followed by an in-depth exploration of AICX through a systematic review of existing literature (Chapter 3). The next chapter (Chapter 4) outlines the overall research design highlighting its philosophical underpinnings. Chapter 5 outlines the scale development process and describes the specific steps taken in developing the AICX scale.

The following two chapters are empirical, presenting the AICX scale development process. Chapter 6 focuses on the qualitative phase, which conceptualizes AICX and includes the generation and refinement of a pool of potential items for the scale. Building on this foundation, Chapter 7 outlines the quantitative phase, which explores the scale's structure, refines it, and establishes its psychometric robustness. A discussion chapter (Chapter 8) follows, evaluating the thesis's contributions against the research objectives and considering its relevance to the broader CX framework. Finally, the concluding chapter (Chapter 9) synthesizes the main contributions of the thesis and discusses their broader implications. A detailed summary of each chapter is provided below:

Chapter 2 reviews the literature on CX, tracing its evolution from early theoretical foundations to modern conceptualizations shaped by technological advancements and the rise of AI. It examines AI's transformative impact on CX, focusing on the role of AI-enabled technologies (AI-ETs) in reshaping customer interactions while addressing challenges such as ethical considerations, data privacy, and customer trust. The chapter introduces AI-enabled customer experience (AICX) as an emerging phenomenon within CX literature, emphasizing its fragmented and multidimensional nature. It concludes by calling for further research to deepen the understanding of AICX, particularly its experiential dimensions and transformative effects on customer behaviour.

Chapter 3 presents the SLR conducted to explore the emerging phenomenon of AICX. The review adopts the Theory, Characteristics, Context, and Methods (TCCM) framework to provide a descriptive analysis of the existing literature, offering a structured understanding of the field's current state. The chapter synthesizes prior research, identifying the need for a comprehensive framework to address the fragmented nature of technological literature. This framework also accounts for the interactive nature of AICX and incorporates enduring characteristics that represent its core elements. As part of this effort, the chapter develops the AI-ET Cube, a conceptual model to capture and represent these characteristics effectively. In addition, the chapter identifies five key themes representing gaps in current knowledge and emphasizes their importance in shaping future research directions. These themes highlight areas that require further exploration, providing a roadmap for advancing the understanding of AICX.

Chapter 4 outlines the research design that underpins the remainder of the thesis. It begins by re-articulating the overarching aim and specific objectives, followed by a critical evaluation of the philosophical paradigms of positivism and interpretivism, highlighting their respective strengths and limitations. Critical realism is then introduced and justified as the most appropriate philosophical framework, given its alignment with the study's ontological and epistemological assumptions. The chapter subsequently discusses the adopted approach to theory development, situating it within the broader methodological orientation. It concludes by presenting the sequential exploratory design within a mixed methods framework, demonstrating its coherence with the principles of critical realism and its suitability for addressing the research objectives.

Chapter 5 provides a comprehensive overview of the scale development process. It begins by introducing psychometrics as a formal discipline and examining the historical evolution of scale development. The chapter presents both theoretical and methodological frameworks that underpin the process. It highlights the essential roles of reliability and validity as foundational components in developing robust measurement instruments. The chapter also details the main data collection approaches adopted in the AICX scale development, which follows a mixed methods sequential exploratory design. It concludes with a discussion of ethical considerations related to participant selection and data management.

Chapter 6 outlines the qualitative phase of the scale development process, comprising three steps. The phase begins by discussing the AICX construct and its dimensionality, then moves on to outline the polarity and measurement model of the intended scale. Building on this theoretical foundation, the second step employs two sources (1) previously published scales and a (2) qualitative netnography study, to generate an initial pool of scale items. In the third step, expert panels refine this initial pool to finalize the list of items for use in the subsequent quantitative phase through establishing its content and face validity.

Chapter 7 outlines the quantitative phase of the scale development process, comprising three steps. Building on the outcomes of the qualitative phase (Chapter 5), this phase begins with developing and piloting the quantitative measurement tool before proceeding to official data collection. Subsequently, the phase involves three rounds of data collection and analysis to identify the scale's underlying structure, establish its discriminant and nomological validity, and examine its relationships with other relevant constructs, such as customer satisfaction (CS) and customer engagement (CE). The chapter concludes by introducing the final structure of the AICX scale, comprising four dimensions and 12 items.

Chapter 8 synthesizes the key outcomes of this thesis, providing a comprehensive reflection on its contributions. It begins by exploring the paradigm shift in CX driven by technological advancements, with a particular emphasis on the integration of AI-ETs and the introduction of the AICX construct. Central to this chapter is the elaboration of the AI-ET Cube, underscoring its novelty and wide-ranging implications for understanding and categorizing AI-ETs in CX research. The discussion then transitions to the development and validation of the AICX Scale, presented as a robust and empirically grounded measurement tool. This scale offers practical utility for both researchers and practitioners in evaluating AICX. The chapter concludes by emphasizing the alignment of these outcomes with the overarching aim and objectives of the thesis. It demonstrates how the conceptual, theoretical, and empirical components collectively advance understanding in the domain, establishing a strong foundation for future research into AI-driven transformations in the field.

Chapter 9 concludes the thesis by outlining its key contributions. It begins by addressing the theoretical implications of these contributions, reflecting on how they enhance the theory of CX and the broader field of services marketing. Following this, the chapter articulates the practical implications by offering actionable insights for practitioners navigating the integration of AI-ETs in services. The chapter then critically examines the limitations of the research, discussing its scope, boundaries, and areas where further work is needed to build on the study’s foundation. Finally, it directs attention to future research opportunities, pinpointing key topics and emerging areas within the AICX domain to advance understanding and practical application.

Chapter 2 . The Artificial-Intelligence Enabled Customer Experience: Theoretical Foundations

Building on the growing recognition that artificial intelligence is fundamentally reshaping customer interactions and service experiences, this thesis introduces AI-enabled customer experience (AICX) as a central analytical construct. This chapter reviews the customer experience literature and examines how customer-facing AI-enabled technologies are reshaping customer experience, thereby establishing the theoretical foundation for the study of AICX. To ensure conceptual clarity and consistency, the key constructs underpinning this thesis are defined at the outset of the chapter.

The customer experience (CX) definition adopted in this thesis is by Becker and Jaakola, where a customer experience is defined as "customers' non-deliberate, spontaneous responses and reactions to offering-related stimuli along the customer journey "(Becker and Jaakoola, 2020, p. 638). Building on this definition, an AI-enabled customer experience (AICX) is defined as *customers' non-deliberate spontaneous responses and reactions to offering-related stimuli along a customer journey featuring one or more AI-enabled technologies*. In this thesis, AI-enabled technologies (AI-ETs) are understood as customer-facing technologies whose functionality is generated or enhanced through artificial intelligence. Manifesting, for example, as conversational systems, service robots, or immersive digital interfaces, these technologies are distinguished by their adaptive and data-driven nature. They therefore operate as touchpoints that shape customer responses across the customer journey, rather than as fixed or purely transactional service interfaces.

To situate these definitions within the broader literature, this chapter reviews foundational work on customer experience and examines the role of technology, particularly customer-facing AI-enabled technologies, in shaping CX. By synthesizing insights from CX and technology-focused research, the chapter establishes the theoretical foundations for conceptualizing AICX as an emerging phenomenon that warrants further exploration. The chapter concludes by outlining the rationale for conducting a systematic literature review (SLR), which informs the subsequent research objectives and design.

2.1. Understanding Customer Experience

2.1.1. Foundations of Customer Experience

The concept of experience in marketing and consumer behaviour has evolved significantly, shaping the contemporary understanding of CX. Dewey's seminal work on the significance of lived experiences in shaping human behaviour (Dewey, 1922; Dewey, 1925), along with his emphasis on the central role of experience in learning and development, provides a foundational framework for understanding the role of experience in contemporary marketing. Abbott (1955) advanced the idea by emphasizing that the ultimate goal of consumption is the experience it creates. Similarly, Howard and Sheth (1969) highlighted the role of experience in the decision-making process. Oliver (1980) supported this notion by studying the role of previous experiences in influencing customers' attitudes and behaviour.

Early conceptualizations of CX by behavioural theorists primarily focused on its rational dimensions (Ajzen and Fishbein, 1977). Subsequently, experiential theorists began to explore CX, emphasizing its emotional aspects (Hirschman and Holbrook, 1982, Holbrook and Hirschman, 1982, Thompson *et al*., 1989). Holbrook and Hirschman's (1982) work is widely regarded as a significant contribution that established the concept of experience within the marketing discipline. It broadened the understanding of consumer behaviour by introducing the emotional dimension of consumption, which has become a key component in the study of CX in the literature today. This shift in perspective marked a significant advancement in understanding CX, moving beyond a purely rational framework to incorporate the complexities of emotions. In marketing practice, Pine and Gilmore (1998) introduced the concept of the experience economy. They posited that businesses must shift from merely providing goods and services to creating memorable experiences for customers. This shift represents a significant progression in how economic value is defined, emphasizing that value now derives from the holistic experiences surrounding a product rather than from the product itself.

Schmitt (1999) introduced experiential marketing as a new approach to marketing in contrast to traditional marketing. This approach emphasizes that consumers are not merely rational decision-makers but also emotional beings seeking pleasurable experiences. He identifies five types of experiences: sense, feel, think, act, and relate, that marketers can utilize to create engaging CX. This holistic approach integrates individual interactions into a cohesive customer journey, emphasizing the importance of both emotional and sensory dimensions in shaping consumer behaviour. Schmitt argued that in an era of product parity, businesses must create memorable and emotionally engaging experiences to differentiate themselves. Subsequent research has expanded on Schmitt's approach by developing multidimensional frameworks that more fully capture the layered, contextual, and measurable nature of CX.

2.1.2. Multidimensional Frameworks for Customer Experience

Recognizing the importance of CX, Meyer and Schwager (2007) investigated its implications within a retail context. Their research highlighted that CX is both subjective and personal, depending on interactions within the retail environment and shaped by various touchpoints. While this perspective offers a comprehensive understanding of the experience in retail settings, Brakus, Schmitt and Zarantonello (2009) focused specifically on brand experience, arguing that it serves as a key driver of consumer satisfaction, loyalty, and brand equity. They also developed a measurement scale to assess brand experience, providing marketers with a valuable tool to evaluate their brand's performance and contributing to the broader efforts to quantify and understand CX in a competitive marketplace. Verhoef *et al*. (2009) adopted a more holistic approach to CX that did not centre on brand-specific factors. They emphasized that CX encompasses various dimensions, integrating psychological responses (cognitive, affective, emotional, social, and physical) and interactions across multiple touchpoints throughout the customer journey. This conceptualization highlights the complexity of CX, recognizing its dependence on both situational and consumer factors that influence behaviours such as loyalty and patronage.

In the years that followed, CX research continued to grow, with conceptual work gaining prominence (De Keyser *et al*., 2015, Helkkula, 2011, Jain *et al*., 2017, Jaakkola *et al*., 2015, Kranzbühler *et al*., 2018, Lemon and Verhoef, 2016, Lipkin, 2016). Helkkula (2011) identified three primary characterizations for the experience: (1) phenomenological, which focuses on customers' subjective experiences and aligns with service-dominant logic; (2) process-based, which conceptualizes service experience as a sequential journey of interactions; and (3) outcome-based, which links service attributes to measurable outcomes like satisfaction and loyalty (Helkkula, 2011). De Keyser *et al*. (2015) developed a comprehensive framework that captures the complexity of CX in services by integrating multidisciplinary insights from marketing, philosophy, psychology, and sociology. They define CX as "comprising cognitive, emotional, physical, sensorial, and social elements that characterize a customer's direct or indirect interactions with (a set of) market actor(s)" (De Keyser *et al*., 2015, p. 10).

Over time, the understanding of CX has shifted from a transactional perspective to a more comprehensive, process-oriented view. Rather than being defined solely by a single interaction or outcome, CX is now seen as an evolving journey shaped by multiple touchpoints, perceptions, and interactions between customers and firms. Bolton *et al*. (2014) suggest that CX is inherently process-centric, emphasizing the importance of the sequence of interactions throughout the customer journey rather than merely focusing on the final outcome of consumption. Extending this, Jaakkola *et al*. (2015) provided a conceptualization of the experience with a focus on co-creation aspects in services. It emphasized the subjective nature of the experience and its emergence during various stages of the service process, including purchase or use, where experiences can be either lived or imaginary. In a similar vein, Lemon and Verhoef (2016) explored the roots of CX in marketing literature, validating its multidimensional nature across the customer journey. They defined CX as "a multidimensional construct focusing on a customer's cognitive, emotional, behavioural, sensorial, and social responses to a firm's offerings during the customer's entire purchase journey" (Lemon and Verhoef, 2016, p. 71).

Jain *et al*. (2017) viewed CX as a holistic interactive process, shaped by cognitive and emotional cues and controlled by customer-specific and contextual factors, leading to unique memories. Further, the increasing focus on CX within the service sector has led to the emergence of the term "service experience," often used interchangeably with CX. Jain *et al*. (2017) investigated the conceptual overlap between CX and service experience, concluding that both emphasize value co-creation; however, the distinction lies in that CX centres on the individual customer's internal response, whereas service experience encompasses a broader scope by including other stakeholders and their collective involvement in the service process.

In an effort to make CX more actionable while reducing conceptual ambiguity, De Keyser *et al*. (2020) introduced the TCQ nomenclature that identifies and lists the components of CX to reduce misunderstanding related to the construct. The TCQ nomenclature introduces three building blocks for CX: touchpoints (T), context (C), and qualities (Q). Touchpoints refer to points of interaction between the customer and the brand/firm; context encompasses situationally available resources internal and/or external to the customer; and qualities reflect the nature of customer responses and reactions to interactions with the brand/firm. Together, these components provide a comprehensive framework for understanding and analysing CX.

Reviewing the literature highlights shifts in the conceptualization of experience leading to the construct of CX. A significant transition is observable from a managerial perspective of CX to a more customer-centric orientation. Initially, CX was viewed as something staged by brands or service providers, where value was primarily driven by consumption goals (Pine and Gilmore, 1998). However, contemporary literature increasingly acknowledges the active role customers play in shaping their own experiences (McColl-Kennedy *et al*., 2015). In today's interconnected world, consumers have transitioned from being passive recipients of products and services to active participants in the formation of their experiences. This paradigm shift is essential to the evolving dynamics of CX, resulting in more customer-centric conceptualizations that define CX as customers' responses to firm-related interactions (Lemon and Verhoef, 2016; Meyer and Schwager, 2007).

2.1.3. Theoretical Advancements and Addressing Fragmentation in Customer Experience

Early perspectives on experience primarily focused on cognitive aspects, viewing it as a rational process (Abbott, 1955, Howard and Sheth, 1969). Over time, the construct has evolved to encompass emotional, sensory, and physical dimensions.

Current literature widely recognizes the multidimensional nature of CX, although variations persist regarding the specific dimensions that constitute it (De Keyser *et al*., 2015; Lemon and Verhoef, 2016). These variations reflect the acknowledgment that CX is shaped not only by individual interactions but also by the contexts in which these interactions occur.

Furthermore, the literature indicates that CX can be perceived as both an integration of existing marketing constructs and a distinct concept in its own right. While CX is deeply rooted in and influenced by established marketing theories such as relationship marketing (Morgan and Hunt, 1994), service marketing (Bitner, 1990; Zeithaml, Bitner, and Gremler, 2006), brand experience (Brakus, Schmitt and Zarantonello, 2009), and customer engagement (Brodie *et al*., 2011). It reinterprets these constructs through a holistic, journey-based perspective that transcends transactional and channel-specific views (Lemon and Verhoef, 2016). This approach emphasizes the dynamic and multi-touchpoint nature of customer interactions across the entire journey, underscoring the strategic role of CX in shaping perceptions, fostering loyalty, and delivering differentiated value propositions (Verhoef *et al*., 2009; Homburg *et al*., 2017). However, realizing this potential necessitates recognizing the foundational contributions of these established frameworks, which provide the conceptual scaffolding for understanding CX not merely as a reconfiguration of prior theories, but as a comprehensive and integrative paradigm within contemporary marketing thought.

Building on this integrative, journey-based perspective, variations in the interpretation of CX also concern the types of encounters that are considered experiential, encompassing a wide spectrum ranging from extraordinary moments that leave a lasting impact on customers (Arnould and Price, 1993) to routine interactions that may go unnoticed (Carù and Cova, 2003). While some perspectives frame CX as exclusively tied to memorable experiences (Schouten *et al*., 2007), literature challenges this narrow view by positing that all interactions, regardless of their perceived significance, cumulatively shape a customer's overall experience. In this context, CX emerges as a dynamic construct that evolves through ongoing interactions between customers and brands, underscoring the need to understand how both individual encounters and broader journeys shape customer perceptions and behaviours. This view positions CX not as a discrete event, but as an emergent phenomenon unfolding across both momentary interactions and extended journeys.

Beyond differences in the types and temporal scope of encounters considered experiential, CX research also varies in how the boundaries of the experience construct itself are defined and theorized. One contemporary conceptual stream conceptualizes CX as customers' nondeliberate, spontaneous responses to offering-related stimuli (Becker and Jaakkola, 2020; De Keyser et al., 2020; Weidig et al., 2024). From this perspective, the scope of CX includes cognitive, emotional, behavioural, sensorial, and social reactions that emerge during interactions but is also analytically distinct from subsequent conscious evaluations or judgments, such as satisfaction or value assessments (Becker and Jaakkola, 2020). In contrast, a broader stream of CX research defines CX to include customers' evaluative judgments of their interactions and journeys, such as assessments of touchpoint quality and goal attainment (Klaus and Maklan, 2012; Lemon and Verhoef, 2016; Verhoef et al., 2009). Accordingly, the primary distinction between these perspectives lies in whether evaluative outcomes are treated as part of the CX construct or as analytically distinct consequences of it.

Despite these variations, CX is widely understood as a subjective and customer-centric phenomenon that resides in customers' lived perceptions and interpretations rather than in firm-designed offerings or processes (Becker and Jaakkola, 2020; Helkkula, 2011; Lemon and Verhoef, 2016). There is broad agreement that CX is multidimensional, reflecting the complexity of customers' experiences (Schmitt, 1999; Brakus, Schmitt, and Zarantonello, 2009; De Keyser et al., 2015; Lemon and Verhoef, 2016). Moreover, scholars commonly conceptualize CX as a journey-based construct that is shaped cumulatively across multiple interactions and touchpoints, rather than confined to isolated interactions or touchpoints. (Verhoef et al., 2009; Bolton et al., 2014; Lemon and Verhoef, 2016). Context is also widely recognised as constitutive of CX, with situational, social, and personal factors influencing how experiences are formed, lived, and interpreted (Helkkula, 2011; Jaakkola et al., 2015; De Keyser et al., 2020). Finally, although perspectives diverge in how broadly CX is defined specifically, whether the construct is scoped to customers' responses to offering-related stimuli (Becker and Jaakkola, 2020; De Keyser et al., 2020; Weidig et al., 2024) or extended to include evaluative judgments of interactions and journeys (Lemon and Verhoef, 2016; Verhoef et al., 2009). The primary differences in the literature concern the analytical boundaries of CX, rather than its fundamental importance or relevance, providing a shared conceptual foundation upon which further theoretical refinement and integration can build.

Building on this emerging convergence, recent integrative efforts have explicitly sought to reconcile divergent CX perspectives and move the field toward greater conceptual coherence. In particular, Becker and Jaakkola (2020) and De Keyser et al. (2020) synthesize fragmented research streams to articulate fundamental premises and shared building blocks underlying CX, while explicitly acknowledging variation in scope and emphasis. Rather than resolving all definitional differences, these frameworks demonstrate that much of the apparent fragmentation reflects alternative analytical lenses, especially regarding the boundaries between experiential responses and evaluative outcomes, rather than irreconcilable theoretical contradictions. As such, these contributions provide an integrative platform that enables more cumulative CX theory development.

Informed by these integrative efforts, this thesis adopts the definition of customer experience proposed by Becker and Jaakkola (2020) that defines customer experience as: “customers’ non- deliberate, spontaneous responses and reactions to offering-related stimuli along the customer journey “(Becker and Jaakoola, 2020, p. 638). This definition is grounded in a systematic literature review and metatheoretical analysis explicitly aimed at clarifying the conceptual domain of CX and resolving ambiguities across prior research. By integrating insights from eight literature fields and bridging the two dominant research traditions, managerial stimulus–focused and consumption process–focused. This definition provides a conceptually rigorous and context-independent foundation for examining customer experience in the present study.

Importantly, this definition aligns with a stream of CX research that analytically distinguishes customers’ experiential responses from subsequent reflective evaluations, such as satisfaction, perceived value, or quality judgments (Becker and Jaakkola, 2020; De Keyser et al., 2020; Weidig et al., 2024). At the same time, it evolves from earlier multidimensional conceptualizations of experience by preserving the view of CX as encompassing cognitive, affective, sensorial, and social responses, while sharpening the analytical distinction between customer experience, firm-controlled stimuli, and evaluative outcomes. These conceptual distinctions assume particular relevance in AI-enabled contexts, where adaptive, data-driven, and often opaque customer–system interactions intensify the need for clear analytical separation between experiential responses, firm-controlled stimuli, and evaluative outcomes in advancing CX theory within a still nascent and rapidly developing research domain. As such, the adopted definition provides a theoretically robust and integrative foundation for examining customer experience in AI-enabled contexts.

2.2 Technological Impact on Customer Experience

2.2.1 Changes to CX touchpoints

Technological advancements in the 21st century have transformed how businesses interact with customers, adding new layers of complexity to the already dynamic and evolving construct of CX. E-commerce has changed shopping by providing greater convenience and a wider product selection (Kacprzak and Hensel, 2023). Social media has become a key platform for customer feedback, complaints, and real-time engagement (Nuseir *et al*., 2023). Online chat services have further improved customer interactions by offering instant support for inquiries and issue resolution (Sands *et al*., 2021). Additionally, customer relationship management software has helped businesses track interactions and preferences, enabling more personalized experiences (Kumar, Mokha and Pattnaik, 2022). Self-service technologies (SSTs) have empowered customers to manage their own service interactions through intuitive interfaces, improving satisfaction and reducing operational costs (Liu and Hung, 2022). Mobile technologies facilitate seamless access to services and information on-the-go, allowing consumers to engage with brands anytime, anywhere (Dias and Afonso, 2021). Furthermore, Virtual Reality (VR) and Augmented Reality (AR) offer immersive experiences that allow consumers to visualize products in real-world settings or simulate experiences before making a purchase (Vaidyanathan and Henningsson, 2023). Collectively, these technological advancements exemplify how technology has reshaped interactions and the overall

CX landscape by introducing new touchpoints and reconfiguring existing ones (De Keyser *et al*., 2020; Hoyer *et al*., 2020).

A touchpoint refers to any instance of interaction between a customer and a business. Touchpoints occur at different stages of the customer journey, including pre-purchase (research and awareness), purchase (transaction and decision-making), and post-purchase (support, feedback, and engagement) (Straker *et al*., 2015). They can be classified into two main types: firm-controlled touchpoints, such as corporate websites, advertisements, in-store experiences, and customer service interactions, and non-firm-controlled touchpoints, including online reviews, social media discussions, and word-of-mouth recommendations (De Keyser *et al*., 2020).

Touchpoints vary in nature and function, encompassing human touchpoints (e.g., frontline employees and customer service), digital touchpoints (e.g., websites, mobile applications, and chatbots), physical touchpoints (e.g., in-store experiences and product packaging), and hybrid touchpoints that blend digital and physical interactions (e.g., click-and-collect services) (Straker *et al*., 2015). Bolton *et al*. (2018) highlight that these touchpoints exist within an evolving ecosystem where digital, physical, and social realms intersect, influencing the overall CX. They propose a three-dimensional framework that evaluates CX based on digital density, physical complexity, and social presence, emphasizing how firms need to align their strategies across these realms to ensure seamless interactions.

Understanding and optimizing touchpoints is essential for delivering a cohesive and impactful CX (De Keyser *et al*., 2020; Bolton *et al*., 2018). Businesses that strategically manage touchpoints can enhance engagement, strengthen customer relationships, and improve their competitive position in the market (Straker *et al*., 2015). This need has become increasingly important as the number of touchpoints influencing CX throughout the customer journey continues to grow (Lemon and Verhoef, 2016). At the same time, the integration of digital, physical, and social touchpoints further amplifies this complexity (Bolton *et al*., 2018).

Recognizing this complexity, understanding its implications for CX becomes increasingly essential. Accordingly, Rose, Hair, and Clark (2011) examined CX in the online context, highlighting the necessity of a comprehensive understanding of how digital interactions shape the overall customer experience. Similarly, Hoffman and Novak (2018) argue that traditional CX models are insufficient for explaining CX in today's technology-driven landscape.

The impact of technology on CX remains one of the few areas of near consensus in the field. Customer-business interactions now take place across multiple touchpoints, often occurring sequentially and sometimes simultaneously, with the boundaries between different types of touchpoints becoming increasingly blurred (Bolton *et al*., 2018; De Keyser *et al*., 2020). As businesses engage with customers through various platforms and channels, touchpoints continue to play a fundamental role in shaping CX (De Keyser *et al*., 2020). And while these advancements have expanded and reconfigured touchpoints, they also have implications for both service providers and customers, as will be discussed in the following section.

2.2.2 Changes to service providers and customers

As technology continues to redefine the structure and scope of customer touchpoints, it also transforms the nature of interaction within those touchpoints, particularly the balance between humans and machines. Service employees have historically played a central role in fostering emotional connections and building trust, which are often difficult to replicate through automated systems. Human interaction has been shown to significantly enhance customer satisfaction and loyalty, as customers value empathy, emotional intelligence, and personalized attention (Van Vaerenbergh *et al*., 2014). However, the increasing automation of frontline roles across industries is reducing opportunities for human engagement (Leung and Zhang, 2023; Ostrom *et al*., 2019). This shift is evident in the rise of self-service kiosks in retail, automated ordering systems in hospitality, and online platforms replacing personal advisors in sectors like travel and finance. While these systems offer efficiency and cost advantages, they simultaneously alter the interpersonal dimensions of the customer experience.

This technological shift is not only changing service delivery but also reshaping the customer's role within the experience. Where customers were once passive recipients, they are now active co-creators of value (McColl-Kennedy *et al*., 2015). Enabled by self-service technologies, mobile apps, and digital interfaces, customers engage with brands more independently, often managing their own experiences through multiple touchpoints. In banking, for example, mobile applications allow users to perform tasks that once required human assistance. In e-commerce, customer-generated content such as reviews and ratings plays a crucial role in shaping the experiences of others, illustrating how customers now contribute directly to the service ecosystem.

These shifts signify a broader redefinition of CX itself. The traditional, firm-led customer journey has evolved into a dynamic, co-produced process in which boundaries between customers and service providers are increasingly blurred (McColl-Kennedy *et al*., 2015). This reconfiguration raises important questions about how customer satisfaction, engagement, and loyalty are influenced when responsibility for managing the experience is partially transferred to the customer often mediated through technology (Parasuraman *et al*., 2020). The literature calls attention to the fact that this transformation does not merely reflect operational change but also necessitates new ways of thinking about customer roles, expectations, and value creation.

This evolution coincides with the growing strategic focus on CX, recognized for its critical role in driving perceived value, satisfaction, loyalty, and word-of-mouth communication (Hodgkinson *et al*., 2021; Homburg *et al*., 2017; Jain *et al*., 2017; Lipkin *et al*., 2016). As the landscape continues to shift, understanding how technology redefines both service structures and customer agency has become essential. Recent literature further emphasizes that disruptive technologies including the Internet of Things, big data analytics, and blockchain are not only reshaping individual touchpoints but transforming entire service ecosystems (Beheshti *et al*., 2024; Buhalis *et al*., 2019; Rane, 2023). These innovations enhance operational efficiency and enable deeper personalization, y*et al*so demand new models of customer involvement and interaction.

Amid ongoing technological disruptions, artificial intelligence (AI) stands out as a particularly transformative force due to its ability to learn, adapt, and make data-driven decisions at scale. AI holds substantial potential to revolutionize the marketing sector by automating complex tasks, enhancing personalization, and enabling predictive capabilities that were previously unattainable (Huang and Rust, 2021; Vlačić *et al*., 2021; Verma *et al*., 2021). More than any other technology, AI is poised to redefine how services are designed, delivered, and experienced, as it facilitates real-time customer engagement, context-aware interactions, and the continuous optimization of service processes (Buhalis *et al*., 2019; Hoyer *et al*., 2020). The following section introduces AI in further detail and explores its role in reshaping the customer experience landscape, highlighting the need for deeper theoretical and empirical attention to this fast-evolving domain.

2.3 Artificial Intelligence and Customer Experience

Despite its growing significance, AI remains a concept without a single, universally accepted definition (Kaplan and Haenlein, 2019; Russell and Norvig, 2020; Sheikh, Prins and Schrijvers, 2023; Wang *et al*., 2019). Its continuous evolution and integration across various domains often with blurred boundaries have led to numerous perspectives and interpretations, reflecting the complexity and conceptual ambiguity of AI (Sheikh, Prins and Schrijvers, 2023; Wang, 2019). As a result, AI is frequently described as a broad, overarching term that encompasses a diverse range of technologies and applications (Huang and Rust, 2021; Kaplan and Haenlein, 2019). Subfields such as machine learning, expert systems, robotics, computer vision, and natural language processing are commonly visualised as integral components within this broad field (Ghesh, Alexander and Davis, 2024). This diversity reflects both the challenges, and the opportunities associated with understanding AI.

One widely accepted definition describes AI as: “software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected data, reasoning and deciding the best action(s) to achieve the given goal”
(High-Level Expert Group on Artificial Intelligence, 2019, p. 36). This definition captures AI’s adaptability and autonomous decision-making capabilities, while remaining expansive enough to encompass both existing and emerging applications. In service marketing, AI is generally understood as the ability to mimic cognitive

functions such as learning, reasoning, and problem-solving capabilities typically associated with human intelligence (Huang and Rust, 2018). This allows systems to perform tasks traditionally requiring human cognition, such as analysing data, making decisions, and adapting to new contexts. This functional perspective offers a practical foundation for understanding AI's role in service contexts (Huang and Rust, 2021; Verma *et al*., 2021; Vlačić *et al*., 2021).

AI has emerged as a key driver of CX transformation, reshaping the service industry and redefining how businesses engage with their customers (Marinchak *et al*., 2018; Naumov, 2019; Popescu, 2018). By leveraging real-time interactions and data-driven insights, AI fosters more interactive and dynamic interactions, enhances personalization, and deepens customer involvement, thus opening new avenues for co-creation and collaborative engagement (Calvo, Franco and Frasquet, 2023; Gao *et al*., 2022; Peltier, Dahl, A.J. and Schibrowsky, 2024; Perez-Vega *et al*., 2021).

A crucial aspect that sets AI apart as a transformative force is its ability to enhance existing technologies and processes (Bulchand-Gidumal *et al*., 2024). For instance, AI integration has revolutionized customer relationship management (CRM) through predictive analytics (Chatterjee *et al*., 2021), optimized supply chain operations via intelligent forecasting (Ivanov and Dolgui, 2020), strengthened cybersecurity with advanced threat detection algorithms (Nguyen *et al*., 2022), and driven breakthroughs in healthcare through AI-powered diagnostics and personalized treatment planning (Topol, 2019; Jiang *et al*., 2017). These examples underscore the expansive potential of AI and highlight the importance of adopting a flexible, evolving definition that accommodates both current applications and future developments.

This transformative potential is further reinforced by the substantial investments and rapid market growth associated with AI. In 2023, the global AI market was valued at over €130 billion and is projected to approach €1.9 trillion by 2030 (Statista, 2023). A recent McKinsey report (2024) highlights that organizations are incorporating AI across more business functions than ever. Over the past decade, AI advancements have expanded commercial applications, creating transformative business opportunities (Furman and Seamans, 2019). For instance, retailers use AI-driven recommendation systems and augmented reality to personalize shopping experiences (Zimmermann *et al*., 2023); banks leverage predictive analytics to enhance fraud detection (Javaid, 2024); and travel services utilize AI chatbots for customer support (Zhang *et al*., 2024). Companies investing in AI are already seeing substantial growth in sales, employment, and market value as they capitalize on AI's transformative potential (Babina *et al*., 2024).

Alongside these organizational benefits, the growing consumer adoption of AI tools reflects an evolving service landscape. The success of these applications has driven increasing interest in adopting AI-based solutions (Pan, 2016), prompting more studies on customer acceptance (Kelly, Kaye and Oviedo-Trespalacios, 2023; Kim, Giroux and Lee., 2021). For example, retailers increasingly implement chatbots to provide instant assistance and personalized recommendations (Rohit *et al*., 2024). These trends signal a broader recognition of AI's value in enhancing convenience, personalizing interactions, and streamlining processes across industries.

Looking ahead, Hoyer *et al*. (2020) argue that technologies like IoT, service robots, chatbots, augmented reality, virtual reality, and mixed reality typically powered by AI will "result in an entirely new concept of customer experience," requiring further exploration and investigation. Similarly, Buhalis *et al*. (2019) identify three disruptive areas in service experience that require immediate attention: extra-sensory, hyper-personalized, and beyond-automation experiences. These advancements, primarily driven by AI technologies, represent the next frontier in CX and highlight the need to examine how artificial intelligence-enabled technologies (AI-ETs) are reshaping the service landscape.

AI-ETs serve as an umbrella term encompassing both novel AI innovations and existing technologies enhanced through AI integration. However, it is not the only terminology utilized in the field. As AI integration into services continues to expand, the literature has seen a proliferation of terms describing AI's role in various processes and technologies. Previous studies have adopted diverse terminology to articulate the integration of AI within services, processes, and technologies. Commonly used terms include AI-powered (Akter *et al*., 2023; Fountaine *et al*., 2019), AI-enhanced (Bhuiyan, 2024; Rani *et al*., 2024), AI-enabled (Ferraro *et al*., 2024; Chaturvedi *et al*., 2024), AI-augmented (Lingell *et al*., 2023; Rjsé *et al*., 2023; Shmueli *et al*., 2024), AI-generated (Du *et al*., 2024; Zhang *et al*., 2024), AI-based (Vorobeva *et al*., 2024), and AI-driven (Chaturvedi and Verma, 2023; Sheth *et al*., 2022).

Reviewing the literature revealed that there is no discussion of which term to use, even though each term embodies a distinct aspect of impact and conveys a different meaning. For instance, AI-based, AI-generated, and AI-driven suggest that AI is the primary force behind the technology. In contrast, AI-powered, AI-enhanced, and AI-augmented emphasize the positive outcomes of AI integration.

According to Merriam-Webster, the term "enabled" refers to "providing with the means or opportunity." AI-enabled indicates that something has been made possible through a specific factor, in this case, AI. This term conveys a neutral tone that avoids assumptions about improvement, making it the most appropriate label for the intended scope of this thesis.

This neutrality is crucial given the overall aim of this thesis, which explores the broader impact of AI-ETs on CX. The term "AI-enabled" provides a flexible foundation for discussing this impact, which is essential as we are still in the exploratory phase of understanding how AI-ETs are transforming CX. It would be premature to assert that their influence is uniformly positive or consistently results in clear improvements. Terms such as "enhanced," "powered," or "augmented" imply a degree of improvement or seamless integration that is not always accurate. Additionally, terms like AI-based, AI-generated, and AI-driven may divert attention from the central focus of this project the CX, and may not always reflect the technical realities.

Using the term "enabled" acknowledges that AI-ETs facilitate new forms of CX while remaining cautious about generalizing outcomes. This careful, neutral positioning is crucial as the field of AI continues to evolve, ensuring consideration of the varied and context-dependent effects of AI-ETs on CX. It highlights the importance of avoiding overgeneralization, allowing for a nuanced exploration of both the benefits and challenges that AI presents in the service landscape.

In parallel with this expanding terminology, an increasing number of typologies and classifications are emerging in the literature. These frameworks aim to categorize the various AI technologies and their applications while accommodating the growing breadth, fragmentation, and complexity of the field. Russell and Norvig (2016) categorize AI into four groups: systems that think like humans, systems that act like humans, systems that think rationally, and systems that act rationally. Another common categorization distinguishes narrow AI, artificial general intelligence, and superintelligence (Grundner and Neuhofer, 2021). Such categorizations focus on the technical capability and future status of AI topics beyond the scope of this thesis, which instead focuses on the broader impact of AI integration on CX.

To address this gap, Ostrom *et al*. (2019) developed a framework that classifies AI based on its role in the service encounter:

- AI-supported: operates behind the scenes to assist frontline employees or facilitate the encounter.
- AI-augmented: visibly aids frontline employees.
- AI-performed: completely replaces frontline employees.

Based on this framework, AI-ETs can be positioned along a spectrum that ranges from behind-the-scenes technologies, such as personalized recommendations and demand forecasting, to customer-facing technologies, including virtual reality travel experiences, virtual assistants, and chatbots (The AI-ETs spectrum in Figure 2-1). In Ostrom *et al*.'s (2019) framework, AI-supported technologies exemplify behind-the-scenes AI, while both AI-augmented and AI-performed technologies represent more visible forms of AI in the experience.

Research suggests that highly visible forms of AI have a stronger influence on CX due to their higher levels of technological embodiment (Tussyadiah, Jung and Tom Dieck., 2018). This aligns with the concept of automated social presence, which emphasizes that technologies designed to socially engage customers can significantly enhance their service experiences (Van Doorn *et al*., 2017). Expanding on this idea, AI-ETs represent a new generation of customer-facing tools that elevate service interactions through real-time personalization and seamless integration into the customer journey. Traditionally centred on physical artifacts, the concept of peripheral service evidence now extends to AI-ETs, which act as digital counterparts bridging physical and digital interactions in customer-facing contexts (Lee and Lee, 2024).

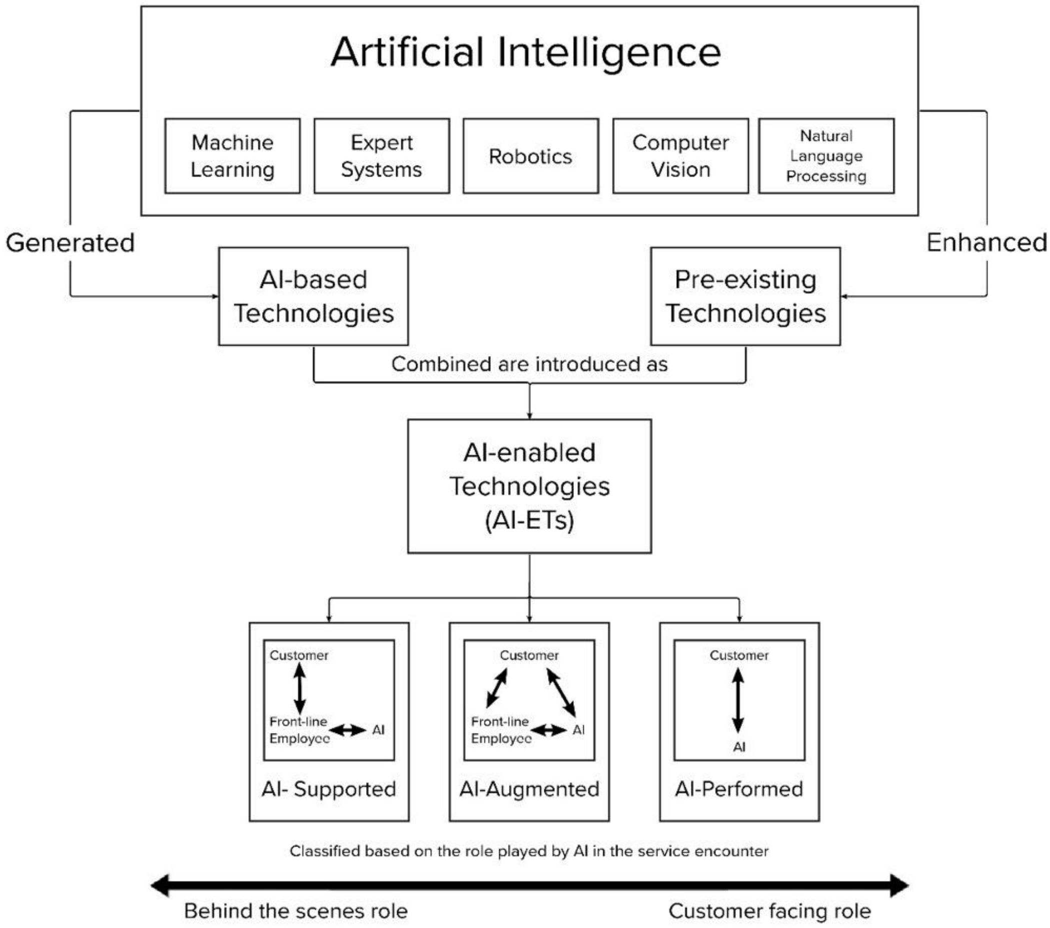


Figure 2-1: The AI-ETs

Collectively, this literature demonstrates that AI-ETs are not merely additional touchpoints but actively reshape how customer experiences are formed across increasingly complex and dynamic customer journeys. In particular, customer-facing AI-enabled technologies, such as chatbots, virtual assistants, and immersive technologies, mediate interactions in real time and often influence customers' perceptions and behaviours beyond their full conscious awareness. As these technologies increasingly assume a visible and interactive role in service encounters, traditional outcome-oriented approaches to customer experience offer limited insight into how experiences are initially formed during interaction.

Building on this foundation, and consistent with the scope of this thesis, attention is therefore directed toward customer-facing AI-enabled technologies (namely AI-augmented and AI-performed service encounters as per the adopted framework), while AI applications that operate primarily behind the scenes or serve managerial support functions are excluded. This focus creates a need for a conceptualization of customer experience that captures customers' immediate responses to AI-enabled technologies as they unfold along the customer journey. The following section addresses this need by introducing and defining AI-enabled customer experience (AICX), which establishes the conceptual groundwork for this thesis.

2.4 The AI-enabled Customer Experience (AICX)

The AICX is defined in this thesis as customers' non-deliberate spontaneous responses and reactions to offering-related stimuli along a customer journey featuring one or more AI-enabled technologies. It asserts that the customer journey serves as the base for the AICX, and the touchpoints, primarily resulting from interactions with AI-ETs, are regarded as the building blocks of AICX thus are the primary focus for its understanding.

To fully comprehend AICXs, it is essential to first understand the nature of its building blocks, the touchpoints. Touchpoints are defined as any point of contact, whether direct or indirect, through which a customer interacts with a service provider (Kim and So, 2024). To date, touchpoints have been the primary unit of analysis in studying CX (Becker and Jaakkola, 2020) However, this focus presents several limitations. Studies that examine CX only at the touchpoint level tend to be either too narrow or lack generalizability. Moreover, research often examines these touchpoints in isolation, failing to consider how they interact across different channels and stages of the customer journey. Additionally, research often focuses on specific, firm-controlled touchpoints, while neglecting other sources of stimuli that can significantly impact CX. This absence of an integrative perspective creates a significant gap in understanding CX, as it fails to provide a comprehensive framework that encompasses the interplay of various touchpoints and stimuli (Becker and Jaakkola, 2020). This gap is further amplified in the context of AICX, where it becomes especially critical given the complex, multitouch, and multichannel nature of contemporary customer journeys.

Voss *et al* (2008) highlights that the CX is a holistic process made up from the customer journey, deriving from the sequence of touchpoints. De Keyser *et al*. (2015) further emphasize that without interaction, there is simply nothing to experience. Thus, in the context of AICX, the sequence of touchpoints across the customer journey enhanced and redefined by AI-ETs shapes the overall experience. With this in mind, this project aims to examine the customer journey featuring one or more AI-ET, providing a more comprehensive understanding of AICX (see Figure 2-2).

The increasing integration of artificial intelligence into customer-facing touchpoints introduces forms of interaction that are adaptive, data-driven, and often opaque to customers. AI-enabled technologies operate in real time, continuously adjust to contextual inputs, and frequently shape interactions in ways that are not fully transparent or consciously processed by customers. In such contexts, focusing exclusively on post-hoc evaluative outcomes such as satisfaction, trust, or loyalty risks overlooking how customer experience is initially formed. This challenge is particularly pronounced when examining emerging phenomena, where established outcome-based measures may fail to capture how experiences unfold during interaction (Meyer and Schwager, 2007; Verhoef et al., 2009; Lemon and Verhoef, 2016).

Reflecting this need, and drawing on a converging stream of customer experience research that conceptualizes experience as a multidimensional, response-based, and journey-oriented phenomenon, AI-enabled customer experience (AICX) is conceptualized in this thesis as customers' non-deliberate spontaneous responses and reactions to offering-related stimuli along a customer journey featuring one or more AI-enabled technologies. This conceptualization aligns with contemporary CX research that emphasizes experience as an emergent and subjective phenomenon arising from customer–firm interactions across multiple touchpoints, rather than as a purely reflective or evaluative assessment (De Keyser et al., 2015; Lemon and Verhoef, 2016; Kranzbühler et al., 2018).

Importantly, this response-based focus does not deny the relevance of evaluative outcomes. Rather, it analytically distinguishes experience formation from subsequent evaluative judgments, such as satisfaction or loyalty, which may be shaped by but are conceptually distinct from customers' experiential responses during interaction (Meyer and Schwager, 2007; Verhoef et al., 2009; Becker and Jaakkola, 2020). This distinction is especially salient in AI-enabled contexts, where customers may respond affectively, cognitively, or behaviourally to AI-enabled interactions before consciously reflecting on or evaluating those encounters.

Within this perspective, the customer journey constitutes the structural foundation of AICX, while touchpoints represent its primary building blocks. Touchpoints are defined as any point of contact, direct or indirect, through which a customer interacts with a service provider (Kim and So, 2024). In the context of AICX, these touchpoints are frequently mediated, augmented, or reconfigured by AI-enabled technologies and function as salient sources of experience-related stimuli that elicit customer responses across different stages of the journey.

Although touchpoints have traditionally served as a central unit of analysis in customer experience research, studies that focus on isolated interactions tend to provide a fragmented understanding of experience. Such approaches often overlook how interactions unfold across channels and stages of the customer journey, privilege firm-controlled touchpoints, and neglect contextual or non-firm-controlled sources of stimuli that can meaningfully shape customer experience (Voss et al., 2008; De Keyser et al., 2015). These limitations become particularly pronounced in AI-enabled service environments, which are characterized by complex, multitouch, and multichannel journeys (Verhoef et al., 2009; Lemon and Verhoef, 2016).

Prior research consistently emphasizes that customer experience is inherently holistic and emerges through the configuration and sequencing of interactions that comprise the customer journey (Voss et al., 2008; De Keyser et al., 2015). Accordingly, in the context of AICX, the arrangement, visibility, and integration of AI-enabled technologies across the journey collectively shape customers' experiential responses.

Building on this premise, this thesis examines customer journeys featuring one or more AI-enabled technologies to develop a more comprehensive understanding of how AI-enabled customer experience is formed and unfolds over time (see Figure 2.2).

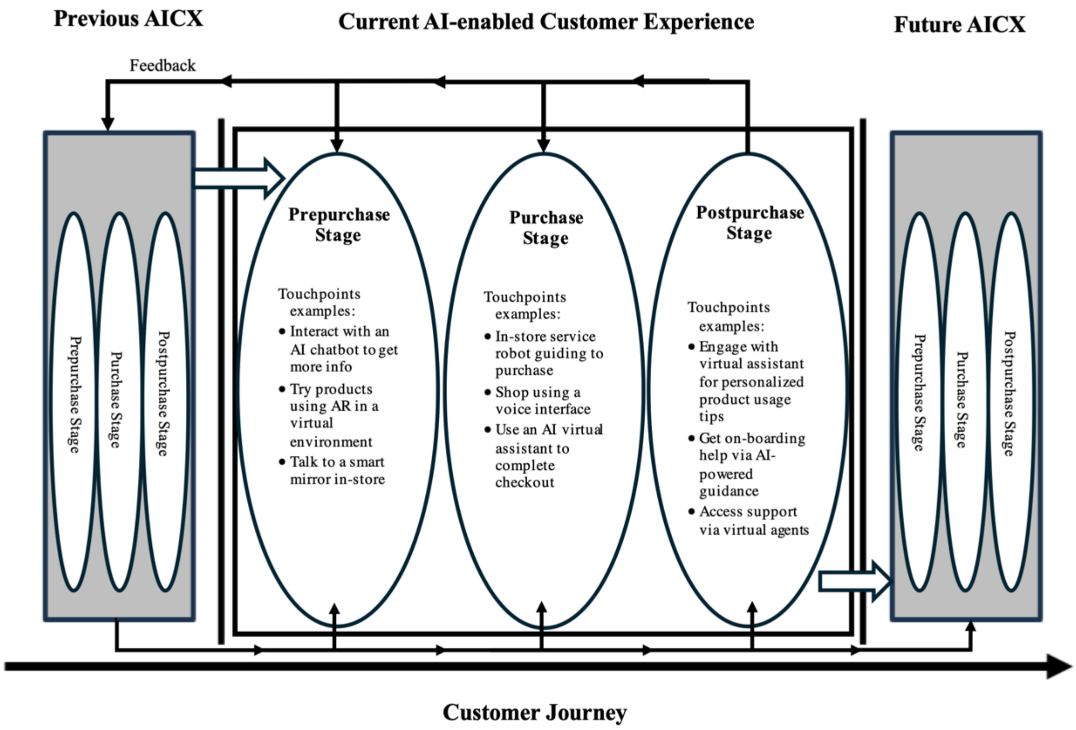


Figure 2-2: Visualization of the AICX (Adapted from Lemon and Verhoef (2016)

2.5 Conclusion

This chapter has shown that existing literature on CX presents fragmented perspectives, highlighting its multidimensional and complex nature. It emphasizes how technology, particularly AI, has significantly transformed CX suggesting it will lead to a paradigm shift that redefines CX as we know it (Buhalis *et al*., 2019; Hoyer *et al*., 2020). As service providers increasingly rely on AI-ETs to reshape the CX (Goel *et al*., 2022), understanding the implications of AI integration emerge as a top priority for academic researchers and marketing professionals alike (Buhalis *et al*., 2019; Hoyer *et al*., 2020; Verma *et al*., 2021). Factors such as advancements in AI, rising customer expectations, and ethical considerations surrounding AI are collectively driving this prioritization (Ameen *et al*., 2021; Jabeen *et al*., 2022).

Despite the growing interest in understanding the implications of integrating AI into the CX, the academic landscape remains significantly underexplored. Existing literature often overlooks the experiential dimensions of AI, leading to a limited understanding of how these technologies affect customer behaviour. This chapter introduces the AICX as a novel construct that encompasses the experiential journey featuring AI-ETs.

As discussed above, AI manifests in various forms and applications throughout the customer journey. Currently, much of the research is fragmented, focusing primarily on the technical aspects of AI such as service robots and chatbots rather than their transformative effects on CX. Moreover, the literature reveals a lack of consensus on defining AI, adding another layer of complexity to the field. Given this fragmentation and the multidimensional complex nature of CX, a systematic approach to understanding the emerging phenomenon of AICX is essential.

To achieve this, a systematic literature review (SLR) is conducted and reported in the next chapter. This review aims to explore AICX by examining relevant literature and identifying key research gaps. In doing so, it sets the AICX phenomenon within a wider research context and informs the empirical phase of the thesis.

Chapter 3 . AICX: A Systematic Literature Review

This chapter presents a SLR conducted to explore the emerging phenomenon of AICX. The chapter begins by discussing the rationale of the SLR and defining its scope. It then details the research approach, including the search strategy and methodology employed. The chapter then transitions to present the outcomes of SLR. Using the Theory, Characteristics, Context, and Methods (TCCM) framework, it offers a comprehensive descriptive analysis of existing research. Following this, the AI-ET Cube,a conceptual model that captures the multidimensional and interactive nature of AICX is introduced. The chapter further synthesizes the literature, identifying key gaps and themes that collectively provide a roadmap for advancing both theoretical and practical understanding of AICX. Building on these outcomes, the following section of the chapter selects one key theme from the identified gaps, providing a focused discussion on the rationale for its selection and emphasizing its significance in advancing the understanding of AICX. By articulating why this theme warrants further investigation, the section establishes a clear direction for the remainder of the thesis. The chapter concludes with a summary of key findings from the SLR and a reflection on their implications for shaping the study's conceptual focus.

3.1 Rationale

Building on the conclusions of Chapter 2, which emphasize the fragmented perspectives and multidimensional nature of CX, along with the transformative role of AI in redefining it, a systematic approach is vital to addressing these challenges. SLRs are particularly effective for identifying new developments in a field, and their use in business research has been steadily growing (Pickering and Byrne, 2014, Snyder, 2019). AI is a prime example of such a development, representing a rapidly evolving field with significant implications for CX. This research, therefore, employs an SLR to explore the complexities of integrating AI-ETs into CX and the emergence of a new form of experience: AICX.

Given their effectiveness in identifying emerging developments and synthesizing complex fields, SLRs have become a widely adopted method in academic research, particularly among postgraduate scholars with studies such as Daigneault *et al*. (2014), Perry and Hammond (2002), Pickering and Byrne (2014), and (Puljak and Sapunar, 2017) emphasizing their effectiveness and reliability. Originally developed to empower decision-makers (Khan *et al*., 2003) and facilitate evidence-based practice and policy development (Boland *et al*., 2017), SLRs provide a structured and rigorous method for synthesizing existing research. Conducting an SLR as the initial study in this PhD aligns with this foundational purpose, offering a robust framework for confidently advancing the research.

Several SLRs have already explored aspects of CX and related fields (see Table 3-1), offering valuable insights and frameworks upon which this study builds. For instance, Becker and Jaakkola (2020) focused on reconciling contradictions in CX research by developing fundamental premises that guide future studies. Chi *et al*. (2020) reviewed the applications of AI in service encounters, particularly in the hospitality industry, while avoiding technical aspects like system design. Kandampully *et al*. (2018) synthesized research on customer experience management (CEM) in hospitality, proposing a comprehensive framework and research agenda. Lu *et al*. (2020) examined the impact of service robots on customers and employees, identifying gaps for further exploration. Samara *et al*. (2020) reviewed AI and big data in tourism, emphasizing their benefits and roles in the industry. Waqas *et al*. (2021) conceptualized CX through consumer culture theory, summarizing past research and introducing a new model for understanding CX. Yung and Khoo-Lattimore *et al*. (2019) reviewed virtual and augmented reality applications in tourism, identifying trends, methodologies, and gaps in this area.

While these studies provide valuable contributions, they do not fully explore the integration of AI-ETs into CX or the emergence of AICX, highlighting the need for this review. This study focuses on the emerging concept of AICX, introduced as a novel construct that captures the transformative integration of AI-ETs into customer interactions. Unlike previous reviews that broadly examine CX or AI in isolation, this SLR investigates their intersection, emphasizing how AI-ETs are driving a paradigm shift that fundamentally redefines CX. Central to this analysis is the exploration of the experiential dimensions of AI-ETs and their pivotal role in reshaping customer interactions and journeys. By examining AICX as a distinct construct, this study bridges the gap between CX frameworks and AI applications, underscoring the critical role of technology in redefining CXs.

The tourism sector provides a particularly relevant context for this investigation due to its experiential nature, economic importance, and the widespread adoption of customer-facing AI-ETs. In fact, Tourism is seen as "reconfigured by technoculture," where technology increasingly shapes and deeply influences identities, behaviours, and meanings (Kozinets, 2024, p. 3). Applications such as augmented reality museum tours, AI-enabled hotel services, intelligent voice assistants for room service, and robotic restaurant staff demonstrate the transformative potential of AICX in revolutionizing the customer journey (Buhalis and Moldavska, 2022, Fusté-Forné, 2021, Ivanov *et al*., 2023, Trunfio and Campana, 2020). These examples highlight the practical relevance of AICX and its implications for reshaping interactions within tourism. By addressing these unique aspects, this SLR advances both theoretical and practical understanding of AICX, providing a foundation for future research into the evolving dynamics of AI-ETs and their impact on CX across experiential industries.

The SLR plays a central role in this thesis, offering a detailed review of existing research on the emerging concept of AICX. By identifying key gaps and organizing fragmented knowledge, it provides a solid foundation for future studies. The findings from the SLR will shape the overall structure, aims, and objectives of this thesis, guiding the empirical research in the chapters that follow.

3.2 Research Approach

A SLR is defined as “A specific methodology that locates existing studies, selects, and evaluates contributions, analyses, and synthesizes data, and reports the evidence in such a way that allows reasonably clear conclusions to be reached about what is and is not known” (Denyer and Tranfield, 2009, p. 671). SLRs typically follow a scientific approach characterised as replicable, transparent, and rigorous to identify, analyse, and synthesise available literature on a given topic (Boell and Cecez-Kecmanovic, 2015, Paul *et al*., 2021a, Paul *et al*., 2021b, Jones and Gatrell, 2014).

The theoretical prominence of systematic reviews in producing reliable and replicable outcomes further reinforces the value of this approach.

Table 3-1 Comparison of the current SLR with Existing SLRs in the field

Author(s) and Year	Focus	Significance
Becker and Jaakkola (2020)	Developing fundamental premises to reconcile contradictions in CX research and guide future studies.	Addresses fundamental theoretical contradictions in CX research.
Chi *et al*. (2020)	Reviewing AI applications in service encounters, particularly in hospitality, with a focus on usage and adoption.	Focuses on the practical use of AI in hospitality services, avoiding technical system aspects.
Kandampully *et al*. (2018)	Synthesizing research on customer experience management (CEM) in hospitality and proposing a framework and research agenda.	Proposes a structured approach to managing CX in hospitality, advancing research agendas.
Lu *et al*. (2020)	Investigating the impact of service robots on customers and employees, identifying gaps for future exploration.	Explores the influence of service robots on both customers and employees, identifying future research needs.
Samara *et al.* (2020)	Examining the role and benefits of AI and big data in tourism, focusing on their applications in the sector.	Highlights the benefits and roles of AI and big data in reshaping tourism practices.
Waqas *et al*. (2021)	Summarizing CX research and introducing a conceptual model based on consumer culture theory.	Combines CX theory with consumer culture insights, providing a novel conceptualization of CX.
Yung and Khoo-Lattimore (2019)	Reviewing virtual and augmented reality (VR and AR) applications in tourism, identifying trends and research gaps.	Examines VR and AR trends in tourism, providing a foundation for further research on immersive technologies.
This Study	Introducing the AICX construct and investigating the intersection of CX and AI-ETs, with a focus on experiential dimensions and applications in tourism.	Establishes AICX as a novel construct, emphasizing its transformative role in redefining CX through AI-ETs, particularly in tourism.

A typical SLR comprises three key stages: (1) Planning the review, (2) Conducting the review, and (3) Reporting the review (Tranfield *et al*., 2003, Xiao and Watson, 2019), but specific implementation and steps may vary to some extent depending on the study design, synthesis methods, and the nature of the research field. The need for a structured and formalized methodology to guide the implementation of systematic reviews became evident (Okoli, 2015), as these reviews gained popularity and recognition as a valuable approach to review-based research (Callahan, 2014, Kraus *et al*., 2020, Thomé *et al*., 2016, Paul and Criado, 2020). Scholars have made significant efforts to develop step-by-step models for conducting SLRs, proposing various approaches across disciplines (Boland *et al*., 2017, Caldwell and Bennett, 2020, Clarke and Horton, 2001, Jesson, 2011, Khan *et al*., 2003, Littell, 2008, Okoli, 2015, Petticrew and Roberts, 2006, Tranfield *et al*., 2003, Xiao and Watson, 2019, Yung and Khoo-Lattimore, 2019, Yang *et al*., 2017). These frameworks provide a strong foundation that should be built upon and followed to ensure methodological rigor and consistency.

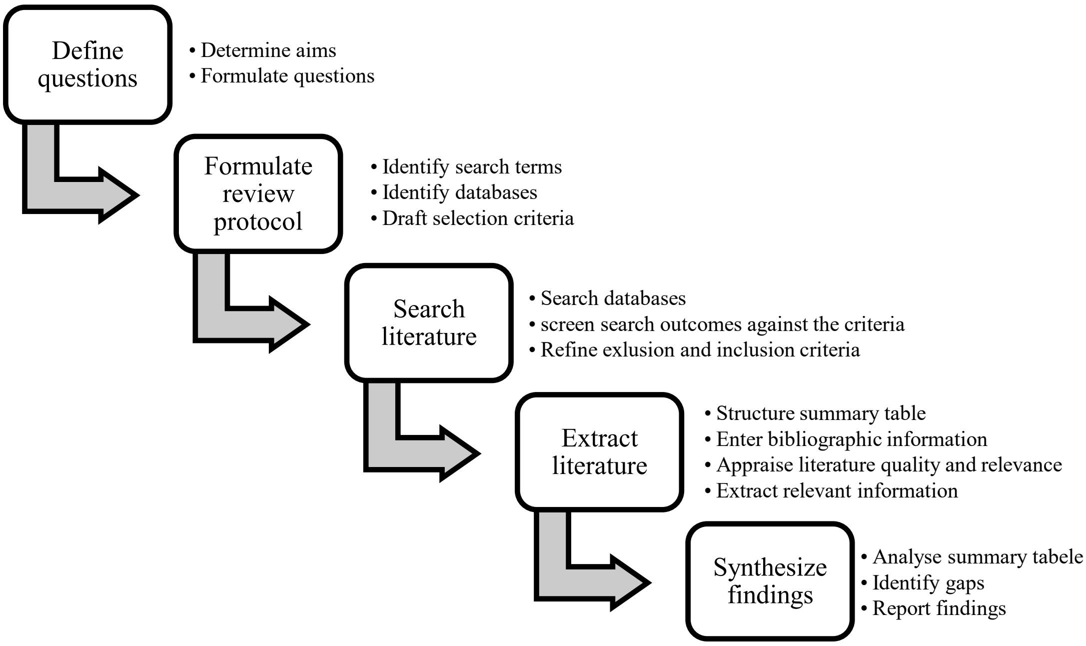


Figure 3-1: Systematic review process. Adapted from Yang et al. (2017)

This SLR adopts and builds upon Yang *et al*.'s (2017) methodology to ensure a systematic and reliable review process suited to the study's objectives. Widely recognized for its rigor in social science research, particularly at the intersection of tourism and technology (Khoo-Lattimore *et al*., 2019, Shafiee *et al*., 2021, Yung and Khoo-Lattimore, 2019). This approach adapts Pickering and Byrne's (2013) original framework to address complexities in challenging research domains. A key strength lies in its clear emphasis on defining the research question and inclusion criteria from the outset, maintaining focus and relevance throughout the review. As shown in Figure 3-1, the Yang *et al*. (2017) methodology involves five key steps, which are detailed in the figure along with the specific procedures involved in each.

CABS AJG as a Quality Threshold

To enhance rigor and reporting clarity, the review incorporates several tools and approaches widely recognized in the literature. A key component is the application of a quality threshold to ensure the inclusion of high-standard studies,a common practice in SLRs to increase the reliability and validity of findings. In this review, the Association of Business Schools Academic Journal Guide (CABS AJG) was used as the quality benchmark, limiting inclusion to articles published in journals listed in the guide. Previous research has employed CABS AJG in various ways as a quality standard (Guler *et al*., 2024, Lu *et al*., 2020, Paul *et al*., 2021a, Park and Jeong, 2019b, Rocha and Veloso, 2024). This approach effectively filters out low-quality studies, ensuring that the review is grounded in a robust and credible evidence base.

PRISMA Framework

In addition to applying a quality threshold, a structured reporting framework was adopted to guide the presentation of the review. To align with best practices in systematic review reporting, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Page *et al*., 2021) was used to enhance reporting quality and transparency. PRISMA provides a standardized structure for presenting the methodology and findings, ensuring the review process is systematic, well-documented, and reproducible. The framework also helps minimize bias and improves clarity for readers by clearly outlining each stage of the review process, from study selection to data synthesis (see Figure 3-2).

TCCM Framework

To guide the analysis and synthesis of the literature, this review adopts the Theory, Characteristics, Context, and Methods (TCCM) framework (Paul *et al*., 2021b; Paul, Khatri, and Kaur Duggal, 2024). While various frameworks are used in SLRs such as the Theory, Context, Mechanism, and Outcomes (TCMO) framework, the Stimulus-Organism-Response (SOR) model, and the Technology-Organization-Environment (TOE) framework .TCCM is selected for its suitability in organizing complex and multidisciplinary research. Renowned for its effectiveness in synthesizing diverse research areas, TCCM enables a multidimensional examination of theoretical, contextual, and methodological aspects. By adopting this framework, the review establishes a structured foundation for exploring the integration of CX and AI-ETs.

Scoping Searches

Before refining the research aim and finalizing the search strategy, scoping searches were conducted as a preliminary step. Scoping searches involve broad, exploratory searches of existing literature to map key concepts, assess the volume of available research, and define the scope of the field under review. This step is essential for clarifying knowledge gaps, avoiding duplication, and ensuring that the review is appropriately focused (Okoli, 2015). In this study, scoping searches supported the formulation of the research aim and questions, confirming their relevance and feasibility for guiding the SLR process.

Search Strategy

Building on insights gained from the scoping searches and prior SLRs in the field, a detailed search strategy was developed. To ensure comprehensive coverage, the most relevant databases for business and management literature were selected, along with commonly used terminology related to CX. The literature search was conducted across five major databases: EBSCOHost, Emerald, Web of Science, ScienceDirect, and ProQuest. These sources are widely recognized for their reliability in indexing peer-reviewed articles in the business domain (Kandampully *et al.*, 2018, Jingen Liang and Elliot, 2021).

A total of sixteen keywords were used across three intersecting domains: AI, CX, and tourism (Yang *et al.*, 2017, Hao, 2020, Jingen *et al.*, 2021) (see Table 3-2). The search query combined one keyword from each of the three domains AI, CX, and tourism using "AND". Where applicable, depending on database limitations, multiple related keywords within the AI domain were grouped using "OR" to broaden the search. All terms were included in a single query to capture studies at the intersection of these domains. The initial database search was conducted in June 2021, followed by an update search in March 2022 to capture the most recent studies and ensure the findings remained current.

Table 3-2 SLR keyword combinations

Domain	Keywords
CX Domain	Tourist Experience, Customer Experience, Visitor Experience
Tourism Domain	Touri*, Trave*
AI Domain	Artificial Intelligence, Intelligent Technolo*, Robot*, Chatbot*, Mixed Reality, Augmented Reality, Virtual Reality, Virtual Assistants, Smart, Humanoid, Automation

Eligibility criteria

To ensure a focused, rigorous, and methodologically sound review, six criteria were carefully developed. These criteria were designed to maintain consistency, ensure relevance to the research objectives, and uphold the quality of the selected studies:

1. **Language**: Only articles written in English were included, as English is the dominant language in business and management research.

2. **Accessibility**: Studies had to be available in electronic format through one of the five selected databases to ensure consistency and ease of access.

3. **Keyword Relevance**: Articles were required to include at least one of the designated keyword combinations in their title, abstract, or keyword list, as supported by prior literature (Hao, 2020, Kaartemo and Helkkula, 2018, Yung and Khoo-Lattimore, 2019, Arrigo, 2018).

4. **Technological Focus**: Studies needed to address CX through a technological lens, specifically involving customer-facing applications of AI.

5. **Context**: The context of the study had to relate to tourism, either through explicit reference to data collection in a tourism setting or publication in a tourism and hospitality journal.

6. **Quality**: Only studies published in journals listed in the Association of Business Schools Academic Journal Guide (CABS AJG) were included, ensuring a high standard of scholarly quality (Kumar *et al*., 2022, Paul *et al*., 2021a).

While there is no set minimum number of studies required for a systematic review, previous research suggests that well-conducted reviews typically include between 15 and 180 studies (Arrigo, 2018, Lu *et al*., 2020, Park and Jeong, 2019a, Yung and Khoo-Lattimore, 2019). Based on this guidance, the eligibility criteria in this review were designed to balance breadth and depth, ensuring the inclusion of a relevant and credible evidence base while keeping the number of articles manageable for in-depth analysis.

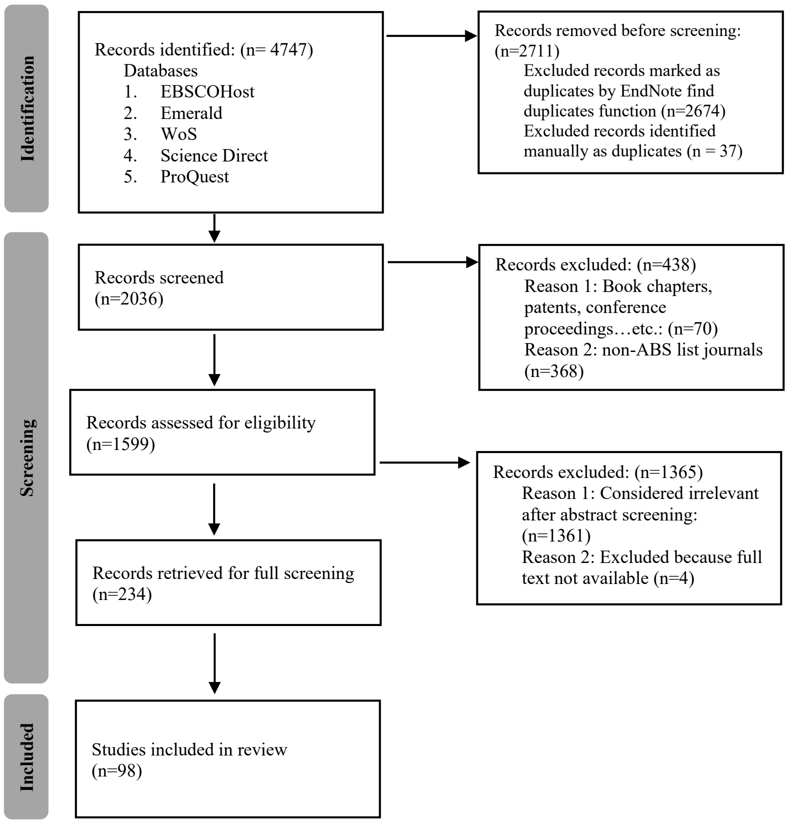


Figure 3-2:PRISMA flowchart

Applying these criteria, irrelevant studies were systematically filtered out during the screening process, as illustrated in Figure 3-2. The first screening phase applied the quality threshold, retaining only articles published in journals listed in the CABS AJG 2021. In the second phase, abstracts of the remaining articles were reviewed, and those that failed to meet one or more of the inclusion/exclusion criteria were excluded. If the abstract lacked sufficient detail for a confident judgment, the article advanced to the third phase for full-text screening.

Examples of excluded articles across these three phases include those not focused on technology (Prentice, 2020), studies conducted in non-tourism contexts such as retail (Kim, 2021), banking (Lappeman *et al*., 2021), fashion (Park *et al*., 2021), and sports

(Nyadzayo *et al.*, 2016), as well as those addressing non-customer-facing AI technologies (Mirzaalian and Halpenny, 2019). Articles that mentioned CX or AI only in passing without linking them to empirical findings or conceptual analysis were also excluded (e.g., Mele *et al.*, 2021). This rigorous, multi-stage screening ensured that only studies meeting the defined criteria were retained for analysis.

3.3 Analysis and interpretation

The analysis began with a quantitative approach grounded in the Theory, Characteristics, Context, and Methods (TCCM) framework (Paul *et al.*, 2021b; Paul *et al.*, 2024). This framework was employed to systematically categorize and quantify the studies deemed relevant for the review (Paul and Criado, 2020; Thomas and Gupta, 2022). By focusing on measurable aspects such as the number of studies associated with specific contexts, theoretical foundations, and methodological approaches, the TCCM framework provided a structured means of assessing the distribution and focus of the existing literature. This quantitative analysis offered valuable insights into the prevalence of particular research themes and trends, while also highlighting gaps and imbalances within the field. These findings set the stage for a more detailed exploration using thematic analysis.

Thematic analysis, a widely recognized method for identifying and summarizing key themes within a body of literature, was then employed to interpret the findings (Dixon-Woods *et al.*, 2005; Nowell *et al.*, 2017). This approach integrates qualitative and quantitative evidence, organizing the data into thematic headings for further analysis. Thematic analysis can be either data-driven (inductive), where themes emerge directly from the literature, or theory-driven (deductive), focusing on specific themes evaluated within theoretical frameworks (Braun and Clarke, 2008; Dixon-Woods *et al.*, 2005; Stein and Ramaseshan, 2016).

For this study, inductive thematic analysis was applied to the 98 articles remaining after the inclusion and exclusion criteria were employed. This method enabled the identification of key themes, aligning with the study’s objectives and providing an organized framework for synthesizing the findings. By combining thematic analysis with the prior quantitative approach, the review achieved a structured exploration of recurring patterns and gaps in the research, offering valuable insights into the intersection of CX and AI-ETs. The outcomes of these analyses are detailed in the following sections.

3.4 Descriptive Overview (TCCM)

3.4.1 Theories

Eighty-one theories and models were identified from various fields, including information systems (IS), psychology, consumer behaviour, sociology, economics, marketing, and management. This study classified the identified theories based on the aim of the study, utilizing the theory, which resulted in five main clusters: Acceptance and Adoption, Evaluation, Marketing and Advertising, Organizational Perspective, and Consumer Behaviour. First cluster 'Acceptance and Adoption' includes theories used to study the AICX at the early stages of the customer journey. Second cluster 'Evaluation' introduces the different theories used to assess the AICX. Third cluster 'Marketing and Advertising' presents theoretical underpinning used to study the AICX from in marketing. Fourth cluster 'Organisational Perspective' addresses the managerial perspective on the AICX. Final and fifth cluster 'Consumer Behaviour' is about theories aimed at explaining the behavioural outcomes of the AICX. Table 3-3 illustrates these five clusters and provides examples from retrieved literature.

Table 3-3 Emerging theories clusters

Emerging Theory Cluster	Examples from retrieved articles
Acceptance and Adoption	Unified Theory of Acceptance and Usage of Technology (UTAUT2) (e.g., Paulo *et al*., 2018), Service Robot Acceptance Model (Fuentes-Moraleda *et al*., 2020), Diffusion of Innovations (Kim and Han, 2020), Technology Acceptance Model (e.g., Shin and Jeong, 2020) (6), Value-based acceptance model (Zhong *et al*., 2021)
Evaluation	Stereotype content model (Zhu and Chang, 2020), Expectancy Disconfirmation Theory (Ducros and Euzéby, 2021), Cognitive-affective-conative model (Huang *et al*., 2021a), Social Exchange Theory (Loureiro *et al*., 2021), Cognitive appraisal theory (Zhang *et al*., 2021)
Marketing and Advertising	The hierarchy-of-effects theory (Lyu *et al*., 2021), Product Level Theory (Ma *et al*., 2021), Service Dominant Logic (Neuhofer, Magnus and Celuch, 2021), Five-sense experiences framework (Chen *et al*., 2021), Value Co-creation (Jung and Tom Dieck, 2017), Experience Economy (Tung and Law, 2017)
Organisational Perspectives	Job Design Theory (Tuomi, Tussyadiah and Hanna, 2021), Process Theory (Wei *et al*., 2019), Stakeholder Theory (Serravalle *et al*., 2019)
Consumer Behaviour	Theory of Planned Behaviour (e.g., Cha, 2020) (4), SOR Framework (Kim and Han, 2020), Variance Theory (Lacka, 2020), Theory of Reasoned Action (Aluri, 2017)

3.4.2 Characteristics

The 98 articles included in this review were published in 29 different academic journals (see Table 3-4). Most articles were published in tourism and hospitality journals, with the remainder in services, business, and management journals. Figure 3-3 shows that all the included articles in the SLR are published after 2011, corresponding with the introduction of AI into the sector, with the number increasing year on year.

Table 3-4 Distribution of articles by journal

Journals Titles	**Number of retrieved articles**
International Journal of Contemporary Hospitality Management, Journal of Hospitality and Tourism Technology (n=2)	23
Journal of Service Management, Tourism Management Perspectives, Current Issues in Tourism, Tourism Review (n=4)	5
Tourism Management (n=1)	4
International Journal of Hospitality Management (n=1)	3
Technological Forecasting and Social Change, The TQM Journal, Journal of Travel and Tourism Marketing, Journal of Destination Marketing and Management (n=4)	2
Asia Pacific Journal of Tourism Research, The International Journal of Tourism Research, Qualitative Market Research: An International Journal, Electronic Markets, Cornell Hospitality Quarterly, Industrial Management and Data Systems, Leisure Studies, Computers in Human Behavior, International Journal of Engineering Business Management, Journal of Place Management and Development, International Journal of Event and Festival Management, Journal of Promotion Management, Journal of Business Research, International Hospitality Review, Worldwide Hospitality and Tourism Themes, Area, Journal of Hospitality Marketing and Management (n=17)	1
Grand Total	**98**

3.4.3 Context

The intersection between tourism and technology provides two different viewpoints to look at the context of retrieved articles. From a technological standpoint, the key identified AI-ETs were: service robots (e.g. Ma *et al*., 2021), intelligent voice assistants (IVAs) (e.g. Loureiro *et al*., 2021), chatbots (e.g. Pillai and Sivathanu, 2020), AR (e.g. Tom Dieck *et al*., 2018), VR (e.g. Lee *et al*., 2020), and mixed reality (MR) (e.g. Trunfio, Campana and Magnelli, 2020). Analysis here indicates that literature on VR, AR, and service robots is more mature, whereas research on IVAs, chatbots, and MR remains in its infancy.

From a sectoral standpoint, studies commonly focus on hotels (e.g. Shin and Jeong, 2020), restaurants (e.g. Kim, Choe and Hwang, 2021), and museums (e.g. Serravalle *et al.*, 2019). Additionally, research extends to festivals (e.g. Tom Dieck *et al.*, 2018), events (e.g. Neuhofer, Magnus and Celuch, 2021), religious destinations (e.g. Allal-Chérif, 2022), cruises (e.g. Simoni *et al.*, 2022), cultural heritage sites (e.g. Jung *et*

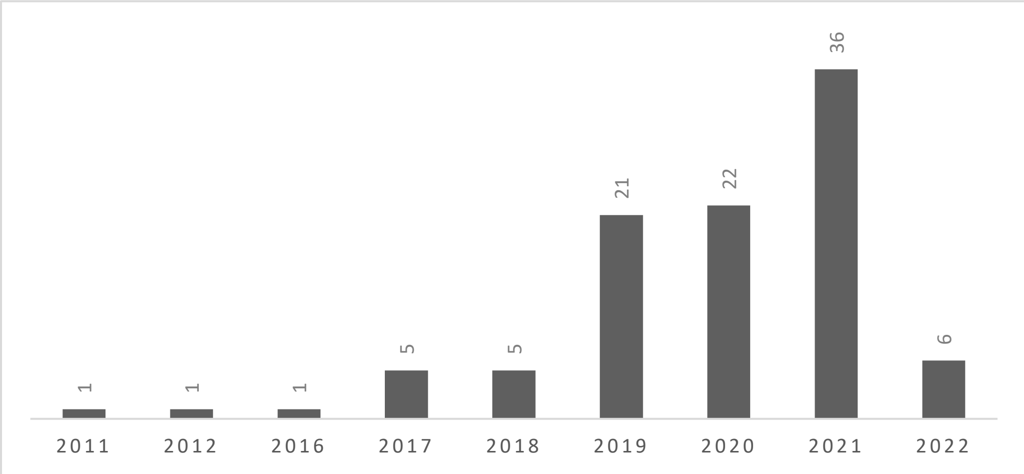


Figure 3-3 Distribution of articles by year

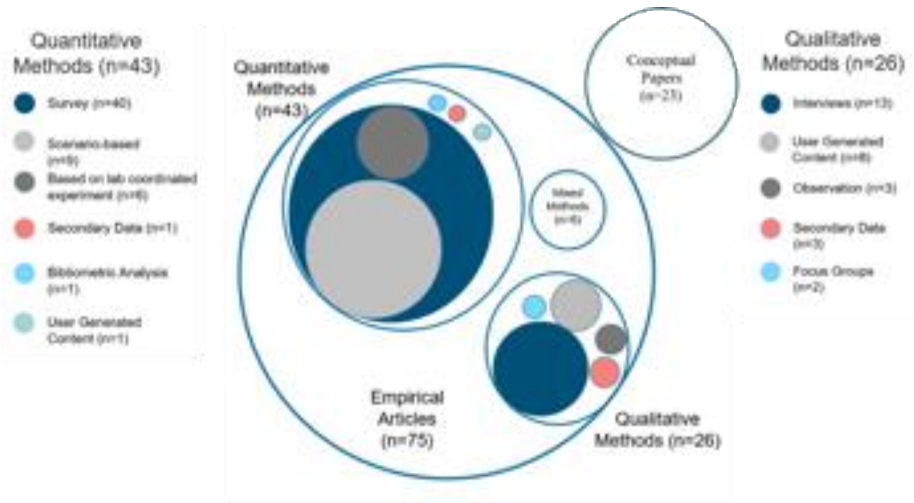
al., 2018), art galleries (e.g. Han, Tom Dieck and Jung, 2019), and theme parks (e.g. Milman, Tasci and Zhang., 2020). Other studies address the sector holistically.

3.4.4 Methods

Both empirical work (n=75) and conceptual/review papers (n=23) were identified (see

Figure 3-4). The empirical studies employed a variety of quantitative (n=43), qualitative (n=26), and mixed-method (n=6) designs. Surveys (quantitative) and semi-structured interviews (qualitative) were common methods used, with technology playing a role in data collection techniques. Examples include: online surveys (e.g. Milman, Tasci and Zhang, 2020), technology-enabled experimental designs (e.g. Lyu *et al*., 2021), user-generated content on social media (e.g. Çakar and Aykol, 2021), and video-enhanced scenarios (e.g. Paulo *et al*., 2018).

Figure 3-4: Methodological choices of the retrieved papers



3.5 Towards a Typology for Classifying AI-ETs – The AI-ET Cube

The SLR aimed to identify the range of AI-ETs currently adopted within the field, uncovering a variety of technologies such as VR, AR, MR, chatbots, service robots, and AI assistants applied across various stages of the customer journey. In addition to mapping these technologies, the review highlighted several critical insights, some of which already pose or have the potential to pose challenges within the field. One major challenge lies in the difficulty of clearly defining and understanding the scope of AI. The term “AI” is often used inconsistently, sometimes applied to technologies that are neither AI-based nor enhanced by AI. This lack of clarity in defining AI and its scope contributes to a second challenge: the tendency of research on AI integration into CX to focus on specific devices or applications. As a result, studies often concentrate narrowly on individual AI-ETs, leading to a fragmented body of literature. This fragmentation is further exacerbated by the rapid advancements in AI and the fast-changing nature of the field, which hinder the development of unified theories and broader insights.

To address these conceptual challenges, this thesis introduced the term AI-ETs, encompassing both novel AI-based innovations and pre-existing technologies enhanced by AI. This concept not only provides a clearer and broader foundation for examining these technologies but also aims to resolve the fragmentation identified in the literature. By offering a more inclusive framework, AI-ETs facilitate a move beyond narrow, technology-specific perspectives toward a holistic understanding of their role in CX. However, while the introduction of AI-ETs addresses the conceptual fragmentation, effectively studying these technologies also requires frameworks that capture their diverse roles and interactive dynamics in CX.

Existing typologies, though valuable for their technical insights, often fail to address the social and experiential dimensions of AI-ETs that are pivotal in shaping CX (Lemon and Verhoef, 2016). Frameworks such as those proposed by Huang and Rust (2018, 2021, 2022), Grundner and Neuhofer (2021), and Russell and Norvig (2016) provide important contributions to understanding AI technologies. However, these frameworks primarily focus on technical aspects and overlook critical considerations for marketing research. This includes the socially interactive constructs and engagement dynamics that are fundamental to understanding how customers interact with and respond to AI-ETs.

To overcome these limitations, there is a pressing need for a more unified and comprehensive approach to the study of AI-ETs. By critically evaluating and improving existing typologies, it becomes possible to better integrate the technical, social, and interactive dimensions of these technologies. Such an approach, which combines technological insights with the complex and evolving nature of CX, can foster a deeper understanding of AI-ETs, accommodating their overlapping functions and dynamic roles in shaping CXs.

Building on the identified AI-ETs and addressing the conceptual challenges highlighted in the field, this thesis introduces a three-dimensional typology inspired by Flavián, Ibáñez-Sánchez and Orús (2019) Embodiment-Presence-Interactivity Cube. The AI-ET Cube is designed to classify AI-ETs by emphasizing their experiential integration within the CX, focusing on the interplay between the customer, the technological device, and the AI itself. The typology categorizes AI-ETs along three core dimensions: AI capabilities**,** technological embodiment, and interactivity**.** AI capabilities capture the functional potential of AI-ETs, technological embodiment emphasizes the sensory engagement required from customers (Verbeek, 2008), and interactivity reflects the dynamic and participatory nature of modern CX (McLean and Wilson, 2016; Novak *et al*., 2000; Prahalad and Ramaswamy, 2004) (see Figure 3-5).

Departing from traditional typologies, the AI-ET cube shifts focus from purely technical characteristics to non-technical attributes that align with socially interactive constructs central to marketing and the AICX. Unlike static frameworks, it acknowledges the fluid and rapidly evolving nature of AI by presenting its dimensions as continua rather than fixed categories. For instance, technologies once considered cutting-edge may now be viewed as mainstream, while advancements in AI are expected to further influence levels of technological embodiment and interactivity. Reflecting this dynamism, this paper adopts fluid definitions for the

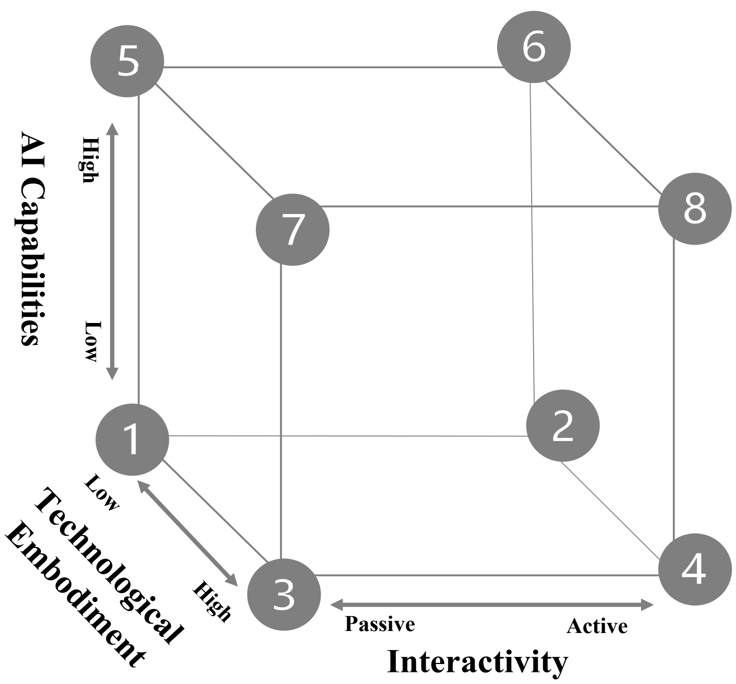


Figure 3-5: The AI-ET Cube

typology components, presenting each as a continuum rather than a dichotomy. This dynamic approach accommodates the diverse and overlapping functionalities of AI-ETs, offering a nuanced understanding of their role in shaping customer interactions. By focusing on touchpoints within the customer journey, the typology provides a comprehensive framework for examining how AI-ETs contribute to the evolving landscape of CX (Flavián, Ibáñez-Sánchez and Orús, 2019; Hoyer *et al*., 2020; Tussyadiah, Jung and Tom Dieck., 2018).

On the cube, each point represents a unique combination of the three dimensions. For example, a point in the top-front-left corner (vertex 7) of the cube represents an AI-ET with high AI capability, passive interactivity, and high technological embodiment. Conversely, a point in the bottom-back-right corner (vertex 2) represents an AI-ET with low AI capability, active interactivity, and low technological embodiment.

Subsequent sections provide an exploration of each dimension within the typology. These discussions are enriched with examples drawn from the existing AICX literature, as summarized in **Error! Reference source not found.**. It is important to note, however, that existing research on AI is typically bound by its technological context,namely the specific device or application being studied. Thus, the examples provided are illustrative rather than exhaustive, reflecting insights from the retrieved literature in the SLR. Additionally, even when two AI-ETs are categorized under the same label, such as "high intelligence," this does not imply they utilize the same level of AI capability. Instead, these classifications should be viewed as relative. For instance, when two technologies are located along the same axis of the cube, it is more meaningful to compare them as dyads, concluding that one exhibits relatively higher or lower than the other.

AI Capabilities

AI capabilities are defined as the varying degrees of intelligence demonstrated by an AI system, enabling it to perform a wide range of tasks with increasing effectiveness and sophistication. These capabilities are visualized as a continuum, ranging from low to high levels of intelligence, reflecting the system's ability to mimic various forms of human cognitive functions.

Huang and Rust (2018) categorize AI intelligence into four distinct types needed for service-related tasks: mechanical, analytical, intuitive, and empathetic. These levels vary in their complexity and the tasks they can effectively perform. At the foundational level, mechanical intelligence handles straightforward, consistent, and routine tasks, such as basic operational functions. Analytical intelligence builds on this by incorporating logical reasoning, data-driven decision-making, and problem-solving capabilities. Moving further, intuitive intelligence addresses complex, unpredictable, and highly personalized tasks that rely on contextual understanding. At the highest level, empathetic intelligence equips AI systems with the ability to engage in sophisticated social and emotional interactions, often requiring advanced communication skills.

The progression from mechanical to empathetic intelligence highlights the increasing complexity and difficulty of designing AI systems capable of replicating human intelligence (Huang and Rust, 2022). For example, a robot concierge performing basic tasks like greeting guests and providing information demonstrates low intelligence, but with advanced features like facial recognition and personalization, it ascends to higher levels of capability. Therefore, by defining AI capabilities through the framework of these intelligence levels, we establish a structured approach to understanding how AI systems can be designed and evaluated. This definition integrates the varying types, tasks, and complexities outlined by the framework, providing a comprehensive lens for addressing AI's role and potential in CX and the broader services framework.

Technological Embodiment

Technological embodiment is defined here as the level of interaction between a technological device and human senses and is characterized by dimensions of agency, location, and ownership. Agency refers to the sense of control and autonomy experienced by the user while interacting with the technology, location pertains to the physical sharing of space between the user and the technology, contributing to a sense of proximity and presence, and ownership relates to the level of immersion and the user's sense of unification with the technology, where it feels like an extension of oneself (Tussyadiah, Jung and Tom Dieck., 2018).

This concept builds on the broader notion of embodiment, which emphasizes the connection between the human mind and body and how physical experiences and interactions shape cognitive processes and our understanding of the world (Longo *et al*., 2008). Within the philosophy of technology, Goldman *et al*. (1991) highlight how technology is embedded in human life, with the power to shape and reshape our lived experiences. This integration has introduced the idea of technological embodiment, which captures how technology becomes an integral part of everyday life and interactions (Verbeek, 2008).

Research highlights the link between high levels of technological embodiment and enhanced CXs, as technology increasingly integrates with human senses and interactions (Flavián, Ibáñez-Sánchez and Orús, 2019; Flavián, Ibáñez-Sánchez and Orús 2021). For example, wearable devices, such as VR glasses, provide a greater sense of ownership compared to external devices like voice assistants. Similarly, a mobile app-based chatbot demonstrates higher technological embodiment than a receptionist service robot due to its greater sense of agency. These examples illustrate how technological embodiment exists on a continuum, ranging from low to high levels of interaction and integration.

By framing technological embodiment through the dimensions of agency, location, and ownership, this definition provides a structured approach to understanding how varying degrees of technological integration influence human experiences, particularly in shaping enhanced interactions and engagement with technology.

Interactivity

In this study, interactivity is defined from a technological perspective as a dynamic process involving two-way communication, control, and real-time environment modification (Flavián, Ibáñez-Sánchez and Orús, 2019; Mollen and Wilson, 2010). Interactivity plays a pivotal role in shaping CX, as it enhances how customers engage with marketing stimuli through technology-enabled touchpoints. CX, in turn, is comprised of customers' cognitive, affective, emotional, social, and sensorial reactions to these stimuli (Lemon and Verhoef, 2016). These reactions occur across various touchpoints along the customer journey and are considered the key building blocks of the overall experience.

The integration of technology into CX enables the emergence of new touchpoints and experiential forms, expanding the scope and depth of interactions (Hoyer *et al.*, 2020). Additionally, it fosters increased interaction between humans and technology, enriching the experience through dynamic engagement (Dix, 2017; Neuhofer, Buhalis and Ladkin, 2014). Given the multiple viewpoints and the lack of an agreed-upon definition of

Table 3-5: AI-ET Cube components

AI-ET Cube Component	Definition	Level	Example
AI Capabilities	the varying degrees of intelligence displayed by an AI system, enabling it to effectively perform a wide range of tasks.	Low	Robot concierge providing basic services including greeting guests, providing information about the hotel and local attractions, making restaurant reservations, and assisting with check-in and check-out.
		High	Robot concierge that could personalize interactions using facial recognition technology.
Technological Embodiment	the level of interaction between a technological device and human senses, and is characterized by dimensions of agency, location, and ownership.	Low	VR tour of heritage location using a mobile device where users are immerses in a completely virtual environment.
		High	AR museum tour using a wearable device where virtual elements are overlayed onto the real world, blending digital content with the user's physical surroundings.
Interactivity	a dynamic process involving two-way communication, control, and real-time environment modification.	Passive	Voice-activated virtual assistant which respond to user commands and inquiries but do not engage in proactive or dynamic interactions.
		Active	Chatbots with advanced natural language processing capabilities which can ask follow-up questions, provide proactive suggestions, and engage in back-and-forth interactions to gather information and understand user needs more comprehensively.

interactivity (Wu and Wu, 2006), this study adopts a technological perspective (Flavián, Ibáñez-Sánchez and Orús, 2019).

Interactivity is conceptualized as a continuum ranging from passive to active interaction. Passive interaction occurs when no direct input from the customer is required (Cho and Choi, 2020), while active interaction takes place when customer inputs are essential for the technology to function. The degree of activeness depends on the tasks allocated to the customer during the interaction process (Montague and Xu, 2012). For instance, mobile AR tours involve more active interaction compared to web-based virtual tours, which are relatively passive. While both formats offer interactive experiences, mobile AR app tours typically provide features such as manipulating objects and navigating virtual environments, allowing customers to play a more significant role in shaping the experience. In contrast, web-based virtual tours are often limited to pre-defined interactions.

Thus, the customer assumes a greater role and exerts more influence over the experience during mobile AR interactions than in pre-structured web-based tours, underscoring the importance of interactivity in enhancing technologically integrated CXs.

3.6 Identified gaps in literature

Beyond the typology offered by the AI-ET Cube, the review also uncovers several conceptual and empirical gaps within the AICX literature. The findings of this SLR reveal that advancements in AI-enabled technologies have catalyzed significant transformations across the services sector. These changes have led to operational restructuring, reshaped competitive dynamics, and, in turn, altered customer expectations, experiences, and behaviours. The literature increasingly focuses on how such technologies influence consumer perception, adoption, and decision-making processes, as well as their broader behavioural outcomes. Parallel to this, research has sought to conceptualize the evolving relationship between business operations and customer interactions in technology-mediated environments. By examining the intersection of AI and CX, this review contributes to a deeper understanding of this emerging construct and highlights directions for future inquiry. The insights generated have implications for a wide range of stakeholders in tourism and service contexts,including service and technology providers, customers, and regulatory authorities,particularly in facilitating collaborative approaches to AI-driven transformation. To structure the discussion of these insights, the identified gaps are organized into five key themes, each representing a distinct area requiring further research: (1) AICX Definition and Dynamics, (2) AICX Implementation, (3) AICX Outcomes and Measurement, (4) Consumer Perspectives of AICX, and (5) Contextual Lenses for AICX. The sections that follow explore each theme in greater detail.

3.6.1 Gap 1: AICX Definition and Dynamics

The SLR reveals a fundamental gap in the conceptualization and theoretical grounding of AICX. Given rapid developments of AI-ETs and the relative novelty of the domain, there is uncertainty surrounding the conceptualization of AICX (Huang *et al*., 2021a). Very little is known about the underlying dimensions of this emerging form of experience. Limited knowledge is available concerning value creation in the context of AICX (Chen *et al*., 2021; Neuhofer, Magnus and Celuch, 2021). Further, the dynamics between customers, technology, and frontline employees have yet to be investigated (e.g. Odekerken-Schröder *et al*., 2022). From a more practical perspective, it is now well-established that utilizing AI-ETs (e.g. remote virtual tourism) is transforming traditional tourism and leading to significant industry changes, including hiring strategies, job reskilling, and process redesign (Ivanov *et al*., 2019; McCartney and McCartney, 2020; Solnet *et al*., 2019). However, research attention remains scarce in exploring the implications and practical aspects associated with these changes (e.g. Allal-Chérif, 2022).

Addressing this gap is expected to advance theoretical clarity and lay the foundation for future AICX research. A clearer conceptualization would enable organizations to better understand the mechanisms of value co-creation, optimize the interplay between human and technological actors, and align their strategies with the evolving AI-driven service landscape.

3.6.2 Gap 2: AICX Implementation

The SLR also highlights a lack of clarity and direction in the implementation of AI within tourism and hospitality, particularly in the management of CX. While AI adoption is accelerating, the review reveals that existing literature offers limited guidance on how organizations can effectively integrate AI technologies into service operations (e.g., Fuentes-Moraleda *et al*., 2020; Simoni *et al*., 2022). Persistent scepticism and practical concerns, despite growing investment in AI, underscore the need for actionable, evidence-based implementation frameworks (e.g., Collins, 2020).

Research evaluating AI performance, exploring implementation strategies, and identifying barriers remains scarce (e.g., Pillai and Sivathanu, 2020). A critical gap exists in understanding which AI applications generate the greatest value and how their roles can be aligned with specific tourism functions (e.g., Lee *et al*., 2021). Moreover, the challenge of achieving compatibility between AI and human employees remains unresolved. Although maintaining the 'human touch' is vital in tourism and hospitality, limited research addresses staff attitudes, behaviours, and concerns particularly regarding job displacement, role transformation, and technology acceptance (e.g., Qiu *et al*., 2022; Lei, Shen and Ye, 2021).

Addressing this gap could equip organizations with the strategic and operational insights needed to implement AI more effectively. It would support efforts to balance technological innovation with human-cantered service delivery, improve employee-AI collaboration, and ultimately enhance both CX and operational efficiency.

3.6.3 Gap 3: AICX Outcomes and Measurement

The SLR shows that the outcomes of AICX remain underexplored, both at the individual and organizational levels. Limited research has examined how AI interactions shape psychological and emotional responses, including user emotions, cognitive processing, and subsequent behavioural intentions (e.g., Ivanov and Webster, 2021; Oh and Kong, 2022; Tuomi, Tussyadiah and Hanna, 2021). Much of the existing work relies on hypothetical or experimental settings, highlighting the need for field studies that capture real-world interactions and consider the influence of prior CXs (e.g., Fusté-Forné, 2021).

At the organizational level, research is lacking on key business outcomes associated with AICX ,such as customer acquisition, loyalty, engagement, brand attachment, and competitive advantage (e.g., Loureiro *et al*., 2021; McCartney and McCartney, 2020). Another critical gap lies in the absence of validated measurement tools for AICX. Despite its growing importance, little progress has been made in developing scales that capture the variables and dimensions that define a holistic AICX (e.g., Kabadayi *et al*., 2019).

Moreover, the literature has paid insufficient attention to the potential negative or unintended consequences of AI adoption. Topics such as customer privacy concerns, psychological risks, and the "dark side" of AI remain under-investigated (e.g., Grundner and Neuhofer, 2021). Similarly, the economic and operational implications such as implementation costs, return on investment, and economies of scale, have yet to be fully examined (e.g., Ivanov *et al*., 2019). Despite growing public concern, environmental, legal, ethical, and cybersecurity considerations are also largely absent from current AICX research (e.g., Celuch, 2021; Fusté-Forné, 2021).

Addressing this gap is essential to generating comprehensive insights into the value and risks associated with AICX. Advancing research in this area will support the development of effective measurement tools, inform customer-centric design strategies, and guide responsible AI implementation aligned with societal, ethical, and sustainability goals.

3.6.4 Gap 4: Consumer perspectives of AICX

Findings from the SLR point to a lack of empirical studies examining consumer perspectives of AICX in applied, experiential contexts. While prior research has explored customer intentions, perceptions, and attitudes toward AI integration, much of it is based on hypothetical scenarios or controlled environments. As a result, limited attention has been paid to the hedonic, immersive, and social aspects of AI-enabled experiences (e.g., Celuch, 2021). Uncertainty remains around what customers expect from AICX, their willingness to engage, preferred features, and the degree to which they are open to AI-mediated interactions (e.g., Han, Tom Dieck and Jung, 2019).

Conversely, customer motivations for resisting AI, their concerns about non-human interfaces, and their preferences for traditional, human-led experiences have not received sufficient attention (e.g., Çakar and Aykol, 2021). Other underexplored areas include consumer reactions to AI-ETs, such as their willingness to pay for fully automated services, perceived appropriateness, and preferences for specific AI formats or interfaces (e.g., Ivanov and Webster, 2021).

Further gaps relate to the roles of interactivity, immersion, and emotional response in shaping AICX (e.g., Chiang *et al*., 2022), as well as the influence of AI type, context, and form on behavioural outcomes (e.g., Fuentes-Moraleda *et al*., 2020). There is also a lack of research into customer responses to AI service failures, particularly regarding blame attribution, emotional reactions, and complaint behaviour in comparison to failures involving human employees (e.g., Tuomi, Tussyadiah and Hanna, 2021).

Addressing this gap may offer valuable insights for enhancing the design of more personalized and emotionally attuned AICX. It could help guide decision-making processes that are more closely aligned with customer preferences and expectations, while also contributing to the development of more effective service recovery strategies in AI-mediated environments.

3.6.5 Gap 5: Contextual Lenses for AICX

The SLR indicates that while CX is inherently contextual, existing AICX research has yet to sufficiently explore the influence of contextual variables on the design and delivery of AI-enabled experiences. Core CX literature emphasizes that experiences are shaped by a range of situational, cultural, and personal factors (Becker and Jaakkola, 2020), yet such considerations are often underrepresented in the current AICX discourse particularly in tourism contexts.

The review identifies several contextual lenses that warrant closer examination, including those related to the customer journey, culture, personal attributes, and demographic differences. These lenses highlight the importance of considering the full breadth of the CX, encouraging service providers to invest in each stage of the journey to enhance AICX. By integrating these factors, organizations could tailor AI-driven experiences more effectively and responsively. The following sections explore these contextual considerations further, outlining their potential impact on AICX and their relevance for future research and practice.

The Cultural Lens

There is a significant gap in cross-cultural studies on AICX. Comparative studies involving customers from different cultural backgrounds would enhance our understanding of potential variations in AICX (e.g. Trunfio and Campana, 2020). Exploring cultural differences in attitudes towards AI, adoption, acceptance preferences, engagement, satisfaction, memorable experiences, and perceived service quality within the tourism sector can provide valuable insights (e.g. Jung *et al*., 2018).

Tourism Sub-Contexts

The receptivity of different tourism sectors to AI has not been closely examined, particularly in understudied sub-contexts such as international events, entertainment destinations, fairs and festivals, and religious monuments (e.g. Allal-Chérif, 2022). While previous studies provided some theoretical projections of AI integration, there is still very little understanding of this in real-world tourism contexts. A systematic comparison highlighting the differences between the various tourism contexts is also still lacking (e.g. Ducros and Euzéby, 2021).

Beyond the Encounter Stage

Existing research on AICX has primarily concentrated on the encounter stage, thus offering a limited understanding of the broader customer journey that includes the pre- and post-encounter stages. Current literature falls short in examining anticipatory (e.g. AI in promoting tourist attractions) and reflective phases (e.g. leveraging post-travel experiences to further promote the overall experience) of the experience (e.g. Tung and Law, 2017).

Moderating Variables

Insufficient attention has been given to the moderating variables of AICX, which indicates a research gap. Variables such as personal and demographic factors, including generations, age groups, regions, and genders, have not been thoroughly examined (e.g. McCartney and McCartney, 2020). Furthermore, behavioural and value-based segmentation, such as customers' technological skills, innovation readiness, and prior technology experience, have not received the necessary research attention (e.g. Zhu and Chang, 2020).

In conclusion, this systematic literature review identifies five critical gaps within the emerging AICX domain: conceptual ambiguity, limited implementation guidance, insufficient attention to outcomes and measurement, underexplored consumer perspectives, and a lack of contextual consideration. Collectively, these gaps point to the nascent state of AICX research and call the need for more theoretically rigorous, empirically grounded, and context-specific research efforts. Addressing these areas may contribute to the development of a more cohesive theoretical foundation, enhance the practical integration of AI in service contexts, and support the delivery of more adaptive, inclusive, and meaningful experiences.

3.7 Discussion

The five emerging gaps identified in the SLR reflect the growing complexity and evolving nature of AICX. Together, they reveal critical tensions between rapid technological advancement and the slower pace of theoretical development, organizational adaptation, and customer readiness. These gaps highlight not only gaps in the literature, but also practical challenges faced by service providers in aligning AI-ET integration with meaningful and human-centred experiences. This section discusses these gaps in relation to broader industry trends, theoretical debates, and strategic priorities, offering a deeper understanding of the implications of AICX for research and practice.

3.7.1 Challenges in Leveraging AI-ETs

The outcomes of the SLR reveals a prominent gap between the rapid advancement and practical implementation of AI-ETs in the service sector and the corresponding academic research. While industry reports and market analyses, such as those from McKinsey and Company (2024), document a significant increase in AI-ET integration, scholarly research is evolving yet remains insufficient. Notably, gaps persist in areas such as implementation strategies and consumer perspectives (Ghesh, Alexander and Davis, 2024). Specifically, existing literature has yet to thoroughly investigate how consumers perceive, interact with, and respond to AI-enabled service encounters (Celuch, 2021; Han, Tom Dieck and Jung, 2019; Ivanov and Webster, 2021;). Likewise, there is limited guidance on practical frameworks for integrating AI-ETs in ways that fulfil both customer expectations and business objectives (Fuentes-Moraleda *et al*., 2020; Pillai and Sivathanu, 2020).

These gaps indicate that many service providers are likely adopting AI-ETs primarily in response to prevailing trends, rather than aligning these technologies with their specific business goals or customer needs. The pressure to stay competitive in an increasingly digital landscape may be driving these decisions. Additionally, the complexity of integrating AI-ETs with existing infrastructure and the rapid pace of technological advancements could lead organizations to prioritize short-term adoption over long-term strategic alignment. This is particularly concerning given the high cost of AI-ETs and their implementation, coupled with the evident lack of knowledge regarding both the practical integration of these technologies and consumer perspectives on their use.

3.7.2 Transforming Service Models with AI-ETs

In parallel with implementation challenges, the adoption of AI-ETs is also reshaping fundamental aspects of service delivery models. The identified gaps highlight the widespread adoption of various AI-ETs in multiple roles throughout the customer journey. For example, chatbots now handle customer inquiries across websites, social media platforms, and mobile apps, offering instant support at any time of day. This pervasive integration has not only transformed the CX, but also suggests a re-evaluation of service design and the evolving roles of service personnel. With AI-ETs now supporting everything from data analysis to customer interactions, service models are increasingly designed around AI capabilities rather than solely human-centred touchpoints. As AI-ETs assume more functions, such as: voice assistants managing bookings, automated kiosks enhancing in-store experiences, or robots performing repetitive tasks in hospitality and healthcare, the traditional boundaries of service delivery are increasingly shifting. No longer are customers confined to waiting for human assistance; instead, they interact with AI to resolve issues, make purchases, and receive recommendations. This shift is prompting businesses to rethink how they design their service. The role of human personnel may now be more focused on overseeing AI processes or handling more complex, emotionally charged customer interactions, areas where AI has yet to match human empathy and judgment. Service personnel must adapt to these changes by taking on new responsibilities that involve collaborating with AI-ETs. This shift calls for refined hiring strategies and the development of tailored training programs to equip new employees with the skills necessary to work effectively alongside these technologies.

3.7.3 Behavioural shifts in the age of AI-ETs

Another key area emerging from the SLR is the influence of AI-ET integration on consumer behaviour. The outcomes contribute significantly to the broader literature linking the integration of AI with changes in consumer behaviour (Bai, 2022; Dellaert *et al*., 2020, Melumad *et al*., 2020; Puntoni *et al*., 2021). As AI technologies become more prevalent across industries, their influence on consumer actions, preferences, and decision-making processes has become increasingly evident. These findings not only highlight the transformative role of AI in shaping how consumers interact with service providers, but also shed light on the broader behavioural shifts that accompany this transformation. By exploring this intersection, the research provides critical insights into the evolving dynamics between AI integration and consumer behaviour, advancing academic discussions on customer acceptance of AI-ETs, complaint handling behaviours, and the changing role of emotional expression in service interactions.

An essential consideration for the long-term adoption of AI-ETs is the evolving nature of customer expectations. As consumers become increasingly familiar with AI-ETs in their daily interactions, their demands for service quality, efficiency, and responsiveness are likely to shift. Previous research on cutting-edge technologies highlights how technical attributes such as complexity and compatibility, along with psychological factors like curiosity, shape consumer attitudes and behavioural intentions (Acikgoz, Elwalda and De Oliveira, 2023). Rogers' Diffusion of Innovations further emphasizes the significance of compatibility in influencing behavioural intentions, illustrating how consumer attitudes mediate the relationship between these factors and the decision to adopt new technologies (Rogers, 2003, 2019). This evolution in expectations highlights the need for continuous research into customer perspectives and behaviours related to AI-ET integration. Such efforts are critical for businesses to anticipate and adapt to these changing demands, maintain a competitive edge, and continuously refine their service offerings to meet the needs of an increasingly AI-savvy consumer base.

3.7.4 AI-ETs monitoring and evaluation

A final dimension of the discussion concerns the ongoing evaluation of AI-ET performance and its alignment with dynamic customer expectations. As customer expectations evolve, businesses must regularly assess their AI systems' performance and impact on CXs, ensuring they align with emerging needs and standards. By establishing processes for continuous evaluation, organizations can better anticipate shifts in consumer behaviour, fine-tune their AI applications, and ensure that their offerings remain relevant and competitive in an increasingly dynamic marketplace.

Further, service providers must conduct a thorough evaluation of the scalability and flexibility of their integration of AI-ETs. The rapid evolution of market conditions, consumer behaviours, and technological advancements means that organizations cannot afford to treat AI-ET integration as a static solution. For instance, the surge in demand for personalized experiences, requires AI systems that can scale quickly to handle growing volumes of data while maintaining high levels of personalization. Similarly, businesses need AI tools that are not only capable of managing increasing customers' interactions but also flexible enough to adapt to new regulatory requirements or shifts in service delivery models. The ability to adapt and expand AI-ET applications is essential for achieving long-term success and sustainability. Organizations that prioritize scalability by selecting AI-ETs that can grow alongside their customer base or service offerings and flexibility by adopting AI-ETs that can easily integrate with emerging technologies or pivot to new operational models will be better positioned to respond to changing circumstances. Ultimately, organizations that integrate AI-ETs with an eye toward scalability and flexibility will be better equipped to navigate the complexities of a dynamic marketplace and effectively meet the changing demands of their customers.

As the field of AI continues to evolve, so too do the regulatory frameworks govern its use. Research on trustworthy AI, which emphasizes principles such as beneficence, non-maleficence, autonomy, justice, and explicability, highlights the importance of aligning AI development and deployment with ethical, legal, and societal expectations to build trust among stakeholders (Thiebes, Lins and Sunyaev, 2021). Compliance with these evolving regulations not only influences the implementation of AI-ETs but also shapes the overall AICX. Consumer sentiment, particularly around data privacy and ethical AI usage, often drives regulatory changes, adding another layer of complexity to AI integration. For instance, the increasing demand for transparency and accountability has prompted attention to establish robust AI governance frameworks (Huang *et al*., 2022; Jobin, Ienca and Vayena, 2019; Krijger *et al*., 2023). This interplay between regulatory compliance, consumer expectations, and situational factors calls for adopting a proactive approach. By staying informed about regulatory developments and aligning their strategies with principles of trust and transparency, businesses can mitigate risks, enhance customer trust, and foster satisfaction, ultimately enabling a more sustainable and successful implementation of AI-ETs.

3.8 Conclusion

The integration of AI-ETs across the customer journey is transforming the nature of CX in tourism and other service industries. This thesis introduces *AICX* as a novel and increasingly relevant construct that captures the evolving interface between AI technologies and customer interactions. Drawing on a SLR of 98 peer-reviewed articles and guided by the TCCM framework, this study provides a comprehensive bibliometric analysis of the current AICX research landscape. It contributes a conceptual typology (the AI-ET Cube) which offers a structured lens for classifying AI applications in CX contexts.

Furthermore, the review identifies five key thematic gaps in the existing literature, offering critical directions for future research. These themes highlight areas in need of conceptual clarity, practical guidance, consumer insight, contextual understanding, and evaluative rigor.

By synthesizing fragmented insights and proposing an integrated research agenda, this thesis advances both theoretical understanding and practical application of AI in CX. As AI continues to reshape service ecosystems, the findings of this study provide a timely foundation for researchers, practitioners, and policymakers seeking to navigate the opportunities and challenges of AICX.

3.8.1 Theoretical Implications

Through building upon the prior research conducted by Hoyer *et al*. (2020) on CX transformation through technologies, and Buhalis *et al*. (2019) identification of disruptive areas in service experience, this study breaks new ground by introducing AICX as a standalone holistic construct representing a new form of the experience. It is the first to introduce the term 'AI-ETs' as a hypernym, encompassing both novel AI-based technologies and existing technologies enhanced through AI integration. This study broadens the current theoretical understanding of CX by introducing AICX as a novel form of experience, capturing customers' reactions and responses to various AI-ETs integrated and implemented across the customer journey. In other words, its novelty lies in its scope, and the aggregate impact of AI-ETs, rather than focusing solely on individual touchpoints.

Further, the SLR presents a novel framework, known as the AI-ET Cube, for classifying AI-ETs. This framework provides a structured and comprehensive approach to categorize the diverse range of customer-facing AI-based and AI-empowered technologies implemented across the customer journey in the tourism sector. It extends previous literature on the classification of AI in services (Huang and Rust, 2018; Huang and Rust, 2022; Puntoni *et al*., 2021) and offers guidance for future research on exploring the interplay between AI, technology, and CX. A more detailed discussion of these theoretical implications are provided in Section 8.1.

3.8.2 Managerial Implications

Building on the above theoretical contributions, this study offers several important implications for managers aiming to leverage AI-ETs to enhance CXs. First, by introducing AICX as a holistic construct, the research underscores the need for a shift in managerial thinking from optimizing isolated touchpoints to designing and managing cohesive, AI-enhanced journeys. Managers are encouraged to consider the aggregate influence of AI-ETs across the entire customer lifecycle rather than treating AI as a back-end efficiency tool or a novelty at selected interfaces.

Second, the introduction of AI-ETs as a conceptual umbrella provides practitioners with a clearer lens to identify, assess, and strategically implement a wide spectrum of AI-based and AI-empowered technologies. This framing helps organizations move beyond fragmented technology adoption toward a more integrated, customer-centric approach.

Lastly, the AI-ET Cube offers a practical tool for evaluating the positioning, functionality, and impact of AI-ETs across the customer journey. Managers can use this framework to map existing technologies, identify potential gaps, and inform future investment decisions. In doing so, they can align technological innovation with CX strategy, ultimately fostering more meaningful, responsive, and adaptive engagements.

3.8.3 Implications for future research

Beyond the theoretical and managerial implications, this study also outlines key directions for future research, providing a structured foundation for ongoing scholarly inquiry into AICX. It offers insights into the existing body of research, emphasizing the growing significance of this area and highlighting the need for further academic attention. The research agenda, developed through thematic analysis of relevant literature and identified gaps, is presented in detail in Appendix L.

Future research should explore the multidimensionality of AICX, identifying its core dimensions and assessing how AI-ETs contribute to value creation across diverse CX touchpoints. Comparative analysis between AI-led and human-led service encounters is critical to evaluate differences in emotional engagement, interaction quality, and service outcomes. Scholars should also examine the dynamic interplay between AI-ETs, FLEs, and customers, rethinking traditional marketing principles in AI-enhanced environments. Research into AI utilization across industries should investigate adoption levels, enablers, and outcomes such as revenue growth, operational efficiency, and customer satisfaction. Studies should identify best practices and strategic approaches for AI integration, especially those that strike the right balance between automation and the human touch. It is equally important to assess the emotional and behavioural effects of AI integration on customers, including trust, loyalty, engagement, and complaint behaviour.

Evaluating AICX requires the development of comprehensive KPIs that can measure the effectiveness and quality of interactions across channels and journey stages.

Future studies should expand consumer-focused research to include expectations, value perception, motivation, service failure responses, and emotional dynamics. Contextual variables such as culture, demographics, technological readiness, and personal traits must be considered to understand the variability in customer responses to AI-ETs. Finally, research should address emerging AI-enabled business models and their implications for service design, stakeholder roles, and value creation. Understanding customer preferences for AI formats, levels of interactivity and immersion, and perceived experiential value will be crucial in guiding AI-driven CX strategy and innovation.

3.8.4 Limitations

The increasing prominence of AICX as a research domain, alongside the considerable scholarly attention it has garnered in recent years and is expected to continue receiving, introduces certain limitations to this SLR. Despite adopting a comprehensive search strategy, there is still a possibility that papers were excluded due to a lack of clear relationships with CX research, a lack of clear relationships with tourism research, the use of a contextual label for the CX (e.g., museum experience), or not being included in one of the 5 selected databases for identifying relevant literature on the AICX. Furthermore, given the challenges scholars face in distinguishing AI and occasional mislabelling of non-AI applications, coupled with the impracticality of verifying technical details for every mentioned application in articles, there is a possibility that certain articles in our research have been inaccurately categorized under the AI domain.

3.8.5 AICX Scale development as a direction for the PhD

The outcomes of the SLR serve as a foundational basis, guiding the research aim, objectives, and overall design of the thesis. Five key research gaps were identified, one of which pertains to the outcomes and measurement of AICX. Notably, the findings revealed the absence of a dedicated scale for measuring AICX, highlighting a significant and unique research opportunity. While addressing any of the identified gaps is expected to provide valuable theoretical and practical advancements, the development of a dedicated scale for measuring AICX is anticipated to yield more profound contributions to both theory and practice. This is because developing a measurement scale represents a foundation for defining, operationalizing, and investigating AICX. It provides a tool that enables the exploration of the construct across different contexts. Compared to other gaps that focus on specific areas, a scale could be key for cumulative, comparable, and replicable research, making it valuable for both theoretical development and practical application.

The complexity of CX, being conceptualized as a multidimensional along with its diverse interpretations, presents significant challenges in its measurement, often necessitating the development of new, context-specific scales. Furthermore, there is a growing recognition of the need to capture unique aspects of CX that traditional scales may overlook, particularly in rapidly evolving contexts such as interactions with AI-ETs (Bueno *et al*., 2019).

From a theoretical standpoint, the scale will enhance the understanding of AICX by addressing foundational aspects such as its definition and dynamics. Conceptualizing AICX serves as a critical first step to scale development, offering the clarity required to operationalize the construct effectively. From a practical standpoint, the scale will provide a valuable tool for measuring and benchmarking AICX, generating insights that can inform its implementation and optimization in different contexts and industries. These theoretical and practical contributions directly align with two key gaps identified in the SLR: the need to define and understand the dynamics of AICX, and the importance of guiding its effective implementation.

In addition, this focus indirectly supports other key gaps identified in the review. For example, the scale will facilitate a deeper exploration of consumer perspectives on AICX by enabling the measurement of their experiences, expectations, and reactions. As part of the scale validation process, some consumer perspectives will be addressed directly, further enriching the construct. Moreover, the scale lays the groundwork for examining contextual lenses of AICX, providing a foundation for future studies that seek to understand its variations across cultural, sectoral, and technological dimensions.

The development of this scale bridges the gap between theoretical frameworks and practical applications, offering both a deeper understanding of AICX and a systematic tool for its evaluation. By illuminating how AI-ETs shape CXs, this research lays the groundwork for broader applications of AICX across diverse service environments, providing actionable insights for both academia and industry. Recognizing the anticipated impact of this scale in advancing theoretical knowledge and informing practical implementation, the empirical phase of this PhD focused on designing a robust and comprehensive scale to measure the emerging phenomenon of AICX.

Chapter 4 . Research Design

This chapter establishes the philosophical foundation for the empirical part of the thesis, guiding its approach to theory development and overall design. It begins by introducing the thesis aim and objectives. This is followed by a discussion of two key philosophical standpoints, positivism and interpretivism. Critical realism is then introduced and highlighted in terms of how it integrates and transcends the strengths and limitations of these two perspectives. Critical realism is introduced as the guiding philosophical standpoint for this thesis. The chapter also discusses the approach to theory development, explaining its alignment with the thesis aim and objectives. Finally, the chapter introduces mixed methods research, exploring its designs, particularly the sequential exploratory design, and indicates its suitability for scale development studies.

4.1 Thesis aims and objectives

Chapter 2 introduced AICX as an emerging phenomenon within the broader field of CX, holding significant potential for both academic research and practical application. The transformative role of AI-ETs in redefining CX highlighted the importance of understanding AICX as a distinct concept, necessitating focused exploration and study. To address this need, a broad research aim was established to direct the investigation:

Research Aim:
To explore AI-enabled customer experiences and measure their impact on associated behavioural outcomes.

This aim embodies the dual focus of the research, combining exploratory and practical dimensions to investigate the phenomenon of AICX while addressing the need for a robust framework to measure and understand its broader implications. However, the growing interest in AICX, as reflected in the expanding body of literature on the topic, highlights the need for a more comprehensive exploration to better understand current state of knowledge on the topic. To address this need, the following research objective was proposed:

Research Objective 1:
To understand and map the research landscape on the role of AI in shaping customer experiences.

This objective was addressed through a SLR, undertaken as the first phase of the research. The findings of the SLR, which are presented and discussed in Chapter 3, provided a critical overview of the current knowledge landscape. The review identified key gaps and opportunities that were instrumental in shaping the overall research design, refining subsequent objectives, and guiding the methodological approach for later phases. Building upon the outcomes of the SLR, a second research objective was formulated:

Research Objective 2:
To develop a scale for measuring the AICX.

This second objective guides the empirical component of the thesis, which comprises both qualitative and quantitative phases to ensure a comprehensive approach to scale development. This objective necessitates a rigorous methodological approach to ensure the validity and reliability of the resulting scale. Achieving this requires thoughtful consideration of the underpinning philosophical standpoints, the overall design of the study, and the methodological choices made throughout the scale development process. The following sections in this chapter discuss these aspects in detail, outlining the philosophical underpinnings, research design, and specific methods employed to achieve this objective.

4.2 Philosophical position

"There is no such thing as philosophy-free science, only science whose philosophical baggage is taken on board without examination"

(Dennett, 1996, p. 21)

Scientific research is shaped by underlying philosophical foundations that should be clearly articulated (Creswell, 2009). These foundations form the basis of research, and failing to address them, as some scholars suggest, can undermine its rigor and credibility (Easterby-Smith, Thorpe and Jackson, 2008). Such oversight may lead to misaligned methods, weak theoretical contributions, and limited insights, ultimately affecting the reliability and impact of the research. By translating these philosophical foundations into clear, actionable directions regarding what to study, how to study it, and how to interpret the findings, researchers can effectively justify their methodological choices and ensure alignment with broader theoretical perspectives (Creswell, 2009; Easterby-Smith, Thorpe and Jackson, 2008; Ma, 2015). This reflects an important step that researchers must address and ensure as a fundamental aspect of their research.

The importance of this step is well-recognized; however, the complexities of philosophical terminology present significant challenges, as it is often vague, overlapping, and applied inconsistently or interchangeably (Saunders, Lewis and Thornhill, 2023; Wittgenstein, 2009). Terms such as *philosophical standpoint*, *worldview*, *research philosophy*, *research paradigm*, and *school of thought* are frequently used in academic literature to articulate the philosophical foundations of research. These terms are often employed without standardized definitions and are subject to varied, sometimes overlapping, interpretations within the field. (Crotty, 2011; Kuhn, 1970; Morgan, 1980; Saunders, Lewis and Thornhill, 2023). Recognizing these complexities, this research adopts the term *research philosophy position* to refer to the stance taken within the broader belief system encompassing ontology, epistemology, and axiology,one that fundamentally shapes and guides the overall research approach. (See Table 4-1).

Ontology (the study of being), epistemology (the study of knowledge), axiology (the study of values), and methodology (the study of methods of inquiry) serve as the foundational pillars of philosophical discussions (Anand, Larson and Mahoney, 2020; Creswell and Poth, 2016; Crotty, 2011; Killam, 2013; Saunders, Lewis and Thornhill, 2023). Assumptions about these concepts underpin research philosophies, positioning researchers and their work along a multidimensional spectrum of philosophical positions. These assumptions guide philosophical positions into actionable directions, profoundly shaping the formulation of research questions, the selection of data collection and analysis methods, and the interpretation of findings. Thus, articulating a clear philosophical position is not merely an academic formality but a critical step that directly influences the practical execution and outcomes of research.

Table 4-1 Underlying philosophical assumptions. (Adapted from Guba and Lincoln 1994; Saunders, Lewis and Thornhill, 2023)

Philosophical assumption	Definition
Ontology	Concerns assumptions about the nature of reality and existence, directly shaping a researcher's perception of truth.
Epistemology	Pertains to the nature and scope of knowledge, focusing on how truth is discovered or constructed.
Axiology	Examines values, including ethical considerations, influencing the researcher's stance on what is deemed important or worth investigating.
Methodology	Focuses on the processes and strategies used to generate knowledge, aligning with the researcher's ontological, epistemological, and axiological assumptions.

As academic disciplines advance, research philosophy positions undergo continuous evolution, reflecting broader trends in philosophical thought and responding to new intellectual, technological, and societal challenges. This evolution is exemplified in the emergence of new research philosophy positions, such as critical realism and pragmatism, which seek to address the limitations of existing frameworks. In turn, this evolution has prompted ongoing scholarly debates concerning the appropriateness of philosophical approaches for specific research contexts (Tsoukas and Knudsen, 2003). The proposition of a single "best" research philosophy is widely regarded as problematic, given that each philosophy contributes distinct and valuable perspectives to the advancement of knowledge (Saunders, Lewis and Thornhill, 2023). In alignment with this view, Ozanne and Hudson (1989) assert that endorsing the dominance of a singular paradigm within a discipline lacks scientific rigor, highlighting the necessity of recognizing and accommodating the characteristics of philosophical approaches. Johnson, Onwuegbuzie and Turner (2007) emphasizes the importance of considering various research philosophies and selecting one that aligns with the research question. This alignment is crucial because each philosophy offers a distinct perception of knowledge, which in turn shapes the data collection methods employed to address the research question (Lee and Lings, 2008).

Articulating a philosophical position requires both a thorough understanding of diverse philosophical perspectives and their differences (Tashakkori, Johnson and Teddlie, 2020; Teddlie and Tashakkori, 2010) and a critical reflection on one's assumptions regarding the nature and acquisition of knowledge (Creswell and Plano Clark, 2017). This may appear complex; however, it becomes more manageable through the analysis of ontological, epistemological, axiological, and methodological philosophical assumptions (Guba and Lincoln, 1994; Saunders, Lewis and Thornhill, 2023). This structured framework enables researchers to critically evaluate philosophical perspectives within their field, ensuring the selection and justification of a suitable philosophical stance and an aligned research approach.

As a relatively nascent discipline, business and management studies have developed by integrating philosophical positions from the natural sciences, social sciences, arts, and humanities, resulting in a diverse range that includes positivism, postpositivism, interpretivism, critical realism, constructivism, pragmatism, and postmodernism (Creswell and Creswell, 2023; Saunders, Lewis and Thornhill, 2023; Tashakkori, Johnson and Teddlie, 2020; Teddlie and Tashakkori, 2010). While certain positions have gained greater prominence within more established disciplines such as positivism in economics or interpretivism in sociology, this is less the case in business and management research, where no single position consistently prevails.

As previously noted, this diversity necessitates a conscious, well-reasoned articulation of philosophical alignment in light of specific research aims, therefore calling for thoughtful comparison and careful consideration to ensure an appropriate and informed choice. In this study, critical realism is identified as the most suitable philosophical position for addressing the research problem. This choice aligns with Morgan’s (2007) view that paradigms should be understood as flexible, community-based belief systems rather than rigid philosophical doctrines. Critical realism reflects this flexibility by offering a philosophically coherent yet adaptable stance that accommodates both the complexity of social phenomena and the practical requirements of applied research.

To justify this selection, a comparative discussion is undertaken between critical realism, positivism, and interpretivism. Positivism, rooted in objectivism, emphasizes an observable, measurable reality governed by universal laws, often aligning with natural science methods. Interpretivism, grounded in subjectivism, focuses on the socially constructed nature of reality and the subjective meanings individuals attach to their experiences, typically favouring qualitative approaches. Critical Realism offers a philosophically robust alternative that reconciles ontological realism with epistemological relativism. This positions critical realism as a compelling middle ground: one that maintains a commitment to the existence of an objective reality while recognising the socially constructed and interpretive nature of our knowledge about it (Bhaskar, 1975; Easton, 2010; Saunders, Lewis and Thornhill, 2023).

The following sections examine these three philosophical positions in greater detail. Table 4-2 then summarises the key distinctions among positivism, interpretivism, and critical realism as discussed in the literature.

4.2.1 Positivism

Positivism, a research philosophy rooted in the works of Auguste Comte, has profoundly influenced scientific inquiry by emphasizing empirical observation, measurable data, and the application of the scientific method to uncover generalizable truths (Hunt, 1990; Fellows and Liu, 2008). As a research philosophy, positivism assumes the existence of universal laws governing natural and social phenomena, asserting that reality is stable, observable, and independent of the researcher (Ponterotto, 2005, Bryman, 2016). Central to this research philosophy is the principle of objectivity, which requires researchers to adopt standardized methods and rely on factual evidence to minimize bias and ensure reproducibility (Ponterotto, 2005; Creswell and Creswell, 2023). By advocating a dualism between the observer and the subject, positivism positions reality as external and measurable, with phenomena considered valid only when they can be empirically observed, quantified, and verified (Bryman, 2016, Ponterotto, 2005).

Positivism is inherently deductive, with theory playing a central role in guiding research. Hypotheses are formulated based on existing literature and tested through rigorous statistical methods, aiming to verify theoretical relationships and establish causal or correlational explanations (Bryman, 2016; Creswell and Creswell, 2023). Quantitative methods are particularly aligned with this research philosophy, as they enable the measurement of defined variables and the analysis of their relationships, facilitating the generalization of findings across larger samples (Ponterotto, 2005). The ultimate goal of positivism is to develop explanations that allow for the prediction and control of phenomena, underscoring its utility in fields that prioritize observable and measurable data (Ponterotto, 2005, Hunt, 1990).

However, positivism has been critiqued for its limitations in addressing the complexities of human interpretation and the latent structures that shape social reality. Scholars argue that its reliance on observable data often overlooks intangible constructs such as emotions, perceptions, and subjective experiences, which are difficult to measure reliably and may introduce bias into research findings (Lee and Lings, 2008; Hunt, 1990). For instance, in studying constructs like AICX, characterized as contextual, subjective, and multidimensional, positivism may fall short due to its inability to fully capture the nuanced and context-dependent nature of such phenomena (Bryman, 2016; Creswell and Creswell, 2023). This limitation highlights the need for complementary research philosophies that prioritize understanding the subjective meanings and social contexts that positivism often neglects (Denzin and Lincoln, 2000).

When applied to AICX, positivism could provide value through the quantification of customers interactions with AI-ETs and the identification of patterns across relevant large datasets. However, it does not fully address the subjective and emotional dimensions of the experience, nor does it engage with the deeper social or technological structures that shape AI interactions. These limitations suggest while positivism has been instrumental in advancing scientific inquiry by promoting objectivity, reproducibility, and generalizability, its applicability is constrained when studying complex, subjective, or latent constructs. Its strengths lie in the study of observable phenomena, but its limitations underscore the importance of considering other philosophical standpoints that are capable of addressing the multifaceted nature of human and social phenomena.

4.2.2 Interpretivism

Interpretivism, emerging as a counterpoint to positivism, centers on understanding the meanings individuals assign to their experiences within specific social, cultural, and historical contexts (Ponterotto, 2005; Guba and Lincoln, 1994). It holds that reality is not a fixed external entity but is instead socially constructed and subjectively experienced. Closely associated with constructivism, interpretivism suggests that knowledge is co-created through interactions between the researcher and participants, allowing for multiple, equally valid interpretations of reality (Berger and Luckmann, 1966; Crotty, 1998). This view assumes that the researcher is not a neutral observer but an engaged participant, and reflexivity is essential for acknowledging how the researcher's values and biases shape the findings (Alvesson and Sköldberg, 2009).

Epistemologically, interpretivism is grounded in intersubjectivity, emphasizing that knowledge emerges through dialogue, shared meanings, and context. It also embraces inductive reasoning, whereby theories and themes emerge from empirical data rather than being imposed by existing models (Charmaz, 2006; Glaser and Strauss, 1967). This inductive, emergent approach encourages openness to new insights and a sensitivity to the participant's perspective (Denzin and Lincoln, 2000; Silverman, 2013). It enables researchers to generate rich, nuanced understandings that prioritize the lived experiences of individuals and the meanings they ascribe to their worlds.

Methodologically, interpretivism Favors qualitative methods such as in-depth interviews, participant observation, ethnography, and narrative analysis. These techniques allow researchers to explore subjective phenomena from the participant's perspective and to generate "thick descriptions" that capture contextually grounded interpretations (Geertz, 1973; Van Maanen, 1988). This is particularly valuable for uncovering how people perceive and engage with technologies such as AI-enabled systems, where emotions, perceptions of trust, and feelings of agency are often central (Hansen, 2004; Lee and Lings, 2008).

Despite its strengths in capturing depth and meaning, interpretivism has been critiqued for its limited generalizability due to reliance on small, purposive samples

(Bryman, 2016; Lincoln and Guba, 1985). Its focus on subjective experiences can also overlook broader structural and technological factors such as algorithmic processes, organizational systems, and institutional constraints that shape individual interactions (Sayer, 1992; Bhaskar, 1978). In studying constructs like AICX, these limitations mean that interpretivist approaches alone may not fully capture the deeper causal mechanisms and wider organizational or technological contexts influencing customer experiences.

Nevertheless, interpretivism remains particularly well-suited for uncovering the nuanced ways in which individuals engage with and interpret AI-enabled technologies. It allows researchers to explore the subjective meanings and emotional dimensions of customer interactions which are areas that are often overlooked in more positivist paradigms. As such, while it may not fully address the complexities of structural causation, interpretivism offers essential insights into the personal, contextual, and relational aspects of AICX that are critical for understanding its multifaceted and dynamic nature.

4.2.3 Critical Realism

Critical realism, as developed by Roy Bhaskar (1975, 1978), offers a philosophically rigorous and methodologically versatile framework for investigating complex, layered, and causally rich phenomena. It combines a realist ontology with a constructivist-informed epistemology, holding that reality exists independently of human perceptions, but that our understanding of it is always mediated through theoretical, social, and historical contexts (Sayer, 2000; Archer *et al*., 1998). This dual stance, ontological realism and epistemological relativism, sets critical realism apart from both positivism and interpretivism. Unlike positivism, which prioritizes empirical regularities and the search for universal laws, or interpretivism, which centres on understanding subjective meanings within specific contexts, critical realism argues that social and technological phenomena have real underlying structures and mechanisms that can be identified, even if our interpretations of them remain provisional and open to revision (Bhaskar, 1978; Sayer, 2000).

At the core of critical realism is a stratified ontology that differentiates among three domains of reality: the empirical (experiences and observations), the actual (events that occur whether observed or not), and the real (underlying causal mechanisms) (Bhaskar, 1978; Danermark *et al*., 2002). This layered view of reality allows researchers to move beyond mere description and explore the generative structures that shape observable events. In the context of this study, this stratification is particularly relevant: while user experiences with AI-enhanced technologies (empirical) are easily captured through observations and interactions, they are shaped by events and processes (actual) that may not be directly visible to users, and these, in turn, are generated by deeper technological, organizational, and socio-cultural mechanisms (real).

Epistemologically, critical realism embraces a mode of reasoning known as retroduction, which involves inferring the most plausible mechanisms that could account for observed patterns (Danermark *et al*., 2002; Fletcher, 2017). For instance, in studying AICX, researchers might detect recurring patterns in customer satisfaction or engagement and then theorize about the cognitive, emotional, or structural factors driving these outcomes. Retroduction thus encourages the development of explanatory models that remain open to refinement and revision, reflecting the fallibility of knowledge while striving for greater explanatory power.

Methodologically, critical realism is characterized by pluralism and supports the use of both qualitative and quantitative approaches (Maxwell, 2012; Easton, 2010). This mixed-methods orientation is especially valuable for complex research topics such as AICX, where both subjective perceptions and objective behaviours play crucial roles. Qualitative methods, including ethnographic interviews, case studies, or user diaries, help to uncover the nuanced meanings and personal experiences that shape AICX. At the same time, quantitative methods such as surveys, usage logs, or behavioural data analyses can test hypotheses and validate patterns across larger samples. This dual capability is vital in capturing the multi-dimensional nature of AICX, which is simultaneously technological, psychological, and contextual.

While some critique critical realism for its abstract terminology and philosophical complexity, others argue that these features are precisely what make it robust and adaptable (Fletcher, 2017). It is not a simple compromise between positivism and interpretivism but rather a distinctive framework that values both structure and agency, causality and context, explanation and understanding (Sayer, 2000; Ackroyd and Fleetwood, 2004). This makes critical realism particularly appropriate for research in business, technology, and management domains, where phenomena are rarely reducible to isolated variables and instead emerge from dynamic interactions between material structures and human interpretations.

In this study, critical realism is identified as the most suitable philosophical stance for investigating AICX. AI-enhanced customer experiences are shaped by observable behaviours and interactions with AI systems, as well as by subjective perceptions, emotional responses, and broader organizational or technological influences. Critical realism's layered ontology enables the researcher to capture these different dimensions of reality and to explore how customer experiences are both constructed and caused. Its support for retroduction aligns with the need to theorize about the mechanisms that underlie observable patterns of engagement, satisfaction, or resistance in the context of AI-enhanced interactions.

Moreover, critical realism's endorsement of mixed methods is essential for addressing the complexity of AICX research. This study integrates interpretive insights from qualitative methods with the explanatory strengths of quantitative techniques to develop a holistic understanding of how customer experiences emerge, evolve, and vary across contexts. In doing so, critical realism provides the conceptual and methodological flexibility needed to capture the interplay between what is experienced and what produces those experiences linking user-level phenomena to deeper technological and organizational mechanisms. By offering a coherent and inclusive philosophical framework, critical realism enables this study to address the complex, emergent, and layered nature of AI-mediated customer experiences, laying a robust foundation for exploring AICX as both a technological and social phenomenon.

Table 4-2 Comparison of Philosophical Standpoints

	Positivism	**Interpretivism**	**Critical Realism**
Ontology	Reality is objective, external, and independent of the observer.	Reality is subjective, shaped by individual perceptions and social contexts.	Reality is stratified (empirical, actual, real) and includes latent constructs that can be indirectly measured.
Epistemology	Knowledge is gained through objective observation, measurement, and verification using standardized methods.	Knowledge is co-created by the researcher and participants, emphasizing subjective understanding and multiple realities.	Knowledge reflects an interplay of objective realities and subjective interpretations, validated through observable dimensions and causal mechanisms.
Axiology	Research is value-free; objectivity is paramount.	Research is value-laden; the researcher's perspectives and participants' values shape findings.	Research is influenced by values but strives for balanced objectivity through mixed methods and critical reflection.
Methodology	Deductive approach; quantitative methods such as experiments and statistical analysis are used to test hypotheses.	Inductive approach; qualitative methods like interviews and focus groups are used to explore subjective experiences.	Mixed-methods approach; integrates quantitative and qualitative techniques to validate and explore constructs.
Role of the researcher	The researcher is a detached, neutral observer ensuring objectivity.	The researcher is an active participant and co-creator of meaning with participants.	The researcher balances objectivity and subjectivity, acknowledging their influence while striving for reliable findings.
Nature of data	Quantitative, numeric data, focused on measurable variables.	Qualitative, narrative data, emphasizing depth and context.	A mix of numeric and narrative data, combining depth with generalizability.

Data analysis approach	Statistical, emphasizing testing and verification.	Thematic or interpretive, emphasizing meaning and understanding.	Integration of statistical and thematic methods to validate and explore constructs.
Level of generalizability	High; findings aim to establish universal truths.	Low; findings provide rich, context-specific insights.	Moderate to high; generalization achieved through combining quantitative validation with qualitative depth.
View on human behaviour	Predictable and governed by universal laws.	Complex and context-dependent, influenced by individual and social factors.	Complex but patterns and relationships can be identified through mixed-method approaches and causal mechanisms.
Treatment of bias	Strives to eliminate bias through standardized methods.	Accepts and incorporates bias as part of the research process.	Recognizes bias but seeks to mitigate it by balancing subjective and objective methods.
Strengths	Objectivity, replicability, and prediction.	Rich, detailed insights and understanding of subjective experiences.	Comprehensive understanding, balancing depth and breadth, suitable for complex phenomena.
Limitations	Struggles with subjective and latent constructs like emotions and perceptions.	Limited generalizability and vulnerability to researcher bias.	Complexity of mixed-methods design and the challenge of integrating quantitative and qualitative findings.
Application to AICX	Limited applicability due to difficulty in measuring subjective and latent constructs like emotions and perceptions.	Effective for exploring perceptions and emotions in AICX but lacks generalizability.	Suitable for studying AICX; incorporates subjective experiences, ensures generalizability, and uncovers underlying mechanisms.

Based on the earlier discussion and comparative evaluation of positivism, interpretivism, and critical realism, this study adopts critical realism as its guiding philosophical position. Critical realism is particularly well-suited to bridging the objectivist orientation of positivism with the subjectivist focus of interpretivism, thereby facilitating a balanced investigation of both observable phenomena and subjective experiences. Given the complexity of AICX which involves both measurable outcomes and context-dependent perceptions,critical realism provides the necessary philosophical and methodological flexibility. It supports the integration of qualitative and quantitative methods while enabling the identification of underlying mechanisms that shape observed patterns. This alignment ensures a comprehensive, rigorous, and contextually grounded understanding of AICX.

4.3 Approach to theory development

Three approaches exist for theory development: inductive, deductive, and abductive (Bell *et al*., 2022; Creswell and Creswell, 2023; Morgan, 2007; Saunders, Lewis and Thornhill, 2023). The inductive approach involves drawing general conclusions from specific observations, identifying patterns and trends in data to formulate theories. It is particularly suited for qualitative research and exploratory studies, where existing theoretical frameworks are insufficient, allowing researchers to build theories from the ground up (Corbin and Strauss, 2014; Thomas, 2022). Inductive reasoning is often associated with grounded theory, which emphasizes generating theory directly from data rather than relying on pre-existing frameworks (Glaser and Strauss, 2017). In contrast, the deductive approach derives specific conclusions from general principles, starting with established theories or hypotheses and applying them to specific contexts to test predictions. This approach is most effective for quantitative research and confirmatory studies, as it emphasizes validating or refuting predefined theories through structured methodologies and empirical evidence (Bell *et al*., 2022; Creswell and Creswell, 2023). Deductive reasoning is central to the scientific method, where hypotheses are tested against empirical data to establish generalizable knowledge (Morgan, 2007; Saunders, Lewis and Thornhill, 2023). Lastly, the abductive approach focuses on generating explanations for unexpected findings or emerging phenomena, offering creative interpretations by integrating existing theories and new observations. Described as "moves back and forth between induction and deductionfirst converting observations into theories and then assessing those theories through action" (Morgan, 2007, p. 71), it is particularly valuable in exploratory research and mixed-method studies, facilitating innovative insights when information is incomplete or ambiguous (Morgan, 2007; Tavory and Timmermans, 2014).

Each of these reasoning approaches is valuable, offering distinct strengths and serving different purposes, and it has been argued that they have a complementary nature (Van Maanen *et al*., 2007). In this thesis, abductive and inductive reasoning are applied in a complementary manner, with each approach utilized at different stages of the research process to address the complexities of the AICX construct. Specifically, inductive reasoning is employed in the SLR to lay the theoretical foundation for the AICX construct, while abductive reasoning guides the subsequent scale development process, integrating insights from the literature with empirical observations and iterative refinement.

A SLR can be considered inductive when it derives generalizable insights, themes, or frameworks from specific studies rather than testing pre-existing hypotheses. This aligns with the definition of inductive research, which builds theories or concepts from data, such as the literature being reviewed (Bell, Harley and Bryman, 2022; Saunders, Lewis and Thornhill, 2023). Methodologically, the SLR employed approaches like thematic synthesis to identify emerging patterns without starting from a predefined framework, reflecting an inductive process (Thomas and Harden, 2008; Braun and Clarke, 2006). Even when synthesizing empirical studies, the activity of integrating findings into broader conceptual themes or frameworks is inherently inductive, as it involves interpreting data to generate new insights (Dixon-Woods *et al*., 2005; Tranfield *et al*., 2003). Furthermore, the exploratory purpose of the SLR, aiming to describe or generate new insights rather than test hypotheses, aligns with an inductive approach (Gough *et al*., 2012). Thus, the SLR's inductive nature is evident in its methodology, purpose, and the conceptual activity of synthesizing literature.

Abductive reasoning served as the foundational approach to theory development in the AICX scale development study. This approach enabled the integration of potential items from previously published scales with context-specific insights derived from a netnography study. The initial pool of items was further refined through expert reviews, where retained items were iteratively compared against the theoretical definition of AICX and its dimensions. The process culminated in a quantitative phase, where insights from the qualitative phase were empirically evaluated. Established statistical methods were systematically applied to assess the robustness, reliability, and applicability of the measurement tool. This iterative process ensured that the scale accurately reflected the AICX construct, with continuous movement between data analysis and theoretical refinement to validate and refine the scale.

Given the nascent nature of the AICX construct and the limitations of existing frameworks, this approach was particularly suitable. The process began by identifying potential items from previously published scales, which provided a theoretical foundation. Concurrently, the netnography study yielded empirical observations that captured the contextual nuances of AICX. Through iterative cycles of comparison and refinement, first between items from published scales and those generated from the netnography study, second during two rounds of content and face validity assessments, and later during the quantitative analysis, theoretical and empirical insights were integrated. This iterative process involved revisiting and revising the item pool to ensure conceptual clarity and avoid redundancy.

4.4 Mixed method research

Mixed methods research has emerged as a distinct methodological approach, often described as the "third research community" (Johnson, Onwuegbuzie, and Turner, 2007; Tashakkori, Johnson and Teddlie, 2020; Teddlie and Tashakkori, 2010). Mixed methods can be traced back to the 1980s when researchers from diverse fields, including sociology, management, and education, independently recognized the potential of combining qualitative and quantitative methodologies (Creswell and Plano Clark, 2017). The origins of the mixed-methods movement can be traced to efforts to enhance research validity through diverse methodological approaches.

Campbell and Fisk's (1959) multi-trait-multi-method matrix introduced the idea of using multiple quantitative methods to distinguish between trait variance and method variance. In the 1970s, this concept expanded to include qualitative methods, with Jick (1979) emphasizing the complementary nature of quantitative and qualitative data, proposing methodological triangulation to improve accuracy and cross-validation when different methods produced consistent results. Similarly, Denzin (1978) advocated for multi-source data collection, and Cronbach (1975) encouraged incorporating qualitative elements into experimental designs. These advancements established a foundation for integrating diverse methods in research.

The formalization of mixed methods research as an independent paradigm was further advanced in the late 20th and early 21st centuries. Mixed methods research has progressed through a series of overlapping stages, each contributing to its development as a robust approach. The formative stage, prior to the 1980s, marked the early use of both qualitative and quantitative methods in an informal and largely exploratory manner, without a structured framework. During the paradigm stage (1980s–1990s), the focus turned to philosophical discussions around the compatibility of differing research paradigms, particularly the integration of positivist and constructivist perspectives. This stage played a key role in establishing the theoretical legitimacy of mixed methods. From the 1980s to the present, the procedural stage has emphasised the development of systematic guidelines, designs, and frameworks to support the effective integration of methods. The advocacy stage, beginning in the early 2000s, focused on promoting mixed methods as a practical and valuable approach for addressing complex research questions. Since the 2000s, the reflective stage has encouraged critical evaluation of mixed methods practice, drawing attention to its challenges, limitations, and opportunities for improvement. Finally, the expansion stage, emerging in the 2010s and continuing to the present, reflects the growing application of mixed methods across diverse research contexts, including program evaluation, longitudinal studies, and scale development, with increased adaptation to evolving technological and disciplinary demands.

The definition of mixed methods has been subject to diverse interpretations over time, with scholars emphasizing distinct dimensions, including its defining attributes, the methodological approaches used to examine it, the philosophical foundations informing its understanding, and the varying perspectives through which it is analysed (Creswell and Plano Clark, 2017; Tashakkori, Johnson and Teddlie, 2020; Teddlie and Tashakkori, 2010). Creswell and Plano Clark (2017) present an integrated perspective that combines methods, research design, and philosophy. They emphasize the key components of designing and conducting mixed methods research, proposing that it is a process in which the researcher:

> "Collects and analyses both qualitative and quantitative data rigoursly in response to research questions and hypothesis, integrates (or mixes or combines) the two forms of data and their results, organizes these procedures into specific research designs that provide the logic and procedures for conducting the study, and frames these procedures within theory and philosophy." (p. 5)

Mixed methods research offers numerous advantages. It enables researchers to draw on the strengths of both qualitative and quantitative approaches to address a broader range of research questions (Johnson and Onwuegbuzie, 2004). Additionally, it provides a holistic understanding of complex phenomena by integrating the depth of qualitative insights with the precision of quantitative data (Davis, Golicic and Boerstler, 2011). Moreover, mixed methods allow researchers to offset the weaknesses of one approach by leveraging the strengths of the other, thereby generating more comprehensive and nuanced findings (Johnson and Onwuegbuzie, 2004).

While offering a robust framework for addressing various research questions, mixed methods is not without challenges. Researchers must navigate the demands of mastering multiple methodological approaches, a process that can be both resource-intensive and time-consuming (Davis, Golicic and Boerstler, 2011). Discussions in the literature reflect on the difficulties inherent in effectively analysing and presenting results in mixed methods studies (Creswell and Creswell, 2023; Creswell and Plano Clark, 2017; Dawadi, Shrestha and Giri, 2021, Salehi and Golafshani, 2010). In the context of doctoral research, these challenges can be alleviated by the extended timelines and iterative nature of the process, enabling researchers to engage deeply with both qualitative and quantitative methodologies. To further navigate these complexities, researchers can choose from several mixed methods designs, each tailored to different research objectives and contexts. The following section explores these designs, highlighting their applications and suitability of the sequential exploratory design for addressing the objectives of this study.

4.4.1 Sequential Exploratory Design

Mixed methods research typically follow one of three core designs (see Table 4-3), each design serves a different intent and works better with different research problems (Creswell and Plano Clark, 2017). Concurrent designs involve the simultaneous collection and integration of data, allowing qualitative and quantitative methods to be used in parallel. In contrast, sequential designs consist of distinct phases, where one method informs the following. For example, in a sequential exploratory design, qualitative data is collected and analysed first to develop insights, which are then tested or expanded through quantitative methods. Conversely, a sequential explanatory design begins with quantitative data collection and analysis, followed by qualitative methods to help explain or interpret the quantitative findings.

Table 4-3: Mixed methods research designs. Adapted from Creswell and Plano Clark (2017)

Design	Details
Concurrent	Both qualitative and quantitative data are collected simultaneously, with integration occurring at the analysis or interpretation stage.
Sequential exploratory	Qualitative data is collected first, followed by quantitative data, with the goal of using qualitative findings to inform the quantitative phase.
Sequential explanatory	Quantitative data is collected first, followed by qualitative data to explain, or further explore quantitative findings.

The decision to conduct a mixed methods approach is largely driven by the nature of the research problem, as some problems are particularly well-suited to or can greatly benefit from this design. Previous literature has demonstrated the adoption of mixed methods in various fields, with scale development being a prominent example where qualitative insights are used to define constructs and generate items, and quantitative methods ensure rigorous validation and refinement. In this thesis, a mixed methods sequential exploratory design is adopted for the empirical part (see Figure 4-1), aligning with the theoretical and methodological requirements for developing scales in social science research (Creswell and Plano Clark, 2017; Creswell and Creswell, 2023).

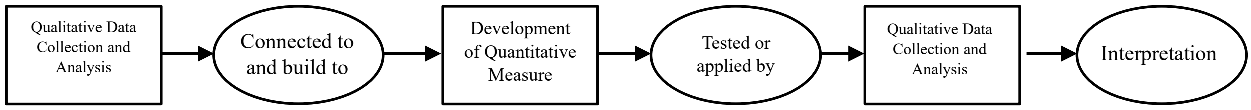


Figure 4-1: Sequential exploratory design. Adopted from Creswell and Plano Clark (2017)

The sequential exploratory design follows a three-stage process that integrates qualitative and quantitative methods to develop robust measurement scales. The qualitative phase is followed by a quantitative phase, with the development of the quantitative measure occurring in between. In this design, integration is a methodological necessity, ensuring that the conceptual insights generated in the qualitative phase directly inform the development and validation of the quantitative instrument (Creswell and Plano Clark, 2017). This alignment allows the exploratory and confirmatory components to form a coherent and rigorous research process.

The process begins with qualitative data collection and analysis to gain a deep understanding of the construct being measured, generate potential items for the scale, and identify key dimensions of the construct, in this case, AICX. In the second stage, the preliminary items generated from the qualitative phase are systematically reviewed and refined based on the rich, contextual insights, thereby informing the development of the quantitative measure. The process concludes with testing and validating the developed scale through statistical analysis based on quantitative data collection. This phase involves collecting quantitative data, which is then subjected to rigorous statistical analysis. Techniques such as factor analysis, reliability testing, and validation studies are employed to assess the scale's psychometric properties. The aim is to ensure that the scale is both reliable and valid, effectively measuring the construct across different contexts and populations.

Combining qualitative and quantitative approaches has become a common practice in recent scale development efforts (Chi, Chi and Gursoy, 2024; Rayburn *et al*., 2024; Zhou, 2019). One key advantage is the comprehensiveness in item generation, as qualitative methods, enable an in-depth exploration of constructs and diverse perspectives (Bryman, 2006a; Collins, Onwuegbuzie and Sutton, 2006). This is complemented by the rigorous validation offered through the sequential structure of mixed methods, which typically involves a qualitative phase to define constructs, an instrument development phase for item generation and refinement, and a quantitative phase to confirm and test the instrument (Creswell and Plano Clark, 2017). Mixed methods allow researchers to ensure that the scale is both theoretically grounded and practically relevant by combining exploratory insights from qualitative data with the empirical precision of quantitative validation. This approach also enhances the scale's ability to capture complex, multidimensional constructs, particularly in areas where existing measures are limited or inadequate.

Lastly, adopting a mixed methods sequential exploratory design aligns well with realism as a philosophical position, which prioritizes practical solutions and emphasizes answering research questions over strict adherence to philosophical traditions. This approach leverages the strengths of qualitative methods to uncover underlying structures, complemented by quantitative methods to test and validate findings. While offering substantial benefits, such as a comprehensive understanding of complex phenomena, mixed methods also present challenges, including managing the intricacies of data collection and analysis, coordinating timelines, and requiring proficiency in both methodologies. Nevertheless, when implemented thoughtfully, this design provides a robust framework for addressing research questions that exceed the capabilities of a single methodological approach, embodying realism’s commitment to both depth and practicality.

Building on this methodological foundation, the following chapter outlines the empirical execution of the sequential exploratory design, detailing the process of developing and validating the AICX scale as the central empirical contribution of this thesis.

Chapter 5 . Scale Development

This chapter presents the methodological foundation for the development of the AICX scale, which constitutes the core empirical contribution of this thesis. It begins with an overview of psychometrics and the evolution of structured measurement within the social sciences, establishing the relevance and rigour of capturing complex constructs such as AICX. Building on this foundation, the chapter outlines the theoretical and methodological frameworks that inform the scale development process, in alignment with the sequential exploratory mixed methods approach introduced in the previous chapter. It then details the key methodological steps undertaken in the development of the AICX scale, including netnography, expert panel reviews and surveys.

5.1 Psychometrics and the Evolution of Scale Development

Psychometrics, a key discipline within psychology, provides the theoretical framework and methodological tools for the development of reliable and valid measurement scales. It focuses on the development and application of methods to assess psychological traits, abilities, attitudes, and other latent, unobservable constructs (Furr, 2021). Although rooted in psychology, psychometrics has broad applications across the social sciences (Rust and Golombok, 2014; Kline, 2014). By offering a structured approach to capturing and quantifying intangible aspects of the social world, such as attitudes, perceptions, beliefs, behaviours, and, in this study, experiences, psychometrics facilitates the rigorous investigation of complex constructs. Central to its practice is the development of measurement instruments, including surveys and tests, that are both reliable and accurate (Furr, 2021; Rust and Golombok, 2014).

This process is grounded in the principles of measurement, a cornerstone of scientific inquiry (Furr, 2021; Netemeyer, Bearden and Sharma, 2003). It establishes clear rules for representing and quantifying phenomena, ensuring accurate and consistent measurement (DeVellis and Thorpe, 2021). Scale development embodies the practical application of psychometric principles, emphasizing the design, refinement, and validation of tools to measure latent constructs with precision and rigor (DeVellis and Thorpe, 2021).

Initially, scale development relied heavily on intuition and placed limited emphasis on statistical validation (DeVellis and Thorpe, 2021). Over time, however, the process has evolved substantially. Researchers have adopted more rigorous validation techniques and expanded the scope of scale development to address increasingly complex and multidimensional constructs. This evolution has also seen the integration of mixed methods, combining qualitative insights with the precision of quantitative analyses, and advanced statistical modeling (Kline, 2014, Zhou, 2019).

Recently, scale development has attracted growing scholarly attention, driven by the need for objective tools to assess emerging theories within the social sciences (Furr, 2021, Kline, 2014). This focus has been further reinforced by advancements in computational technologies and statistical methodologies, which have significantly enhanced both the efficiency and rigor of the process (Netemeyer, Bearden and Sharma, 2003). Consequently, scale development has transitioned from a primarily procedural exercise to a systematic and multidimensional field of study that integrates research design, implementation contexts, and practical applications (Bryman, 2006a; Collins, Onwuegbuzie, and Sutton, 2006; Greene, Caracelli, and Graham, 1989).

5.2 Theoretical and methodological framework: Scale Development

Approaches to scale development vary considerably, shaped by factors such as disciplinary traditions, methodological choices, cultural considerations, and the specific context of application (DeVellis and Thorpe, 2021; Netemeyer, Bearden and Sharma, 2003). Although the fundamental steps involved such as conceptualization, item generation, expert review, and validation, are often similar, the way they are presented whether as distinct steps, combined phases, or subdivided tasks, and the relative emphasis placed on each step can differ across studies depending on the methodological framework adopted. This research draws on established literature in marketing and adapts insights from previously validated scales in CX and related fields (Brakus, Schmitt and Zarantonello, 2009; Churchill, 1979; Gerbing and Anderson, 1988; Klaus and Maklan, 2012; Rossiter, 2002). Informed by this foundation, the study follows a six-step process for developing the AICX scale. Each step employs specific methods to achieve its immediate objectives while also guiding and refining subsequent steps, ensuring that the overall process remains both systematic and iterative.

Recognizing the early stage of research around AICX, this study begins by conceptualizing the construct, a necessary step when existing definitions are lacking, as is often the case with all emerging constructs (Brakus, Schmitt and Zarantonello, 2009). Conceptualizing AICX involves defining and operationalizing the construct to ensure a clear understanding of its dimensionality and scope, thereby laying the foundation for the subsequent stages of the process. The second step involves item generation, creating an extensive pool of items that capture the essence of the construct, drawing from existing scales (Bearden, Netemeyer and Teel, 1989; Brakus, Schmitt and Zarantonello, 2009; Garg *et al*., 2014; Kumar and Anjaly, 2017), as well as from qualitative methods such as interviews, focus groups, or netnography (Klaus and Maklan, 2012; Lin and Hsieh, 2011; Wang *et al*., 2024), as is the case in this project. In the third step, the generated item pool is reviewed by experts in the field to assess face and content validity (Bearden, Netemeyer and Teel, 1989; DeVellis and Thorpe, 2021; Klaus and Maklan, 2012). A measurement tool, a survey, is then typically designed using the refined list of items based on the expert review results and is subsequently used for pilot testing before full data collection (DeVellis and Thorpe, 2021; Froehle and Roth, 2004; Garg *et al*., 2014). The primary goal of the pilot testing phase is to assess the scale's effectiveness by collecting data from a real audience and proactively addressing any potential issues based on their feedback. Steps five and six involve distributing the survey to the target population, analysing the responses, and refining the survey using statistical techniques such as Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), thereby ultimately establishing the final scale (Brakus, Schmitt and Zarantonello, 2009; Klaus and Maklan, 2012; Kumar and Anjaly, 2017; Wang *et al*., 2024).

From a research design perspective, and as outlined in the previous chapter, this study adopts a mixed-methods sequential exploratory design to develop the AICX scale (Schaarschmidt, Walsh, and Evanschitzky, 2022; Zhou, 2019). This approach reflects the growing recognition of mixed methods as a means of enhancing both the conceptual robustness and psychometric quality of scale development (Johnson, Onwuegbuzie, and Turner, 2007; Collins, Onwuegbuzie, and Sutton, 2006; Zhou, 2019). The six steps discussed above are therefore visualized as two phases, each comprising three distinct steps. Steps one, two, and three constitute the qualitative phase of the process (see Chapter 5), while steps four, five, and six comprise the quantitative phase (see Chapter 6). The organization into two phases has been adapted to align with the structure of this thesis and the selected research design. Figure 5-1 illustrates this two-phase, six-step framework.

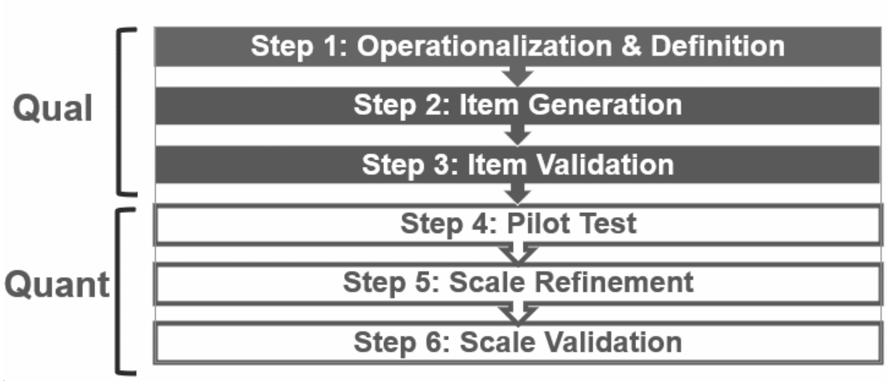


Figure 5-1: The AICX Scale Development Process

Building on the overall research design, it is essential to define the theoretical framework guiding the scale development process. In this study, the design, development, and validation of the AICX scale are grounded in Classical Test Theory (CTT), one of the most established and widely applied frameworks in psychometric research. CTT provides a robust basis for evaluating the reliability and validity of measurement instruments by focusing on the relationship among observed scores, true scores, and measurement error (DeVellis and Thorpe, 2021; Crocker and Algina, 2006). Its simplicity and intuitive structure make it particularly well-suited for early-stage scale development, where conceptual clarity, accessible statistical techniques, and an emphasis on scale-level properties are essential. CTT enables researchers to assess critical indicators such as internal consistency reliability (e.g., Cronbach's alpha), item-total correlations, and dimensionality through techniques like exploratory and confirmatory factor analysis. Furthermore, CTT's assumptions such as the notion that measurement error is random and that each item contributes equally to the true score, align well with the aims of constructing multi-item, theory-driven scales like AICX.

While modern psychometric frameworks such as Item Response Theory (IRT) and Rasch Measurement Theory offer more sophisticated item-level diagnostics, adaptive testing possibilities, and enhanced precision across varying levels of the latent trait (Andrich, 2011; Cai *et al*., 2016; Embretson and Reise, 2013; Petrillo *et al*., 2015), these advantages come at the cost of increased model complexity, larger sample size requirements, and more intensive computational demands. Given that the primary objectives of this study center on developing and validating a theory-grounded, multi-dimensional measurement tool rather than implementing fine-grained item-level scaling or adaptive administration, the use of IRT or Rasch modeling would introduce unnecessary complexity without proportional benefit. Moreover, CTT continues to underpin the vast majority of validated marketing and customer experience (CX) scales (Brakus, Schmitt and Zarantonello, 2009; Klaus and Maklan, 2012), demonstrating its enduring relevance and methodological suitability in fields where practical application and scale-level evaluation are prioritized.

Although CTT presents certain limitations, such as the sample dependence of reliability estimates and the assumption of uniform measurement error across the score range (Crocker and Algina, 2006; DeVellis and Thorpe, 2021), these constraints are not expected to significantly affect the aims or outcomes of the present research. Accordingly, CTT offers a methodologically coherent, pragmatically efficient, and academically sound framework for the development and validation of the AICX scale, as evidenced by its continued application in scale development studies within marketing and customer experience research (Brakus, Schmitt and Zarantonello, 2009; Klaus and Maklan, 2012; Wang *et al*., 2024).

Given the reliance on Classical Test Theory as the foundation for this scale development, particular attention must be directed toward establishing the scale's reliability and validity, two fundamental pillars that determine the quality and utility of measurement instruments (DeVellis and Thorpe, 2021; Netemeyer, Bearden and Sharma, 2003). Reliability focuses on the consistency and stability of the scale, ensuring that it produces dependable results free from random errors across various contexts and times. Validity, on the other hand, evaluates whether the scale measures what it is intended to measure, ensuring the accuracy and meaningfulness of the inferences drawn from its results (Raykov and Marcoulides, 2010). Together, these components form the backbone of a robust scale development process. The interplay between these two elements is crucial, as a scale must be both reliable and valid to provide credible and actionable insights into the construct being measured (DeVellis and Thorpe, 2021; Netemeyer, Bearden and Sharma, 2003; Raykov and Marcoulides, 2010). Without these components, the scale risks being ineffective, undermining the quality of research and decision-making based on its results. The following sections give more details on both.

5.3 Reliability

Reliability refers to the consistency and stability of a scale in measuring a construct across different contexts and samples (DeVellis and Thorpe, 2021; Netemeyer, Bearden and Sharma, 2003; Raykov and Marcoulides, 2010). In scale development, reliability ensures that the instrument provides dependable results that are free from random errors. High reliability is critical, as it confirms the scale's ability to produce stable results across its items, laying the groundwork for meaningful and credible analysis. Internal consistency reliability, often assessed through Cronbach's alpha, examines how well the items within a scale are interrelated, reflecting the coherence of the construct (Brakus, Schmitt and Zarantonello, 2009; Cronbach, 1951; Gahler, Klein and Paul, 2023; Wang *et al*., 2024). Composite reliability, a more robust measure, evaluates the reliability of latent constructs by taking into account the factor loadings and measurement errors of individual items, offering a more nuanced understanding of the scale's consistency (DeVellis and Thorpe, 2021; Bacon, Sauer, and Young, 1995; Peterson and Kim, 2013). . Details on establishing the AICX scale reliability are discussed in the quantitative phase (see Chapter 6).

5.4 Validity

Validity pertains to the extent to which a scale measures what it is intended to measure and supports accurate inferences based on its results (DeVellis and Thorpe, 2021; Netemeyer, Bearden and Sharma, 2003). Instead of viewing validity as divided into distinct types, it is more appropriate to consider it as a unified construct with interconnected facets, where all evidence and procedures collectively determine whether a test accurately measures what it is intended to (Jebb *et al*., 2021). Construct validity is the overarching goal, ensuring that the scale accurately measures the theoretical construct it is intended to represent (DeVellis and Thorpe, 2021; Netemeyer, Bearden and Sharma, 2003). To achieve this, different facets are systematically tested, providing a comprehensive approach to validating the scale under development. Table 5-1 below draws on foundational literature to detail the facets of validity considered in the development of the AICX scale (Borsboom, Mellenbergh, and van Heerden, 2004; Campbell and Fiske, 1959; Cronbach and Meehl, 1955; Fornell and Larcker, 1981; Haynes, Richard, and Kubany, 1995; Nevo, 1985). Details on establishing the AICX scale validity are discussed in the quantitative phase (see Chapter 6).

Table 5-1 Validity facets

Construct Validity Facet	Focus	Application to AICX Scale
Content Validity	Ensuring comprehensive representation of all theoretical dimensions of the construct.	The identified dimensions encompass all theoretically relevant aspects of the AICX construct, based on expert and theory-based reviews.
Discriminant Validity	Ensuring that the dimensions and overall construct are conceptually and statistically distinct.	Each dimension within the AICX scale is conceptually and statistically distinct, ensuring minimal overlap within the construct while maintaining coherence. Discriminant validity is further demonstrated by establishing the scale’s distinction from related constructs, such as customer satisfaction, trust, and engagement.

Convergent Validity	Demonstrating strong interrelationships among items within the same dimension or construct.	Items within individual AICX dimensions (e.g., Affinity, Advancement) exhibit strong internal correlations, supporting their consistency and theoretical alignment.
Face Validity	Evaluating whether the measure intuitively reflects the intended construct.	Experts and stakeholders confirm that the AICX scale aligns with perceptions of AICX and accurately captures its essence.
Nomological Validity	Verifying relationships between the construct and other theoretically connected constructs.	The AICX scale demonstrates predicted relationships with constructs like trust, satisfaction, and perceived value, consistent with theoretical frameworks.
Criterion Validity	Correlating with or predicting theoretically expected real-world behaviours or outcomes.	The AICX scale effectively predicts customer behaviours such as loyalty, advocacy, and engagement, demonstrating practical applicability in AI-driven service environments.

5.5 The AICX scale methodological decisions

The development of the AICX scale, as outlined above, employs a mixed-methods sequential exploratory design. This approach begins with a qualitative phase followed by a quantitative phase, with each phase comprising a series of carefully considered methodological decisions that collectively shape the scale's development. This section offers a discussion of the methods employed at each stage of the study, presented in the sequential order of their application.

Qualitative Phase

The primary objective of the qualitative phase was to establish a strong foundation for the subsequent quantitative phase by generating a comprehensive pool of items that would form the basis of the scale. Building on the thorough conceptualization of AICX, a netnography study was conducted to identify novel dimensions and generate additional potential items from qualitative data. Expert reviews were then employed to refine and evaluate the emerging list of items, ensuring their relevance and clarity. This section presents and discusses the two qualitative methods used for collecting primary data: netnography and expert reviews.

5.5.1 Netnography

Netnography is a qualitative research method that draws on fields like anthropology, sociology, and ethnography to explore the dynamics of the online world, uncovering rich insights into how people communicate, form relationships, and construct identities (Kozinets, 2002; 2010; 2012). Netnography has rapidly gained widespread acceptance and popularity across various disciplines, including services research (Kozinets, 2022). As social media and online platforms continue to play a prominent role in the modern lifestyle, netnography continues to grow as an established methodology. Since coined by Robert Kozinets in the late 1990s, many studies in the domain have adopted netnography (Bartl, Kannan and Stockinger, 2016; Kozinets and Gretzel, 2024), while not very common in scale development, it however started to be used in for this purpose recently (Wang *et al*., 2024; Wilk, Soutar and Harrigan, 2020). In this thesis, netnography is employed in the qualitative phase of the scale development process to generate potential scale items and complement the pool with items that reflect the interactions with AI-ETs.

Netnography can be conducted through two primary approaches: unobtrusive (or lurker) netnography and participative netnography (Azer and Alexander, 2018; Azer *et al*., 2021; Costello, McDermott and Wallace, 2017; Odekerken-Schröder *et al*., 2020). Unobtrusive netnography involves the researcher observing online interactions and behaviours without actively participating in the discussions. This silent observation ensures objectivity and minimizes the risk of influencing the community's dynamics, making it particularly effective for maintaining an unbiased perspective. In contrast, participative netnography requires the researcher to engage directly with the community, contributing to conversations and becoming an active member. This approach provides deeper insights into the community's culture, norms, and dynamics but comes with the potential drawback of introducing researcher bias due to direct involvement (Costello, McDermott and Wallace, 2017; Kozinets, 2010). Each type of netnography offers unique advantages, unobtrusive netnography however aligns more closely with the objectives of this thesis and will therefore be adopted.

Netnography allows researchers to immerse themselves in online communities and make use of publicly available online information, to observe and analyse customer interactions across diverse digital platforms (Kozinets, 2002; 2010). Forums, social media groups, and review websites, serve as vibrant environments where customers actively share their perspectives, recount personal experiences, and express opinions on a wide range of topics. Communities like Reddit threads, Facebook groups, or specialized platforms like TripAdvisor or Trustpilot enable customers to discuss everything from product functionality and customer support to interactions with AI-ET. These forums not only provide a platform for assessing service quality and empowering customers to voice their opinions but also foster peer-to-peer advice, comparisons of service quality, and discussions about emerging trends, offering researchers a wealth of authentic, real-time insights into customer behaviour and preferences (Kozinets and Gretzel, 2024). By leveraging the wealth of insights derived from these communities, researchers can uncover aspects of the experience that might be overlooked in other methodologies. For instance, user discussions may reveal unique emotional responses to interacting with AI-ETs, such as feelings of trust, frustration, or engagement. Such insights can inform the generation of new scale items, reduces potential biases, and ultimately facilitates the development of a comprehensive and contextually relevant pool of items.

Generating items that accurately reflect interactions with AI-ETs is significantly strengthened by drawing on direct experiences of participants who have prior experience with such technologies. However, this approach presents challenges, particularly within the time constraints of recruiting suitable participants for qualitative methods such as interviews, focus groups, or reflective journaling. Additionally, alternative approaches, such as creating a simulated environment to replicate AICX, are often impractical due to their complexity, high costs, and time-intensive nature.

The intended scale aims to measure the customer journey featuring one or more AI-ET, which, as noted earlier, can take diverse forms and serve various purposes throughout the customer journey. Traditional qualitative methodologies, such as ethnography, case studies, or in-depth interviews, often face limitations in capturing this diversity, as they may not fully encompass the breadth of interactions and experiences associated with AI-ETs (Denzin and Lincoln, 2011). Furthermore, time efficiency and the ability to gather data without requiring physical interaction are critical considerations, particularly given the lengthy process of scale development. Netnography, a qualitative research method tailored for online environments, addresses these challenges by enabling the researcher to collect rich, naturalistic data efficiently (Kozinets, 2010; Kozinets, 2015). An added advantage of netnography is its capacity to capture consumer reviews and feedback that are temporally close to the actual experiences being discussed, thereby enhancing the accuracy and relevance of the data (Kozinets, 2015; Heinonen and Medberg, 2018). Considering these factors, netnography emerges as a strategic and practical methodological choice for addressing the complexities of this scale development study.

Despite its advantages and demonstrated suitability, netnography, like many qualitative methods, is not without limitations. The method is heavily dependent on the accessibility and quality of online data, which may not always be representative of broader populations (Langer and Beckman, 2005; Kozinets, 2010). Ethical concerns, such as privacy issues and informed consent, are also prominent challenges when studying online spaces (Kozinets *et al*., 2010). Additionally, the potential for misinterpretation of digital communication, due to the absence of non-verbal cues, can complicate the validity of findings (Kozinets, 2010; Kozinets, 2015). Finally, the method's reliance on publicly available online interactions may lead to sampling bias, as it excludes private or offline perspectives that could provide a more holistic view. Nevertheless, these limitations are manageable, as careful selection criteria, transparent research practices, and adherence to established ethical guidelines can effectively address concerns around data quality and participant privacy. These considerations will be examined in greater detail in the following sections.

Netnography methodological decisions

Adopting netnography as a methodology requires thoughtful and informed decision-making to maximise its effectiveness, including careful attention to site selection, data collection procedures, and ethical considerations (Kozinets, 2010; Langer and Beckman, 2005; Xun and Reynolds, 2010). In this study, this involves selecting online platforms that offer relevant, authentic insights into customers' experiences with AI-ETs, and establishing a structured search strategy to guide data collection.

Both platform selection and search criteria must align closely with the study's objective that is identifying potential items for the development of the AICX measurement scale. Ensuring this alignment is critical to generating a rich, contextually grounded pool of potential items. The following sections outline the selected platforms and the corresponding search strategy in detail.

Platforms

Selecting appropriate online platforms is a critical step in netnographic research, as it directly affects the relevance, quality, and depth of the data collected. In line with Kozinets' (2010, 2020) guidelines on community selection, platforms were evaluated using four key criteria: (1) recent and consistent user activity, (2) a substantial and diverse user base, (3) descriptively rich user-generated content, and (4) evidence of dynamic interactions. These attributes ensure the data reflect authentic experiential engagement and support the robust development of AICX measurement items.

Following this framework, TripAdvisor and the Oculus App Store (now part of the Meta Store) were purposively selected. Both platforms satisfy the criteria and offer complementary perspectives. TripAdvisor represents physical-world service encounters in tourism, while the Oculus Store captures immersive, AI-driven experiences within digital environments, including tourism-related VR applications such as virtual tours, destination simulations, and cultural heritage experiences.

TripAdvisor is a globally recognised platform for travel-related user-generated content, hosting over one billion reviews across more than eight million listings worldwide (Statista, 2024). Users regularly share detailed accounts of their experiences with hotels, attractions, restaurants, and services often accompanied by images and ratings.

Given this study's focus on AI-ETs within the tourism sector, TripAdvisor offers a particularly relevant data source. It has been extensively used in prior netnographic studies to investigate customer engagement, value co-creation, and service experiences (Azer and Alexander, 2018; Garner and Kim, 2022; Islam, 2025; Kodaş, 2024; Küster and Vila, 2024). The platform's scale, high activity levels, and diverse global user base make it well-suited for identifying how travellers interact with AI-ETs.

The second selected platform is the Oculus App Store, now known as the Meta Store. This is the official application marketplace for Meta's VR headsets and serves as a central hub for virtual reality games, applications, and immersive experiences. It enables users to submit ratings and detailed reviews of their experiences, offering a rich and dynamic source of qualitative data. Incorporating the Oculus App Store provides access to the immersive end of extended reality (XR) applications, capturing how users engage with AI-ETs within virtual environments. The platform supports a large and diverse user base, including both tech-savvy individuals and general consumers, which ensures that data collected reflect a broad spectrum of perspectives and user experiences. Moreover, the high volume of verified customer reviews contributes to data credibility and depth, with many reviews offering spontaneous, descriptive feedback shortly after use.

Unlike traditional marketplaces, the Oculus Store also functions as a digital community ecosystem, where user engagement through ratings, comments, and discussions, is integral to its ongoing value (Nagta *et al*., 2022). Although the Oculus Store has not yet been prominently featured in netnographic research, its structural and behavioural characteristics align well with Kozinets' (2020) criteria for platform selection, making it a novel yet methodologically sound setting for exploring AI-influenced customer experiences.

The Oculus App Store is particularly valuable for identifying experiential dimensions relevant to AI-CX scale development. Reviews on the platform often discuss features such as personalization, intelligent responses, and adaptive environments, all of which are crucial for understanding how customers interact with AI-driven systems in natural, immersive settings (Vindenes and Wasson, 2021). As users engage with VR content over time, research suggests that they form habits and emotional attachments to these experiences which Stewart *et al*. (2025) refer to as digital habitats. These environments offer fertile ground for identifying cognitive, affective, and behavioural components of customer experience. Furthermore, the Oculus platform is becoming more relevant given the expanding role of VR and AR in tourism, education, and cultural heritage (Siddiqui *et al*., 2022). The rich, contextually embedded feedback found in user reviews offers strong empirical grounding for developing measurement items that reflect how AI technologies shape contemporary and future customer experiences (Rane, Choudhary, and Rane, 2023).

The second selected platform is Oculus App Store, now part of the Meta Store. It is the official marketplace for Meta's VR headsets. It hosts a wide range of VR games, applications, and immersive experiences, and allows users to submit ratings and in-depth written reviews. These reviews often offer spontaneous and reflective accounts of users' experiences with VR environments, frequently shortly after use contributing to the timeliness and authenticity of the data.

The Oculus Store is not merely a distribution platform; it functions as a digital community where users engage through feedback, questions, and commentary (Nagta *et al*., 2022). While not widely used in netnographic research to date, its behavioural and structural features align with Kozinets' (2020) selection criteria, positioning it as a valuable setting for examining AICX.

Importantly, Oculus reviews provide rich insights into AI features such as personalisation, intelligent responses, and adaptive environments (Vindenes and Wasson, 2021). These characteristics are central to the construction of a nuanced AICX scale. Research suggests that users form emotional attachments and habitual behaviours in immersive environments what Stewart *et al*. (2025) describe as digital habitats, which deepens the potential for understanding affective and behavioural aspects of AICX. However, and as VR and AR gain traction in tourism, education, and cultural heritage (Siddiqui *et al*., 2022), Oculus content becomes increasingly relevant to exploring how AI-ETs shape future-facing customer experiences. Reviews on this platform offer contextually rich feedback, helping to ground the development of empirically supported measurement items (Rane, Choudhary, and Rane, 2023).

As Kozinets (2020) argues, publicly available user-generated content, such as customer reviews, constitutes valid cultural data for netnographic research. Both platforms offer a wide range of tourism-related locations and applications that use and implement AI-ETs, which is the focus of this research study. The dual selection was strategic, aiming to complement one another and ensure the collection of representative data of various AI-ETs. Both TripAdvisor and the Oculus App Store were carefully chosen for this study as they offer a diverse range of tourism-related locations and applications that utilize AI-ETs, aligning closely with the research focus. Further, both platforms generate a high volume of posts, providing a rich and abundant source of data. The large and varied user bases on these platforms further enhance the representativeness of the collected data, capturing a broad spectrum of perspectives. The reviews posted on these platforms are typically detailed and descriptive, offering researchers valuable insights into customers' experiences with AI-ETs. Importantly, these reviews are often shared shortly after the experience, helping to mitigate the time lag issues commonly associated with other data collection methods. Furthermore, while interpersonal interaction among users is not a primary focus of this project, the platforms' ability to facilitate user engagement aligns with the framework guiding platform selection, contributing to the overall quality and depth of the data. These platforms align with Kozinets' framework, providing a strong justification for their selection (See Table 5-2).

Table 5-2 Netnography platforms

Platform	**TripAdvisor**	**Oculus Store**
Activity (Recent/Consistent Communication)	High activity with recent and consistent reviews and discussions.	High activity with frequent user ratings and reviews, as well as questions and answers.
Community (Substantial/Diverse)	Substantial and diverse user base, including travellers worldwide.	Large and diverse user base with a mix of tech enthusiasts and general users.
Data Richness (Descriptive)	Detailed reviews and images providing rich, authentic customer experiences.	Verified customer reviews offering detailed feedback on applications.
Engagement (Dynamic/Fluid Interactions)	Engagement through interactive discussions and responses to reviews.	User interactions are evident in ratings and reviews, fostering engagement.

By integrating TripAdvisor with the Oculus App Store, the study adopts a strategic dual-platform approach that captures a wide range of AI-ET experiences from real-world travel scenarios to cutting-edge immersive applications. This methodology facilitates a multi-contextual understanding of AICX, increasing the robustness and future relevance of the resulting measurement scale. From a methodological standpoint, the study adopts purposive sampling, a non-probabilistic technique commonly used in qualitative research to select data sources that are particularly rich and relevant (Huberman, 1994; Tashakkori, Johnson and Teddlie, 2020; Teddlie and Tashakkori, 2010). This approach ensures that the selected platforms are well-aligned with the research objectives and capable of yielding in-depth insights into customer interactions with AI-ETs.

Search strategy

The selection of platforms was informed by their alignment with the research objectives and their capacity to yield rich, meaningful insights into customers' experiences with AI-ETs. However, the complexity and abundance of data available on these platforms necessitate the development of a carefully designed methodical search strategy. This strategy is critical for filtering and identifying data that is both relevant and representative, ensuring the validity, academic rigor, and credibility of the insights generated. To achieve this, the search approach must strike a balance between comprehensiveness and precision, enabling the study to effectively navigate the dynamic digital landscape while remaining focused on its core objectives.

Developing the search strategy began with compiling a list of keywords representing various AI-ETs, formulated as clusters from the SLR outcomes to be used for platform searches. The process began with the use of generic keywords representing AI-ETs, such as "service robots", "intelligent voice assistants", and "virtual reality application". This initial step aimed to identify previously published reviews that could help inform the development of a more specific keyword list by reflecting the language used by customers in their reviews. Customers often avoid using highly technical terminology, such as "intelligent voice assistants" or "service robots" in their reviews. Therefore, while generic keywords are effective for broad searches, they may lack the richness and specificity required to fully capture customer perspectives. In response to this, the reviews retrieved using generic keywords were analysed to identify more specific terms commonly used by customers. Additionally, industry publications were consulted to further refine and expand the list of specific keywords, ensuring alignment with terminology relevant to the research context.

This iterative approach balanced comprehensiveness and precision, enabling the search strategy to effectively capture high-quality and relevant data.

A final list of 24 keywords was compiled and used to search through TripAdvisor (see Table 5-3). All results retrieved by the search query were retrieved manually and compiled in an excel sheet.

Table 5-3 Keywords for netnography search strategy

Keywords cluster 1	**Keywords cluster 2**	**Keywords cluster 3**
Extended Reality	Service Robots	Verbal and textual bots
Virtual reality	Robot	Alexa
Augmented reality	Robot concierge	Siri
Mixed reality	Yobot	Echo
Immersive reality	Cleo and Leo	Google Assistant
Extended reality	Yoshi and Yoland	Cortana
VR	Pepper	
MR	Connie	
AR	Dash	
XR	BellaBot	
	Whirl	

A comprehensive set of criteria was developed to systematically organize and filter the data. First, locations irrelevant to the search query, such as those where the query appeared only in the name of the location or as the name of a service employee were excluded. Second, locations with the most recent review older than one month were removed to ensure the data captured recent and up-to-date insights from actively reviewed locations. Third, only locations with more than ten direct keyword mentions were included, as this threshold indicated a high level of relevance. Locations that met these criteria were retained, aggregated into a single list, and arranged in ascending order based on the number of direct keyword mentions. For instance, locations retrieved using keywords like "virtual reality," "augmented reality," "mixed reality," "immersive reality," "extended reality," "AR," "VR," and "MR" were combined into a single list and sorted accordingly. This process was repeated for each keyword cluster, ensuring the selection of appropriate, relevant, and timely data sources for the netnography analysis.

Before initiating the data analysis process, a final verification step was undertaken to confirm that the selected locations or applications utilized AI. This step was important given the previously noted prevalence of misconceptions about AI, where its capabilities and integration are often misrepresented (Wang, 2007; Emmert-Streib *et al*., 2020). To mitigate the risk of such inaccuracies, this verification ensured alignment with the conceptualization of AI-ETs and upheld the validity of the subsequent analysis (Ghesh, Alexander and Davis, 2024). For service robots and virtual or textual bots, the devices' names or model numbers were examined to verify their use of AI, confirming their eligibility for inclusion. For XR applications, where the utilization of AI can be more ambiguous, the researcher contacted service providers and technology developers to confirm AI integration in the offered AICX. After this thorough validation, the top two locations with the highest number of direct mentions meeting all previously discussed criteria were selected from each list (see Table 5-4).

The search strategy on the Oculus Store was more straightforward. Generic contextual keywords, specifically "Tourism" and "Travel," were used to identify data sources. Considering the direct utilization of AI in this particular wearable device, all retrieved applications were compiled into a single list. From this list, the two applications with the highest number of ratings were selected for further analysis.

Analytical approach

Various methodological approaches exist for analysing qualitative data (Dixon-Woods *et al*., 2005; Miles, Huberman, and Saldaña, 2020). In this netnography study, thematic analysis was employed to support the objective of identifying potential items for the AICX scale. Thematic analysis is a flexible and widely adopted method in qualitative research that entails systematically identifying, coding, categorizing, and interpreting recurrent patterns or themes within the data (Braun and Clarke, 2006; Nowell *et al*., 2017). This approach facilitates the extraction of meaningful insights while preserving analytical structure and transparency (Guest, MacQueen, and Namey, 2012).

Table 5-4 Overview of netnography platforms and data collected

AI-ET Cluster	AI Subfield	Platform	Location Name	Description	Geographical Location	Number of retrieved reviews
Extended Reality	Computer Vision	TripAdvisor	The Gunpowder Plot	An immersive experience in London that combines live theatre and virtual reality to transport visitors back to 1605, allowing them to become part of the infamous Gunpowder Plot.	United Kingdom	343
	Computer Vision		Historium Brugge	A popular attraction in Bruges, Belgium, offering visitors a journey back to the city's medieval past through interactive exhibits and virtual reality experiences.	Belgium	257
	Computer Vision, Machine Learning	Oculus Store	Wander	An application available on the Oculus Quest platform that allows users to virtually explore various locations around the world, providing an immersive travel experience from anywhere.	Virtual	1037
	Computer Vision		National Geographic Explorer VR	A virtual reality application that offers immersive experiences based on National Geographic's explorations, allowing users to engage with diverse	Virtual	756

				environments and stories from around the globe.		
Service Robots	Robotics, Computer Vision, Natural Language Processing	TripAdvsisor	Yotel Singapore	A modern hotel located in the heart of Singapore, known for its innovative use of technology and compact, efficiently designed rooms that cater to contemporary travellers.	Singapore	906
	Robotics, Computer Vision, Natural Language Processing		Hotel EMC2, Autograph Collection	A boutique hotel in Chicago that blends art and science themes throughout its design, featuring unique amenities and a commitment to creativity and innovation.	USA	389
Verbal and Textual Bots	Natural Language Processing	TripAdvisor	Wynn Las Vegas	A luxury resort and casino located on the Las Vegas Strip, renowned for its opulent accommodations, fine dining, and entertainment options.	USA	249
	Natural Language Processing, Expert Systems		ACME Hotel Company	A boutique hotel in Chicago's River North neighbourhood, offering a trendy and tech-forward experience with modern amenities and a focus on style and comfort.	USA	123

Note: The column 'AI Subfield' refers to the specific area within the broader field of AI to which each AI-ET belongs. These subfields include:

Computer Vision: AI systems that interpret and process visual inputs such as images, video, and facial recognition. **Natural Language Processing**: AI systems that understand, generate, or interact through human language (e.g., chatbots, voice assistants). **Machine Learning**: Algorithms that identify patterns in data to make decisions or predictions. **Expert Systems**: AI that mimics human decision-making by applying rules or domain-specific knowledge bases. **Robotics**: Embodied AI agents that perform physical tasks and may integrate multiple AI capabilities like computer vision and natural language processing

Thematic analysis can be conducted through either an inductive or deductive approach (Braun and Clarke, 2006; Dixon-Woods *et al*., 2005; Stein and Ramaseshan, 2016). An inductive approach allows themes to emerge directly from the data, underscoring an exploratory, data-driven orientation that is particularly well-suited for studies investigating novel or evolving constructs (Thomas, 2006). Conversely, a deductive approach begins with pre-established themes informed by existing theoretical frameworks or research questions, offering a more confirmatory analytical route (Fereday and Muir-Cochrane, 2006).

For the purposes of this netnography study, an inductive thematic analysis was adopted to align with the aim of developing new scale items and to capture the emergent nature of the AICX construct. By allowing themes to arise organically from the rich, user-generated content analysed, this method supports a holistic exploration of customer experiences with AI-ETs. It enables the identification of novel dimensions and insights that may not be anticipated within pre-existing theoretical boundaries. This ensures that the resulting scale reflects the complexity and uniqueness of customer interactions with AI-ETs.

5.5.2 Expert panels reviews

Expert panels or expert judges' reviews are widely recognized as an invaluable step in the process of developing measurement scales (Grant and Davis, 1997; Rossiter, 2002). This approach parallels the established significance of peer review in research evaluation, which plays a critical role in assessing the quality and relevance of academic contributions (Langfeldt, 2004). The primary objective of expert panel reviews is to leverage the advanced knowledge and experience of individuals in a specific domain, obtaining informed feedback on key aspects of the scale under development. They play a central role after the initial conceptualization of the construct by ensuring that the pool of items accurately represents its dimensions and by addressing gaps, ambiguities, or redundancies.

In scale development, expert panel reviews provide essential feedback that ensures rigor and precision while contributing to the validity of scales, particularly content and face validity (Hardesty and Bearden, 2004). Experts review items, evaluate them, and suggest edits to improve their reliability, reduce ambiguity, and eliminate irrelevant ones (De Vellis and Thorpe, 2021), thereby ensuring that the remaining items align closely with the construct's definition and meet standards of clarity and relevance. Further, expert panels offer contextually grounded insights that are otherwise unattainable, often highlighting overlooked dimensions or aspects of the phenomenon under study. This process may lead to a refined or even redefined construct, resulting in improved conceptual clarity, and ensuring that the research instrument is comprehensive and aligned with its theoretical foundations.

Despite their advantages, expert panel reviews are not without challenges. Bias can arise from subjective interpretations, and the process of identifying and engaging experts can be time-intensive and resource-demanding (Langfeldt, 2004). Additionally, a lack of diversity among experts may limit the inclusivity of feedback, restricting the scope and perspective of the resulting scale. To mitigate these challenges, researchers are encouraged to report details such as the number of judges, their qualifications that justify their selection, and the specific procedures followed.

Ultimately, expert panels are viewed as a structured approach to integrating domain-specific knowledge into the research process and a trusted and widely recognized methodological step in scale development. Their involvement not only enhances the psychometric soundness of scales but also reflects best practices for creating robust and valid measurement tools (Hardesty and Bearden, 2004). Researchers are however encouraged to report detailed information about the procedures followed when utilizing expert panel reviews, including the number of judges, their qualifications that justify their selection, and the specific methods employed. This transparency enhances reproducibility and ultimately contributes to the overall rigor of the research (Irwing, Booth and Hughes, 2018; Kyriazos and Stalikas, 2018).

Utilizing expert panels implies using a purposive sampling technique - also known as judgmental or selective sample. Purposive sampling is a non-probability sampling technique where researchers select participants based on specific characteristics or criteria pertinent to the research question (Saunders, Lewis and Thornhill, 2023). This method ensures the inclusion of individuals who possess expertise, knowledge, or traits essential for providing valuable and relevant insights. Unlike random sampling, purposive sampling is intentional and focused, aiming to gather in-depth understanding from a targeted subgroup rather than seeking to generalize findings to a larger population. This aligns with the overall objective of utilizing expert panels to provide insights and feedback based on their knowledge and expertise, as well as the practical approach used to recruit these experts.

In developing the AICX scale, expert reviews were conducted to evaluate the generated pool of potential items, thereby ensuring the content and face validity of the scale. A purposive sampling technique was employed to recruit experts with relevant experience in AICX, including scholars with expertise in a related field and PhD students focusing on relevant research. Potential participants were identified through professional networks and invited via email to take part in the study. A total of 14 experts were invited, of whom 10 accepted the invitation. Literature suggests that recruiting a sufficiently large number of experts, typically between 6 and 15, provides diverse and valuable insights (DeVellis and Thorpe, 2021). Experts who agreed to participate were requested to confirm their consent by replying to the email invitation.

Expert responses were collected using Qualtrics through two distinct surveys designed for this study. The first survey focused on evaluating content validity, while the second, informed by the results of the first, aimed to assess face validity. Experts were divided into two panels: one for evaluating content validity and the other for assessing face validity. Responses from both surveys were transferred to an Excel sheet for detailed examination and manually analysed. A comprehensive overview of the review process, results, full pool of items, and details of items removed and retained is presented in the empirical chapter (see Chapter 5, Section 4).

Quantitative phase

The primary objective of the quantitative phase was to empirically refine and validate the scale by testing the item pool developed during the qualitative phase. Building on the foundation established through netnography and expert input, a series of structured surveys was conducted to evaluate the performance of the items and confirm the underlying dimensions of the AICX construct. The surveys were developed using Qualtrics, which supported the design and delivery of consistent, customizable instruments. Participants were recruited via Prolific, using screening filters to ensure alignment with the target population. A purposive-convenience sampling strategy was employed to ensure both accessibility and relevance. This section provides a detailed account of the primary data collection method employed in this phase, survey, together with the platforms used for survey administration and participant recruitment, the sampling strategy adopted, and the statistical techniques utilised to validate the scale.

5.5.3 Surveys

Surveys are systematic methods for collecting data from a sample of respondents to gather information on their characteristics, opinions, attitudes, and behaviours. They are widely adopted in the broad domain of social sciences (Saunders, Lewis and Thornhill, 2023). Surveys are well-suited for large-scale research projects that involve multiple rounds of data collection and analysis. This positions surveys as a practical and logical methodological choice for scale development, where multiple rounds of data collection and analysis with representative samples are essential.

Surveys provide a structured and standardized approach to data collection, ensuring consistency across participants and supporting data quality, factors essential for refining the scale structure and establishing construct and criterion validity (DeVellis and Thorpe, 2021; Netemeyer, Bearden and Sharma, 2003). Their flexibility, particularly in online distribution through platforms such as Qualtrics or SurveyMonkey, allows researchers to efficiently and effectively reach target populations while reducing administrative burden (Bell, Harley and Bryman, 2022; Fowler, 2014). Additionally, large sample sizes obtained through surveys are crucial for statistical analyses, such as exploratory and confirmatory factor analysis, which underpin the identification and validation of underlying factor structures in scale development (Fabrigar *et al.*, 1999; Worthington and Whittaker, 2006). These methodological strengths make surveys a widely adopted and reliable approach in empirical scale development research (Boateng *et al.*, 2018).

While surveys are highly advantageous, they are not without limitations, which must be carefully considered in the context of scale development. A primary challenge lies in the extensive planning and methodological expertise required to ensure survey effectiveness and accuracy. Survey instruments must be thoughtfully designed with attention to item clarity, appropriate scaling, and conceptual relevance to the construct being measured (Fowler, 2014; Clark and Watson, 1995). In the context of scale development, this process is particularly critical, as the success of the measurement tool depends on how well the items capture the construct's theoretical dimensions (DeVellis and Thorpe, 2021). Expert reviews and pretesting are integral to ensuring these criteria are met, and failure to rigorously validate the survey tool can compromise data reliability and the scale's psychometric soundness (Boateng *et al*., 2018).

Another notable limitation is the challenge of recruiting participants who match the target criteria needed for meaningful responses. This can be particularly difficult when working with niche or hard-to-reach populations, often requiring significant time and resources (Bell, Harley and Bryman, 2022). While surveys are sometimes viewed as cost-effective, the development of high-quality instruments, participant recruitment, and data management require substantial investment. To mitigate these issues, researchers increasingly rely on third-party platforms and online recruitment services—such as Prolific or MTurk—which facilitate targeted recruitment and enable access to specific demographics (Palan and Schitter, 2018; Behrend *et al*., 2011). These tools streamline the data collection process and enhance the feasibility of large-scale studies, particularly in online research contexts.

Ultimately, surveys offer a systematic approach to collecting participant data for the refinement and validation of scales. Their structured nature and compatibility with psychometric testing methods make them a cornerstone in the development of measurement instruments (Netemeyer, Bearden and Sharma, 2003; Worthington and Whittaker, 2006). They also allow for meaningful engagement with the target population, enabling the evaluation of item relevance, clarity, and construct alignment—hallmarks of robust scale development. In line with these methodological best practices, the survey method was employed to develop and validate the AICX scale.

Surveys were integral to the quantitative phase of this research, encompassing the pilot study and all subsequent rounds of data collection and analysis. These surveys were developed using Qualtrics, a highly regarded platform for creating and managing online surveys. Participants were recruited through Prolific, an online participant recruitment platform known for its diverse pool of respondents. To ensure alignment with the study's focus, filters were applied to identify individuals who met specific demographic and behavioural criteria. This approach exemplifies purposive sampling within a broader convenience sample, enabling the collection of relevant and contextually appropriate data. Each round of data collection employed distinct analytical techniques, serving specific purposes in the iterative process of scale development, which ensured a thorough approach to refining and validating the scale. The main analytical techniques employed were exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The following sections provide detailed information about the use of Qualtrics and Prolific as tools for implementing the survey, the adopted sampling approach, and an overview of the key analytical techniques employed—exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Survey Design and Participant Recruitment Tools

Qualtrics

Qualtrics is a widely used online survey platform in academic research, valued for its ability to support complex survey designs, data collection workflows, and participant management across various fields (Holt and Loraas, 2019; Weber, 2021). Researchers use Qualtrics to design surveys tailored to specific research objectives, incorporating various question types, logic flows, and multimedia elements. In this study, Qualtrics was employed to develop and administer surveys used in the quantitative phase, including the pilot study and subsequent data collection rounds, as well as expert panel surveys assessing content and face validity. Its features enabled the seamless design of surveys aligned with the study's focus, ensuring clarity, consistency, and accessibility for respondents. Additionally, Qualtrics' integration with data analysis tools streamlined the export and preparation of collected data for further statistical analyses, supporting the process of scale development.

Prolific

Prolific is an online participant recruitment platform that is widely adopted in academic research for sourcing high-quality and diverse respondents. It is particularly valued for its transparency, ease of use, and its advanced filtering features that enable targeting participants based on specific demographic or behavioural criteria (Palan and Schitter, 2018). Unlike general-purpose crowdsourcing platforms such as Amazon Mechanical Turk (MTurk), Prolific was designed specifically for academic research, offering robust pre-screening tools, fair pay guidelines, and mechanisms to promote ethical research practices. Peer *et al*. (2022) found that Prolific consistently outperformed other platforms on key dimensions of data quality, including attention, comprehension, and honesty, concluding that it was the only platform in their comparative study to provide high-quality data across all measures without applying quality filters.

In this study, Prolific was used to recruit participants for all rounds of data collection, including pilot studies. Filters were applied to purposively sample individuals with prior experience interacting with AI-ETs in service contexts. This purposive sampling within a broader convenience sample allowed for efficient targeting while maintaining methodological rigor. The platform's functionality supported timely recruitment of a representative and contextually relevant participant pool, contributing to the overall reliability and validity of the study data (Palan and Schitter, 2018; Peer *et al*., 2022).

Sampling technique

Purposive sampling and convenience sampling are two distinct non-probability sampling techniques frequently employed in social science and applied research (Etikan, Musa and Alkassim, 2016; Saunders, Lewis and Thornhill, 2023). Convenience sampling involves selecting participants who are easily accessible or readily available, making it a practical and efficient choice for initial recruitment, particularly in large-scale or online studies (Creswell and Poth, 2016). However, convenience sampling alone may lack the precision required to ensure that the selected sample aligns closely with the specific research objectives, potentially limiting the depth and applicability of findings (Palinkas *et al*., 2015).

In contrast, purposive sampling is a deliberate strategy in which participants are selected based on predefined characteristics or experiences relevant to the research question. This technique enables researchers to focus on information-rich cases, particularly those expected to provide deep insights into the studied phenomenon (Teddlie and Yu, 2007; Patton, 2015). Purposive sampling is especially valuable in exploratory studies and scale development, where the relevance of the data is often prioritized over generalizability (Palinkas *et al*., 2015). Campbell *et al*. (2020) further emphasize the importance of targeted participant selection in health and social research, noting that purposive approaches enhance the contextual validity of data when used systematically.

Importantly, these two methods can be combined to form a robust sampling framework. As Teddlie and Yu (2007) note, integrating purposive sampling within a broader convenience sampling strategy can strike a balance between accessibility and specificity—leveraging the logistical ease of convenience sampling while ensuring the sample meets rigorous inclusion criteria.

In this study, Prolific was employed to recruit a diverse participant pool through convenience sampling. To refine the sample, purposive sampling was implemented using pre-screening filters that targeted individuals based on specific demographic and behavioural attributes relevant to the research objective—namely, collecting responses from customers with prior interactions with AI-ETs in service contexts. This integrated approach offered several advantages: it facilitated rapid and scalable access to a large, diverse participant base while ensuring that the final sample was contextually appropriate and methodologically sound. This combination proved particularly valuable in the development and validation of the AICX scale, enabling the collection of high-quality, relevant data aligned with the study's conceptual framework (Palinkas *et al*., 2015; Campbell *et al*., 2020).

Analytical techniques

The development and validation of measurement scales rely on robust analytical techniques to ensure their psychometric soundness and alignment with theoretical constructs (DeVellis and Thorpe, 2021; Hair *et al*., 2019). Two techniques, EFA and CFA, are foundational in scale development studies. EFA is typically employed in the early stages to uncover and explore the underlying factor structure of a construct, while CFA is applied later to test and validate the hypothesized structure against observed data. Together, these techniques provide a systematic and iterative framework for refining and validating scales.

EFA is a statistical technique used to uncover the underlying structure of a set of observed variables (Costello and Osborne, 2005; Hair *et al*., 2019). It is particularly valuable in the initial stages of scale development, where the primary goal is to identify potential dimensions of a construct without imposing a predefined structure (DeVellis and Thorpe, 2021). EFA works by examining the relationships between variables and determining how they group together based on their correlations, providing insights into the latent factors that represent the construct. EFA employ various extraction methods, for example, principal axis factoring (PAF) or maximum likelihood (ML), focusing on shared variance among items (common variance) to identify latent constructs (Carpenter, 2017; Watkins, 2018; Costello and Osborne, 2005). After extraction, rotation methods like Varimax (orthogonal) or Promax (oblique) are applied to clarify the factor solution, making it easier to interpret.

The output of EFA includes factor loadings, which indicate the strength of the relationship between each item and its associated factor, and eigenvalues, which help determine the number of meaningful factors (Fabrigar *et al*., 1999; Tabachnick and Fidell, 2019). EFA therefore aids in refining the item pool by identifying weak items that do not load strongly on any factor or those that cross-load on multiple factors. This iterative process ensures that the final set of items is both representative and distinct for each dimension of the construct. Overall, EFA lays the foundation for subsequent analyses by offering a preliminary understanding of the construct's structure and guiding the refinement of the scale.

Building on the results of EFA, CFA is another statistical technique used to test and validate the identified factor structure. Unlike EFA, which explores potential factor structures, CFA is a theory-driven approach that evaluates the fit of a predefined model to observed data (DeVellis and Thorpe, 2021; Worthington and Whittaker, 2006; Brown, 2015). It serves as a critical step in scale development, ensuring the hypothesized structure aligns with theoretical expectations and empirical data. CFA assesses the relationships between observed variables (items) and their underlying latent constructs (factors/dimensions). It relies on a series of fit indices, such as chi-square (χ^2), root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker-Lewis index (TLI), to determine how well the proposed model fits the data (Kline, 2016; Hu and Bentler, 1999).

Fit indices provide evidence for the validity of the factor structure, including construct validity (how well the scale measures the intended construct) and discriminant validity (how distinct the factors are from one another). In addition, CFA estimates parameters such as factor loadings, measurement errors, and factor covariances, which are essential for evaluating the reliability of the scale and identifying areas for improvement. Based on the modification indices provided by the model, adjustments can be applied to enhance model fit (Brown, 2015, Byrne, 2013). By confirming the factor structure and ensuring the scale's psychometric properties are robust, CFA completes the iterative process of scale development. It provides researchers with confidence that the measurement instrument is both valid and reliable, supporting its use in subsequent empirical research.

Together, EFA and CFA form a comprehensive framework for developing and validating scales. In scale development studies, employing both techniques is considered standard practice, as widely endorsed in methodological literature and consistently applied in empirical research, EFA to explore and identify the factor structure, and CFA to confirm and validate it (Clark and Watson, 1995; Fabrigar *et al.*, 1999; Worthington and Whittaker, 2006; DeVellis and Thorpe, 2021; Brown, 2015; Brakus, Schmitt and Zarantonello, 2009; Wang *et al.*, 2024). While many technical aspects of these approaches could be detailed, the specific discussions are more appropriately situated in Chapter 6. This placement aligns with the iterative nature of scale development, where the technicalities of applying these methods are best addressed alongside the presentation and interpretation of results.

5.6 Ethical Considerations

This research consistently implemented careful practices across its various methodological decisions undertaken, prioritizing the protection and well-being of all participants involved. It was conducted in accordance with the British Psychological Society's latest ethical standards, including the *Code of Human Research Ethics* (British Psychological Society, 2021a), the *Ethics Guidelines for Internet-Mediated Research* (British Psychological Society, 2021b), and the *Code of Ethics and Conduct* (British Psychological Society, 2021c), ensuring the protection, autonomy, and well-being of all participants across both digital and in-person phases of the study.

During the netnography phase, which relied on publicly available data, the requirement for explicit consent was waived, as ethical guidance allows the use of publicly accessible online content without participant consent under certain conditions (Kozinets, 2020; Eysenbach and Till, 2001). In the content and face validity evaluations involving experts, personalized invitations were extended, thoroughly outlining the study's objectives and enabling informed participation (Haynes, Richard and Kubany, 1995; DeVellis and Thorpe, 2021).

Participants recruited through the Prolific platform were presented with a participant information sheet at the beginning of the survey's, clarifying study purposes and obtaining explicit consent through signature confirmation, in line with ethical research practice in digital data collection (Palan and Schitter, 2018; British Psychological Society, 2021a). For experts engaged in content and face validity assessments, a dedicated channel for feedback and communication was established, facilitating an open dialogue to address any queries or concerns, thus emphasizing engagement and autonomy throughout the research process (DeVellis and Thorpe, 2021).

As for participants in scale refinement and validation, the use of Prolific for participant recruitment adhered to robust ethical considerations, with explicit consent obtained and transparent communication regarding the study's objectives, reflecting a strong commitment to ethical practice (Palan and Schitter, 2018; Economic and Social Research Council, 2015). To protect participant identities, rigorous protocols were implemented, ensuring anonymity throughout all phases—data collected from Prolific and experts was anonymized to prevent individual identification (Wiles *et al*., 2008; Braun and Clarke, 2021). Participants were assured of the voluntary nature of their involvement, with the freedom to withdraw from the study at any time without facing repercussions, a principle clearly outlined in the participant information sheet (British Psychological Society, 2021a).

Further, a robust data security protocol was implemented, ensuring secure storage of all collected data on a password-protected university laptop, with access restricted solely to the designated researcher, in line with institutional and national research ethics frameworks (Economic and Social Research Council, 2015; British Psychological Society, 2021c). Finally, the research received thorough review and approval from the department's ethics committee, affirming compliance with the university’s ethical guidelines (British Psychological Society, 2021b). This endorsement reflects the commitment to upholding the highest standards of ethical integrity throughout the research project.

Chapter 6 .The AICX Scale Development - Qualitative Phase

This chapter outlines the qualitative phase of the AICX scale development process, which establishes the foundation for the entire empirical part of the thesis. The process begins with an overview of previously published on CX and related constructs. It then moves on to operationalizing the AICX construct, clearly defining it and identifying its scope and key dimensions. This leads to a comprehensive conceptualization of the intended AICX scale, discussing characteristics such as measurement model, scale polarity and interpretation. Next, a pool of potential items is generated, drawing from two key sources: a thorough review of previously published scales that measure related constructs, as well as insights gained from a netnography study exploring customer reviews of real-life AICX. The phase concludes with an evaluation of the items' face and content validity, ensuring they accurately reflect the AICX construct through an expert review process. Figure 6-1 illustrates the three steps of this qualitative phase.

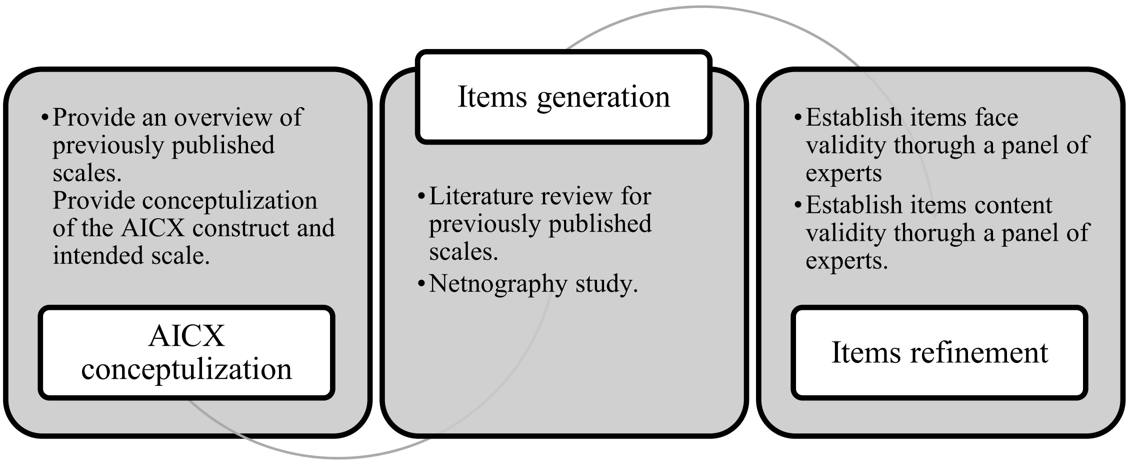


Figure 6-1 The AICX Scale - Qualitative Phase

6.1 AICX Conceptualization

Defining and operationalizing the construct of interest is a critical first step in the scale development process (Brakus, Schmitt and Zarantonello, 2009). A clear and well-articulated conceptualization provides the foundational framework that guides all subsequent stages (DeVellis and Thorpe, 2021). This process begins with a review of existing, validated scales to understand prior conceptualizations and measurement approaches, followed by a careful delineation of the construct's scope and dimensionality to ensure clarity and precision in measurement.

Specifically, this involves both defining the construct itself and articulating the intended purpose, structure, and parameters of the scale. In the context of this study, it entails clarifying the meaning of AICX, identifying its core dimensions, and establishing what the scale is designed to measure, as well as how its results should be interpreted. Accordingly, this section begins with an overview of relevant existing scales, then proceeds to conceptualize and operationalize AICX as a distinct construct. It further outlines the scale's dimensionality, scope, measurement model, and polarity, and concludes with a discussion on how the resulting AICX scores should be interpreted.

6.1.1 Overview of previously published scales

A comprehensive review of previously published scales was undertaken as a foundational step in the conceptualization of the construct (Froehle and Roth, 2004; Wang et al., 2024). This review serves several purposes within the scale development process: it establishes theoretical grounding, identifies conceptual and methodological limitations in existing instruments, avoids unnecessary redundancy, and informs the generation of new items by drawing on established frameworks and best practices (DeVellis, 2016; Boateng et al., 2018).

The identification of relevant scales followed a structured yet exploratory review approach consistent with the objectives of this initial stage. A database search was conducted on Google Scholar using the keywords "experience" AND "scale", complemented by backward and forward snowballing to identify additional instruments and ensure comprehensive coverage of the customer experience measurement literature. This process resulted in the identification of 50 papers, comprising both empirical and conceptual studies. To maintain a manageable pool of potential items for extraction, the search was deliberately bounded, given the substantial number of candidate items identified at this stage, with the understanding that a subsequent qualitative phase would complement this pool through the generation of additional items.

The review of these papers provided a robust empirical and conceptual basis for refining the definition and operationalization of the construct in the subsequent stages of the scale development process. Conceptual studies were excluded from item selection but were retained to inform conceptual clarity and methodological orientation. The review of empirical papers revealed the absence of a scale explicitly designed to capture AICX and highlighted limitations in the extent to which existing measurement instruments account for the characteristics that define AICX.

More specifically, many scales fail to capture the multidimensionality of the construct, often focusing only on cognitive and affective aspects while overlooking other dimensions that have gained importance with the integration of AI. For example, the EXQ scale (Klaus and Maklan, 2012), one of the most widely adopted and replicated scales for measuring CX, focuses primarily on the cognitive component of the experience, neglecting other dimensions within the construct. Other scales often fail to capture the increased active role that customers play in shaping their own experiences. For example, Garg et al.'s (2013) scale for CX in banks is based on the conceptualization of a passive role for customers in the staged experience components provided by service providers and therefore measures the experience accordingly. Further, some scales, such as the one developed by Kumar and Anjaly (2017), emphasize service provider and service process elements over individual experiences, although CX is fundamentally rooted in subjective individual responses. In addition, several existing measures are anchored in evaluations of specific service encounters, thereby capturing touchpoint-level assessments rather than the holistic and cumulative nature of customer experience (Lu, Cai and Gursoy, 2019; Prentice and Nguyen, 2021). Moreover, recent scales that address experiences with AI often emphasize technical capabilities rather than the actual experiential outcomes and interactions resulting from AI integration. For example, Wang et al.'s

(2024) scale for AI-enabled products focuses on technical attributes while overlooking the broader experiential implications of AI-enabled services.

Taken together, this review highlights a persistent gap in the customer experience measurement literature. Existing scales either adopt a limited dimensional scope, assume a passive customer role, remain anchored in touchpoint-level evaluations, or prioritize technical attributes over experiential outcomes. While these instruments have proven valuable within their original contexts, they are not equipped to capture the distinctive characteristics of AI-enabled experiences, which are shaped by technological agency, dynamic human–AI interactions, and cumulative experiences across service journeys. Consequently, there remains a clear need for a dedicated measurement instrument that conceptualizes and operationalizes AICX as a holistic, multidimensional, and evolving form of CX. Addressing this gap provides the foundation for the scale development undertaken in the present research.

6.1.2 AICX Definition

Conceptualized as an emerging form of CX, this thesis defines AICX as: customers' non-deliberate spontaneous responses and reactions to offering-related stimuli along a customer journey featuring one or more AI-enabled technologies. This definition anchors AICX within established CX principles, namely, human responses to firm- or brand-related stimuli, while also reflecting the transformative changes AI-ETs introduce into customer interactions. AI-ETs redefine traditional stimuli and touchpoints, introduce new ones, and expand the scope of CX beyond human-only interactions, reshaping how businesses engage with customers. Interactions with chatbots, service robots, intelligent voice assistants, and immersive experiences enabled by extended reality (XR) technologies exemplify this transformation. These novel interactions elicit spontaneous responses, offering opportunities to uncover new dimensions of CX.

Although AICX remains grounded in the core dimensions of CX, observable changes within specific aspects of these dimensions reveal new facets of the construct, reflecting the unique characteristics of AI-ETs and their ability to evoke responses distinct from traditional CX. Thus, AI-ETs redefine the AICX construct—not by discarding foundational CX principles, but by expanding and adapting them.

While AICX remains fundamentally human-centric, its anticipated novelty is expected to emerge at the indicator level, resulting in a restructured dimensional framework. This evolving framework integrates new facets within existing dimensions and introduces novel understandings of customer experience through the lens of AI. Ultimately, AICX retains the essence of human response, but its uniqueness lies in how these reactions are shaped through interactions with AI-ETs. By evoking distinct responses and revealing previously unconsidered experiential aspects, AI-ETs may seamlessly integrate into existing dimensions, refine them, or highlight particular facets—thereby enriching the overall construct.

6.1.3 AICX Dimensionality

Customer experience is widely recognized in the literature as a multidimensional construct—one of the few aspects on which researchers generally agree. Despite this consensus, various conceptualizations propose different dimensional structures, reflecting the complexity and evolving nature of the field. To address this fragmentation, Becker and Jaakkola (2020) emphasize the value of building on established frameworks. Specifically, they recommend leveraging the dimensional structure proposed by Lemon and Verhoef (2016) as a foundation for future scale development.

In line with this theory-driven approach, the development of the AICX scale adopts Lemon and Verhoef's framework, which includes cognitive, emotional, behavioural, sensorial, and social dimensions of CX. Accordingly, AICX is conceptualized as a multidimensional construct encompassing customers' cognitive, emotional, behavioural, sensorial, and social responses to the integration of AI-ETs throughout the customer journey.

This framework serves as the foundation for the initial phase of scale development, while allowing for further refinement as the research evolves. Importantly, the proposed definition and dimensional structure are not intended to rigidly constrain the conceptualization of AICX. Rather, they provide a theoretically grounded starting point that supports adaptation and expansion in subsequent research stages.

This approach ensures that the scale remains anchored in established CX theory while accommodating the unique experiential characteristics introduced by AI-ETs.

6.1.4 AICX Scope

The AICX scale is designed to measure individuals' subjective experiences during interactions with AI-enabled technologies (AI-ETs). It captures how customers perceive, respond to, and evaluate these interactions, offering insights into the broader implications of AI-ET integration in everyday service contexts. Positioned between a general CX scale and one focused on specific touchpoints, the AICX scale targets customer-facing AI-ETs and traces the experiential responses they trigger across the customer journey.

While previous studies have emphasized the need for comprehensive CX measurement (Rahman *et al*., 2022), this research aligns with ongoing efforts to address fragmentation in the literature by proposing a context-sensitive scale tailored to AI-ET interactions. As Becker and Jaakkola (2020) argue, advancing CX theory requires not only conceptual clarity but also a deeper sensitivity to the specific contexts in which experiences unfold. The AICX scale responds to this call by capturing dimensions of experience that emerge uniquely through interactions with AI-ETs.

Defining the scope of the scale requires recognizing that AI-ETs are not passive tools but active components of the service environment. As Puntoni *et al*. (2020) note, these technologies shape the experience itself rather than merely facilitating it. In this context, AI-ETs function as stimuli that elicit spontaneous customer responses. It is important to distinguish between the technological features of AI-ETs and the human experiences they evoke; the latter is the true focus of measurement.

Accordingly, the AICX scale emphasizes customer reactions and responses as the core of experience. Rather than concentrating on staged or pre-defined elements of the service encounter, the scale aims to capture the authentic essence of experience from the customer's perspective. This experiential focus is in line with Godovykh and Tasci's (2020) argument that customer reactions serve as key indicators of genuine CX.

6.1.5 Measurement model

Within the domain of social sciences, the creation of scales is a common place endeavour aimed at quantifying and assessing diverse constructs. Such scales may take the form of either formative or reflective measures (Coltman *et al*., 2008). Formative and reflective scales share the same purpose of measuring constructs and concepts, and both follow a certain process of development that involves data collection and statistical tests. However, the details of the process vary, and there are several key differences between the two types of scales (see Table 6-1).

While the reflective perspective is prevalent in the field of management science (DeVellis and Thorpe 2021; Netemeyer, Bearden and Sharma, 2003), its dominance alone is not a complete justification for this choice. A more thorough examination of theoretical considerations is imperative. Jarvis *et al*. (2003) provided a framework for determining the appropriate measurement model by focusing on four key considerations. First, the framework examines the direction of causality between the construct and its indicators, determining whether the construct influences the indicators (reflective) or the indicators define the construct (formative). Second, it evaluates the interchangeability of indicators, assessing whether individual items can be replaced without altering the meaning or conceptual domain of the construct. Third, it considers the extent to which the indicators covary, as reflective indicators are expected to correlate strongly due to their shared underlying construct. Lastly, the framework emphasizes the importance of the nomological net, ensuring that the indicators share consistent antecedents and consequences in alignment with the theoretical definition of the construct. Together, these factors guide researchers in selecting whether a reflective or formative model is most suitable for their construct.

Table 6-1 Reflective vs. formative measurement models

Characteristics	Reflective Scales	Formative Scales
Base of measurement	Combine observable indicators that are resulting from the latent construct	Combines observable indicators to make up the latent construct
Causality relationship	From construct to items	From items to construct
Inter-item correlation	High intercorrelation	Low Intercorrelation
Conceptualization	Driven by theory	Driven by empirical considerations
Nature of the construct	Exists independent of the items	The construct is a combination of its indicators
Perception of Error	Inability to fully explain the measurement items	Perceived as inability to fulling explain the construct
List of items	Does not have to be comprehensive	Must be comprehensive
Impact of deleting an indicator	Does not change the meaning of the construct	Can lead to changes in the meaning of the construct

The reflective model aligns well with the definition and conceptualization of AICX in the literature, which focuses on customers' responses to the integration of AI-ETs into the CX. This conceptualization is consistent with the guidelines for construct measurement outlined by Jarvis *et al*. (2003). Furthermore, reflective models are not only dominant in management studies (DeVellis and Thorpe, 2021) but are also widely employed in previously published CX scales (e.g., Brakus, Schmitt and Zarantonello, 2009; Gahler, Klein and Paul, 2023; Liu and Hung, 2022). A reflective model ensures that the AICX construct is measured effectively, as its indicators are interchangeable and adaptable across various contexts without compromising the construct's conceptual integrity. This approach supports practical applications by enabling businesses to assess AICX using fewer items, while maintaining the scale's reliability and robustness.

6.1.6 Polarity

In the context of scale development, polarity refers to the way a scale captures the direction or nature of the construct being measured (Cabooter *et al*., 2016;

Netemeyer, Bearden and Sharma, 2003). Traditionally, scales may use polarity to reflect opposites, such as positive versus negative or satisfaction versus dissatisfaction (Höhne, Krebs, and Kühnel, 2021; Netemeyer, Bearden and Sharma, 2003). However, in some cases, polarity can also represent a continuum of intensity, extent, or level of engagement, where the focus shifts from dichotomous judgments to a more refined assessment of the construct (Cabooter *et al*., 2016; Höhne, Krebs, and Kühnel, 2021; Netemeyer, Bearden and Sharma, 2003). For the AICX scale, polarity is not designed to measure positive or negative experiences. Instead, it reflects a continuum of the level of experience evoked by AI-ETs. The scale captures the extent and strength of customer reactions, visualized as a spectrum ranging from weak to strong. Importantly, a weak score does not inherently signify a bad or unfavourable experience, nor does a strong score necessarily imply a positive one.

In conceptualizing a new scale to measure AICX, this study adopts a dual focus on the extent and breadth of experience—where extent refers to the continuum of customer responses evoked by AI-ETs, and breadth captures the range of distinct experiential themes that may arise during such interactions. This orientation reframes polarity away from traditional dichotomies like positive versus negative or satisfaction versus dissatisfaction (Cabooter *et al*., 2016; Höhne, Krebs, and Kühnel, 2021; Netemeyer, Bearden and Sharma, 2003), instead recognizing that CXs are often multifaceted, layered, and context dependent. The AICX scale's emphasis on the strength and variety of responses avoids oversimplifications that could obscure important nuances in behaviour and perception. Grounded in affective and consumer psychology (e.g., Barrett and Gross, 2001; Scherer, 2005) and supported by literature on brand and service experience (Brakus, Schmitt and Zarantonello, 2009; Klaus and Maklan, 2012), this approach acknowledges that even a "strong" response may include both challenge and satisfaction, while a "weak" response may still indicate subtle yet meaningful engagement. By capturing the level rather than the valence of experiences, the AICX scale provides a more holistic and actionable understanding of how AI-ETs shape CXs across diverse contexts and touchpoints.

6.1.7 Conceptual interpretation of the AICX Scale

This step establishes the conceptual foundations for the development of the AICX scale as part of the broader scale development process. It integrates key elements discussed in the preceding sections including the definition, dimensionality, scope, polarity, and measurement model of the construct, and provides a framework for interpreting the outcomes of the scale once developed and validated. AICX is defined as customers' non-deliberate spontaneous responses and reactions to offering-related stimuli along a customer journey featuring one or more AI-enabled technologies. These responses span cognitive, emotional, behavioural, sensorial, and social dimensions, reflecting the complex and multifaceted nature of experiences shaped by emerging technologies.

The AICX construct is operationalized through a reflective measurement model, with the resulting score interpreted as the level of experience evoked by AI-ETs. Positioned along a continuum from weak to strong, this score captures the extent rather than the valence of the customer experience. A weak score does not indicate a negative or unfavourable experience, nor does a strong score necessarily imply a positive one; instead, the score reflects the degree of experiential engagement elicited by the interaction. This enables researchers and practitioners to assess not merely whether an experience occurred, but how deeply and broadly it resonated across experiential domains.

Grounded in this interpretive framework, the scale offers a nuanced and actionable basis for examining how AI-ETs shape customer experience across diverse contexts. With this conceptual structure in place, the next step involves generating and evaluating potential items that accurately capture the dimensions of the AICX construct. Figure Figure 6-2 presents the conceptualization of AICX and outlines the key steps discussed in this chapter.

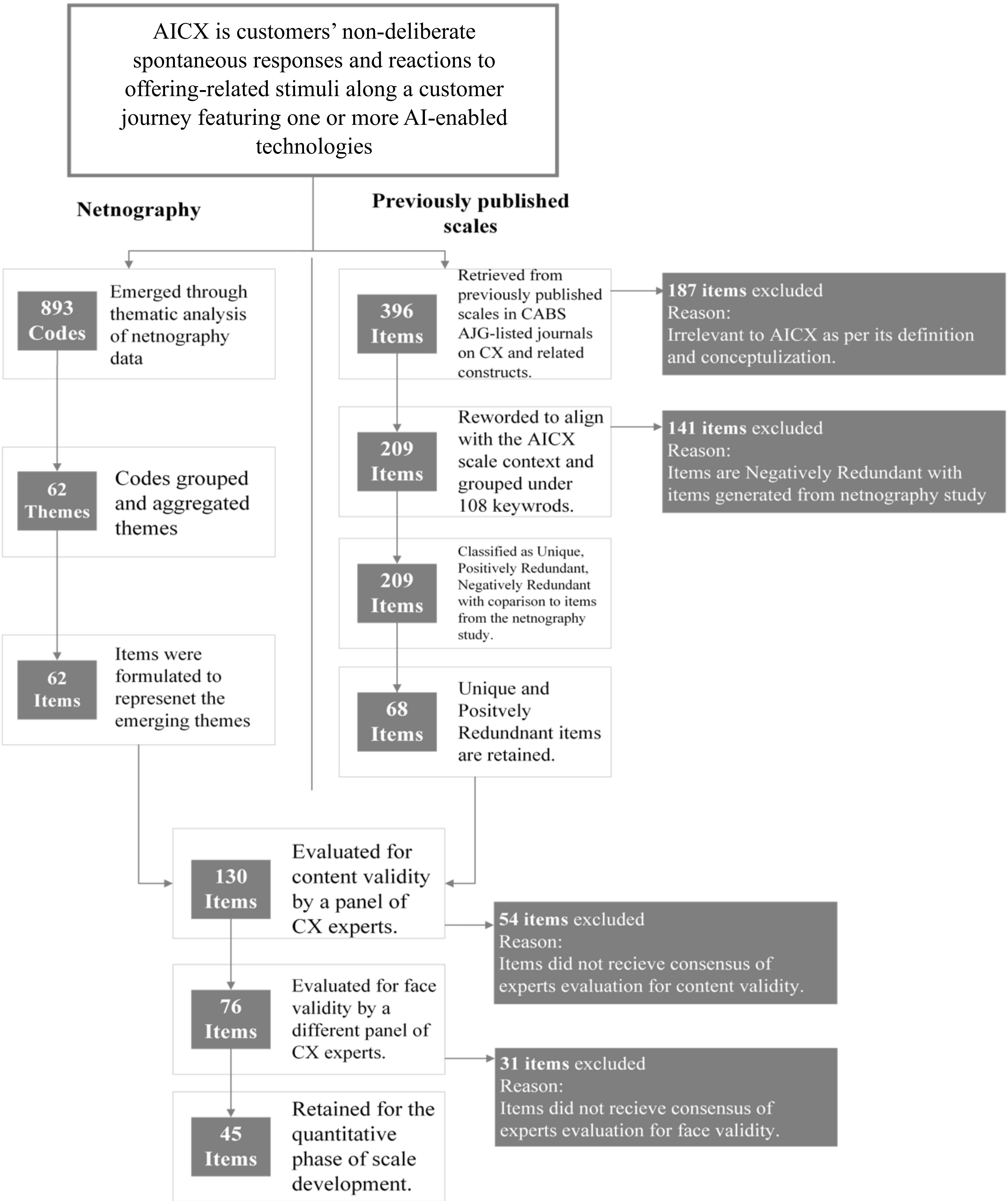


Figure 6-2: Visual summary of the qualitative phase

6.2 Items generation

Building on the conceptual foundation established in the previous step, the item generation process aims to create a comprehensive pool of items that accurately capture the construct of interest. This process typically begins by sourcing items from previously published and validated scales to form an initial pool of potential items. Additional items are then developed using qualitative methods to ensure content validity and comprehensive domain coverage (Garg, Rahman, and Qureshi, 2014; Netemeyer, Bearden, and Sharma, 2003; Brakus, Schmitt and Zarantonello, 2009; Wang *et al*., 2024). In line with this approach, item generation for the AICX scale began with sourcing items from previously published scales. This was complemented by a qualitative netnography study, which analysed customer reviews of real-life interactions involving AICX. Further details on both stages are provided in the following sections.

6.2.1 Items from previously published scales

Previously published scales were identified at an early stage of the research to establish the study's novelty, confirm the presence of a conceptual gap, and validate the need for developing a new measurement instrument (see Section 6.1.1). This process resulted in the identification of a broad body of relevant literature comprising both empirical and conceptual studies, encompassing a diverse range of scales, including generic, sector-specific, experience-stage-specific, and technology-mediated instruments.

The identified empirical scales were used to form the initial pool of potential items. However, and to ensure a robust empirical foundation and enhance the reliability of the research outcomes, these scales underwent a systematic screening process. Only scales that had been cited in the literature or empirically tested were retained, ensuring that the reviewed instruments had been operationalised beyond their original publication and had contributed to cumulative empirical knowledge.

The inclusion criteria further prioritised experiential dimensions that were transferable across technological contexts, rather than being tied to a single interface, system, or touchpoint. Accordingly, scales focusing primarily on functional attributes rather than experiential perceptions, those measuring constructs beyond the scope of the present research, and those that were overly specific to particular touchpoints—such that rewording into a more generic form would compromise item integrity—were excluded. In addition, a quality threshold was applied by retaining only scales published in journals listed in the CABS Academic Journal Guide, with the rigorous peer-review standards of these outlets further supporting the reliability of the retained instruments. Following this screening process, 21 scales remained (see Table 6-2), from which items were extracted, resulting in an initial pool of 396 items.

Table 6-2 Previously published scales on CX and relevant constructs

Scale Scope	Dimensions	Number of scale items	Reference
Banks	Servicescape, Core Service, Customisation, Value Addition, Convenience, Marketing Mix, Employees, Speed, Service Process, Customer Interaction, Presence of other customers, Online Aesthetics, Online hedonic elements, Online functional elements	41	Garg *et al*. (2014)
Brand	Sensory, Affective, Behavioural, Intellectual	12	Brakus, Schmitt and Zarantonello (2009)
Self-Service Technology Versus Human Service in Hospitality	Cognitive, Actional, Fresh, Social, Affective	22	Liu and Hung (2022)
Experience Quality in Services	Product experience, Outcome focus, Moments of truth, Peace of mind	19	Klaus and Maklan (2012)
AI-Enabled Products in Retailing	Data Capture Experience, Classification Experience, Delegation Experience, Social Experience, Anthropomorphic Experience	18	Wang *et al*. (2024)
Self-Service Technology in Retailing	Functionality, Enjoyment, Security/Privacy, Assurance, Design, Convenience, Customization	20	Lin and Hsieh (2011)
Post Purchase Experience in Retailing	Delivery, Product-In-Hand, Return and Exchange, Customer Support, Benefits, Feel Good Factors	35	Kumar and Anjaly (2017)
Perceptions of Technology-mediated Service Experience	Information Richness, Learning, Usefulness, Duration Appropriateness, Intimacy Appropriateness, Attitude towards contact medium, Attitude towards contact episode, Attitude towards service provider, Intention to use medium for future contact, Intention to use service provider in future	31	Froehle and Roth (2004)
In Store Physical Retail Experience	Cognitive, Affective, Physical, Social (a) with customers, Social (b) with employees	15	Bustamante and Rubio (2017)
Shopping Experience Memory Scale	Attraction, Structure, Affect, Social	14	Flacandjia and Krey (2020)
Transcendent customer experience	Unidimensional	11	Schouten *et al*. (2007)
Customer Experience in Omnichannel Environments	Affective, Cognitive, Physical, Relational, Sensorial, Symbolic	18	Gahler, Klein and Paul (2023)
Service Experience in Tourism	Hedonics, Peace of mind, Involvement, Recognition	23	Otto and Ritchie (1996)
Experience in Online Environments	Arousal/Challenge, Exploratory behaviour Flow, Focused attention, Importance, Playfulness Positive Affect, Skills/Control, Telepresence/Time Distortion	63	Novak *et al*. (2000)
Enjoyment of Web Experience	Engagement, Fulfilment, Positive Effect	12	Lin *et al*. (2008)

Memorable Tourism Experiences	Hedonism, Novelty, Local culture, Refreshment, Meaningfulness, Involvement, Knowledge	24	Kim, Ritchie and McCormick (2012)
Experience Quality	Physical surroundings (a) Atmosphere, Physical surroundings (b) Concentration, Physical surroundings (c) Imagination, Physical surroundings (d) Surprise, Service Providers, Other customers' negative public behaviours, Customers companies, Customers' themselves (a) Having Fun, Customers' themselves (b) Cognitive Learning	38	Chang and Horng (2010)
Event Experience Scale	Affective engagement, Cognitive engagement, Physical engagement, Experiencing Novelty	18	De Geus *et al*. (2016)
Co-creation experience	Hedonic experience, Cognitive experience, Social/personal experience, Pragmatic/economic experience	19	Verleye (2015)
Gastronomy Tourism	Unidimensional	5	Hsu *et al*. (2022)
AI Customer Experience	AI autonomy, AI uniqueness, AI parasocial ability, AI reliability, AI dialogue ability	29	Keng *et al*., (2025)

Based on the established conceptualization of AICX and the intended scale, the 396 items were carefully reviewed to evaluate their relevance to the construct of interest. As a result, 209 items were identified as relevant, primarily exemplifying reflective indicators of the experience that represent customer reactions and responses. Items that did not align with this focus were excluded, such as “X is capable of handling complaints,” I remember the order in which the events occurred” and “I do not feel good when other customers are shouting loudly.”. Items deemed as relevant were reworded to align with the intended AICX scale. For example, the original item “ While visiting the Web pages, I was absorbed intently.” was reworded to “ While interacting with AI-ETs, I was absorbed intently.” and “ I learn something new when staying in the store.” was reworded to “ I learned something new as a result of interacting with AI-ETs.”.

Redundancy can be beneficial in scale development, but it is essential to avoid negative redundancy (DeVellis and Thorpe, 2021). To address this, the 209 retained items were organized into 108 keywords, forming coherent groups to streamline the item pool. For instance, the items “In general, SSTs (Employees) in my hotel made customers feel uncomfortable/made customers feel comfortable,” “The environment of this retail store, including the display of its products and services, makes me feel comfortable,” and “During this shopping experience, I felt very comfortable” were grouped under the keyword comfort. From this group, the reworded item selected for the scale was: “Interacting with AI-ETs made me feel comfortable.”. This grouping process facilitated the reduction of redundancy by enabling direct comparisons and informed decisions about which items to retain or exclude. Ultimately, this approach refined the item pool to a more manageable size while preserving its representativeness. A visual summary of this step is presented in Figure 6-3.

Although the retained items encompass several key aspects of AICX, a comparison with the construct’s conceptual definition suggests that they do not fully capture the critical facets related to the integration of AI, which are fundamental to the intended scale. In alignment with established practices in scale development, this limitation was addressed through a qualitative netnography study, which is outlined and discussed in detail in the following section.

Figure 6-3 Refinement of items from previously published scales

6.2.2 Items from netnography

The netnography study served as a supplementary source for identifying potential items for the AICX scale, specifically targeting facets that reflect the integration of AI. To achieve this, customer reviews from individuals with real-life experiences of AI-ETs were collected and analysed. Reviews were retrieved from two platforms: TripAdvisor and the Oculus Store. The sampling and selection criteria for specific locations and applications on these platforms were carefully developed to align with the research objectives and are detailed in the methodological decisions of the AICX scale (see section 5.5, Netnography methodological decisions).

The data analysis, conducted through thematic analysis using an inductive approach, was carried out in two phases. In the first phase, reviews were analysed from the Wynn Hotel, Gunpowder Plot, Wander, and Yotel. In the second phase, reviews were analyzed from ACME, Historium Brugge, National Geographic, and EMC2. This phased approach facilitated a structured and systematic process, beginning with open coding to identify patterns and followed by axial coding to group these patterns into themes.

Table 6-3 Coding Examples from the Netnographic Analysis and Mapping to AICX Dimensions

Excerpt from data	Open Code	Axial Code/Theme	AICX dimension
There is also an Alexa in the bedroom which we unplugged…it felt a little invasive.	We unplugged	Avoidance and neglect	Behavioural
The sense of presence is fantastic and the experience is very memorable.	Experience is very memorable	Memorability	Cognitive
Room service are supported by funny looking robots.	Funny looking robots	Aesthetics	Sensorial
Some of the views are stunning, I was truly thrilled to see the whales swimming near my kayak.	Thrilled to see	Excitement	Emotional
I loved the use of robots to do repetitive work and their intelligence as well - they could be trained to be more polite	Be more polite	Respect	Social

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below illustrates this analysis process.

Table 6-3 Coding Examples from the Netnographic Analysis and Mapping to AICX Dimensions

Saturation

In netnography, data saturation denotes the point in the research process at which further analysis of data fails to yield additional insights relevant to the research objectives (Fusch, Patricia and Lawrence, 2015; Saunders, Lewis and Thornhill, 2023). It signifies that the richness and diversity of the data are adequate to achieve a comprehensive understanding of the phenomenon under investigation (Fusch, Patricia and Lawrence, 2015; Saunders, Lewis and Thornhill, 2023). Establishing data saturation is crucial in qualitative data analysis, as it provides a solid foundation for drawing meaningful and reliable conclusions with academic rigor. In this netnography study, data saturation was assessed visually, as illustrated in Figure 6-4, which shows the distribution of emerging codes across locations and the overall count of themes. The graph demonstrates that the number of emerging themes stabilizes at 58, indicating that no new themes are being identified despite continued data analysis. This stabilization confirms that the data is sufficiently comprehensive and diverse to address the research objectives, ensuring the robustness and reliability of the findings.

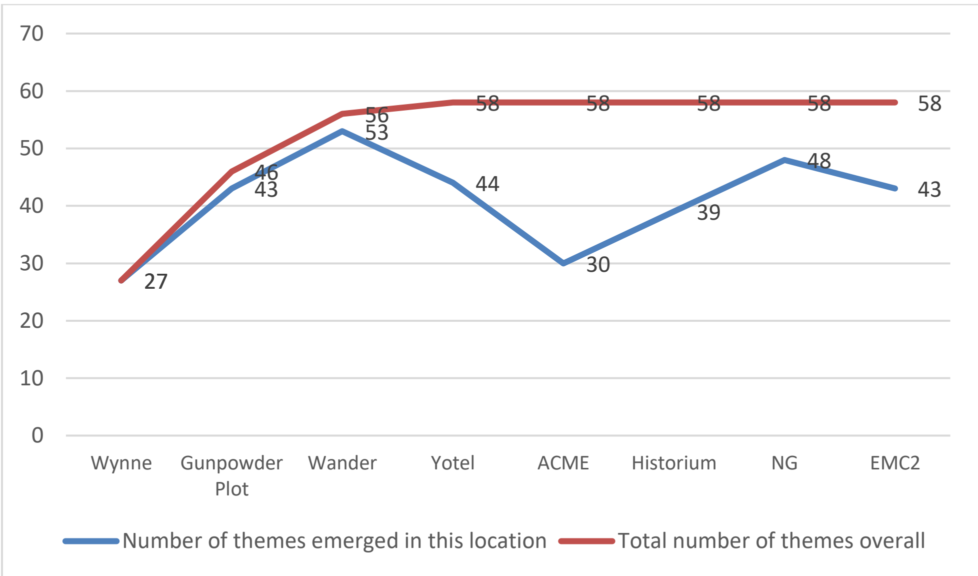

Figure 6-4 Netnography data saturation

Coding crosschecking

Coding crosschecking is an important step in qualitative research, designed to enhance the consistency and reliability of the coding process while addressing potential researcher bias and subjectivity (Braun and Clarke, 2006; Jonsen and Jehn, 2009). This typically involve systematic reviews of the coding framework and application to ensure that codes are applied uniformly across the dataset. By fostering a collaborative approach, it allows researchers to identify and resolve discrepancies and ensure that the assigned codes accurately represent the data. A key goal of coding crosschecking is to mitigate individual researcher bias, which can arise due to subjective interpretations of the data. Bringing together multiple perspectives helps to challenge assumptions and align interpretations, thereby increasing the objectivity of the analysis. Beyond enhancing consistency, coding crosschecking contribute to the validity of the coding framework by ensuring that it is comprehensive and aligned with the research objectives. It also serves as an opportunity to refine codes, merge overlapping categories, and ensure that emerging themes are accurately captured. This iterative process strengthens the analytical rigor and provides a solid foundation for deriving meaningful and credible insights from the data.

In this netnography study, following Creswell and Creswell (2023) recommendations, coding cross-checking was conducted during the data analysis process in collaboration with the supervisory team. This involved a dedicated session to discuss and refine the coding. During the session, the researcher presented the team with a comprehensive table that detailed the 58 emergent themes, each classified under its respective AICX dimension. The table also included clear definitions for each theme to ensure a shared understanding and facilitate the review process (See Appendix A).

The supervisory team thoroughly evaluated the researcher's independent coding efforts by reviewing each theme and its associated codes and considered excerpts from the data (see Table 6-4). Based on the team's comments, feedback, and discussions during the session, the researcher refined and adjusted the themes, resulting in a finalized list of 62 themes (see Appendix K).

The 62 themes were then transformed into scale items, the supervisory team then conducted a thorough review of the wording of the formulated scale items. The wording of the scale items adhered to established best practices and guidelines, ensuring that the items were short, simple, and addressed a single issue (DeVellis and Thorpe, 2021; Netemeyer, Bearden and Sharma, 2003). Additional considerations

Table 6-4 Examples of coded data

Emerging theme	Codes	Excerpt from data
Behavioural Dimension		
Interactivity	Activity level	*"…The activity level in this pleasantly surprised me!..."*
	Seek interaction with AI-ETs	*"…and I admit I ordered things I didn't really need to use the robot butler…"*
	Interactive	*"…The VR segments weren't great quality - quite blurry. And it would have been more fun if it was a bit more interactive overall, for example with more clues/puzzles for the group to solve together…"*
Cognitive Dimension		
Capabilities	Can control everything	*"…Then it gets even better, you notice an Alexa on the desk and find out that you can control everything with voice command, it can control the lights, shades and thermostat…"*
	Powerful	*"…Robots are very powerful, they can do everything…"*
	Brings the world to you	*"…You can travel to Tunisia, Brazil, and Spain, all before breakfast 🤣 It brings the world to you…"*
Emotional Dimension		
Entertainment and enjoyment	Fun	*"…It's beautiful and the robots are a fun touch!..."*
	Enjoyment	*"Alexa" In the room was a treat and made my stay even more enjoyable…"*
	Adrenaline rush	*"…The VR experiences were phenomenal and added thrill, excitement and a little fear, a real adrenalin rush!..."*
Sensorial Dimension		
Aesthetics	Visually appealing	*"…The app is visually appealing…"*
	Gender of Robot	*"…Only thing is that Yolanda sings a goodbye tune but Yoshi just say good bye. Thus its better to get the female robot to deliver items to the room…"*
	Grabs attention	*"…The robot in the lobby caught our attention…"*
Social Dimension		
Courtesy	Politeness	*"…I loved the use of robots to do repetitive work and their intelligence as well - they could be trained to be more polite…"*
	Lacks Warmth	*"…However, the check in and out experience a little unfriendly like the robot service without the least of warmth in customer service…"*
	Friendly	*"…ironically the pair of in-house robots portrayed a greater semblance of friendliness…"*

included ensuring readability, avoiding jargon or technical language, and steering clear of double-barrelled items (Boateng *et al*., 2018). These principles were critical because while precision in wording is essential, it is equally important that the items are concise and easily understood by the target population. If the items are too complex or difficult to comprehend, participants may provide inaccurate responses, compromising the reliability and validity of the scale. Following two iterative rounds of feedback and refinement, a list of 62 scale items were approved, as shown below (see Table 6-5).

There is no definitive rule for determining the optimal number of items in an item pool for scale development (DeVellis and Thorpe, 2021). However, it is crucial to include a sufficiently large number of items, especially when designing a scale for a multidimensional construct like the AICX scale. A larger item pool enhances the likelihood of capturing the full range of variation within the construct and identifying potential issues with individual items. At this stage of scale development, it is generally better to err on the side of being overly inclusive rather than risk underrepresentation. Nonetheless, it is important to keep the number of items manageable.

In developing the initial item pool for the AICX scale, careful attention was given to redundancy—an essential consideration in scale construction that balances comprehensiveness with parsimony (DeVellis and Thorpe, 2021; Netemeyer, Bearden, and Sharma, 2003). While some redundancy can enhance construct coverage and support item refinement, excessive or uninformative overlap may inflate measurement error and obscure conceptual clarity (Clark and Watson, 2016; Hinkin, 1998). To address this, items derived from previously validated scales and those generated through netnographic analysis were systematically compared. Items from the published scales were then categorized as unique, positively redundant, or negatively redundant. This classification was informed by the principle that not all redundancy is detrimental—items addressing similar content may still contribute valuable nuance depending on their framing or contextual relevance (MacKenzie, Podsakoff, and Podsakoff, 2011; Clark and Watson, 2016). Unique items introduced new aspects of the construct not captured elsewhere. Positively redundant items were retained when they enriched the construct by adding depth or offering alternative, contextually meaningful interpretations. Negatively redundant items, by contrast, were excluded when they duplicated content without contributing additional value, consistent with best practices for optimizing item pools and maintaining theoretical coherence (Boateng *et al*., 2018).

Table 6-5 Items list formulated from the netnography study

ID	Code	Definition	Potential Item/s
Behavioural Dimension			
1.1.	Avoidance	Intentional disregard or disinterest in engaging with AI-ETs.	I actively seek alternatives to using AI-ETs during my experience.
1.2.	Change in behaviour	Refers to shifts in actions, habits, and preferences caused by engagement with AI-ETs, prompting people to explore new behaviours or step outside their comfort zones.	Interacting with AI-ETs has encouraged me to embrace new behaviours.
1.3.	Selecting the AI-ETs or AICX	Involves individuals consciously selecting or favouring AI-ETs or AICX for some reason.	I willingly interact with AI-ETs during my experience.
1.4.	Decision making	How the reliance on AI-ETs influence customer decision-making processes to choose the AICX.	The presence of AI-ETs significantly influence my decision to select this experience.
1.5.	Repeat purchase	Reflects individuals' intention and willingness to repeatedly purchase or use AI-ETs.	Interacting with AI-ETs increase the likelihood I will choose a similar experience in the future.
1.6.	Negative consequences	Undesirable outcomes resulting from interactions with AI-ETs.	My interactions with AI-ETs have sometimes led to unfavourable outcomes.
1.7.	Interactivity	Reflects the level of interaction individuals have with AI-ETs or AICX.	I value the interactivity offered by AI-ETs within the experience.
1.8.	Involvement	Reflects the level of involvement individuals have with AI-ETs or AICX.	The presence of AI-ETs allows me to be more involved during the experience.
1.9.	Abandonment	Giving up on interactions with AI-ETs.	I gave up using AI-ETs during my experience.
Cognitive Dimension			
2.1.	Capabilities	Perception of the capabilities of AI-ETs.	I have a clear understanding of the abilities of AI-ETs.
2.2.	Limitations	Perception of the limitations of AI-ETs.	I am aware of the constraints and limitations of AI-ETs.
2.3.	Concerns	Worries regarding interactions with AI-ETs.	I have some concerns regarding my interactions with AI-ETs.
2.4.	Cautiousness	Carefulness regarding interactions with AI-ETs.	I adopt a cautious approach in any interactions with AI-ETs.
2.5.	Customization	Tailoring AICX to personal preferences.	Interactions with AI-ETs allowed me to tailor my experience to match my personal preferences.

2.6.	Errors	Errors occurring during the AICX and how are these perceived by customers.	When errors occur during my interactions with AI-ETs, it negatively influences my overall service experience.
2.7.	Evaluation and comparisons	Assessing AICX relative to alternatives.	I consistently assess my interactions with AI-ETs in comparison to technology-free alternatives.
2.8.	Functionality	How well AI-ETs perform their intended tasks.	The functionality of AI-ETs contributed positively to my experience.
2.9.	Comprehension	How well customers understand, are aware of and are familiar with the AI-ETs in use.	Understanding how AI-ETs were integrated into my service journey contributed to my overall experience.
2.10.	Learning and knowledge	Acquiring new information or skills through AI interactions.	I gained new knowledge while interacting with AI-ETs during my experience.
2.11.	Memorability	Involves the lasting impact of AI-ET interactions on individuals' memory and perception, encompassing instances where these experiences are remembered, referenced, or stand out over time.	My interactions with AI-ETs were memorable.
2.12.	Negative perception	Unfavourable opinions or views about AI technology.	Overall, I have negative perception about AI-ETs.
2.13.	Added value	Perceptions of added benefits, wastefulness, and whether AI-ETs enhance the overall value of interactions.	My interactions with AI-ETs added value to my overall experience.
2.14.	Tech dominance	Looks into individuals' autonomy in interactions.	I maintained a sense of autonomy and control during my interactions with AI-ET.
2.15.	Human-tech balance	Refers to the balance between AI-ETs' and human touch	I appreciate having a balance between the integration of AI-ETs and the human touch.
2.16.	Technical quality	Explores UX with AI-ETs through technical aspects like hardware, graphics, interface design.	The technical quality of the AI-ET was pivotal in shaping my overall experience.
2.17.	Trustworthiness	Explores customers' assessment of reliability and credibility regarding AI-ETs.	I have confidence in the performance of AI-ETs.
2.18.	Scepticism	Customers' doubts and reservations regarding AI-ETs.	I have reservations about the performance of AI-ETs.
2.19.	Upgrades and improvements	The changes of AI-ETs over time, considering both enhancements driven by competition and user feedback.	The AI-ETs in use would benefit from further technical upgrades and improvements.
2.20.	Usability	How easily customers can interact with AI-ETs and make use of its features.	It was easy to use the features of the AI-ET.
2.21.	Utilization	Considers how well ideas are implemented and executed.	AI-ETs are effectively utilized within the overall experience.
2.22.	Value for money	Explores whether the cost of the AICX aligns with perceived benefits. It assesses if individuals	The cost I paid for my AICX was aligned with the value I received.

		find the price justified based on the value and features received.	
2.23.	Failure recovery	Perception towards how mistakes are handled.	The resolution of problems and mistakes related to AI-ETs was handled appropriately.
2.24.	Potential	Perceived level of future possibilities of AI-ETs.	I believe that AI-ETs have the potential to further shape future experiences.
Emotional Dimension			
3.1.	Anger (Annoyance to Rage)	Feeling upset or annoyed because of AI-ETs.	My interactions with AI-ETs made me feel angry.
3.2.	Diminished positivity	The fading or reduction of initial positive emotions and attitudes toward AI-ETs over time.	My initial positive feelings towards AI-ETs have faded with repeated use.
3.3.	Surprise (Distraction to Amazement)	Focuses on unexpected and captivating elements that trigger feelings of wonder and surprise.	I have experienced moments of wonder and amazement during my interactions with AI-ETs.
3.4.	Disappointment and regret	Feeling let down or wishing for better outcomes and interactions with AI-ETs.	I have felt let down during my interactions with AI-ETs.
3.5.	Entertainment and enjoyment	Captures the fun, excitement, and entertainment aspects of interactions.	My interactions with AI-ETs added a sense of fun and excitement to my experience.
3.6.	Escape	AICX is a way to temporarily escape reality.	Interacting with AI-ETs provided me with a momentary escape from reality.
3.7.	Fear (Apprehension to Terror)	Covers emotions like anxiety, apprehension, and being scared or threatened by the technology.	I felt nervous or afraid when using AI-ETs.
3.8.	Joy (Serenity to Ecstasy)	Captures instances of happiness.	I felt happy while interacting with AI-ETs.
3.9.	Mood and emotional state	Impact of interactions with AI-ETs on the emotional state.	My interactions with AI-ETs impacted on my emotional state and overall mood.
3.10.	Negative perception	Unpleasant perceptions or feelings arising from AI-ETs interactions.	My overall experience with AI-ETs was upsetting.
3.11.	Personal impact and connection	Focuses on customers' individual experiences and emotional connections when engaging with AI-ETs.	While interacting with AI-ETs, I have experienced a personal connection.
3.12.	Positive impressions	Forming favourable opinions about AI-ETs or AICX.	I have formed favourable opinions about AI-ETs during my experience.
3.13.	Novelty and uniqueness	Perceiving AI interactions as new and distinct.	My interactions with AI-ETs felt novel and unique.
3.14.	Highlight of or main feature of	Recognizing the interaction with AI-ETs as a central element in the overall experiences.	My interactions with AI-ETs were the highlight of my overall experience.
3.15.	Laughter and humour	Finding things funny during the AICX.	My interactions with AI-ETs brought laughter.
Sensorial Dimension			
4.1.	Aesthetics	Visual attributes and design elements of AI-ETs	The design of AI-ETs was important in shaping my AICX.
4.2.	Realism	Impressions of how well AI-ETs replicate real-world experiences	The AI-ET provide a realistic portrayal of real-world experiences.

4.3.	Negative sensations	Experiencing negative sensations from AI.	I experienced negative sensations while using AI-ETs.
4.4.	Multisensory	Involving multiple senses in interactions with AI-ETs.	My interactions with AI-ETs required the use of multiple senses.
4.5.	Physical comfort	Physical involvement and comfort levels during interactions with AI-ETs.	My interactions with AI-ETs did not impact on my physical comfort.
4.6.	Technological embodiment	How much does AI-ETs have human-like attributes or behaviours.	The AI-ETs had human-like attributes and behaviours.
Social Dimension			
5.1.	Accessibility, diversity, and inclusivity	AI-ETs accommodate diverse users, including different ages, cultures, languages, and needs. It focuses on breaking barriers and promoting inclusion through technology design and usage.	The AI-ETs offer adaptability across age, culture, language, and needs.
5.2.	Sharing	Discussing the AICX with others, how they work, what do they think about the experience and so on.	I have actively shared my experiences with AI-ETs with others.
5.3.	Advocacy	Promoting interactions with AI-ETs with others and encouraging them to give it a try.	I have encouraged others to try AI-ETs out.
5.4.	Positive impact on human connection	How these technologies can create absence of social engagement.	My interactions with AI-ETs reduced my social engagement during the experience.
5.5.	Negative impact on human connection	How these technologies can enhance meaningful connections.	My interactions with AI-ETs deepened the sense of connection I felt throughout the experience.
5.6.	Perception of others	How individuals' interactions with AI-ETs are perceived by others	I pay attention to how others perceive my interactions with AI-ETs.
5.7.	Relation with AI-ETs	The perceived nature of the relationship between customers and AI-ETs.	I perceive my interactions with AI-ET as distinct and meaningful.
5.8.	Courtesy	The level of consideration and courtesy represented by AI-ETs.	Interaction with AI-ETs are marked by courtesy and politeness.

An item was classified as unique if it addressed an aspect not previously covered by any of the items from earlier scales, offering entirely new perspectives that enhanced the scale’s comprehensiveness. Items were deemed positively redundant if they explored aspects already covered by items from previously published scales but added additional value, depth, or meaning. These items refined or enhanced the understanding of a concept by providing a fresh or contextually relevant interpretation. In contrast, items were categorized as negatively redundant if they addressed aspects already covered by previous items but failed to add any significant value or meaning. Such items were considered repetitive and did not contribute to a better understanding of the construct.

Negative redundancy can be seen in some examples from the item pool. For example, the item "I feel unoriginal when I interact with AI-ETs," which was identified as negatively redundant with "My interactions with AI-ETs felt novel and unique." While one frames the concept positively and the other negatively, both address the same underlying theme—novelty and uniqueness. Similarly, the item "The interactions with AI-ETs teach me interesting things" was identified as negatively redundant with "I gained new knowledge while interacting with AI-ETs during my experience." Both items address the same idea—learning and knowledge acquisition—but differ only in phrasing (teaching vs. gaining knowledge), making one sufficient to represent the dimension effectively.

Having addressed negatively redundant items, it is important to consider positively redundant items, which provide additional depth and value to the construct. For instance, the item "Interacting with AI-ETs is just like being in another imaginative space" is identified as positively redundant with "Interacting with AI-ETs provided me with a momentary escape from reality." While both items explore the theme of escape, they capture different nuances: the former emphasizes the imaginative and creative nature of the experience, whereas the latter focuses on the temporary disconnection from reality. Similarly, the item "I maintained a sense of autonomy and control during my interactions with AI-ET" is considered positively redundant with "AI-ETs gave me more control over my experience." Although both address the concept of control, the first highlights the user's active role in maintaining autonomy, while the second emphasizes the AI-ET's role in facilitating that control. Another example is the item "My actions during the interactions with AI-ETs were new" which is positively redundant with "My interactions with AI-ETs felt novel and unique." Both capture the themes of novelty and uniqueness, but the former introduces the specific perspective of actions taken during the interaction. Indeed, retaining such items enriches the scale by capturing subtle variations in how users experience escape, autonomy, and control during interactions with AI-ETs, ensuring a comprehensive and nuanced representation of the construct.

Moving beyond positively redundant items, the focus shifts to unique items that address aspects not explicitly covered by the emerging netnography themes but included in previous scales. These items are particularly valuable as they have been tested, validated, and widely used in prior research, lending credibility to their inclusion. Examples of such unique items include: “I forget about my immediate surroundings when I interact with AI-ETs,” which captures the sense of immersion; “AI-ETs delight me,” emphasizing the emotional response to interactions; and “AI-ETs made me feel cool,” reflecting the social and self-perception dimensions of the experience. Retaining these items ensures that the scale incorporates established insights while maintaining a comprehensive scope.

Based on this classification, items identified as negatively redundant were excluded to maintain a balance between conciseness and comprehensiveness in the scale structure while avoiding unnecessary duplication or items that added little value. Although negatively redundant items were excluded, they still contributed to the process by informing the wording of items formulated from the emergent netnography themes. Since these items had been tested and validated in previous scales, their wording was considered reliable and valuable. Conversely, items classified as positively redundant or unique were retained, as they contributed meaningful perspectives to the construct.

Prior to proceeding to items refinement, item wording checks were conducted. This process involved three rounds of review. In the first two rounds, supervisors individually reviewed the items and provided feedback. In the third round, three PhD students from the marketing department at the University of Strathclyde reviewed the items and offered their feedback. During the item wording checks, several examples of revisions were made to enhance clarity and precision. For instance, a double-barrelled statement such as "Interacting with AI-ETs has encouraged me to embrace new behaviours and approach things differently" was simplified to "Interacting with AI-ETs has encouraged me to embrace new behaviours." Similarly, complex ideas were streamlined, such as revising "Interactions with AI-ETs allows me to tailor my experience to match my personal preferences" to "Interactions with AI-ETs allows me to tailor my AICX to match my personal preferences." Adjustments were also made to improve word choice, with "I regularly compare encounters with AI-ETs to traditional ones" refined to "I consistently assess my interactions with AI-ETs in comparison to technology-free alternatives." Simplifications included editing "I have reservations and doubts about the performance of AI-ETs" to "I have reservations about the performance of AI-ETs." Lengthy statements were split into two concise ones, such as "I have actively shared and advocated my positive experiences with AI-ETs with others, encouraging them to try them out," which was revised to "I have encouraged others to try AI-ETs out" and "I have actively shared my experiences with AI-ETs with others." Finally, tense and verb adjustments were made, with "My interactions with AI-ETs are novel and unique" revised to "My interactions with AI-ETs felt novel and unique." These revisions reflect the careful approach taken to refine item wording for clarity and focus. After addressing the comments and feedback, the list was refined and ready for item refinement. The final list of items to be considered for the subsequent step comprised 130 items.

6.3 Items refinement

Item refinement represents the third and final step in the qualitative phase. Using expert panel reviews, the refined list of items generated in the previous step undergoes further evaluation. This collaborative approach mitigates potential biases that may have emerged earlier in the process. The primary focus of this step is to establish two critical components of the intended scale: content validity and face validity. These components are achieved through comprehensive evaluation and expert feedback, ensuring the accuracy and robustness of the final scale.

The process involved two distinct stages, each utilizing a different of experts. A total of 10 experts were recruited with 5 experts assigned to each stage of item refinement. Two surveys, specifically designed for the respective stages, facilitated this process. The first stage commenced with an initial list of 130 items, which was reduced to 76 based on a content validity assessment conducted by the first panel. Subsequently, the second stage further refined the list to 45 items following a face validity evaluation by the second panel. Figure 6-5 illustrates the process, which comprises two stages: content validity and face validity. The following sections provide a detailed discussion of each stage. For clarity and transparency, Appendix B provides comprehensive details on how items were classified during both content and face validity assessments.

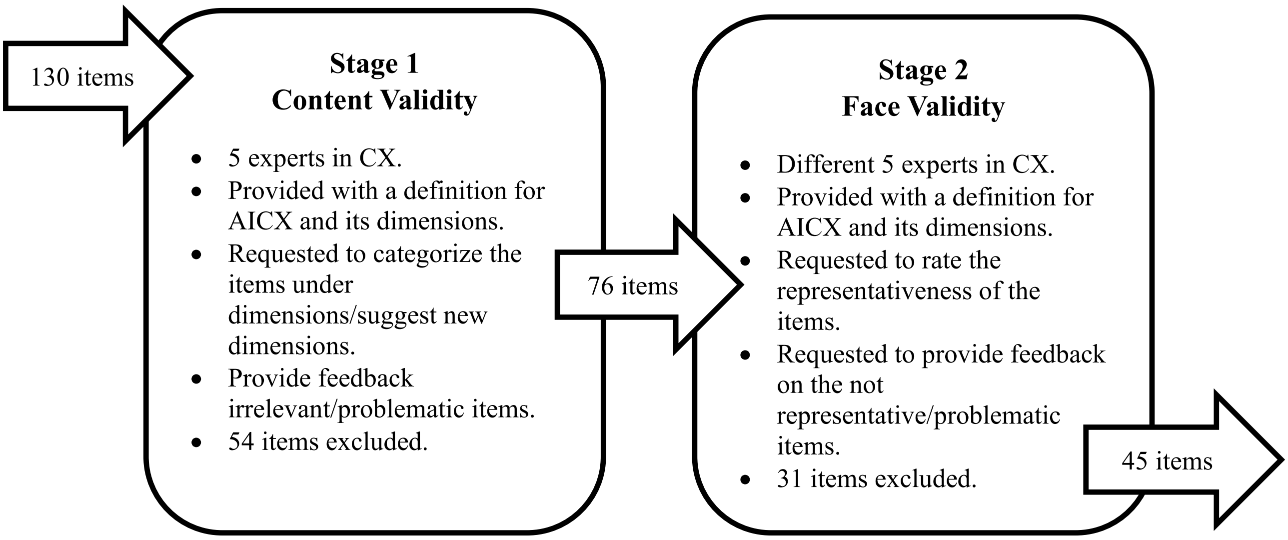

Figure 6-5: Item Refinement

6.3.1 Content Validity

Content validity refers to the degree to which a measurement instrument adequately represents the entire theoretical domain of the construct it is intended to assess (Haynes, Richard, and Kubany, 1995). It is a foundational aspect of construct validity, ensuring that a scale's items systematically reflect all relevant facets—attributes, dimensions, or elements—of the construct of interest (Boateng *et al.*, 2018). Without this, even the most rigorous statistical validation may be rendered meaningless if the construct is not comprehensively captured (Netemeyer, Bearden, and Sharma, 2003).

The process of establishing content validity typically begins with a detailed construct definition, grounded in a thorough review of relevant theoretical frameworks and empirical literature (DeVellis and Thorpe, 2021). This conceptual clarity informs item generation and ensures that the initial item pool is sufficiently broad. As emphasized in psychometric and marketing research, content validity must be established before other forms of validation can proceed, as it lays the theoretical foundation for the entire measurement process (Rossiter, 2002).

Expert panels play a central role in content validation. Subject-matter experts are asked to assess whether the items are clear, relevant, and representative of the construct's domain (Klaus and Maklan, 2012; Liu and Hung, 2022; Tian, Bearden, and Hunter, 2001). Experts are typically provided with a clear definition of the construct and its dimensions and asked to evaluate each item using a structured rating system—assessing relevance, clarity, and representativeness—or to classify items under pre-defined dimensions or conceptual categories (Klaus and Maklan, 2012; Liu and Hung, 2022; Tian *et al*., 2001). In addition to quantitative ratings, experts are encouraged to provide qualitative feedback to identify unclear wording, overlapping content, or missing aspects of the construct—an established practice in marketing scale development (Netemeyer, Bearden and Sharma, 2003; Yoo and Donthu, 2001; Brakus, Schmitt, and Zarantonello, 2009).

In fields such as marketing, where constructs are often abstract, multidimensional, and context-sensitive, content validity is especially critical (Netemeyer, Bearden and Sharma, 2003). Poorly specified constructs can result in instruments that fail to discriminate between theoretically distinct dimensions or that omit essential experiential components of the phenomenon. Therefore, content validity is not merely a preliminary step—it is a fundamental requirement for developing a valid, reliable, and interpretable scale (Clark and Watson, 2016; Worthington and Whittaker, 2006).

During the first stage, the panel of experts was tasked with assessing content validity (see Appendix C). They were provided with a list of 130 potential items, along with the definitions of AICX, its dimensions, and AI-ETs, including examples. The experts were instructed to categorize the items based on the predefined dimensions of the AICX construct: cognitive, behavioural, social, sensorial, and emotional (Lemon and Verhoef, 2016). Items deemed irrelevant to any of these dimensions or the construct itself were to be marked as irrelevant. For items categorized as irrelevant, judges were asked to provide justifications and were given the opportunity to suggest additional dimensions if applicable. Additionally, judges were encouraged to comment on and provide feedback for any item they found confusing, unclear, or poorly worded, ensuring a comprehensive review of the item pool.

Judges' responses were compiled and analysed systematically. Items deemed irrelevant by two or more judges, without any dimension suggested for them, were excluded directly, resulting in the removal of 40 items. Additionally, items that failed to achieve consistent categorization from at least three out of five judges (n = 5) or items that lacked consistent categorization and were deemed irrelevant by one judge (n = 7) were also excluded. These criteria align with common practices in scale development studies (Bearden, Netemeyer and Teel, 1989; Bottger *et al.*, 2017; Tian, Bearden and Hunter, 2001). The exclusion of these items was deemed necessary, as they were considered potentially ambiguous or unclear, likely eliciting varied interpretations, and therefore unsuitable for inclusion in the scale (see Table 6-6).

Table 6-6 Examples of items removed during item refinement

Stage	Reason for removal	Removed item
Content validity	Failed to receive consistent categorization from at least 3 out of 5 judges.	While interacting with AI-ETs, I have experienced a personal connection.
	Failed to receive consistent categorization from at least 3 out of 5 judges, with one judge classifying it as irrelevant.	AI-ETs gave me more control over my experience.
	Classified as irrelevant by two or more judges.	I have encouraged others to try AI-ETs out.
Face Validity	Classified as not representative by one of the judges.	Resolution to conflicts with AI-ETs is easy.
	Evaluated as somewhat representative by three or more judges.	My initial positive feelings towards AI-ETs have faded away with repeated use.

6.3.2 Face Validity

Face validity refers to the degree to which a measurement instrument appears to measure what it is intended to measure (Allen, Robson and Iliescu, 2023). Face validity focuses on whether the items seem appropriate, relevant, and clear to both experts and potential respondents, ensuring that the instrument is intuitively acceptable and understandable. Unlike content validity, which relies on a detailed assessment of the construct's dimensions, face validity is more concerned with the surface-level plausibility and alignment of the items with the construct (Allen, Robson and Iliescu, 2023; Hardesty and Bearden, 2004). This type of validity is often established through expert panels reviews, where items are evaluated for their clarity, wording, and overall suitability (Brakus, Schmitt and Zarantonello, 2009; Grag, Rahman and Qureshi, 2014; Kuppelwieser and Klaus, 2020; Rahman *et al*., 2022). Although considered a more preliminary form of validity, face validity plays a vital role in enhancing respondent engagement and trust in the measurement instrument, serving as an important preliminary step in scale development (Allen, Robson and Iliescu, 2023; Brakus, Schmitt and Zarantonello, 2009; Grag, Rahman and Qureshi, 2014; Kuppelwieser and Klaus, 2020; Rahman *et al*., 2022).

During the second stage, a new panel of experts was assigned to assess the face validity of the scale. They were presented with a list of 76 items, along with the definitions of AICX, its dimensions, and AI-ETs, accompanied by examples (See Appendix D). The experts were asked to evaluate the representativeness of each item for the AICX construct using three categories: “not representative,” “somewhat representative,” and “representative” (Albinsson *et al*,. 2016; Bearden, Netemeyer and Teel, 1989; Grag, Rahman and Qureshi, 2014). They were also invited to provide written feedback on items they classified as not representative. Additionally, experts were encouraged to offer comments on any items they found problematic, unclear, or inconsistent with the construct’s dimensions, ensuring a thorough evaluation process.

Judges' responses were compiled and analysed systematically. Items classified as not representative by even one judge out of five were excluded from the scale, resulting in the removal of 23 items. Additionally, items rated as only somewhat representative by three or more judges were also excluded (n = 8). These criteria align with established practices in scale development studies, ensuring the validity, clarity, and appropriateness of the final items (Bearden, Netemeyer and Teel, 1989; Tian, Bearden and Hunter, 2001). Following this rigorous refinement process, the list of items was narrowed down to 45, which will be utilized in the subsequent stages of the study.

6.3.3 Qualitative comments and feedback of the experts

As outlined earlier, judges in both stages of item refinement were invited to provide feedback on items they categorized as irrelevant or evaluated as not representative.

They were also encouraged to offer comments on any items they found problematic or to highlight any other concerns. This feedback provided valuable insights into the judges' perspectives and the reasoning behind their item classifications and evaluations. It contributed in several ways, starting with refining the list of items and guiding decisions on item retention and exclusion. Additionally, it enhanced the conceptualization of AICX by identifying correlations among potential emerging dimensions, which influenced subsequent decisions regarding the extraction method, rotation, and other methodological aspects, as will be detailed later. The feedback also emphasized the importance of clearly defining the scale's scope and ensuring a precise discussion of what the scale measures. This was particularly important given the fragmented perspectives in the literature on the nature and boundaries of the experience.

During the first stage of item refinement, one of the judges noted that some of the sensorial and behavioural items were more generic compared to the more specific cognitive items, highlighting an imbalance in item specificity across different dimensions. Among the 130 items, the judge categorized 26 under the behavioural or sensorial dimensions, considering them to be more generic than items in other dimensions. Of these 26 items, only 6 passed the experts' review stage, while the remaining 20 were excluded. Refinements of the 6 retained items were considered to enhance their specificity, as suggested by the expert, and are detailed in Table 6-7 below.

Table 6-7 Reworded items based on experts qualitative feedback

Items deemed too general by one of the reviewers and passed the experts review stage	**Reworded items**
I actively seek alternatives to using AI-ETs during my experience.	Throughout my experience, I seek out options that don't involve relying on AI-ETs, actively exploring alternative approaches
I was active while interacting with AI-ETs.	I played an active role during my interactions with AI-ETs.
This experience with AI-ETs is action oriented.	The nature of this experience with AI-ETs is action-driven, emphasizing my proactive involvement and contribution to the outcome of the experience.
My interactions with AI-ETs required the use of multiple senses.	Engaging with AI-ETs involved employing a combination of senses such as sight, touch, and sound to gather comprehensive information.

The interactions with AI-ETs made a strong impression on my senses.	The interactions with AI-ETs left a profound impact on my senses, specifically intensifying my visual and auditory perceptions, creating a lasting impression.
The interactions with AI-ETs result in bodily experience.	Interacting with AI-ETs resulted in a tangible bodily experience, where I could feel specific sensations or movements triggered by the nature of the interaction.

The discrepancy in specificity across dimensions can be attributed to the inherent differences in how various experiences are conceptualized. Cognitive reactions and responses naturally lend themselves to greater specificity, as they are often segmented and detailed by nature. Our conceptualization of the AICX scale emphasizes this, suggesting that cognitive dimensions are not a single entity but rather a collection of distinct facets, each reflecting different cognitive aspects. This specificity is crucial for cognitive items. In contrast, sensorial and behavioural dimensions are inherently different. Sensorial experiences are typically holistic and subjective, making it difficult to break them down into highly specific items without oversimplifying their complexity. Similarly, behavioural dimensions often involve observable actions and patterns that can be categorized more straightforwardly but do not necessarily require the same level of specificity as cognitive dimensions. As a result, the approach to item development for these dimensions must naturally differ, reflecting their unique characteristics.

The reflective nature of the scale further supports this variability in item specificity. A reflective scale is designed so that the construct is indicated by its items, allowing for flexibility in the inclusion or exclusion of dimensions or items. Removing a dimension does not invalidate the entire scale but may only reduce the total variance explained. This ensures that the scale remains robust and meaningful even when adjustments are made. Given this, the variability in specificity across dimensions is not only acceptable but also aligned with the reflective scale’s design principles, ensuring the scale's validity and applicability remain intact.

Given the constraints of time and limited access to expert panels, the current process was prioritised, with any necessary refinements to be addressed during the scale purification stage. This approach was further justified by the fact that none of the other reviewers raised concerns about the specificity, relevance, or overall fit of these six items within the scale. Collectively, these considerations support the decision to retain the items as they are, ensuring that the scale development process remains both efficient and theoretically grounded.

On a more practical level, the insights derived from the qualitative feedback are reflected in the exclusion of several items for specific reasons. Some items were excluded because they were identified as falling outside the scope of the experience, such as 'I was attracted by the AI-ETs,' which was considered an antecedent of the experience. Others reflected individual contextual factors, like 'I have reservations about the performance of AI-ETs' and 'I have a clear understanding of the abilities of AI-ETs.' Items describing AI-ET characteristics rather than the experience itself were also removed, including 'The AI-ETs offer adaptability across age, culture, language, and needs' and 'The design of AI-ETs was important in shaping my AICX.' Additionally, items such as 'Overall, I have a negative perception about AI-ETs' were excluded for not necessarily representing responses to the experience. Some items, like 'AI-ETs were convenient,' were considered overly general and lacking the specificity required for the AICX scale.

Finally, items that were difficult to categorize within the construct's dimensions were also excluded. For instance, 'My imagination is being stirred during the interaction with AI-ETs' was removed because its phrasing hinted at multiple dimensions but lacked clarity. One reviewer noted that while imagination might relate to sensorial or emotional dimensions, the item's cognitive framing in its description and questioning made it challenging to classify. Similarly, some items were inherently ambiguous in their nature. For example, 'After the interaction with AI-ETs, I felt more positive about myself' was considered applicable to multiple dimensions, further complicating its categorization.

Reviewing the judges' feedback highlighted divergent perspectives from the literature regarding the boundaries of the experience—where it begins, where it ends, and which elements are included versus excluded from its scope. This feedback highlighted the ongoing need to address these ambiguities and reinforced the importance of establishing a clear and precise conceptualization of AICX. Clarity in this regard is crucial for navigating these divergences and ensuring that the scale development process adheres to a well-defined theoretical framework. Moreover, ambiguous items or those subject to varying interpretations were identified by judges and subsequently excluded by the researcher. Such items introduced variability in expert evaluations due to differing understandings of the construct. While this overlap reflects the inherent complexity of experiences, it poses risks to the clarity and reliability of the scale. Ambiguity can blur boundaries between dimensions, complicate interpretability, and lead to inconsistent perceptions among respondents, ultimately undermining the scale's validity and reliability.

This refinement process highlights a key challenge in scale development: balancing conceptual inclusivity with methodological precision. The exclusion of problematic items illustrates the critical role of scale developers in ensuring alignment with the construct's theoretical framework while maintaining psychometric rigor. It is essential to recognize a critical distinction in this process: while experts contribute valuable insights into the construct, they may lack familiarity with methodological guidelines for scale development. Scale developers, equipped with expertise in psychometric processes, may need to override certain expert suggestions to enhance the scale's methodological soundness and ensure its reliability and validity.

Overall, this chapter outlines the qualitative phase of the AICX scale development process, which, along with a subsequent quantitative phase, forms the comprehensive scale development framework. It begins by conceptualizing AICX as customers' non-deliberate spontaneous responses and reactions to offering-related stimuli along a customer journey featuring one or more AI-enabled technologies. The AICX scale is framed as a reflective measurement model, designed to generate a score representing the intensity of experiences along a continuum from weak to strong. Following this conceptualization, potential scale items were generated from two primary sources: a review of previously published scales measuring related constructs and insights from a netnography study analysing real-life customer reviews, resulting in a pool of 130 items. A two-stage item refinement process was then undertaken to evaluate and refine these items, reducing the pool from 130 to 45 while establishing content and face validity through expert review to ensure alignment with the construct's dimensions. This systematic approach establishes a rigorous foundation for the scale's subsequent quantitative phase discussed in detail in the following chapter.

Chapter 7 . The AICX Scale Development - Quantitative Phase

This chapter outlines the quantitative phase of the AICX scale development process. The phase aims to explore the factor structure, refine, and validate the scale using commonly agreed quantitative methods (Bearden, Netemeyer and Teel, 1989; Carpenter, 2018; Costello and Osborne, 2005; DeVellis and Thorpe, 2021; Tian, Bearden and Hunter, 2001; Worthington and Whittaker, 2006). The phase consists of four rounds of data collection and analysis (see Figure 7-1) The pilot round is designed to test the survey with a real audience before the main data collection. 2) The first round explores the factor structure of the scale through exploratory factor analysis (EFA). 3) The second round evaluates the emerging factors from the first round and validates the AICX scale structure using confirmatory factor analysis (CFA). Additionally, the nomological validity and discriminant validity of the scale

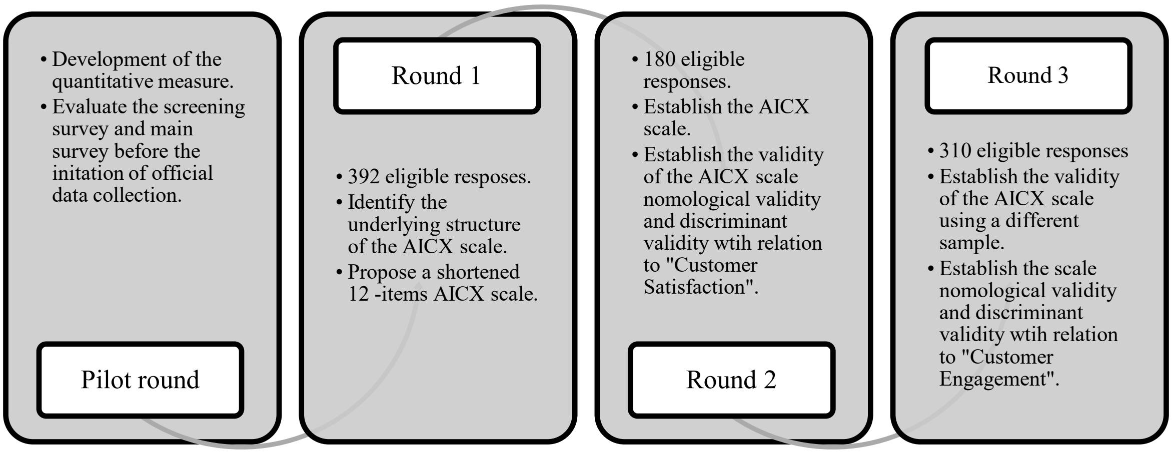

Figure 7-1 Overview of the Qualitative Phase

are tested in relation to CS. 4) In the third round, the AICX scale is validated again through CFA, and the scale's nomological validity and discriminant validity are tested in relation to customer engagement (CE).

Throughout the four rounds, the surveys were designed using Qualtrics, and participants were recruited through Prolific. The following sections present each round separately, outlining the methodological decisions, statistical tests used for psychometric evaluation, data analysis procedures, and the findings from these analyses at each round. Figure 6-1 illustrates the four rounds comprising the quantitative phase of the process.

7.1 Pilot round

The quantitative phase of the AICX scale commenced with a pilot round. Pilot testing is crucial for identifying and addressing any potential issues prior to initiating the primary data collection and is a common and recommended practice in scale development empirical studies and methodological literature (DeVellis and Thorpe, 2021; Froehle and Roth, 2004; Liu and Hung, 2022). In this study, this round serves two main purposes: first, to evaluate the effectiveness of the screening criteria for determining participant eligibility and to estimate the time needed to complete the survey; and second, to assess the readability of the items by involving a sample of representative participants from the target population.

To effectively serve the purposes of the pilot round, a two-part questionnaire was designed. The first part included a screening process in which respondents were presented with examples of AI-ETs and asked to indicate whether they had prior experience with such technologies. Respondents who did not meet the experience criteria were instructed to exit the survey at that point. Those who confirmed relevant experience within a service context proceeded to the second part, which comprised 45 items evaluated on a 7-point Likert scale ranging from 1 (Strongly disagree) to 7 (Strongly agree). In addition to the scale items, three attention check questions were embedded to assess response attentiveness and identify participants who failed to engage meaningfully with the survey content. In line with Johanson and Brooks (2010), who recommend a sample size of approximately 30 representative participants for pilot studies involving preliminary surveys or scale development, a total of 37 responses were collected and reviewed.

A review of the pilot responses revealed an average survey completion time of 6 minutes and 40 seconds. Additionally, the data indicated that the generic nature of some screening questions in the second part led to numerous irrelevant responses. Several participants reported no prior interaction with AI-ETs or referred only to basic verbal or text-based bots. Notably, many respondents incorrectly equated the use of generative AI tools such as ChatGPT with having an AICX. These findings pointed to a general misunderstanding of what constitutes an AI-ET and a lack of clarity regarding the specific technologies targeted in this study. In response, the screening process was separated from the main survey and implemented as a standalone pre-survey, allowing the researcher to assess participant eligibility prior to granting access to the main questionnaire. Appendix E includes a copy of the pilot survey before the amendments, while Appendix F provide copies of the different screeners used to recruit eligible participants after these changes were implemented.

The screening survey was restructured based on insights from the pilot study, with the goal of balancing clarity around the specific types of AI-ETs targeted in the research and inclusivity of the varied experiences reported by respondents. Three versions of the pre-survey were developed to reflect this balance—each tailored to align with participant responses, the filtering options available on the Prolific platform, the categories of AI-ETs identified in the systematic literature review, and the technological clusters used for collecting customer reviews in the netnography study. Specifically, one version was designed for each of the following clusters: service robots, verbal and textual bots, and extended reality technologies. This targeted approach was intended to minimize confusion about the type of technology being studied and ensure that participants were appropriately matched to the focus of the research (see Figure 7-2).

A second pilot round was carried out using this revised approach, and 61 responses were collected and analysed. Participants were first asked to complete one of three versions of the screening survey. Based on their answers, only those who met the eligibility criteria were invited to complete the main survey. The results indicated that the revised approach enhanced clarity and improved the recruitment of a sample more closely aligned with the characteristics of the target population. With the screening and survey instruments finalised, the study then advanced to Round 1 of the main data collection.

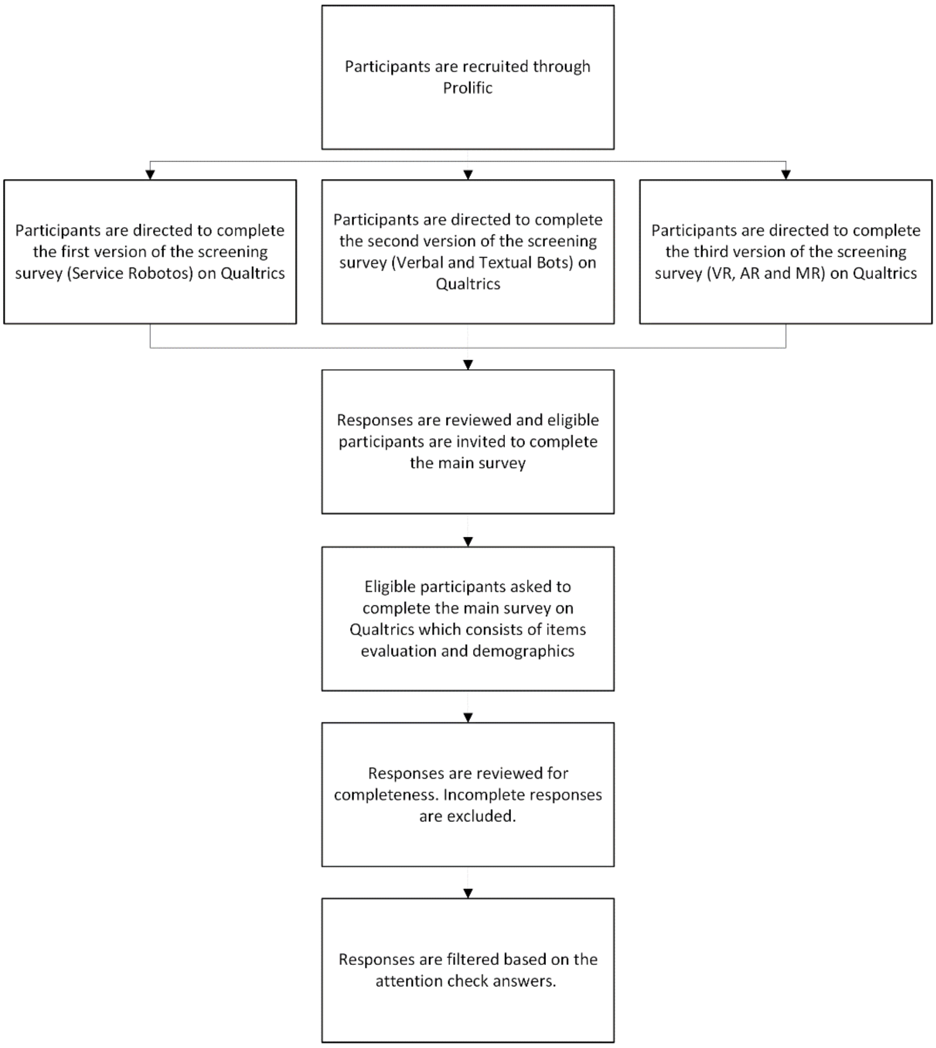

Figure 7-2 Approach to participants screening

7.2 Round 1: Identifying the AICX Scale Structure

The first round of the quantitative phase focused on identifying the initial structure of the AICX scale through exploratory factor analysis (EFA). Responses were collected from participants with prior experience using AI-ETs, following the approach established during the pilot phase. A total of 421 responses were collected via Qualtrics and reviewed for completeness. After excluding 19 incomplete or returned responses and 10 that failed the attention checks, 392 valid responses remained for analysis. Figure 7-3 presents a visual summary of Round 1.

To examine whether the type of AI-ET customers had prior experience with—service robots (SR), verbal/textual bots (VT), or extended reality applications (XR)—impacted customer experience (CX) evaluations, a one-way ANOVA was conducted using scores from the initial exploratory item pool. This method is appropriate for comparing mean differences across three or more independent groups (Hair *et al*., 2019). The results revealed a statistically significant difference between groups, $F(2, 330) = 3.85$, $p = .022$; however, the effect size was small ($\eta^2 = .023$), indicating that only a minor proportion of variance in CX ratings was attributable to the type of AI-ET experienced. Post-hoc comparisons using Tukey's HSD showed that the VT group (M = 4.29, SD = 0.79) reported significantly lower experience scores than both the SR group (M = 4.55, SD = 0.80, $p = .041$) and the XR group (M = 4.53, SD = 0.69, $p = .048$), with no significant difference between SR and XR users ($p = .994$).

In this preliminary phase, the overall CX score was calculated as the average of all 45 exploratory items. As some of these items were later deemed less relevant or outside the refined construct structure, this likely introduced measurement noise, which may have contributed to the observed statistical significance despite the small effect size. While the initial findings suggested a potential difference in CX evaluations based on AI-ET type, the subsequent scale development and analysis were carried out with this consideration in mind, ensuring that the potential influence of interface type was monitored throughout the refinement process. Furthermore, during response screening, some participants reported prior experience with more than one type of AI-ET (e.g., both a service robot and a virtual reality application). These participants were instructed to respond based on their most recent interaction; however, because the specific AI-ET type was not explicitly recorded in such cases, their responses were excluded from the

-based group comparisons to ensure clear attribution of experience to a single interface type. These responses were nonetheless retained for broader, non-grouped analyses where specific categorisation was not required.

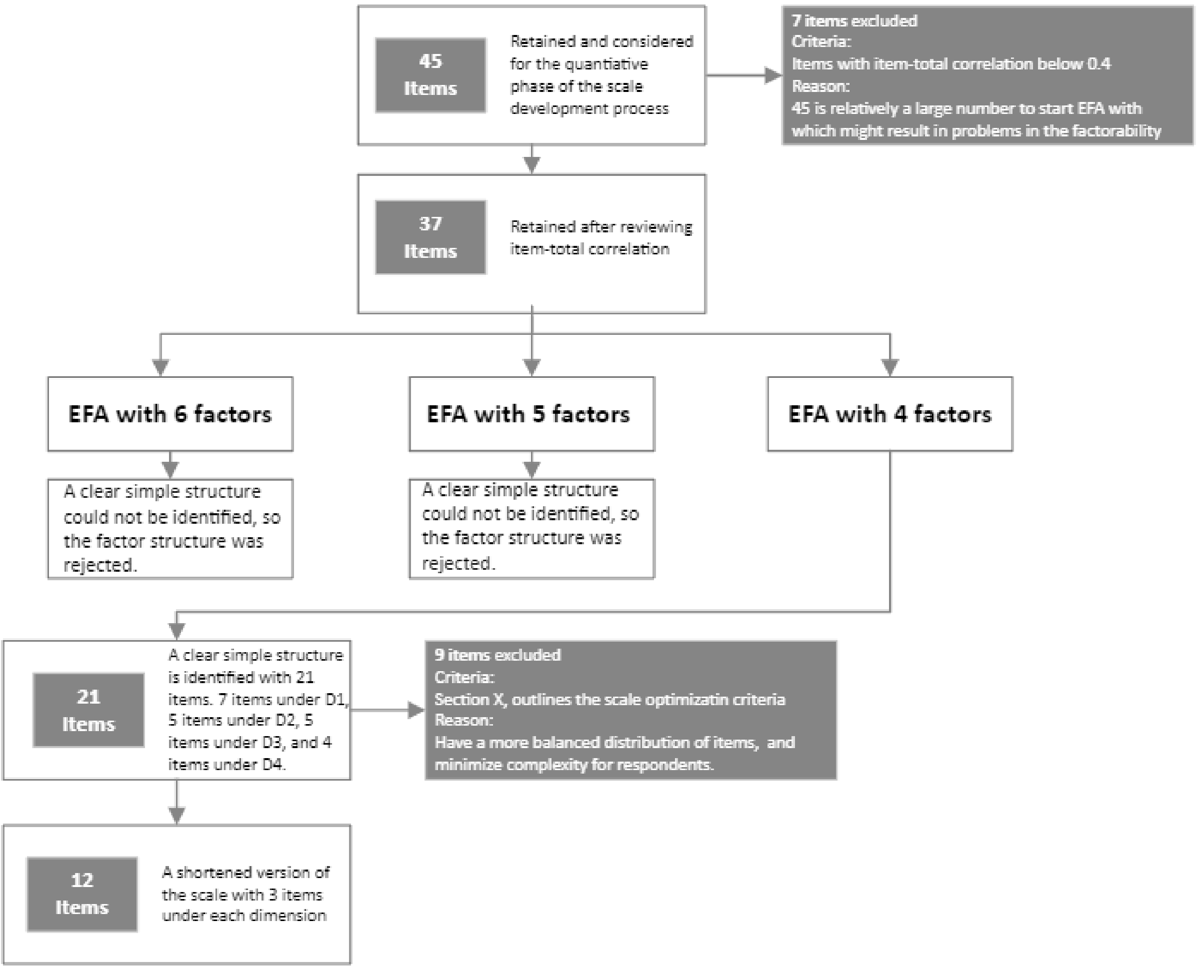

Figure 7-3: Visual summary of Round 1

7.2.1 Sample characteristics

EFA typically requires a large sample size; small samples can lead to unstable factor structures and limit the generalizability of the results. Determining an appropriate sample size can be guided by rules of thumb or item ratios (Carpenter, 2018). The sample size of 392 in this study meets the recommended minimum participant-to-item ratio of 5:1 (Hair *et al.*, 2018), aligns with Comrey and Lee's (2013) benchmark of 300 as a good sample size, and adheres to the general guideline of at least 300 responses being sufficient (Carpenter, 2018; Henson and Roberts, 2006).

The demographic characteristics of the sample provide important context for understanding the data. Table 7-1summarizes the descriptive statistics for key demographic variables including age, gender, education, income, and employment status for rounds 1, 2 and 3 . The sample in round 1 consisted of 392 participants, of whom 52.04% were female. Most of the respondents are aged between 26 and 35 years (42.35%), followed by those aged 18 to 25 (40.56%), with fewer respondents in older age groups. Nearly half of the sample holds undergraduate degrees (46.94%), with large numbers having completed high school (24.74%) or earned a master's degree (25.26%). A small fraction of respondents has doctoral degrees (0.51%) or hold other qualifications (2.55%). Income distribution shows that most participants earn less than $1,000 per month (38.27%) and only 3.32% earning above $6,000 per month. Employment status varied, with the majority (54.85%) employed full-time, 14.29% employed part-time, 7.14% unemployed, and 21.17% identifying as students.

Table 7-1: Demographic characteristics of samples

Variable	Characteristics	Round 1 (n=392)	Round 2 (n =180)	Round 3 (n=310)
Age	18 – 25	40.56%	43.88%	40.00%
	26 – 35	42.35%	38.88%	39.67%
	36 – 45	11.48%	12.22%	13.22%
	46 – 55	3.32%	3.33%	4.51%
	Above 55	2.30%	1.66%	2.58%
Gender	Male	47.96%	50.00%	50.64%
	Female	52.04%	50.00%	49.35%
Education	High School Diploma	24.74%	20.00%	22.85%
	Undergraduate	46.94%	50.55%	53.22%
	Master	25.26%	26.11%	18.70%
	Doctoral	0.51%	1.66%	3.22%
	Others	2.55%	1.66%	2.25%
Income	Less than 1000$	38.27%	38.33%	27.74%
	1000$ - 2000$	31.63%	31.66%	26.77%
	2001$ - 3000$	14.29%	13.33%	15.80%
	3001$ - 4000$	7.14%	7.77%	9.35%
	4001$ - 5000$	3.83%	3.33%	7.74%
	5001$ - 6000$	1.53%	2.22%	3.87%
	Above 6000$	3.32%	3.33%	8.70%
Employment	Full-time employed	54.85%	55.00%	62.90%
	Part-time employed	14.29%	11.66%	12.58%
	Unemployed	7.14%	8.88%	8.06%
	Student	21.17%	21.11%	14.38%
	Retired	0.00%	1.11%	0.64%
	Other	2.55%	2.22%	0.96%

7.2.2 Data Suitability for Factor Analysis

Prior to conducting EFA, it is crucial to assess data suitability for factor analysis (Carpenter, 2018). Statistical tests are employed to ensure that the data meet the assumptions necessary for valid and meaningful results. Commonly used tests for this purpose include the Kaiser-Meyer-Olkin (KMO) Test and Bartlett's Test of Sphericity (Klaus and Maklan, 2012).

The Kaiser-Meyer-Olkin (KMO) measure is a statistical tool used in the initial stages of factor analysis to assess whether a dataset is suitable for extracting meaningful factors. The KMO measure ranges from 0 to 1, with higher values indicating better suitability for factor analysis. A KMO value close to 1 suggests that variables in the dataset share a significant amount of common variance, making factor analysis appropriate. Lower KMO values indicate less shared variance, suggesting potential challenges in using factor analysis with the given data. Researchers therefore use KMO as a diagnostic tool to determine the adequacy of their dataset before proceeding with factor analysis (Lloret *et al*., 2017; Tabachnick and Fidell, 2007; Watkins, 2018).

The Bartlett test of homogeneity of variances is another statistical test used to assess whether the variances of observed variables are equal across different groups or conditions. Specifically, in the context of factor analysis, the test is employed to examine the suitability of a correlation matrix for factorization. The null hypothesis of the Bartlett test assumes that the observed correlation matrix is an identity matrix, indicating equal variances and no correlation between variables. A significant result, indicated by a low p-value, suggests that the variances across variables are not uniform, providing evidence against the null hypothesis. In such cases, the correlation matrix is considered suitable for factor analysis, as there are indications of variability among the observed variables. The Bartlett test is a crucial diagnostic tool in factor analysis, helping researchers make informed decisions about the appropriateness of their data for further exploration of underlying factors (Klaus and Maklan, 2012; Mardia *et al*., 2024).

The dataset has a KMO value of 0.946, which indicates an excellent level of sampling adequacy. This signifies that the data is highly suitable for factor analysis. The strong observed correlations among the variables allow for effective factor extraction. Additionally, Bartlett's Test of Sphericity produced a significant Chi-square statistic X^2=9720.494, df 990, $p< 0.001$). The null hypothesis for Bartlett's Test of Sphericity is that the correlation matrix is an identity matrix, where all off-diagonal elements are zero, indicating no correlation among the variables. The significant result ($p<0.001$) suggests that the null hypothesis can be rejected, the correlation matrix deviates significantly from an identity matrix, confirming that the variables are sufficiently inter-correlated. This indicates that the data meets the assumptions necessary to proceed with factor analysis.

After confirming the suitability of the data for factor analysis, it's important to make well-informed decisions about EFA. This includes selecting an appropriate model for the factor analysis, determining the factor extraction method, identifying the optimal number of factors to extract, and deciding whether to apply factor rotation. These crucial decisions should be guided by both the conceptual understanding of the construct of interest, as discussed in Chapter 5, and the empirical characteristics of the data sample.

7.2.3 Descriptive analysis

In order assess the dataset's suitability for further analysis. Key metrics, including means, variances, standard deviations, skewness and kurtosis, floor and ceiling effects, were examined to evaluate item performance and ensure the reliability of the scale (see Table 7-2).The mean scores for these items range from 2.92 to 5.36, indicating a diverse range of average responses across items. The standard deviations vary between 1.11 and 1.55, reflecting the degree of variability in responses. Items with higher standard deviations suggest greater variability in how respondents perceive or react to these items. The variance for the items ranges from 1.345 to 3.252, indicating a continuum of consistency and variability within the dataset. Skewness and kurtosis for the 45 potential items ranged between -2 and +2. This aligns with the established criteria outlined by Hair *et al*. (2010) and Byrne (2010) for evaluating data normality, which define normal data as having skewness values between -2 and +2 and kurtosis values between -7 and +7. This indicates that, despite minor deviations, the dataset maintains sufficient normality to support robust statistical analyses.

The results also indicate no evidence of floor or ceiling effects. Floor and ceiling effects occur when responses cluster at the lowest or highest ends of a scale, respectively, limiting variability and potentially distorting results. In scale development, these effects can impact the correlation matrix, which underpins factor extraction. Limited variability due to extreme clustering can obscure meaningful patterns, compromise the interpretability of factors, and reduce the scale's ability to measure the full range of the construct effectively. The literature suggests an acceptable threshold of 15-20% for responses at these extremes (McHorney and Tarlove, 1995). In this study, no evidence of floor or ceiling effects was found, with response distributions falling well within acceptable limits and only one item scoring a borderline floor effect. This suggests that the items effectively capture the full range of the intended construct, confirming the absence of measurement issues.

7.2.4 Scale Purification

There is no strict rule in the literature regarding the number of items to begin EFA with. The initial pool of items should be comprehensive enough to capture the full range of the construct of interest, ensuring sufficient items remain after addressing potential issues such as redundancy or poor fit. However, testing EFA with the existing number of items in this study indicated that the item pool was too large, leading to challenges in factor extraction and interpretation. For instance, the factor structure showed signs of cross-loadings and redundancy, making it difficult to identify clear and distinct factors. Additionally, some items displayed low communalities, further complicating the analysis. Reducing such items beforehand simplifies the analysis by removing those that do not contribute meaningfully to the factors, allowing for a focus on the most relevant and robust indicators. It also mitigates the risk of overloading the analysis with excessive items, which could negatively affect the clarity and interpretability of the factor structures. Ultimately, this process results in a more manageable and meaningful pool of items for scale development.

Table 7-2: Descriptive statistics - Round 1

	Mean	Std. Deviation	Variance	Skewness	Kurtosis	Floor Effect	Ceiling Effect
Item 1: I actively seek alternatives to using AI-ETs during my experience.							
	3.74	1.467	2.151	0.199	-0.698	19	10
Item 2: I was active while interacting with AI-ETs.							
	5.26	1.160	1.345	-0.980	1.177	2	39
Item 3: This experience with AI-ETs is action oriented.							
	5.03	1.117	1.247	-0.615	0.429	1	24
Item 4: During the interactions with AI-ETs, I was explaining and interpreting things for myself.							
	3.22	1.369	1.875	0.578	-0.065	32	5
Item 5: I concentrate fully during my AI-ETs interaction.							

5.30	1.243	1.545	-0.806	0.607	3	61
Item 6: I engage in a lot of thinking when I interact with AI-ETs.						
4.60	1.439	2.071	-0.423	-0.437	8	29
Item 7: I gained new knowledge while interacting with AI-ETs during my experience.						
5.24	1.438	2.068	-0.985	0.680	8	73
Item 8: I have confidence in the performance of AI-ETs.						
4.96	1.284	1.648	-0.560	0.128	3	40
Item 9: I used my intellect during the interactions with AI-ETs.						
5.11	1.245	1.549	-0.699	0.235	2	41
Item 10: Interacting with AI-ETs enables me to come up with new ideas.						
5.05	1.467	2.153	-0.855	0.310	9	56
Item 11: My imagination is being stirred during the interaction with AI-ETs.						
4.47	1.430	2.045	-0.442	-0.249	12	23
Item 12: My interactions with AI-ETs felt novel and unique.						
4.58	1.358	1.845	-0.373	-0.405	5	22
Item 13: My total attention was on the AI-ETs.						
4.79	1.421	2.020	-0.654	0.030	10	35
Item 14: The interactions with AI-ETs awakened my creativity.						
4.58	1.446	2.091	-0.431	-0.394	9	28
Item 15: The interactions with AI-ETs piqued my curiosity.						
5.36	1.214	1.475	-0.903	0.917	2	61
Item 16: Using AI-ETs challenges me and tests my ability.						
4.50	1.391	1.934	-0.341	-0.596	5	19
Item 17: When I am interacting with AI-ETs, I feel that I am in flow.						
4.46	1.330	1.768	-0.448	-0.199	7	14
Item 18: While interacting with AI-ETs, I was absorbed intently.						
4.49	1.351	1.826	-0.333	-0.389	6	18
Item 19: I feel good being able to use AI-ETs.						
5.35	1.190	1.416	-0.658	0.581	2	69
Item 20: I feel playful when I interact with AI-ETs.						
4.84	1.543	2.381	-0.569	-0.324	10	54
Item 21: I felt happy while interacting with AI-ETs.						
4.83	1.311	1.719	-0.443	0.205	7	37
Item 22: I felt nervous or afraid when using AI-ETs.						
5.04	1.482	2.195	-0.511	-0.539	4	68
Item 23: I felt pleased while interacting with AI-ETs.						
4.83	1.213	1.472	-0.472	0.354	3	28
Item 24: I felt positively connected with AI-ETs.						
4.55	1.356	1.839	-0.483	0.076	11	21
Item 25: I felt safe in my interactions with AI-ETs.						
4.81	1.294	1.674	-0.444	-0.012	5	31
Item 26: I have experienced moments of wonder and amazement during my interactions with AI-ETs.						
4.91	1.405	1.974	-0.769	0.158	7	37
Item 27: I was indulged in the interactions with AI-ETs.						
4.70	1.241	1.540	-0.500	0.119	4	18
Item 28: My interactions with AI-ETs added a sense of fun and excitement to my experience.						
5.01	1.248	1.557	-0.808	0.963	5	37
Item 29: My interactions with AI-ETs brought laughter.						
4.03	1.559	2.431	-0.157	-0.777	22	17
Item 30: The interactions with AI-ETs made me feel in a good mood.						
4.75	1.306	1.706	-0.690	0.433	7	24
Item 31: The interactions with AI-ETs made me feel worried.						
4.97	1.554	2.416	-0.466	-0.761	3	69
Item 32: The interactions with AI-ETs make me feel optimistic.						
4.56	1.272	1.618	-0.426	0.155	8	16
Item 33: While interacting with AI-ETs, I felt contended.						
3.89	1.259	1.584	0.451	0.191	5	16
Item 34: My interactions with AI-ETs required the use of multiple senses.						
4.16	1.499	2.246	-0.162	-0.860	12	15
Item 35: The interactions with AI-ETs made a strong impression on my senses.						
4.26	1.435	2.060	-0.396	-0.361	16	15
Item 36: The interactions with AI-ETs result in bodily experience.						
3.37	1.491	2.224	0.149	-0.911	41	4
Item 37: Interacting with AI-ETs gives a social image of being tech savvy.						
4.83	1.462	2.137	-0.723	0.125	11	41
Item 38: AI-ETs made me feel cool.						
4.60	1.560	2.435	-0.492	-0.468	13	37
Item 39: I established a personal relationship with AI-ETs.						
2.92	1.641	2.692	0.630	-0.575	88	8

Item 40: I pay attention to how others perceive my interactions with AI-ETs.						
3.63	1.803	3.252	0.103	-1.163	54	20
Item 41: My interactions with AI-ETs deepened the sense of connection I felt throughout the experience.						
4.02	1.517	2.301	-0.291	-0.637	26	14
Item 42: My interactions with AI-ETs reduced my social engagement during the experience.						
4.04	1.586	2.515	0.142	-1.049	12	21
Item 43: The interaction with AI-ETs was socially rewarding.						
3.94	1.525	2.326	-0.157	-0.725	24	14
Item 44: The interactions with AI-ETs made me feel important for a few moments.						
3.84	1.695	2.873	-0.081	-0.978	40	19
Item 45: The interactions with AI-ETs made me feel like I belonged to a community.						
3.65	1.720	2.959	-0.012	-1.078	52	15

Existing literature offers various methods for item reduction. Techniques include evaluating item communalities (Worthington and Whittaker, 2006) and factor loadings (Costello and Osborne, 2005), with items commonly removed if they exhibit low communalities, low loadings, cross-loadings, or if they function independently. Other methods involve analysing item difficulty and discrimination indices, conducting distractor efficiency analysis, and considering inter-item or item-total correlations (Boateng *et al*., 2018).

Item-total correlation is a widely used preliminary metric for scale purification and refinement prior to running EFA (Bearden, Netemeyer and Teel, 1989; Tian *et al*., 2001; Wolfinberger and Gilly, 2003). It assesses how well each item aligns with the overall construct, guiding the refinement process. Items with low item-total correlations may be removed due to poor alignment, while those with high correlations are retained for their strong contribution to the scale's reliability and validity. Literature suggests various cut-off points for retention, including 0.30 (Cristobal *et al*., 2007), 0.40 (Loiacono *et al*., 2002), and 0.50 (Francis and White, 2002; Kim and Stoel, 2004). For this study, the item retention strategy proposed by Wolfinberger and Gilly (2003) is adopted, which recommends retaining items with an item-to-total correlation exceeding 0.40. This threshold balances retaining a sufficient number of items while excluding those less relevant to the construct.

Following Bearden, Netemeyer and Teel (1989), item-total correlations were calculated before conducting EFA. Items with correlations below 0.40 were removed, resulting in the elimination of items 1, 3, 4, 6, 9, 22, 31, and 42, leaving 37 items for EFA. The item-total correlation measures the relationship between an individual item and the total score of the scale. However, because this calculation includes the item itself in the total score, it can artificially inflate the correlation value by introducing bias (DeVellis and Thorpe, 2021). This inflation may overestimate the item's relationship with the overall construct being measured. To address this limitation, the corrected item-total correlation was used in this study. By excluding each item from the total score during calculation, this method ensures an unbiased evaluation of the item's independent contribution to the scale. Using the corrected metric allows for a more accurate identification of items that align well with the underlying construct and highlights items requiring refinement, ultimately enhancing the scale's reliability and validity (see Table 7-3).

Table 7-3: Corrected Item-to-total correlations

Item1*	**-0.102**	**Item16**	**0.525**	**Item31***	**0.227**
Item2	0.465	**Item17**	0.704	**Item32**	0.662
Item3*	0.304	**Item18**	0.639	**Item33**	-0.431
Item4*	-0.140	**Item19**	0.731	**Item34**	0.513
Item5	0.452	**Item20**	0.474	**Item35**	0.670
Item6*	0.317	**Item21**	0.739	**Item36**	0.486
Item7	0.607	**Item22***	0.089	**Item37**	0.512
Item8	0.628	**Item23**	0.745	**Item38**	0.712
Item9*	0.379	**Item24**	0.731	**Item39**	0.574
Item10	0.550	**Item25**	0.536	**Item40**	0.448
Item11	0.557	**Item26**	0.607	**Item41**	0.676
Item12	0.554	**Item27**	0.627	**Item42***	-0.139
Item13	0.572	**Item28**	0.718	**Item43**	0.639
Item14	0.661	**Item29**	0.550	**Item44**	0.645
Item15	0.595	**Item30**	0.717	**Item45**	0.628

*Highlighted items removed before running EFA because item-total correlation is below 0.4

The remaining 37 items were evaluated for suitability for factor analysis, utilizing both KMO test and Bartlett's Test of Sphericity. The KMO measure demonstrated a value of 0.955, suggesting strong interrelationships among the variables. Furthermore, the outcomes of Bartlett's Test of Sphericity revealed a highly significant result (χ^2(8606.585), $p < 0.001$), indicating a robust association among the examined variables. This finding negates the null hypothesis of no correlation, thereby affirming the dataset's suitability for factor analysis. Collectively, these results provide substantive evidence supporting the dataset's appropriateness for factor analysis.

7.2.5 Factor Model for Running EFA

Factor Analysis includes two distinct models with different objectives and computational methods: principal component analysis and common factor analysis. Principal component analysis is used for reducing the number of variables and capturing the most variance. It aims to reduce data dimensionality by creating new variables, called components, that capture as much information from the original variables as possible without assuming underlying constructs. In contrast, common factor analysis is used for exploring the underlying factors that drive the observed relationships among variables. It seeks to identify latent constructs that explain correlations among measured variables by partitioning variance into common (shared) and unique (specific and error) components. While principal component analysis is ideal for simplifying data, common factor analysis is preferred for identifying meaningful underlying constructs in theoretical and measurement development (Carpenter; 2018; Watkins, 2018; Yong and Pearce; 2013).

Literature suggests that common factor analysis is preferred when the goal is to identify latent constructs for developing measurement tools (Fabrigar and Wegener, 2012; Haig, 2005; Worthington and Whittaker, 2006). Principal component analysis focuses on maximizing the variance explained by observed variables without considering latent constructs and, thus, can inflate the size of the components by including error variance, which often results in retaining more components than necessary (Costello and Osborne, 2005). Accordingly, and given the objective of the study at hand, common factor analysis is selected as the factor model for running EFA.

7.2.6 Extraction method for EFA

In common factor analysis, various extraction methods have been developed to replicate the observed correlation matrix as accurately as possible (Finch and French, 2015). For example, maximum likelihood (ML), principal axis factoring (PAF), unweighted least squares, generalized least squares, minimum residual, alpha factoring and image factoring (Carpenter, 2018; Tabachnick and Fidell, 2007; Yong and Pearce, 2013). Each method represents a distinct mathematical approach to estimating the relationships between observed variables (items) and factors (dimensions of AICX). While there is still much to learn about the specific advantages and disadvantages of each method (Osborne, 2014), ML and PAF are recognized as the most used techniques in research (Carpenter, 2018).

ML estimates factors by maximizing the likelihood that the observed data came from a model with those factors, using iterative algorithms to find the best-fitting solution and is more suitable for confirmatory factor analysis. PAF identifies underlying factors by iteratively estimating and refining communalities to explain the shared variance among observed variables, thereby revealing the underlying patterns in the data and aligning well with exploratory factor analysis (Coughlin, 2013; Fabrigar *et al*., 1999; Osborne and Costello, 2005). Given that the goal of this stage is to explore the structure of the AICX construct, PAF is the most appropriate method for conducting EFA.

Choosing PAF is supported by the fact that multivariate normality cannot be guaranteed, particularly in social sciences. The literature recommends PAF over ML when data do not meet normality assumptions (Costello and Osborne, 2005; Young and Pearce, 2013). While ML relies on data normality and can be compromised if this assumption is violated, PAF is more robust to deviations from multivariate normality (Carpenter, 2018; Young and Pearce, 2013). This robustness makes PAF the optimal choice for the current stage of analysis.

7.2.7 Rotation in EFA

In EFA using PAF as an extraction method, rotation can be applied, but it is not strictly necessary; however, it is often used to improve the interpretability of the factor structure. Rotation is a mathematical procedure that involves adjusting the orientation of the factor axes aimed at simplifying the interpretation of factor loadings and achieving a simpler and theoretically more meaningful solution (Watkins, 2018). Rotation has two main types: orthogonal and oblique (Carpenter, 2018). The two types mainly differ in allowing or not allowing factors to be correlated. Orthogonal rotation, such as varimax, quartimax, and equamax, assume the independence of factors. This assumption simplifies interpretation by maximizing the loading of each variable on one factor while minimizing its loading on others, as the factors are assumed to be uncorrelated. Conversely, oblique rotation methods, like Promax or Oblimin, allow the axes to rotate independently, reflecting correlations between factors.

Oblique rotation methods are generally preferred in social science research, where factors are often correlated (DeVellis, 2012). Oblique rotation provides a more realistic representation of the complex relationships between the emerging factors, though it may also complicate interpretation. The decision between orthogonal and oblique rotation ultimately depends on theoretical assumptions about whether the factors are expected to be correlated or uncorrelated (Netemeyer, Bearden and Sharma, 2003). In the AICX scale, the items reflect customers' reactions and responses to the integration of AI-ETs, the emerging dimensions are therefore expected to correlate, as these reactions often are correlated. Consequently, an oblique rotation method, specifically Promax rotation, is employed. While other oblique rotation methods, like Oblimin or Orthoblique, also allow for factor correlations, Promax is preferred for its simplicity, lower computational complexity, and robustness (Carpenter, 2018, Thompson, 2004).

7.2.8 Number of Factors in EFA

Following the application of rotation to improve factor interpretability, a critical aspect of EFA is determining the optimal number of factors to extract (Fabrigar and Wegener, 2012; Watkins, 2018). This can be approached from either a theoretical or empirical perspective. Theory-driven approaches often guide the decision based on the conceptualization of the construct, existing literature, or established frameworks (Carpenter, 2018). Alternatively, empirical methods such as the Kaiser criterion, scree plots, parallel analysis, and minimum average partials offer data-driven estimates for factor retention (Carroll, 1978; Cattell, 1966; Horn, 1965; Velicer, 1976), ensuring a robust and evidence-based selection of factors.

This thesis introduces AICX as a novel form of experience, necessitating exploration beyond traditional CX frameworks (Ghesh, Alexander and Davis, 2024). However, it is anticipated that the new dimensions may not stray far from the established CX framework. This expectation arises because, despite the expanding scope and diversity of customer reactions, they remain within the fixed boundaries of human capabilities. The potential for new insights emerges from how these reactions interact with AI, revealing dimensions that may either integrate existing ones or focus on specific aspects of them, thus uncovering previously unconsidered dimensions. To address this, the study combines factor structures from established CX research with data-driven methods to determine the number of factors. This approach provides flexibility and avoids premature conclusions about the scale's dimensionality.

In this study, SPSS 29 and R were used for the factor retention analysis, with specialized R packages including: psych, factoextra, lavaan, and nFactors. Since no single method is definitive for identifying the optimal number of factors, experts recommend using a combination of approaches to ensure robust results (Fabrigar *et al*., 1999; Henson and Roberts, 2006; Pett, Lackey and Sullivan, 2003; Watkins, 2018) (see Table 7-4). The scree plot indicated 4 factors, while the minimum average partials method suggested retaining 5. Both the Kaiser criterion and parallel analysis recommended extracting 6 factors. Such variability in outcomes is common, and the literature advises starting with the highest number of factors and refining the model iteratively (Costello and Osborne, 2005). This approach ensures the identification of the most parsimonious and meaningful factor structure.

Table 7-4: Factor retention tests and number of factors for extraction

Test name	Explanation	Number of factors
Scree Plot	A graphical method that plots the eigenvalues in descending order. The point where the plot levels off (the "elbow") suggest the number of factors.	4
Parallel Analysis Method (PAM)	Compares the eigenvalues of the data with those obtained from random data sets. Factors are retained if the actual eigenvalues are larger than those from random data.	6
Kaiser Criterion	A rule of thumb based on calculating the eigenvalues, this method retains factors with eigenvalues greater than 1.	6
Minimum Average Partials	Involves controlling for an increasing number of factors and computing the average partial correlation among the remaining variables. The optimal number of factors is indicated by the point at which the average partial correlation reaches its minimum	5
CX conceptualization		5

7.2.9 Items retention criteria

With the approach to determining the number of factors to retain established, it was essential to outline a clear retention criterion. Various guidelines and thresholds for factor loadings and cross-loadings are applied across different contexts and domains in factor analysis (Cristobal *et al*., 2007; Francis and White, 2002; Kim and Stoel, 2004; Loiacono *et al*., 2002), therefore, selecting a rigorous criterion was crucial to enhance the robustness and precision of factor analysis. This study follows the guidelines outlined by Hair *et al*., (1998) which have been employed in widely cited previous scale development studies in relevant domains, such as Wolfinberger and Gilly's (2003) work on online retailing quality. According to this retention criteria items are retained if (1) have factor loadings above 0.5, (2) did not have cross-loading – factor loading above 0.5 on two or more factors, and (3) they have item-total correlation above 0.4.

In parallel, Watkins' (2018) developed guidelines to identify “a simple structure”. The resulting structure should include more than three items per every emerging factor, with items having a salient loading on only one factor. Each emerging factor must achieve a Cronbach's alpha above 0.70, indicating high reliability. Additionally, all emerging factors should be conceptually meaningful and theoretically relevant to the construct of interest. In the context of this scale development study, Wolfinbarger and Gilly's (2003) criteria for retaining items and Watkins' (2018) criteria for identifying a simple structure were jointly applied to systematically evaluate and identify the most appropriate factor structure.

7.2.10 EFA results

After establishing the factor model, extraction method, rotation type, retention criteria, and criteria for a simple structure, EFA was conducted. Following the literature's recommendation to start with the highest number of factors and gradually reduce them, EFA was performed using SPSS 29. This analysis employed principal axis factoring with Promax rotation on 45 potential items for the AICX scale, exploring solutions with no restrictions on the number of factors, 6 factors, 5 factors, and 4 factors.

Before extracting with a restricted number of factors, an initial EFA was conducted without limiting the number of factors. Retention was based on eigenvalues, and the rotation converged after 7 iterations, explaining 61.467% of the cumulative variance. Subsequently, extraction was performed with a restricted number of factors. The pattern matrices for solutions with 6, 5, and 4 factors were generated and reviewed to identify a simple structure, following the established criteria for item retention.

Accordingly, items with low loadings on all factors (below 0.5) or high cross-loadings on two or more factors (above 0.5) were sequentially removed. This process, commonly used in scale development studies (Klaus and Maklan, 2012;

Parasuraman *et al*., 2005), was followed by re-conducting the factor analysis on the remaining items. Neither the six-factor nor the five-factor solutions met the criteria, as they either lacked at least three items per factor or produced factors with low reliability (Watkins *et al*., 2018). These issues are critical for ensuring robust analysis in later stages, and therefore, both solutions were discarded. The four-factor solution, however, produced a clear and well-defined structure with 21 items, explaining a cumulative variance of 65.211%. This solution met the simple structure criteria, with factors arranged as follows: 7 items for F1, 5 items for F2, 5 items for F3, and 4 items for F4 (see Figure 7-4). The EFA results revealed that the loadings of the 21 items ranged from 0.550 to 0.951. Additionally, Cronbach's alpha values for all emerging dimensions exceeded 0.75, indicating strong internal consistency (Nunnally, 1994) (see Table 7-5).

Pattern Matrix[a]

	Factor			
	1	2	3	4
Item45	**.894**	.031	-.168	.069
Item39	**.814**	.053	-.017	-.114
Item44	**.791**	.014	.047	-.028
Item40	**.728**	-.159	.089	-.084
Item41	**.626**	.121	.084	.009
Item43	**.615**	.023	.066	.097
Item36	**.550**	-.043	.031	.077
Item25	-.075	**.951**	-.145	-.115
Item23	-.051	**.697**	.199	.040
Item8	.038	**.696**	-.164	.182
Item24	.105	**.683**	.063	.039
Item21	.034	**.550**	.210	.082
Item29	.078	-.262	**.770**	.072
Item26	-.021	-.064	**.710**	.097
Item30	.042	.256	**.668**	-.128
Item28	-.063	.173	**.645**	.074
Item27	.045	.080	**.645**	-.041
Item10	-.110	-.019	.001	**.839**
Item7	-.052	.123	-.029	**.701**
Item14	.127	-.042	.099	**.629**
Item11	.091	-.041	.086	**.561**

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Figure 7-4: EFA pattern matrix - Round 1

7.2.11 Seeking parsimony and shortening the scale

Developing and validating shorter versions of measurement scales is a well-established practice in the scale development literature, aimed at achieving parsimony (DeVellis and Thorpe, 2021; Stanton *et al*., 2002). This approach seeks to streamline the measurement instrument, ensure a well-balanced set of factors, reduce respondent burden, and ultimately enhance the efficiency of data collection and analysis (Brakus, Schmitt and Zarantonello, 2009; Boateng *et al*., 2018; Netemeyer, Bearden and Sharma, 2003; Worthington and Whittaker, 2006). By minimizing the time and cognitive effort required from respondents while preserving the instrument's psychometric properties, this method ensures that the scale continues to accurately capture the construct of interest.

Table 7-5: Initial AICX scale structure

Factor	Item
Dimension 1 (α: 0.890)	I had confidence in the performance of AI-ETs. (Item8)
	I felt happy while interacting with AI-ETs. (Item21)
	I felt pleased while interacting with AI-ETs. (Item23)
	I felt positively connected with AI-ETs. (Item24)
	I felt safe in my interactions with AI-ETs (Item25)
Dimension 2 (α: 0.880)	I have experienced moments of wonder and amazement during my interactions with AI-ETs. (Item26)
	I was indulged in the interactions with AI-ETs. (Item27)
	My interactions with AI-ETs added a sense of fun and excitement to my experience. (Item28)
	My interactions with AI-ETs brought laughter. (Item29)
	My interactions with AI-ETs put me in a good mood. (Item30)
Dimension 3 (α: 0.849)	My interactions with AI-ETs resulted in a bodily experience. (Item36)
	I established a personal relationship with AI-ETs. (Item39)
	I paid attention to how others perceived my interactions with AI-ETs. (Item40)
	My interactions with AI-ETs deepened the sense of connection I felt throughout the experience. (Item41)
	My interaction with AI-ETs was socially rewarding. (Item43)
	The interactions with AI-ETs made me feel important for a few moments. (Item44)
	The interactions with AI-ETs made me feel like I belonged to a community. (Item45)
Dimension 4 (α: 0.781)	I gained new knowledge while interacting with AI-ETs during my experience. (Item7)
	Interacting with AI-ETs enabled me to come up with new ideas. (Item10)
	My imagination was stirred during the interaction with AI-ETs. (Item11)
	The interactions with AI-ETs awakened my creativity. (Item14)

The proposed AICX scale consists of 21 items spread across four dimensions: D1 and D2 each have 5 items, D3 includes 7 items, and D4 contains 4 items. While the scale is not overly lengthy, the uneven distribution of items among the dimensions could be improved for better balance. By carefully selecting and retaining the most essential items for each dimension, the researcher can ensure the scale’s reliability and validity. This approach will also help achieve a more balanced distribution of items, reduce redundancy, and minimize complexity for respondents.

When optimizing the length of a scale, it is crucial to consider four key indicators: factor loadings, cross-loadings, internal consistency, and conceptual consistency (Worthington and Whittaker, 2006). Items that fall short on these criteria are strong candidates for removal. Specifically, items with low factor loadings do not contribute meaningfully to the underlying construct and should be reevaluated. Items with high cross-loadings, which load on multiple factors, can undermine the clarity and focus of the scale. Items that negatively affect or do not improve internal consistency compromise the reliability of the entire scale. Lastly, items that do not align with the conceptual framework of the emerging factor weaken the scale's overall effectiveness.

In shortening the AICX scale, careful consideration was given to four key indicators (see Table 7-6). Items with the highest factor loadings and corrected item-total correlations were prioritized. The conceptual relevance of each item within its respective dimension was crucial in the decision-making process. Additionally, the impact on Cronbach's Alpha was monitored to ensure that removing any item would not significantly compromise the reliability of the dimensions. Figure 7-5 below details the optimization criteria.

In optimizing the scale's length, internal consistency was prioritized to ensure the validity and reliability of the scale. Internal consistency is crucial because it confirms that items within each dimension consistently measure the same underlying construct. To achieve this, item-to-total correlations were evaluated to identify and retain the most representative items, while Cronbach's Alpha was used as a key measure of reliability. By focusing on these indicators, the scale was refined to maintain robust reliability while reducing the number of items, ensuring that the streamlined version remains both efficient and theoretically sound.

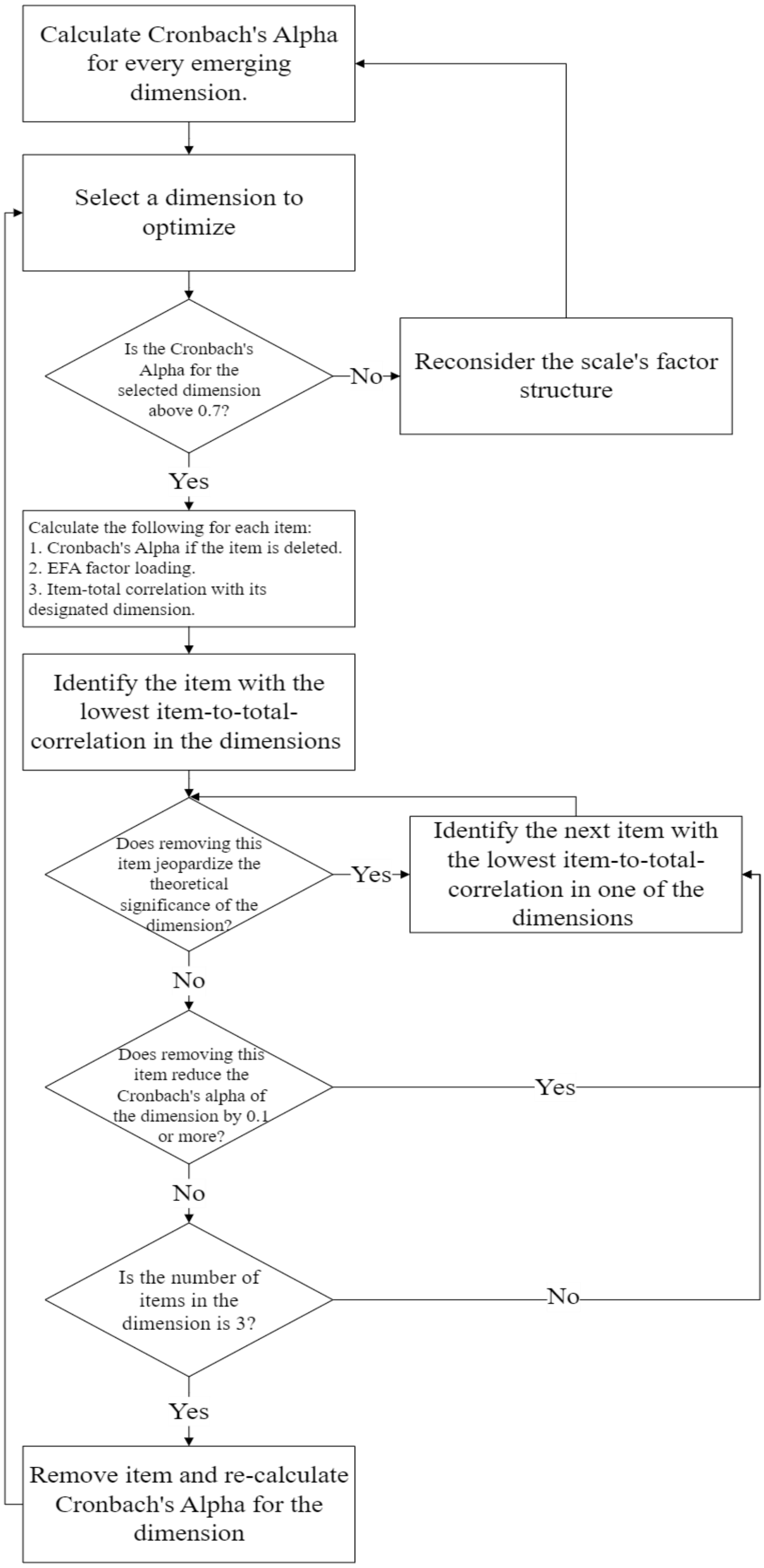

Figure 7-5: Scale optimization criteria. Adapted from Wolfinberger and Gilly (2003) and Watkins (2018) based on the framework presented in their work.

Following the literature's recommendation to retain at least three items per dimension (Carpenter, 2017; Costello and Osborne, 2005; Fabrigar *et al*., 1999), the top three items for each dimension were selected based on the previously mentioned criteria. This approach ensured that the remaining items were well-aligned with their respective dimensions and the overall construct, providing a solid foundation for further scale development and validation.

Table 7-6: Summary of key indicators for scale length optimization

	Item Name	**Item Factor loading**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item deleted**
AICXD1 (α 0.890)	Item36*	0.550	.558	0.888
	Item39	0.841	.720	0.869
	Item40*	0.728	.603	0.885
	Item41*	0.626	.711	0.871
	Item43*	0.615	.675	0.875
	Item44	0.791	.760	0.864
	Item45	0.894	.777	0.862
AICXD2 (α 0.880)	Item8*	0.696	.652	0.868
	Item21*	0.550	.720	0.852
	Item23	0.679	.785	0.838
	Item24	0.683	.761	0.842
	Item25	0.951	.651	0.868
AICXD3 (α 0.849)	Item26	0.710	.655	0.820
	Item27	0.645	.651	0.821
	Item28	0.645	.706	0.808
	Item29*	0.770	.604	0.838
	Item30*	0.668	.706	0.807
AICXD4 (α 0.809)	Item7	0.701	0.619	0.764
	Item10	0.839	0.659	0.745
	Item11*	0.561	0.575	0.785
	Item14	0.629	0.652	0.749

*Removed items

In the initial stages of EFA, factors are often assigned provisional labels such as D1, D2, and so forth, for ease of reference. Once clarity is achieved regarding the items to retain under each factor, the next step—an important step in the process—is typically naming the factors (Carpenter, 2017). When an a priori approach, which builds on an established theoretical structure, is not followed, the naming process involves examining the items on each factor, as these items provide the clearest representation of the underlying latent variable (DeVellis and Thorpe, 2021; Watkins, 2019). The assigned names should accurately capture the essence of the factor, remaining concise, descriptive, and theoretically grounded (DeVellis and Thorpe, 2021; Watkins, 2019). As shown in Table 7-7, the D1 dimension retained items 39, 44, and 45; the D2 dimension retained items 23, 24, and 25; the D3 dimension retained items 26, 27, and 28; and the D4 dimension retained items 7, 10, and 14. After reviewing the items retained under each dimension, the dimensions were named as follows: D1 as Affiliation, D2 as Affinity, D3 as Amusement, and D4 as Advancement.

The emerging dimensions of the AICX scale scored high Cronbach's alpha values, (Affiliation: 0.854 , Affinity: 0.829 , Amusement: 0.809, Advancement: 0.785) indicating strong internal consistency. The retained items demonstrated strong conceptual relevance both within each individual dimension and across all dimensions in relation to the overall AICX construct. This means that each item effectively represents its assigned dimension and contributes meaningfully to the overall concept of AICX. This aligns with established guidelines for effective scale development and dimensionality assessment outlined in literature (Watkins, 2018).

Table 7-7: Proposed shortened AICX scale structure

Factor	**Item**
D1: Affiliation (α: 0.854)	I established a personal relationship with AI-ETs. (Item39)
	The interactions with AI-ETs made me feel important for a few moments. (Item44)
	The interactions with AI-ETs made me feel like I belonged to a community. (Item45)
D2: Affinity (α: 0.829)	I felt pleased while interacting with AI-ETs. (Item23)
	I felt positively connected with AI-ETs. (Item24)
	I felt safe in my interactions with AI-ETs. (Item25)
D3: Amusement (α: 0.809)	I have experienced moments of wonder and amazement during my interactions with AI-ETs. (Item26)
	I was indulged in the interactions with AI-ETs. (Item27)
	My interactions with AI-ETs added a sense of fun and excitement to my experience. (Item28)
D4: Advancement (α: 0.785)	I gained new knowledge while interacting with AI-ETs during my experience. (Item7)
	Interacting with AI-ETs enabled me to come up with new ideas. (Item10)
	The interactions with AI-ETs awakened my creativity. (Item14)

7.3 Round 2: Confirming the AICX Scale Structure

The second round of the quantitative phase focuses on validating the proposed four-factor, 12-item AICX scale through CFA. It also aims to establish the nomological and discriminant validity of the AICX scale in relation to CS. As part of the preliminary analysis of the validated AICX dimensions, a one-way ANOVA was conducted to assess whether prior AI-ET experience continued to influence customer evaluations on the refined scale. Of the four AICX dimensions, only D2 (Amusement) showed a statistically significant difference across groups, $F(2, 177) = 6.31$, $p = .002$, with a moderate effect size ($\eta^2 = .067$). Tukey's HSD post-hoc tests revealed that participants in the VT group ($M = 4.34$) rated D2 lower than those in the SR ($M = 4.86$, $p = .044$) and XR ($M = 5.07$, $p = .002$) groups, with no significant difference between SR and XR users. The other three dimensions—D1 (Affinity), D3 (Affiliation), and D4 (Advancement)—showed no significant group differences (all ps > .05), each with small or negligible effect sizes. Since the effects for three of the four AICX dimensions were negligible and only one showed a moderate effect, we proceeded with the subsequent analyses in Round 2.

7.3.1 Sample and descriptive analysis

Using the same data collection and screening methods as in round 1, 215 responses were collected via Qualtrics from participants with relevant AICX experience. After reviewing for completeness, 18 responses were excluded. Additionally, 17 responses were removed based on an attention check, leaving 180 valid responses for further analysis (See Table 6-1 for the characteristics of the sample). Descriptive statistics for the sample from round 2, are provided in Table 7-8. In this round, CFA was the primary statistical method used. Like EFA, CFA requires a large sample size to produce reliable results. With a sample size of 180, the study meets the recommended sample size guidelines for CFA, as suggested by Carpenter (2018), Comrey and Lee (2013), Hair *et al*. (2018), and Henson and Roberts (2006).

Table 7-8: Descriptive statistics - Round 2

Item	Mean	Std Deviation	Variance	Skewness	Kurtosis
AICXD1_1	5.06	1.253	1.556	-.811	.801
AICXD1_2	4.75	1.348	1.767	-.617	.349
AICXD1_3	5.11	1.327	1.743	-.768	.440
AICXD2_1	4.79	1.518	2.389	-.448	-.500
AICXD2_2	4.62	1.283	1.675	-.259	-.025
AICXD2_3	4.85	1.526	2.359	-.718	-.062
AICXD3_1	2.83	1.600	2.423	.781	-.084
AICXD3_2	3.64	1.667	2.768	.024	-1.057
AICXD3_3	3.45	1.621	2.620	.332	-.669
AICXD4_1	5.33	1.354	1.874	-1.114	1.120
AICXD4_2	4.42	1.581	2.544	-.453	-.518
AICXD4_3	4.95	1.372	1.938	-.651	.066

7.3.2 Preliminary EFA and CMB

As a preliminary step to identify any potential issues, EFA was conducted before performing CFA. The KMO value of 0.885 and the significant result of Bartlett's Test ($p < .001$) indicate that the data is appropriate for factor analysis, suggesting that the variables are sufficiently correlated to be organized into underlying factors. The EFA results, detailed in Table 7-9, show that all items significantly loaded onto their designated factors with no cross-loadings. The dimensions obtained demonstrated strong internal consistency, with Cronbach's alpha values of 0.811, 0.761, 0.855, and 0.850 for D1, D2, D3, and D4, respectively.

Table 7-9: EFA results - Round 2

Dimension	Item name	Factor loading
D1: Affinity (α : 0.811)	**AICXD1_2**	.809
	AICXD1_1	.727
	AICXD1_3	.702
D2: Amusement (α : 0.761)	**AICXD2_1**	.660
	AICXD2_3	.649
	AICXD2_2	.562
D3: Affiliation (α : 0.855)	**AICXD3_3**	.963
	AICXD3_1	.733
	AICXD3_2	.680
D4: Advancement (α : 0.850)	**AICXD4_3**	.966
	AICXD4_2	.765
	AICXD4_1	.594

Additionally, the potential for common method bias (CMB) was evaluated using Harman's single-factor test. This involved performing an unrotated principal components analysis on the items. The analysis revealed that the first principal component explained 47.55% of the total variance, which is within the acceptable range as indicated by previous research (Podsakoff *et al*., 2003). The results from both the EFA and Harman's single-factor test suggest that there is no significant common method bias, making it appropriate to proceed with the CFA.

7.3.3 CFA and Convergent Validity

CFA was conducted using AMOS 29 to verify the scale's dimensionality (see Table 7-10). The factor loadings for the four dimensions ranged as follows: 0.626 to 0.897 for Dimension 1, 0.662 to 0.778 for Dimension 2, 0.747 to 0.859 for Dimension 3, and 0.791 to 0.831 for Dimension 4. All loadings exceeded the acceptable threshold of 0.5. The composite reliabilities for these dimensions were 0.821, 0.766, 0.859, and 0.852, respectively, with all significantly above 0.6. Additionally, the average variance extracted (AVE) values were 0.610 for D1, 0.523 for D2, 0.671 for D3, and 0.657 for D4, all surpassing the 0.5 criterion. These findings confirm that both composite reliability and AVE meet the required standards, thus supporting the convergent validity of the scale (Cheung, 2023).

Table 7-10: CFA results – Round 2

Dimension	Items	Mean	Std Deviation	Std Estimate***	CR	AVE
D1	AICX1	5.06	1.253	0.897	0.821	0.610
	AICX2	4.75	1.348	0.796		
	AICX3	5.11	1.327	0.626		
D2	AICX4	4.79	1.518	0.726	0.766	0.523
	AICX5	4.62	1.283	0.662		
	AICX6	4.85	1.526	0.778		
D3	AICX7	2.83	1.600	0.747	0.859	0.671
	AICX8	3.64	1.667	0.859		
	AICX9	3.45	1.621	0.848		
D4	AICX10	5.33	1.354	0.791	0.852	0.657
	AICX11	4.42	1.581	0.831		
	AICX12	4.95	1.372	0.811		

7.3.4 Discriminant Validity of the AICX Scale Dimensions

Discriminant validity is a key element in validating a scale (DeVellis and Thorpe, 2021). This involves assessing both the discriminant validity of the dimensions within the scale and the validity of the scale in relation to other relevant constructs. In this round of analysis, both aspects will be examined. The discussion will begin by evaluating the discriminant validity among the dimensions of the AICX scale itself.

Once this is established, the focus will shift to comparing the AICX scale with the CS construct to confirm its validity relative to other theoretically relevant measures.

When evaluating the discriminant validity of the dimensions within a scale, the objective is to ensure that each dimension measures a unique aspect of the overall construct, without high correlations between them. This step is essential for verifying that each dimension captures a distinct facet of the construct in question. Discriminant validity is usually assessed by comparing the correlations between dimensions using methods like the Heterotrait-Monotrait Ratio (HTMT) or the Fornell-Larcker criterion (Hensler *et al*,. 2015).

A discriminant validity assessment was performed using the Fornell-Larcker criterion. According to this method, to establish discriminant validity, the square root of the Average Variance Extracted (AVE) for each dimension must be greater than the correlations between that dimension and the other dimensions. In Table 7-11 below, the diagonal elements of the correlation matrix represent the square root of the AVE for each dimension, while the off-diagonal elements show the correlations between dimensions. The results show that, in general, the square root of AVE for each dimension exceeds its correlations with other dimensions. However, there were marginal cases where the AVE was nearly equal to the correlations between dimensions D1 and D2, as well as between D2 and D4.

Table 7-11: Fornell-Larcker criterion for discriminant validity – Round 2

Dimensions	D1	D2	D3	D4
D1	**0.781**			
D2	0.794	**0.723**		
D3	0.504	0.678	**0.819**	
D4	0.717	0.726	0.592	**0.811**

To address these concerns and further validate the discriminant validity of the AICX scale dimensions, an additional method, the Heterotrait-Monotrait Ratio (HTMT), was employed. The HTMT approach is increasingly recognized in the literature as a more reliable approach for establishing discriminant validity, particularly in marketing research (Hensler *et al*., 2015; Vorhees *et al*., 2016). It provides a robust assessment of the discriminant validity. It compares the average correlations between indicators of different constructs to the average correlations between indicators of the same construct (Hensler *et al*., 2015). The 0.85 cutoff for the HTMT ratio is often viewed as the standard for strong discriminant validity (Clark and Watson 1995; Henseler *et al*., 2015 Kline 2011), however, a threshold of 0.90 is also considered acceptable in many cases (Gold *et al*., 2001; Teo *et al*., 2008).

Table 7-12: AICX scale dimensiosn HTMT ratios – Round 2

HTMT Ratio	
D1-D2	0.798
D1-D3	0.507
D1-D4	0.720
D2-D3	0.679
D2-D4	0.726
D3-D4	0.593

Table 7-12 shows the HTMT ratios for the AICX scale dimensions. Since all values are below the 0.85 threshold, this indicates that the dimensions are sufficiently distinct from one another. In other words, the dimensions measure different aspects of AICX and demonstrate strong discriminant validity. Figure 7-6 provides a visualization of the first-order four-factor model structure used in AMOS for conducting the CFA and other analyses.

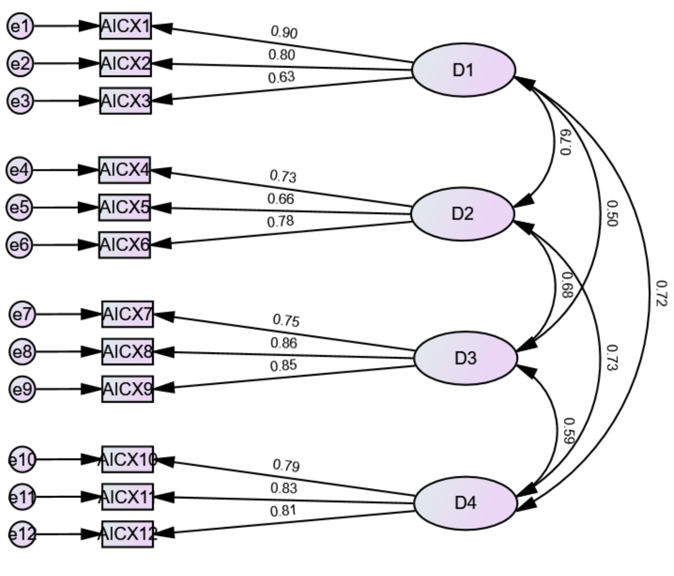

Figure 7-6: First order four factor model structure

7.3.5 Model Comparisons

After confirming the convergent and discriminant validity of the scale, it is important to determine which model best represents the underlying construct. This decision has both theoretical and practical implications. The AICX construct can be represented either as a first-order multidimensional model or a second-order reflective model. A first-order multidimensional model consists of multiple distinct dimensions, each with its own set of observed indicators. In this model, the dimensions are correlated but separate, and each directly reflects its associated observed variables. Conversely, a second-order reflective model includes a higher-order factor that influences multiple first-order factors. These first-order factors, in turn, reflect their observed variables. This model assumes that the higher-order factor accounts for the shared variance among the first-order factors, providing a hierarchical structure that clarifies the relationships between the construct and its dimensions. Both models address multidimensional constructs, but the second-order model offers a more structured approach to understanding how the higher-order construct influences and integrates the various first-order dimensions.

In a first-order model, AICX is seen as four distinct components treated as separate, independent dimensions. Each component reflects a distinct part of AICX—such as how connected they feel, or how enjoyable their interactions are. Each of these components is important on its own and measured by its own set of indicators. In contrast, a second-order model assumes that these four components are connected through an overarching AICX construct. Instead of treating the components as fully independent, the second-order model suggests that all four are influenced by a larger, overarching idea of AICX. This model would mean that the overall AICX explains the relationships between the different components, showing that they are all reflections of a broader, unified construct.

The choice influences how the construct is interpreted and applied in practice. It is therefore important to compare the fit indices of competing models to determine the best-fitting representation of the construct. This ensures that the scale not only aligns with theoretical expectations but also enhances practical utility. Additionally, a single-factor model where all 12 items loaded onto one factor was included in the comparison to establish the multidimensionality of the scale. Accordingly, three models were compared: first, a single-factor model (M1); second, a multidimensional four-factor first-order model (M2); and third, a second-order reflective model (M3) (see Table 7-13).

Comparing M1 with M2 and M3 confirmed the multidimensionality of the model. Further comparison between M2 and M3 revealed that M2 fits the data better. M2 demonstrated a χ^2/df ratio of 1.916, well within the acceptable range (< 5), indicating a good balance between model complexity and fit. Additionally, M2 exhibited the highest Comparative Fit Index (CFI = 0.960) and Tucker-Lewis Index (TLI = 0.946). The Root Mean Square Error of Approximation (RMSEA) for M2 was 0.072, comfortably within the acceptable limit (≤ 0.08), suggesting a minimal error in the model approximation. Moreover, M2 had the lowest Akaike Information Criterion (AIC = 151.969), indicating it is the most parsimonious model, effectively balancing fit and complexity better than the other models.

It is important to note that although both the first-order and second-order models demonstrated acceptable fit indices with minimal differences, the data indicated that the four-factor first-order model (M2) provided a slightly better fit. Nonetheless, proposing AICX as a reflective second-order four-factor model remains acceptable.

Table 7-13: CFA model fit comparisons – Round 2

	Description	**χ^2**	**df**	**χ^2/df**	**CFI**	**TLI**	**RMSEA**	**AIC**
Result to indicate good fit				**< 5**	**≥ 95**	**≥ 95**	**≤ 0.08**	**Lower results are better**
M1	First order one factor model	336.709	54	6.235	0.745	0.689	0.171	384.709
M2	First order four factor model	91.969	48	1.916	0.960	0.946	0.072	151.969
M3	Second order reflective model with four factors	99.6554	50	1.993	0.95	0.941	0.074	155.654

After confirming the validity of the AICX scale and identifying the best-fitting model, round 2 expanded the scope of analyses and moved to test the discriminant and nomological validity of the overall AICX scale in relation to other relevant constructs. In particular, customer satisfaction (CS).

7.3.6 CS for Establishing Nomological and Discriminant Validity

Nomological validity is an essential aspect of construct validity, reflecting the degree to which a construct behaves as anticipated within a network of related constructs, according to theoretical predictions. This validity is established by demonstrating that the relationships between the construct of interest and other related constructs align with theoretical expectations, whether those relationships are positive or negative. Discriminant validity is another aspect of construct validity. It is concerned with proving that conceptually similar constructs are distinct and not overlapping, ensuring that the scale measures a unique aspect of the broader concept.

Customer satisfaction serves as a suitable option for establishing both the nomological and discriminant validity of the AICX scale. It is a well-recognized outcome of CX (CX) in numerous previous scholarly works (Brakus, Schmitt and Zarantonello, 2009; Grewal *et al*., 2009; Rose *et al*., 2011; Rose *et al*., 2012; Thomas and Veloutsou, 2013). Analysing the relationship between AICX and CS can therefore confirm that the AICX scale behaves as anticipated within its broader theoretical framework, as higher scores on the AICX scale correlating with higher CS would support the nomological validity of the AICX scale. Regarding discriminant validity, while CS is related to CX, the two constructs are conceptually distinct. Establishing the empirical distinction between the AICX scale and CS further contributes to demonstrating that the AICX scale captures something novel and specific to AICX.

The measurement of CS referred to the scale developed by Fornell *et al*. (1996). The scale items were "The AICX closely matched my ideal experience.", "My AICX was better than I expected.", and "I am satisfied with the overall AICX." These items were measured using a 7-point Likert-type scale, with responses ranging from 1 (strongly disagree) to 7 (strongly agree). The analysis examined the relationship between the four dimensions of AICX and overall CS. Figure 7-7 shows the AMOS model used for testing the nomological and discriminant validity of AICX in relation to CS.

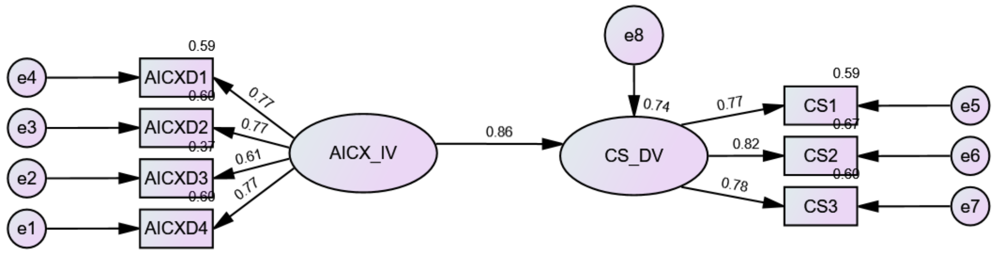

Figure 7-7: Nomological validity AMOS model – AICX with CS

The relationship between AICX and CS in the model demonstrates strong nomological validity. The standardized regression weight of 0.862 indicates a significant positive relationship, suggesting that higher levels of AICX are associated with increased CS. Additionally, the critical ratio (C.R. = 8.862) and p-value (< 0.001) confirm that this relationship is statistically significant. The good overall model fit, with indices such as CFI = 0.986 and RMSEA = 0.058, further supports the robustness of this finding. Overall, the results confirm the nomological validity of the AICX in relation to CS (see Table 7-14).

Table 7-14: Nomological validity with CS results

Independent variable	**Dependent variable**	
	CS	
	β	t value
AICX	0.862***	8.862
R2	0.742	
X2/df	1.604	
CFI	0.986	
TLI	0.978	
IFI	0.987	
RMSEA	0.058	

Discriminant validity of the AICX in relation to CS was assessed using the Fornell-Larcker criterion and the HTMT method. The results indicate that the square root of AVE for each construct is higher than its correlations with other constructs, except for marginal results for some dimensions. Specifically, the square root of AVE was very close to the correlations between dimensions D1 and D2, as well as between D1 and CS (see Table 7-15).

Table 7-15: Fornell and Larcker criterion -Rround 2 for AICX with CS

	D1	D2	D3	D4	CS
D1	**0.776**				
D2	0.777	**0.72**			
D3	0.458	0.66	**0.816**		
D4	0.716	0.735	0.586	**0.812**	
CS	0.77	0.717	0.553	0.721	**0.787**

The values of HTMT ratios are all below the recommended threshold of 0.85 (see Table 7-16), suggesting acceptable discriminant validity between the AICX scale dimensions and CS. This indicates that while AICX and CS are related constructs, they are sufficiently distinct from each other, thereby validating the discriminant validity of the AICX scale in relation to CS.

Table 7-16: HTMT for AICX with CS – Round 2

Pair	Monotrait Correlation	Heterotrait Correlation	HTMT Ratio
D1	0.583		
D2	0.516		
D3	0.662		
D4	0.662		
CS	0.619		
D1-D2		0.429	0.782
D1-D3		0.286	0.461
D1-D4		0.446	0.718
D1-CS		0.465	0.774
D2-D3		0.386	0.661
D2-D4		0.429	0.733
D2-CS		0.405	0.717
D3-D4		0.388	0.585
D3-CS		0.354	0.553
D4-CS		0.461	0.719

The findings from Round 2 provide strong evidence of the AICX scale's validity, ensuring that the scale is both robust and precise in distinguishing related constructs. These results lay a solid foundation for the subsequent phase, where the focus shifts to further confirming the scale's structure and evaluating its validity in relation to CE.

To further support nomological validity, a one-way ANOVA was conducted to test whether CS, used as an external criterion, differed significantly across the three groups (VT, SR, XR). Results indicated a marginal, non-significant group effect, $F(2, 177) = 2.28$, $p = .105$, $\eta^2 = .025$, suggesting that CS did not vary across the groups, thereby reinforcing the stability and generalizability of the AICX scale across different AI-ET experience types.

7.4 Round 3: Establishing AICX Scale Validity

The third round of the quantitative phase focuses on confirming the structure of the AICX model and establishing its validity by examining its relationship with customer engagement (CE) through a simple mediation model.

7.4.1 Sample and descriptive analysis

The same data collection and screening procedures used in previous rounds were followed. Respondents with relevant AICX experience were invited to participate in the main survey, yielding 380 responses through Qualtrics. After excluding 23 incomplete responses, the remaining 357 underwent an attention check, which led to the exclusion of 47 more responses. This left 310 valid responses for further analysis, meeting recommended sample size guidelines (Carpenter, 2018; Comrey and Lee, 2013; Hair *et al*., 2018; Henson and Roberts, 2006). Descriptive statistics for the sample from round 3, are provided in Table 7-17. A one-way ANOVA again assessed group differences across the four finalized dimensions. No statistically significant differences were found across AI-ET types (all $p > .05$), indicating strong cross-group stability for the refined scale.

Table 7-17: Descriptive statistics of dataset - Round 3

Item	Mean	Std Deviation	Variance	Skewness	Kurtosis
AICXD1_1	5.52	1.329	1.765	-1.293	1.877
AICXD1_2	5.05	1.494	2.231	-.764	.165
AICXD1_3	5.35	1.337	1.788	-.919	.584
AICXD2_1	5.38	1.530	2.341	-1.036	.627
AICXD2_2	5.09	1.462	2.138	-.821	.389
AICXD2_3	5.38	1.458	2.126	-.985	.642
AICXD3_1	3.64	1.932	3.734	.124	-1.218
AICXD3_2	4.37	1.839	3.381	-.282	-.946
AICXD3_3	4.10	1.879	3.531	-.173	-1.142
AICXD4_1	5.82	1.281	1.642	-1.625	1.172

AICXD4_2	5.23	1.588	2.520	-1.001	.466
AICXD4_3	5.27	1.578	2.489	-1.041	.440

7.4.2 Preliminary EFA and CMB

The KMO measure of sampling adequacy was 0.909, indicating that the sample was well-suited for factor analysis. Bartlett's test of sphericity was significant ($\chi^2(66) = 2559.759$, $p < .001$), confirming that there were sufficient correlations among the variables to justify conducting factor analysis. An EFA was then performed with a predetermined number of factors, and all items loaded onto their respective dimensions (see Table 7-18). Additionally, a test for common method bias revealed no significant concerns, as the first component accounted for 43.00% of the total variance.

Table 7-18: EFA results - Round 3

Dimension	Item name	Factor loading
Dimension 1 (α : 0.805)	**AICXD1_1**	.968
	AICXD1_3	.654
	AICXD1_2	.534
Dimension 2 (α : 0.859)	**AICXD2_1**	.877
	AICXD2_2	.735
	AICXD2_3	.671
Dimension 3 (α : 0.898)	**AICXD3_1**	.882
	AICXD3_3	.874
	AICXD3_2	.778
Dimension 4 (α : 0.875)	**AICXD4_3**	1.096
	AICXD4_2	.678
	AICXD4_1	.598

7.4.3 CFA and Convergent Validity

CFA was then performed using AMOS 29 to further confirm the dimensionality of the scale (see Table 7-19). The factor loadings for the four dimensions ranged from 0.581 to 0.877 for D1, 0.830 to 0.861 for D2, 0.840 to 0.882 for D3, and 0.769 to 0.887 for D4, all exceeding the acceptable threshold of 0.5. Furthermore, the composite reliabilities for the four dimensions were 0.816, 0.888, 0.898, and 0.882, with all critical ratios significantly above 0.6. The average variance extracted values were 0.604, 0.724, 0.746, and 0.713, all above the 0.5 criterion. These results indicate that both composite reliability and average variance extracted meet the required standards, supporting the convergent validity of the scale.

Table 7-19: CFA results - Round 3

Dimension	Items	Mean	Std Deviation	Std Estimate***	CR	AVE
D1	AICX1	5.52	1.329	0.877	0.816	0.604
	AICX2	5.05	1.494	0.840		
	AICX3	5.35	1.337	0.581		
D2	AICX4	5.38	1.530	0.830	0.888	0.724
	AICX5	5.09	1.462	0.863		
	AICX6	5.38	1.458	0.861		
D3	AICX7	3.64	1.932	0.840	0.898	0.746
	AICX8	4.37	1.839	0.870		
	AICX9	4.10	1.879	0.882		
D4	AICX10	5.82	1.281	0.769	0.882	0.713
	AICX11	5.23	1.588	0.873		
	AICX12	5.27	1.578	0.887		

7.4.4 Discriminant Validity of AICX Scale Dimensions

A discriminant validity assessment was conducted using the Fornell-Larcker criterion. In the table below, the diagonal line of the correlation matrix represents the square root of AVE for each emerging dimension, while the off-diagonal elements show the correlations between these dimensions. The results indicate that the square root of the average variance extracted for each construct is higher than its correlations with other constructs, except for marginal results for some dimensions. Specifically, the square root of AVE was very close to the correlations between dimensions D1 and D2 (see Table 7-20).

Table 7-20: Fornell-Larcker criterion for discriminant validity – Round 3

	D1	D2	D3	D4
D1	0.777			
D2	0.819	0.851		
D3	0.71	0.755	0.864	
D4	0.659	0.722	0.662	0.844

To address this further validate the discriminant validity of the AICX scale dimensions, the HTMT method was employed (see Table 7-21). All results are below 0.85 which suggests that the emerging dimensions are distinct from each other. This indicates good discriminant validity, meaning the dimensions are adequately separated and measure different facets of AICX.

Table 7-21: AICX scale HTMT ratios – Round 3

HTMT Ratio	
D1-D2	0.824
D1-D3	0.715
D1-D4	0.664
D2-D3	0.755
D2-D4	0.723
D3-D4	0.661

7.4.5 Model Comparisons

A model comparison analysis was conducted using data from the third round (see Table 7-22). The analysis evaluated the data fit between a four-factor first-order model and a four-factor second-order reflective model. Both models were assessed based on key fit indices to determine which best captured the underlying data structure. The first-order model had a χ^2 value of 134.154, yielding a χ^2/df ratio of 2.795, which is well below the acceptable threshold of 5. The CFI and TLI values indicated excellent model fit, as they exceeded the minimum cutoff of 0.95. The RMSEA value fell within the preferred range of ≤ 0.08, suggesting acceptable error levels.

The second-order reflective model had a higher χ^2 value, but the χ^2/df ratio remained well within the acceptable range. The CFI and TLI values also showed excellent fit. The RMSEA value of 0.074 was likewise within acceptable bounds. In terms of AIC, the second-order reflective model had the lowest value, indicating it may provide a slightly better balance of fit and parsimony. Overall, both models demonstrated good fit, but the second-order reflective model stood out due to its lower AIC, suggesting a more optimal balance between complexity and fit. Accordingly, a second-order reflective model is adopted to represent the AICX construct.

This decision reflects the construct's multidimensional nature where it's defined by the interrelated four dimensions. Such approach not only aligns with the theoretical foundations of CX, but also emphasizes its holistic essence. A second-order model enables a unified representation of AICX, facilitating its application in practical settings where an overarching measure is often more actionable for businesses and researchers. Nevertheless, choosing a second-order does not diminish the value of individual dimensions, as each contributes uniquely to the construct's overall meaning. Future research could delve deeper into the first-order dimensions, exploring their individual roles and relationships in varied contexts. This dual focus ensures that while AICX is presented as a second order multidimensional construct, opportunities remain to further refine and understand its multidimensional intricacies.

Table 7-22: CFA model fit comparisons – Round 3

Fit Index	Good Fit Criteria	Four-factor first-order model	Reflective second-order model with four factors
χ^2	—	134.154	153.728
df	—	48	50
χ^2/df	< 5	2.795	2.715
CFI	≥ 0.95	0.966	0.966
TLI	≥ 0.95	0.953	0.955
RMSEA	≤ 0.08	0.076	0.074
AIC	Lower is better	194.154	191.728

7.4.6 Criterion Validity of the AICX Scale

After successfully validating the AICX scale with a new sample, the analysis proceeds by developing a simple mediation model, positioning Customer Engagement (CE) as the dependent variable and Autonomy as the mediator. The primary aim of this model is to establish the criterion validity of the AICX scale. In what follows, the conceptual relationships between AICX, CE, and Autonomy are discussed through an integrated review of the relevant literature, leading to the development of three hypotheses.

AICX and CE

Customer Engagement (CE) has recently emerged as a key construct in the field of marketing (Brodie *et al*., 2011; Van Doorn *et al*., 2010). It has captured the attention of scholars and practitioners alike (Lim *et al*., 2022), leading to an increased interest in its theoretical development and resulting in diverse conceptualizations. For instance, while Van Doorn *et al*. (2010) sees engagement as behavioural manifestations, Brodie *et al*. (2011) conceptualizes it as a psychological state during interaction. Storbacka *et al*. (2016) defines it as a natural tendency to act, whereas

Maslowaska *et al*. (2016) considers it a multi-step process within the customer decision-making journey. This variation has led to different perspectives regarding its dimensionality. While initially conceptualized as a unidimensional construct emphasizing its observable manifestations, recent studies have come to a consensus regarding its multidimensional nature. Nonetheless, there are debates surrounding the definition of these dimensions (Hollebeek, Sprott and Brady, 2021).

As research on engagement grew, the need to broaden its scope became increasingly recognized (Hollebeek, Sprott and Brady, 2021). Current interpretations now transcend traditional company-customer relationships to encompass interactions within service ecosystems and networks (Brodie *et al*., 2019). This perspective defines CE as a disposition that includes cognitive, emotional, behavioural, and connectedness dimensions among various actors (Brodie *et al*., 2019; Sim *et al*., 2022). These dynamics interact to shape the overall engagement experience. To gain a comprehensive understanding of engagement, it is important to consider valence and intensity (Van Doorn *et al*., 2010). Changes in engagement valence and intensity can influence other dynamics, such as engagement disposition, resource investments, and connectedness (Storbacka *et al*., 2016).

Valence means that engagement may take positive or negative forms. Disengagement is not simply the absence of engagement; negative engagement has distinct manifestations (Azer and Alexander, 2018). Dessart *et al*. (2016) proposes that CE includes cognitive, affective, and behavioural aspects. The affective includes enthusiasm and enjoyment, cognitive involves attention and absorption, and behavioural includes sharing, learning, and endorsing. In contrast, Azer and Alexander (2018) showed that negative engagement includes discouraging others, discrediting others' work, expressing regret, or deriding.

Intensity also plays an important role. It can be studied across individual, dyadic, and network levels (Wang *et al*., 2023). This study focuses on individual engagement, which relates to affective and cognitive tone and the degree of resource investments such as effort, time, and activeness (Wang *et al*., 2023). For example, a customer engaging with a chatbot may exhibit varying levels of interaction depending on emotional state, attention, and effort. A highly engaged customer might explore features and offer detailed feedback, while a less engaged customer might respond briefly or disengage.

A substantial body of work has been carried out to explore the impact of AI-ETs on the marketing discipline and resulting consumer behaviour (Davenport *et al*., 2020; Gao *et al*., 2022; Huang and Rust, 2018; Huang and Rust, 2022; Henkens *et al*., 2024; Hollebeek, Sprott and Brady, 2021; Hollebeek *et al*., 2024). AI has revolutionized CX and resulted in the emergence of new forms of the construct where AI-ETs are playing a more visible role in the formation of the experience (Ameen *et al*., 2021; Bolton *et al*., 2019; Hoyer *et al*., 2020; Ostrom *et al*., 2019). The characteristics of AI-ETs have introduced new dynamics into the interactions between customers and service providers, enriching the overall CE (Gupta *et al*., 2024). Research by Prentice and Nguyen (2020) empirically demonstrated that AI service experiences are closely related to customer engagement, emphasizing the role of AI as a service provider and contrasting it with employees to highlight preferences and outcomes. Gao *et al*. (2022), on the other hand, focused on the stimuli enabled by AI, finding that perceived personalization and interactivity positively influence CE.

In this thesis and given that the objective is to validate the AICX scale through the development of the model, the focus is on bridging two theoretical perspectives, leveraging AICX as a novel form of CX specific to AI-ETs, while focusing on the behavioural manifestations of customer engagement. Literature highlights that the thoughtful and strategic utilization of AI-ETs has the potential to positively influence desirable engagement outcomes (Hollebeek, Sprott and Brady, 2021). However, as advancements in the field of AI continue to evolve, understanding the implications on CE has grown increasingly complex. This complexity arises from the interplay of various factors, including the subfield of AI to which an AI-ET belongs (e.g., machine learning, deep learning, robotic process automation), each of which offers distinct capabilities and potential outcomes. Further, CE is influenced by the style of engagement (active vs. passive) and the nature of the interaction (relational vs. transactional), adding layers of variability to the overall impact of AI-ETs on CE (Hollebeek, Sprott and Brady, 2021). While an in-depth exploration of these factors could uncover meaningful insights, such an analysis extends beyond the scope of this study. Instead, this research focuses on the broader relationship between AI-ETs and CE.

In line with this discussion, the following hypothesis is proposed:

H1: AICX has a positive effect on positive CE.

AICX and Autonomy

Within psychology, Basic Psychological Needs Theory (BPNT) is a sub-theory within the broader framework of Self-Determination Theory (SDT) (Ryan and Deci, 2017; Vansteenkiste, Ryan and Soenens, 2020). SDT posits that when basic needs are met, individuals experience greater motivation and therefore desire for engagement in various aspects of life (Deci and Ryan, 1987). The theory pinpoints autonomy as a psychological need driving intrinsic motivation (Ryan and Deci, 2017). Autonomy pertains to the internal process of approving one's own actions and making decisions that reflect one's identity. It involves taking responsibility for one's actions and ensuring they are in line with personal values and goals (Deci and Ryan, 1987). In the consumer context, autonomy refers to the capacity of consumers to independently make and implement decisions, without being influenced by external agents (Wertenbroch *et al*., 2020).

Driven by their ability to deliver outcomes like convenience, personalization, and efficiency, AI-ETs are increasingly integrated across the customer journey (Ameen *et al*., 2021; Hollebeek, Sprott and Brady, 2021; Hoyer *et al*., 2020; Sidaoui, Jaakkola and Burton, 2020). However, research has also identified negative consequences, including reduced human connectedness, social isolation, and ethical concerns (Castelo and Lehmann, 2019; Castillo *et al*., 2021; Davenport *et al*., 2020). One such concern is the loss of perceived autonomy. Studies suggest that AI can undermine customers' sense of autonomy, negatively affecting how they perceive control over their interactions (Andre *et al*., 2018; Davenport *et al*., 2020). Although AI enhances CX through personalization and self-service, it can also limit user choice or create a sense of being controlled. Understanding autonomy is therefore key to understanding AI's impact on CX.

AI systems are designed to learn, adapt, and make decisions independently (Chowdhary, 2020). More advanced AI-ETs typically exhibit higher levels of autonomy, allowing them to perform complex tasks with reduced human intervention (Huang and Rust, 2021). This increased autonomy, though varying in degree based on specific applications and ethical considerations, is anticipated to influence customers' perceptions of their own autonomy during the experience (Davenport *et al*., 2020). Certain dynamics within the way AI systems work might contribute to this. For example, AI's decision-making process lacks transparency and offers limited control over the experience; customers can feel like they're simply following a pre-determined path (Felzmann *et al*., 2020). AI's current limitations in handling emotions (Assunção *et al*., 2022; Huang and Rust, 2020) could possibly leave customers feeling unheard and misunderstood, diminishing their sense of control. Possible mistakes that yield undesirable results can also be seen as biased, leaving customers with a sense of being treated unfairly, and significantly lowering perceived autonomy.

As AI-ETs continue to advance, they are expected to offer higher levels of personalization, interactivity, and automation. These advancements contribute to what can be described as a "strong AICX," characterized by dimensions such as Affinity, which fosters a sense of trust and connection with AI systems; Amusement, which creates engaging and enjoyable experiences; Advancement, which facilitates personal growth and learning through interactions; and Social Connectedness, which enhances users' sense of belonging. Together, these dimensions work to maximize customer engagement. While these features enhance engagement, they may also produce unintended consequences. As AI-ETs increasingly take over decision-making processes, users may feel a loss of control, perceiving their autonomy as constrained by the system’s influence. The immersive and structured nature of strong AICX can overwhelm users with AI-driven content and limit their freedom to navigate experiences independently. This perceived reduction in agency may make interactions feel more predetermined than personal. Thus, while strong AICX improves CX, it also raises critical concerns about preserving users’ autonomy within increasingly intelligent service environments.

Given the previous discussion and the significance of autonomy to AICX, the following hypothesis is put forward:

H2: The stronger the AICX the lower the level of perceived autonomy.

Autonomy and CE

Literature have proposed that human behaviour is predominantly influenced by needs (Latham and Pinder, 2005). SDT theory highlights the role of intrinsic motivation, particularly when the three psychological needs of autonomy, competence and relatedness are met, in impacting behaviour (Deci and Ryan, 1987; Ryan and Deci, 2017).

Satisfying an individual's intrinsic need for autonomy can lead to increased levels of engagement during an activity (Deci and Ryan, 1980, 2000; cited in Hsieh and Chang, 2016). Research by An and Han (2020) strengthens this connection by demonstrating that customers with high intrinsic motivation, resulting from the satisfaction of the psychological needs, are more likely to actively participate in that given activity. Previous research indicates that fostering autonomy in consumers significantly influences their engagement and decision to adopt AI in purchasing contexts (Husairi and Rossi, 2024). These insights emphasize the important role autonomy plays in driving engagement behaviour. Building on this, the following hypothesis is put forward:

H3: Perceived level of autonomy has a negative effect on positive CE.

The proposed hypotheses are shown in Figure 7-8 below. According to the model, the lack of perceived autonomy can affect the relationship between AICX and resulting CE. The study suggests that perceived autonomy will mediate the relationship between AICX and CE. As AICX become more intense, the perceived level of autonomy decreases. This loss of autonomy is then linked to a negative impact on positive CE and reluctance to engage, contrasting with the typically expected direct positive relationship between AICX and resulting positive CE. The success of AICX in enhancing CE hinges on maintaining customers' sense of autonomy. AI technologies that diminish perceived autonomy could lead customers to feel like they have no choice during interactions, thus ultimately reducing desirable positive CE. These considerations formed the basis for our proposed hypotheses and analysis.

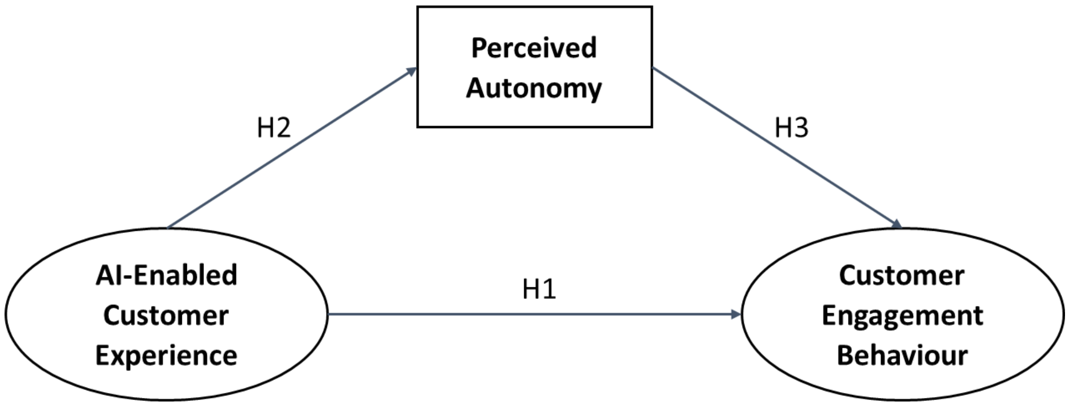

Figure 7-8: Proposed conceptual model

CE was measured using the scale developed by Elmashhara *et al*. (2024), comprising 12 items across three dimensions: Behavioural Engagement, Cognitive Engagement, and Emotional Engagement. Autonomy was assessed using the scale developed by Van de Broeck *et al*. (2010). All items were rated on a 7-point Likert-type scale, with responses ranging from 1 (strongly disagree) to 7 (strongly agree). (see Table 7-23).

Prior to conducting the mediation analysis, a CFA was performed to assess the adequacy of the measurement model. The results indicated poor model fit, prompting further examination of the underlying structure. Specifically, issues of discriminant validity emerged between the constructs of CE and Autonomy, with high inter-construct correlations suggesting substantial conceptual overlap. For example, the square root of the AVE for each construct was not consistently higher than the inter-construct correlations, violating standard criteria. These concerns cast doubt on the distinctiveness of the constructs and the overall reliability of the model. Consequently, the mediation analysis yielded nonsignificant results that could not be interpreted with confidence. To preserve the rigour and integrity of the findings, the mediation analysis was excluded from the final interpretation. However, it is reported here for transparency and completeness.

Rather than discarding the data, the analysis was redirected to conduct a further validation of the AICX scale. While this was the third round in the overall quantitative phase, it was the second round specifically aimed at reassessing nomological and discriminant validity. This round used the CE construct and its three dimensions to evaluate the AICX scale. By using a multidimensional construct closely related to AICX, the analysis provided a deeper and more theoretically grounded assessment. Re-examining the relationship between AICX and CE allowed for a more rigorous and independent confirmation of the scale's validity.

Table 7-23 Scale items for the mediation model

Construct		**Scale Item**	**Adapted from**
AICX	**Affinity**	I felt pleased while interacting with AI-ETs.	AICX Scale
		I felt positively connected with AI-ETs.	
		I felt safe in my interactions with AI-ETs	
	Amusement	I have experienced moments of wonder rand amazement during my interactions with AI-ETs.	
		I was indulged in the interactions with AI-ETs.	
		My interactions with AI-ETs added a sense of fun and excitement to my experience.	
	Affiliation	I established a personal relationship with AI-ETs.	
		The interactions with AI-ETs made me feel important for a few moments.	
		The interactions with AI-ETs made me feel like I belonged to a community	
	Enrichment	I gained new knowledge while interacting with AI-ETs during my experience.	
		The interactions with AI-ETs awakened my creativity	
		Interacting with AI-ETs enabled me to come up with new ideas.	
Customer Engagement	**Behavioural CE**	During the AICX, I spent a lot of time seeking ideas and information from the AI-ET.	Elmashhara *et al*. (2024)
		During the AICX, sought help from the AI-ET.	
		During the AICX, I thought of promoting the AI-ET.	
		During the AICX, I thought of getting others interested in the AI-ET.	
	Cognitive CE	During the AICX, I invested a lot of concentration.	
		During the AICX, I fully attached myself to the AI-ET.	
		During the AICX, I had difficulties to detach myself.	
		During the AICX, I forgot everything around me.	
	Emotional CE	During the AICX, I devoted a lot of enthusiasm.	
		During the AICX, I devoted a lot of dedication.	
		During the AICX, I was emotionally attached.	
		During the AICX, I was emotionally satisfied.	
Perceived Autonomy	**Need for Autonomy**	I feel like I can be myself during the AICX	Van de Broeck *et al*. (2010)
		During the AICX, I often feel like I have to follow the AI-ETs commands.	
		If I could choose, I would do things during the AICX differently.	
		The things I do during the AICX are in line with what I really want to do.	
		During the AICX, I feel free to do things the way I think it could best be done.	
		During the AICX, I feel forced to do things I do not want to do.	

7.4.7 CE for Establishing Nomological and Discriminant Validity

CE serves as an appropriate construct for establishing both nomological and discriminant validity of the AICX scale. It is a well-recognized outcome of CX and customer interactions with service providers (Azer and Alexander, 2024; Gao *et al*., 2022; Henkens *et al*., 2024; Hollebeek *et al*., 2024; Prentice and Nguyen, 2020). Examining the relationship between AICX and CE can validate that the AICX scale aligns with theoretical expectations, as higher AICX scores should correspond with increased engagement. This correlation supports the nomological validity of the AICX scale within its conceptual framework.

Regarding discriminant validity, while CE is influenced by CX, it is conceptually distinct. CE focuses on the customer's emotional and behavioural involvement with the brand, whereas CX encompasses the holistic journey. Demonstrating a clear empirical distinction between the AICX scale and CE ensures that AICX measures a unique aspect of AI-enabled interactions, reinforcing its validity.

The analysis of a model with AICX as the independent variable and CE as the dependent variable reveals a strong and significant positive relationship between AICX and CE (see Table 7-24) . The standardized regression weight is 0.915, with a critical ratio of 10.100. Both AICX and CE were modelled as second-order constructs, as this structure provided a better model fit, indicated by a CMIN/DF ratio of 2.740, a CFI of 0.917, and a TLI of 0.905. The squared multiple correlation for CE is 0.838, indicating that the model explains nearly 84% of the variance in CE. This demonstrates strong predictive power and supports the theoretical relevance of AICX. These results also confirm the nomological validity of AICX in relation to CE.

Table 7-24: Nomological validity with CE results - Round 3

Independent variable	**Dependent variable**	
	CE	
	B	**t value**
AICX	0.915***	10.100
R2	0.838	
X2/df	2.740	
CFI	0.917	
TLI	0.905	
IFI	0.918	
RMSEA	0.075	

Discriminant validity between AICX and CE was assessed using both the Fornell-Larcker criterion and the HTMT method. The Fornell-Larcker criterion did not confirm discriminant validity, as the correlations between all constructs exceeded the square root of the AVE for each construct pair. However, the HTMT method showed that all ratios were below the 0.85 threshold (see Table 7-25), except for the ratio between AICX and EMO, which was 0.878. Although this value exceeds 0.85, it remains below the more lenient 0.90 threshold suggested by some authors (Gold *et al*., 2001; Henseler *et al*., 2015; Teo *et al*., 2008). Therefore, the results support the discriminant validity of AICX in relation to CE.

Table 7-25: HTMT ratios for AICX with CE

HTMT Ratio	
BEH - EMO	0.851
BEH - COG	0.749
BEH - AICX	0.838
EMO - COG	0.784
EMO - AICX	0.878
COG - AICX	0.773

7.5 Conclusion

This chapter has provided a comprehensive overview of the four rounds of the quantitative phase—comprising the pilot and three rounds of data collection—culminating in the development of the AICX scale. Through iterative refinement and validation, a robust 12-item measurement instrument for assessing AICX was introduced. The empirical results consistently demonstrated high reliability and strong construct validity, including clear evidence of nomological and discriminant validity with key constructs such as CS and CE. These rigorous outcomes confirm the psychometric soundness of the AICX scale and highlight its theoretical and practical significance. As such, the validated scale provides a solid foundation for future scholarly research and managerial application, positioning AICX as a valuable tool for analysing customer interactions with AI-enabled technologies in service contexts. The next chapter brings together the core contributions of this thesis by discussing the conceptual foundations of the AICX construct, introducing the AI-ET Cube typology, and reflecting on the empirical development and validation of the AICX scale.

Chapter 8 . Discussion

This chapter synthesizes the outcomes of this thesis critically evaluating their alignment with its overarching aim and objectives. The first section addresses outcomes relevant to the first research objective, to understand and map the research landscape on the role of AI in shaping customer experiences, beginning with the introduction of the AICX construct and building to the development of the AI-ET Cube. The second section then addresses the second research objective, to develop a scale for measuring the AICX, focusing on the resulting scale and its emerging dimensions, which collectively capture the emerging phenomena of AICX and offer deeper insights into customer interactions with AI-ETs.

8.1 Understanding AICX

The first section addresses the first research objective of the thesis:

Objective 1: *To understand and map the research landscape on the role of AI in shaping customer experiences.*

This objective addresses the growing integration of AI-ETs and their impact on CX, resulting in the emergence of new forms of the experience and as highlighted by many scholars (Ameen *et al*., 2021; Buhalis *et al*., 2019; Calvo, Franco and Frasquet, 2023; Chaturvedi and Verma, 2023; Chen and Prentice, 2024; Hoyer *et al*., 2020; Larivière *et al*., 2024; Peruchini, da Silva and Teixeira, 2024; Puntoni *et al*., 2021). While the transformative role of AI-ETs is widely acknowledged in the literature, a limited understanding exists regarding their cumulative impact with most literature acknowledging this either conceptual or review based (Chaturvedi and Verma, 2023; Chen and Prentice, 2024; Chen, Tran-Thiem and Florence, 2021; Larivière *et al*., 2024; Liu *et al*., 2024; Lv, Qiu and Cho, 2024; Peruchini, da Silva and Teixeira, 2024; Puntoni *et al*., 2021). Exploring the emerging phenomenon of AICX highlights the transformative impact of AI-ETs on CXs, while examining their influence at an aggregate level. In doing so, it addresses the shortcomings identified in the existing literature. The section opens with a discussion on the introduction of the AICX construct, establishing a conceptual foundation for the analysis that follows. It then continues by discussing the AI-ET Cube, a typology developed to classify the AI-ETs identified in the literature.

8.1.1 AICX as a novel form of experience

This thesis makes a significant contribution to the study of CX and services marketing by introducing the concept of AICX. Drawing on established frameworks of CX (Becker and Jaakkola, 2020; Lemon and Verhoef, 2016), AICX repositions AI-ETs not as passive background tools, but as dynamic, embedded agents of transformation that co-create experiences with customers. This perspective moves beyond the conventional treatment of AI as an external influence and instead presents AI as a constitutive element of the experience itself, shaping its structure, flow, and outcomes.

The thesis demonstrates that when AI-ETs are integrated across the entire customer journey, rather than limited to isolated functions, they have the capacity to fundamentally transform the experience. By connecting various touchpoints, AI-ETs such as chatbots, service robots, intelligent assistants, virtual reality, and augmented reality create a seamless and responsive journey that adapts in real-time to customer behaviours and preferences. In doing so, they do not simply enhance existing processes; they reconfigure how value is co-created and delivered. This finding addresses a critical gap in the literature, where AI-ETs are frequently examined only at the level of specific touchpoints or as stand-alone interventions (Chen, Tran-Thien and Florence, 2021; Larivière *et al*., 2024). These prior studies offer important insights but leave a gap for research that can consider the cumulative and systemic influence of AI across the customer journey.

By framing AICX as a cohesive and integrated framework, this thesis responds to the limitations of more nuanced approaches. It shows that AI-ETs are not simply add-ons to traditional CX processes but are reshaping the foundational principles of customer experience itself. This reframing also draws attention to the evolving role of the customer—from a largely passive recipient of services to an active co-creator who interacts with both human and non-human agents in real time. The study's findings show that customer input, behaviour, and feedback are now continuously processed by AI-ETs, which adapt the experience accordingly. This dynamic and reciprocal form of engagement challenges linear models of CX and calls for more fluid, interactive frameworks.

AICX also introduces a deeper ontological shift in how customer experience is conceptualised. While prior literature has acknowledged the contextual and co-created nature of CX (Becker and Jaakkola, 2020; De Keyser *et al*., 2020; Lemon and Verhoef, 2016), this thesis argues that the integration of AI-ETs requires a more fundamental reassessment of the experience's structure. Specifically, AICX reveals how AI technologies transform the temporal, spatial, and mechanistic dimensions of the experience (see Table 8-1). Temporally, AI-ETs enable real-time engagement that is not limited by traditional business hours or sequential service processes. Technologies such as chatbots and intelligent recommendation engines allow for continuous, asynchronous interaction that supports immediate problem-solving and seamless continuity across service phases. Spatially, AI-ETs dissolve the traditional boundaries between physical and digital environments. For instance, immersive tools such as virtual reality allow customers to preview destinations or products, effectively merging the digital research phase with the physical consumption experience. Mechanistically, AI systems automate and personalise service processes, replacing or augmenting human effort with algorithmic precision. This results in consistent and adaptive experiences that respond to individual customer needs through predictive insights and real-time adjustments.

These shifts collectively transform the fundamental nature of customer experience. The traditional model, which emphasises face-to-face human interactions, is increasingly being replaced by a hybrid system in which both human and non-human actors collaborate in creating value. As Ostrom *et al*. (2019) and Larivière *et al*. (2017) suggest, this blurring of boundaries between human and AI agents has major implications for how service interactions are understood. Building on this, the AICX framework proposed in this thesis offers a structured way of conceptualising this hybrid landscape and the interplay between technological capabilities and customer participation.

The contribution of this thesis is not only theoretical but also methodological. AICX provided a conceptual framework for the SLR conducted as part of this study, enabling a more targeted exploration of how AI-ETs are represented in existing research. The SLR identified critical knowledge gaps—particularly the lack of integrated perspectives on AI's role in CX—which then informed the study’s objectives, research design, and thematic analysis. As the field evolves, continued advances in AI-ETs, such as more sophisticated natural language processing, predictive personalisation, and emotionally intelligent service robots, will further deepen the AICX model. These developments will likely increase the complexity of customer experiences, requiring marketing theory to evolve in response.

In sum, this thesis reveals that AI-ETs are not just tools within the customer journey—they are reshaping the very foundations of customer experience. By introducing the AICX framework, this study contributes to a growing recognition of AI’s embedded, relational, and dynamic role in the service landscape. It advances the literature on CX by offering a more holistic, integrated, and ontologically grounded understanding of how experiences are constructed in the age of intelligent systems. Furthermore, it invites future research into how AI-ETs interact with other key marketing constructs such as engagement, satisfaction, loyalty, and expectations.

Table 8-1: Proposed ontological shifts

Aspect	Interactions with human service personnel	Interactions within the AICX framework
Temporal	Limited by human availability; slower and sequential interactions due to working hours and fatigue.	Always available, with real-time responsiveness enabled by automation and AI's ability to process information instantly, providing continuous engagement and instant problem resolution.
Spatial	Localised; tied to physical infrastructure, requiring customers to visit specific locations to engage.	Spatially independent, leveraging cloud-based systems and virtual interfaces to offer scalable, personalised experiences anywhere, including augmented and virtual reality environments.
Mechanistic	Relies on human effort, which can lead to variability in service quality due to emotional or physical factors.	AI-driven processes ensure consistency, efficiency, and accuracy, while personalisation algorithms adapt services to individual needs, offering predictive insights and tailored solutions.

8.1.2 The AI-ET Cube

This thesis introduces the AI-ET Cube as a conceptual framework developed to advance understanding of how AI-ETs transform customer experience (CX). Emerging from the broader construct of AICX, the Cube responds to the fragmented and often technically siloed treatment of AI-ETs in existing literature. It offers a structured way of analysing AI-ETs by focusing on non-technical characteristics that reflect their experiential, perceptual, and interactive qualities, rather than their technical functionalities. In doing so, it addresses the limitations of classification systems that overemphasise technical affordances, and instead foregrounds the lived, dynamic, and socially embedded nature of AICX with customer-facing AI-ETs in services contexts.

The AI-ET Cube is designed to support both researchers and practitioners by providing an accessible framework that captures the collective and overlapping capabilities of AI-ETs such as service robots, chatbots, intelligent voice assistants, and various extended reality applications. These technologies often span multiple AI domains and are rarely limited to one type of interaction. As such, the Cube avoids binary classification and instead presents its three dimensions as continua. This approach makes it possible to account for hybrid and evolving AI-ETs, while also accommodating emerging tools that do not conform neatly to fixed categories or legacy definitions.

In developing the Cube, this thesis emphasises the importance of analysing AI-ETs at the touchpoint level, where customer interactions take place. This approach aligns with established CX frameworks that stress the temporally and contextually dynamic nature of customer journeys (Lemon and Verhoef, 2016). Each dimension of the Cube captures a key aspect of the experience, focusing not only on what AI-ETs do but also on how they are perceived, experienced, and engaged with by customers. Together, these dimensions help explain how AI-ETs participate in shaping the flow, depth, and meaning of customer interactions—extending the foundational principles of AICX into a usable analytical tool.

The first dimension, Technological Embodiment, emphasises the tangible integration of AI-ETs into the CX, focusing on the sensory engagement they require from customers (Flavián, Ibáñez-Sánchez and Orús, 2019; Verbeek, 2008). For example, service robots or voice-based systems stimulate more human-like interactions, which literature suggests can significantly enhance immersion and emotional engagement (Flavián, Ibáñez-Sánchez and Orús, 2019; Verbeek, 2008; Tussyadiah, Jung and Tom Dieck., 2018). This dimension highlights a shift from functional utility toward sensorial and perceptual richness, helping define how AI-ETs contribute to more memorable and emotionally resonant experiences within AICX.

The second dimension, Interactivity, reflects the degree to which an AI-ET facilitates active and reciprocal engagement with customers. Rather than passive consumption, interactivity implies mutual influence, where both the customer and the technology adapt and respond. This perspective aligns with views of co-creation and value-in-use in services marketing (Hoffman and Novak, 1996; Jaakkola, Helkkula and Aarikka-Stenroos, 2015; McColl-Kennedy *et al*., 2015). Within AICX, interactivity captures the shift from static, one-way delivery models toward more dynamic, participatory exchanges—where customers are not only recipients of value but also shape the experience through active involvement.

The third dimension, AI Capabilities, positions AI as an active participant in CX, emphasising that different AI-ETs contribute distinct functions that vary in their impact on the customer experience (Huang and Rust, 2018). This dimension considers how various functionalities, such as personalised interactions, automated responses, and real-time support (Davenport and Ronanki, 2018), actively shape and enhance the overall experience. By tailoring interactions to customer needs and providing seamless support, AI-ETs demonstrate their potential to redefine traditional service roles. As Van Doorn *et al*. (2017) suggest, these capabilities not only improve efficiency but also create opportunities for deeper engagement, positioning AI Capabilities as a key component of AICX.

Together, these three dimensions form a cube that represents how AI-ETs can be positioned and understood according to their role in the experience. To illustrate this structure, Table 8-2 presents the eight possible configurations resulting from different combinations of high and low levels across each dimension. These configurations reflect varying degrees of experiential potential, ranging from basic tools with limited interactivity and intelligence to immersive systems with high levels of sensory engagement and adaptive capabilities. The figure visualises how AI-ETs vary across the three continua—AI Capabilities, Interactivity, and Technological Embodiment—positioning each configuration within a three-dimensional space.

As summarised in Table 8-2 below. Each represents a distinct combination of the three dimensions and captures how different types of AI-ETs may influence the customer experience. The configurations reflect variations in how intelligent, responsive, and immersive an AI-ET can be, helping to distinguish between tools that offer basic support and those that deliver more personalised, engaging, and context-aware interactions. This structure allows the Cube to function as both a diagnostic model for current technologies and a generative framework for future design and evaluation.

Table 8-2: Eight Configurations of AI-ETs in the AI-ET Cube

Configuration	Characteristics as per the AI-ET Cube	Example from the literature (SLR articles)	Visual representation of cube location
1	• Low level of intelligence • Passive interaction • Low tech embodiment	Website-based virtual tour (Lee *et al.*, 2020)	
2	• Low level of intelligence • Active interaction • Low tech embodiment	Robotic restaurants experience (Ma *et al.*, 2021)	
3	• Low level of intelligence • Passive interaction • High tech embodiment	Wearable VR Museum experience (Errichiello *et al.*, 2019)	
4	• Low level of intelligence • Active interaction • High tech embodiment	Mixed Reality experience in a museum (Trunfio and Campana, 2020)	
5	• High level of intelligence • Passive interaction • Low tech embodiment	AI-based chatbots (Pillai and Sivathanu, 2020)	

6	• High level of intelligence • Active interaction • Low tech embodiment	AI voice assistants (Loureiro *et al.*, 2021)	
7	• High level of intelligence • Passive interaction • High tech embodiment	Mobile based virtual assistants (Buhalis *et al.*, 2019)	
8	• High level of intelligence • Active interaction • High tech embodiment	Virtual tourism experiences accessible through wearable devices (Allal-Chérif, 2022)	

These eight combinations reflect not only existing technologies but also serve as guidelines for designing and evaluating future AI-ETs. For example, a basic chatbot with limited intelligence and minimal sensory interface would fall into configuration 1, while an emotionally intelligent, voice-interactive service robot would align more closely with configuration 8. Mapping AI-ETs along these dimensions allows researchers and practitioners to assess not only what a system does, but how it shapes the customer's perception, engagement, and co-creation of value within the service process.

By offering a multidimensional framework, the AI-ET Cube helps researchers and practitioners assess the strategic potential of AI technologies in experience design. It also bridges the gap between technical classifications and experiential outcomes, making it particularly useful for marketers, designers, and scholars exploring the intersection of AI and services. The Cube supports a more integrated understanding of how intelligent technologies affect the "how," "when," and "where" of customer interactions, reinforcing the broader contribution of AICX to service experience research.

The AI-ET Cube contributes to this thesis by offering a structured, adaptable, and future-ready model for understanding how AI-ETs interact with customers. It deepens the theoretical contribution of AICX and offers a practical lens for navigating the expanding and increasingly complex landscape of intelligent service technologies. In doing so, it supports further research into the layered, evolving nature of customer experience in the AI era and encourages new approaches to design, implementation, and strategic alignment of AI-ETs across industries.

8.2 The AICX scale

The second section will focus on the second objective of this thesis:

Objective 2: *To develop a scale for measuring the AICX.*

The scale developed in this study directly addresses the identified research gap—the absence of a dedicated measurement tool that captures the transformative nature of AICX and its unique dynamics. Following an exploratory sequential mixed-methods design, the research produced a four-dimensional reflective scale comprising Affiliation, Affinity, Amusement, and Advancement.

This section begins by discussing the foundation of the AICX scale, positioning it within the broader context of CX research and highlighting its significance and contributions. It then delves into the methodology of integrating qualitative and quantitative components, illustrating how this integration informed the scale's development. Following this, the section explores the multidimensional nature of AICX, providing a detailed analysis of its four key dimensions—Affinity, Affiliation, Amusement, and Advancement—and how they draw from and extend existing CX frameworks. The discussion then revisits anticipated dimensions that did not emerge in the final scale, offering critical reflection on why these dimensions were not observed. Finally, the section contextualizes the AICX scale within related CX frameworks, underscoring its distinctiveness and relevance in capturing the transformative potential of AI-enabled interactions.

8.2.1 Methodological Reflections: Integration Across Phases

Integration is widely recognized as the hallmark of mixed methods research, referring to the purposeful combination of qualitative and quantitative components within a single study to capitalize on the strengths of each and provide a more comprehensive, nuanced understanding of the research problem (Creswell and Plano Clark, 2017; Tashakkori, Johnson and Teddlie, 2020; Teddlie and Tashakkori, 2010). It is not simply the co-presence of different methods but the extent to which they are meaningfully connected throughout the research process. As Fetters, Curry, and Creswell (2013) emphasize, integration can occur at three distinct but interconnected levels: the design level, the methods level, and the interpretation and reporting level. Achieving robust integration at these levels enhances the coherence, credibility, and utility of mixed methods findings.

This study exemplified integration across all three levels. At the design level, it adopted a sequential exploratory approach, wherein qualitative data collection and analysis preceded the quantitative phase. This design is particularly suited to scale development, as it facilitates in-depth conceptual exploration before formal operationalization (Onwuegbuzie and Leech, 2006; Creswell and Plano Clark, 2017). The qualitative phase identified key themes and domains central to the construct of interest, which directly informed the structure and content of the scale. This approach supports methodological complementarity, enabling the generation of rich, context-sensitive insights followed by empirical validation. It allowed the research process to remain grounded in the underlying complexity of the phenomenon while still ensuring rigor in measurement.

At the methods level, integration occurred through the building approach, one of the core strategies described by Fetters, Curry and Creswell (2013). In this study, insights from the qualitative phase—such as emergent themes, participant language, and conceptual categories—were systematically used to construct the scale items. This form of integration not only ensures instrument fidelity (Collins, Onwuegbuzie and Sutton 2006) but also reflects a deeper commitment to grounding measurement in participants' lived realities. It parallels the logic of “following a thread,” as described by O’Cathain, Murphy, and Nicholl (2010), wherein key qualitative insights are carried forward into the quantitative phase to ensure conceptual continuity and analytic relevance.

At the interpretation and reporting level, the study employed a contiguous narrative strategy, presenting the qualitative and quantitative findings in separate, sequential sections. While each dataset was reported independently to preserve methodological rigor, their sequential presentation underscored the logical flow from exploratory insight to empirical testing. This structure, while not merging data per se, allows for explicit linkage and contextual layering of findings, contributing to richer interpretation. As Morgan (2007) argues, the integration of methods is as much a matter of methodological practice as it is of philosophical alignment; what matters most is how well the combined approaches illuminate the research questions at hand.

Taken together, the integration achieved in this study was both methodological and conceptual, consistent with best practices in mixed methods research. It exemplifies how qualitative inquiry can be used to develop constructs and instruments that are then quantitatively validated, all within a coherent and purposively designed framework. This multilevel integration produced an instrument that is both psychometrically sound and meaningfully grounded in participant perspectives, demonstrating the unique power of mixed methods to advance theory, practice, and understanding.

This process is visually represented in Figure 8-1, which illustrates the sequential integration pathway from the adaptation of original scale items and incorporation of netnographic data, through item rewording, content validation, factor analysis, and eventual refinement into the final scale dimensions. Additionally, the integration table (see Appendix J) further exemplifies this process by tracing specific scale items from their qualitative origins—such as thematic excerpts from participant narratives—through iterative item refinement, and indicating whether each item was retained or excluded based on content validity and factor analysis results. Together, these tools provide concrete evidence of how qualitative data were systematically embedded into the scale development process and transformed into quantifiable measurement constructs.

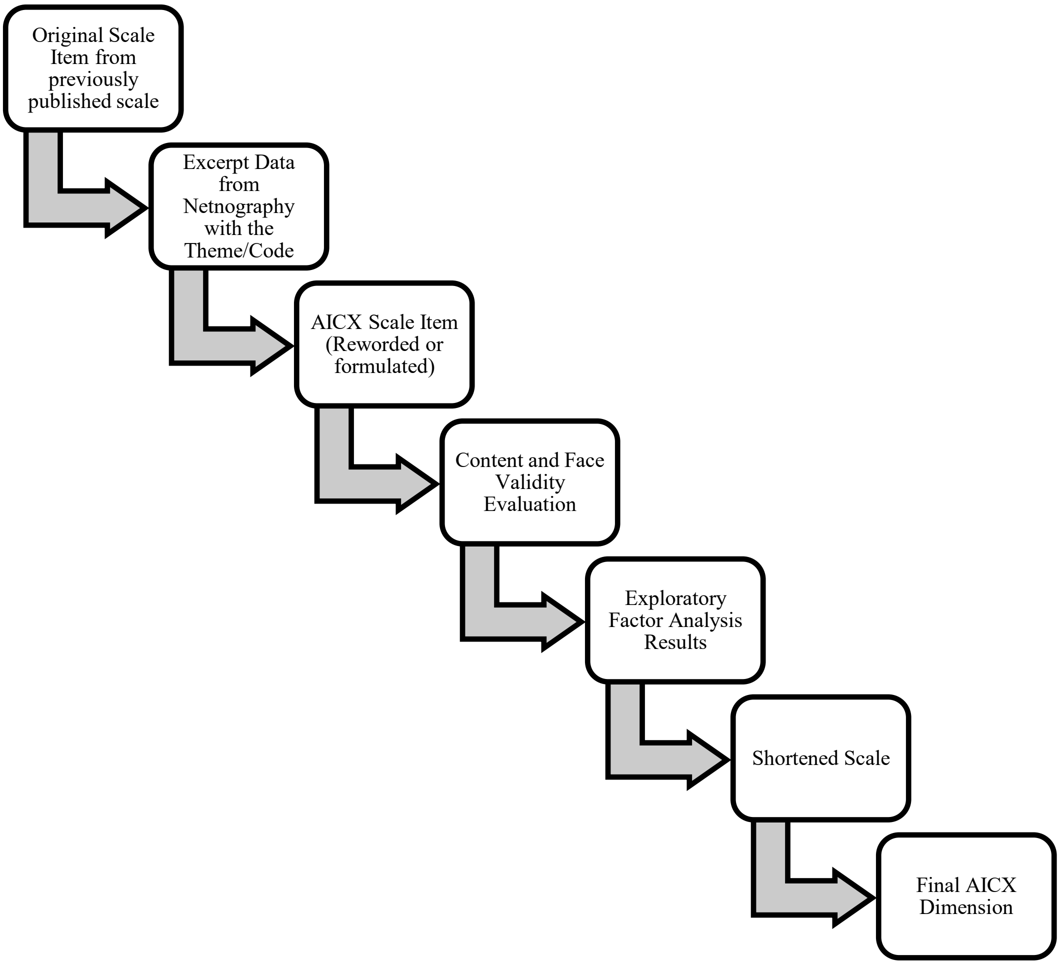

Figure 8-1: The integration of qualitative and quantitative analysis

8.2.2 Multidimensional AICX: a discussion on the key dimensions

The thesis demonstrates that AICX is a multidimensional construct, comprising four distinct dimensions: Affinity, Affiliation, Amusement, and Advancement. Together, these dimensions reflect the evolving nature of customer interactions with AI-ETs, establishing that AICX represents more than a mere extension of traditional customer CX.

Affiliation refers to the sense of belonging and connection customers feel during AI interactions. It includes the perception of forming a personal relationship with an AI-ET, being momentarily valued during the interaction, and belonging to a broader community through these engagements. *Affinity* captures the emotional bond and attachment that customers may develop toward AI-ETs. This includes feelings of pleasure during interaction, emotional warmth, and a sense of safety in engaging with AI-ETs. *Amusement* emphasizes the enjoyment and entertainment that AI-ETs can provide. Customers may experience wonder, indulgence, and the added sense of fun and excitement —especially when AI surprises or engages them in novel ways. *Advancement* represents personal growth and learning. AI-ETs can stimulate new ideas, inspire creativity, and help customers acquire knowledge or skills, thus playing an active role in the user's cognitive and emotional development.

The emerging AICX dimensions integrate dimensions from foundational CX frameworks—cognitive, affective, physical, sensory, and social (Becker and Jaakkola, 2020; Lemon and Verhoef, 2016; Schmitt, 1999; Verhoef *et al*., 2009) as well as dimensions from technology driven CX scales - as relational, hedonic, and functional (Gahler, Klein and Paul, 2023; Lin and Hsieh, 2011) to either reveal previously overlooked aspects of core customer experience components or bring them together in innovative ways. This reframing suggests that the foundational elements of CX now carry varying degrees of significance within the AICX model.

For example, affiliation merges social and affective aspects emphasizing the importance of connection and belonging within AI interactions. Affinity brings together emotional, cognitive, and relational aspects, capturing a sense of positive connection and trust in these interactions. Amusement taps into both hedonic and social enjoyment. Advancement merges functional, cognitive, emotional, and relational elements, reflecting the potential for learning, growth, and personal achievement within AI-enabled interactions. This reconfiguration of traditional experience components or technology driven experiences sets AICX apart from conventional frameworks and provides a more nuanced way to assess CX in AI-driven environments.

While the four dimensions—Affinity, Amusement, Affiliation, and Advancement—were empirically derived, they also resonate strongly with existing theoretical and empirical insights from interdisciplinary literature. The following discussion draws on relevant frameworks and studies to further contextualize and substantiate each dimension, illustrating how they reflect broader patterns in AICX.

Literature suggests that AI-ETs can evoke varied emotional responses depending on their intelligence type (Pantano and Scarpi, 2022). This emotional engagement may be enhanced through artificial empathy, as recent research on AI marketing agents posits that artificial empathy can bridge the emotional gap between AI and humans, generating positive value for both customers and firms (Liu-Thompkins, Okazaki and Li, 2022). Similarly, emotional design research highlights the importance of fostering positive feelings through technology (Norman, 2004). Related findings indicate that people mindlessly apply social rules, such as trust and reciprocity, to interactions with computers (Nass and Moon, 2000), highlighting the potential for AI-ETs to shape emotional experiences. These insights underpin the ***Affinity*** dimension of the AICX scale, which captures the emotional warmth, comfort, and relational ease that users may develop through emotionally attuned AI interactions.

Further, research on memorable experiences demonstrates that the introduction of novel elements significantly influences customer perceptions and behaviours, particularly by affecting emotions, attention, memory, and overall engagement (Skavronskaya, Moyle and Scott, 2020). This understanding of novelty as a key driver of emotional impact in CX can be extended to the context of AI-ETs. The ***Amusement*** dimension reflects this dynamic, capturing the delight, curiosity, and playful engagement users may experience when interacting with AI-ETs designed to surprise, entertain, or introduce unexpected elements in the service journey.

The emergence of the ***Affiliation*** dimension within AICX can be effectively understood through the lens of Actor-Network Theory (ANT). ANT provides a framework for analysing the interactions and relationships between human and non-human actors within complex networks (Doolin and Lowe, 2002; Latour, 1987, 2005; Law, 1992). Central to this theory is the idea that non-human entities—including technologies like AI-ETs—can function as *actors* that shape and influence social dynamics (Ozuem, Howell and Lancaster, 2008; Ozuem *et al*., 2021). Within the context of AICX, AI-ETs act as embedded participants in the customer journey, influencing perceptions, emotions, and behaviours through repeated interactions across various touchpoints. As these technologies become more responsive, adaptive, and contextually aware, they begin to function not merely as tools, but as relational entities that customers affiliate with—thereby reinforcing the sense of social presence and connection that defines this dimension.

The ***Advancement*** dimension of the AICX aligns with the Extended Mind Thesis (EMT), which posits that human cognition extends beyond the brain and body to encompass external tools and the environment, including technology (Clark and Chalmers, 2010; Menary, 2010; Gallagher, 2023). In this context, AI-ETs serve as integrated tools within the user's cognitive system, enhancing personal growth, learning, and creativity. Rather than merely supporting these processes, AI-ETs actively contribute to advancing cognitive capabilities, illustrating how technology plays a pivotal role in cognition as part of a larger system (Salomon, Perkins and Globerson, 1991; Shanmugasundaram and Tamilarasu, 2023).

Together, these dimensions—Affinity, Amusement, Affiliation, and Advancement—suggest that interactions with AI-ETs may extend beyond purely transactional exchanges to include emotional and cognitive elements that potentially foster a sense of connection, positivity, curiosity, and personal development. These dimensions indicate that AI-ETs could play a role in facilitating a sense of belonging and social resonance by enabling experiences that are emotionally engaging, growth-oriented, and enjoyable—experiences in which customers might feel recognized and more meaningfully involved.

The emerging dimensions also highlight a significant shift in how users may begin to perceive and interact with AI-ETs. No longer seen solely in transactional roles, AI-ETs hold the potential to support environments where customers feel connected and experience interactions that are meaningful, enjoyable, and tailored. These dimensions suggest that AI-ETs could help bridge the gap between functional efficiency and experiences that foster long-term, relational engagement—distinct from but inspired by human-led interactions.

Through advanced personalization, AI-ETs may increasingly cater to individual preferences, values, and needs in ways that adapt over time, offering not only practical support but also emotionally resonant and engaging experiences. Unlike traditional interfaces, AI-ETs offer scalability and consistency that could enable rich, value-aligned engagement across varied customer segments and contexts. This represents a shift in possibility: from task-based interactions toward AI-ETs as enablers of deeper connections, personal development, and user enjoyment—an evolution that could meaningfully enrich the customer journey at each touchpoint.

As AI-ETs evolve, they appear increasingly capable of fostering affinity by learning and responding to users' values and preferences, potentially deepening user connection. Affiliation could also be enhanced through features that encourage shared experiences and real-time collaboration. Additionally, there is scope for AI-ETs to support advancement by offering tools for personal growth, such as interactive feedback or immersive learning. Finally, incorporating elements of amusement—such as humour or gamification in chatbots and service robots—may contribute to memorable, enjoyable interactions. For designers and developers, this suggests a promising trajectory: one in which AI-ETs are developed not only for efficiency but also for their potential to act as strategic tools for relational and experiential value creation. However, realizing this potential will require further empirical exploration to validate these capabilities and outcomes at scale.

8.2.3 Revisiting anticipated dimensions

While the emergent dimensions offer strong alignment with several established CX components, the absence of others commonly referenced in the literature invites further reflection on how AICX is framed within broader CX theory.

The literature suggests that AI-ETs—particularly embodied agents such as service robots or virtual assistants with human-like avatars—demand greater customer effort and engage multiple sensory channels, including sight, sound, and occasionally touch (Schmitt, 1999; Verhoef *et al*., 2009). Given these interactions often involve visual cues, vocal responses, and simulated facial expressions, one might expect sensorial and behavioural responses to feature prominently in AICX. However, these dimensions did not emerge in the final scale. A likely explanation is that current AI-ETs still lack the expressive nuance of human interaction—such as microgestures, emotional intonation, or adaptive body language—which limits the perceived depth of physical engagement. As a result, customers may not interpret these encounters as sensory-rich or behaviourally significant. Instead, AICX appears to be shaped more by relational and experiential qualities, including emotional connection (affinity), enjoyment (amusement), and personal growth (advancement), indicating a shift in emphasis from physical input to abstract, human-like engagement.

A similar absence is observed in relation to privacy and security concerns, which are frequently cited in AI literature as critical factors influencing customer trust and adoption (Belanche *et al*., 2020; Hu and Min, 2023). Despite their prominence in theoretical discussions, these dimensions did not emerge in the final AICX scale. One explanation may be that customers treat privacy and data security as baseline expectations—issues that shape adoption decisions but not day-to-day experience unless a breach occurs. In many service contexts where AI-ETs are used for routine tasks—such as providing information or entertainment—customers may prioritise immediate experiential value over potential risk. As such, emotional and cognitive outcomes like enjoyment, learning, or connection may play a more notable role in shaping the overall experience with AI-ETs.

The literature on service and technology consistently highlights functional elements—such as efficiency, reliability, and technical performance—as critical to customer experience, though they are often only noticed when absent (Palmer, 2010). In AI-ET interactions, delays, miscommunication, or unmet expectations can shape perceptions, particularly in co-created contexts where users engage actively with the technology (Heidenreich *et al*., 2015). Despite this, no retained items in the AICX scale reflected functional performance. This may suggest that customers take such capabilities for granted, focusing instead on how the interaction feels. For example, with virtual assistants like Alexa, satisfaction may hinge less on task accuracy—often unverifiable in real time—and more on tone, response speed, or perceived empathy. These relational and experiential cues may carry more weight than technical precision in shaping overall AICX.

Alternatively, customers may be more forgiving of service lapses when interacting with AI-ETs. Errors—such as misinterpreted requests or incomplete responses—may be seen as limitations of the technology rather than failures in service quality. Unlike human agents, AI systems are often viewed as tools, not social actors, and therefore carry less emotional weight or perceived responsibility. In contrast, similar mistakes by human representatives may be interpreted as lapses in care or competence, prompting stronger negative reactions.

8.2.4 The AICX Scale: General Discussion

The AICX scale is a new methodological tool designed for measuring CXs with AI-ETs. By emphasizing the dimensions—Amusement, Affinity, Affiliation, and Advancement, this scale distinguishes itself from other existing CX scales.

The development of the AICX scale is grounded in the foundational shifts that redefined the experience. AI-ETs have reshaped the when, where, and how of interactions, fundamentally altering the essence of experiences and challenging traditional assumptions about what constitutes an interaction, how it unfolds, and its broader implications within the service context. By blurring the boundaries between humans and technology, AI-ETs have created a new paradigm for interaction, characterized by unique dynamics such as the active role of customers, the more visible presence of AI-ETs, personalization, and real-time interaction. Consequently, the resulting form of the experience is unlikely to evoke the same reactions and responses as those observed in human-led interactions, basic self-service technologies, or entirely digital-free experiences. Failing to recognize these distinctions risks oversimplifying the nature of AICX or overlooking critical aspects.

Existing scales (Brakus, Schmitt and Zarantonello, 2009; Lemon and Verhoef, 2016; Schmitt, 1999), while valuable, are unlikely to be sufficient for measuring AICX. These scales were predominantly designed for human-centred interactions, either directly with a human or under the supervision of a service employee. Human experiences are often shaped by emotional, symbolic, and sensorial dimensions, while AI-driven interactions prioritize personalization, efficiency, and adaptability. Although AI-driven interactions may elicit emotional, symbolic, or sensorial responses, these dimensions cannot carry the same weight and should not be the primary focus of measurement. More recent frameworks adopt a broader and more holistic approach, aiming for adaptability across various contexts (Gahler, Klein and Paul, 2023). However, certain dimensions within these frameworks are either less relevant or insufficiently emphasized in the context of AICX, as AI-ETs do not yet elicit the same depth of emotional or symbolic engagement typically associated with human-to-human interactions. Consequently, a dedicated measurement framework is essential to capture the unique dynamics of AI-ET interactions and their transformative impact on CX. This shift represents more than a refinement; it is a necessary step for accurately understanding and leveraging the potential of these technologies.

To contextualize the AICX scale within the broader CX literature, Table 8-3 presents a comparison with five established frameworks: the Self-Service Technologies (SST) scale (Liu and Hung, 2022), the Omnichannel Experience Scale (Gahler, Klein and Paul, 2023), the AI-products scale (Wang *et al.*, 2024), and the Perceptions of Technology-Mediated Service Experience Scale (Froehle and Roth, 2004). Service-related and technology-driven scales provide valuable insights into contexts where technology plays a central role in shaping the CX, making them a meaningful foundation for understanding how the AICX scale extends and enriches existing frameworks. While these models offer distinct contributions—ranging from transactional efficiency to sensory and interactional complexity—they predominantly emphasize functional or human-centric dynamics. In contrast, the AICX scale introduces the dimensions of Affinity, Amusement, Affiliation, and Advancement, which foreground emotional connection, personal growth, and social belonging. These dimensions offer a more holistic perspective on AI-enabled experiences, capturing how AI-ETs contribute to deeper, long-term customer engagement.

Table 8-3: Conceptual comparison of the AICX Scale and related CX frameworks

Scale	Focus	Key Contribution
Self-Service Technologies (SST) scale (Liu and Hung, 2022)	Task-oriented, focusing on functional satisfaction such as ease of use and convenience. Assumes functional satisfaction as the key driver of CX.	Valuable for understanding transactional aspects of AI interactions but overlooks emotional and psychological dimensions.
Omnichannel Experience Scale (Gahler, Klein and Paul, 2023)	Human interactions, sensory and symbolic dimensions of engagement, and emotional nuances of human interaction.	Useful for capturing sensory and symbolic engagement in human-to-human interactions but less applicable to AI-ETs.
AI-products scale (Wang *et al.*, 2024)	Functional and interactional aspects of AI-enabled products, centred on mechanical and object-oriented nature.	Centres on practical, task-oriented interactions with AI-enabled products, lacking deeper emotional exploration.

Perceptions of Technology-Mediated Service Experience Scale (Froehle and Roth, 2004)	Evaluating perceptions of technology-mediated service experiences, emphasising transactional and attitudinal outcomes.	Robust framework for transactional and perceptual assessments but limited focus on affective and relational dynamics.
Measuring Artificial Intelligence Customer Experience (Keng, Sung and Chen, 2025)	Functional and interactional capabilities of AI-enabled devices. Emphasizes how users perceive the operational intelligence and interpersonal behaviours of AI.	Offers a multidimensional, device-agnostic measure of customer experience with AI, bridging functional performance and human-like interactional qualities. Useful for evaluating both technical and relational aspects of experiences.
AICX Scale	Holistic view of CX, capturing both functional and emotional dimensions (e.g., Amusement, Affinity, Affiliation, Advancement).	Extends beyond functional interactions to capture emotional, relational, and growth-oriented dimensions, offering richer insights into CX with AI-ETs.

From the table above, it can be concluded that while existing CX scales offer valuable frameworks tailored to specific contexts, they fall short in capturing the broader, transformative impact of AI-ETs on customer experiences. By integrating the dimensions of Amusement, Affinity, Affiliation, and Advancement, the AICX scale advances the understanding of customer interactions with AI-ETs. These dimensions reflect the evolving role of AI-ETs—not merely as contextual tools but as active participants in the customer journey. By fostering enjoyment, emotional connection, a sense of belonging, and personal growth, AI-ETs are positioned to enhance engagement, reshape expectations, and contribute to sustained customer loyalty. The AICX scale, therefore, represents a critical step in capturing the complexity of AI-enabled interactions, distinguishing itself from traditional CX measures by addressing the unique relational and developmental dynamics introduced by AI technologies.

The AICX scale is concise and easy to administer, comprising 12 items across four dimensions. Despite its brevity, the scale demonstrates strong psychometric properties, including high internal consistency and reliability across diverse samples, ensuring its effectiveness in capturing the multidimensional nature of AICX. Moreover, it exhibits robust discriminant validity, distinguishing AICX from related constructs such as customer satisfaction (CS) and customer engagement (CE), and confirms nomological validity by aligning theoretically with both. Together, these findings underscore the distinctiveness and relevance of the AICX construct, positioning the scale as a valuable tool for advancing academic research and informing practice in AI-enabled service contexts.

Chapter 9 . Conclusions

The aims of this thesis were to explore customer experiences enabled by AI and measure their impact on associated behavioural outcomes. These aims were achieved through two primary objectives: first, to understand and map the research landscape on the role of AI in shaping customer experiences, and second, to develop a robust scale for measuring this emerging form of experience. This concluding chapter elaborates on the three key contributions of this work: (1) the conceptualisation of AICX as a novel experiential construct, (2) the development of the AI-ET Cube as a framework for understanding AI-ET interactions, and (3) the creation of the AICX Scale as a reliable measurement tool. Each of these contributions is linked to existing literature and highlights the distinctive insights generated by this research. This chapter also discusses the theoretical and practical implications of these findings for the broader services marketing literature. Furthermore, it evaluates the study's limitations and identifies key areas for future research, offering a clear agenda for further exploration and practical application.

9.1 Theoretical Contributions and Implications

This thesis makes three key contributions to the CX literature and the broader field of service marketing by addressing an emerging research issue: the emergence of new forms of experiences driven by the integration of AI-ETs. While empirically situated within AI-enabled experiences in tourism, its conceptual contributions provide a foundation for future research on AICX across other service contexts. This section elaborates on these contributions and discusses their theoretical implications.

9.1.1 AICX: A novel emerging form of the experience

The first objective of this study was to understand and map the research landscape on the role of AI in shaping customer experiences. This was achieved through a SLR that synthesised the fragmented yet nascent body of literature surrounding AICX. This review laid the foundation for understanding AICX as a distinct and dynamic concept. It culminated in the first contribution of this thesis: the formal establishment of AICX as a new framework for examining customer experiences in the age of AI.

Introducing and conceptualizing AICX as: customers' non-deliberate spontaneous responses and reactions to offering-related stimuli along a customer journey featuring one or more AI-enabled technologies (Becker and Jaakkola, 2020; Brakus, Schmitt and Zarantonello, 2009; Pine and Gilmore, 1999; Lemon and Verhoef, 2016), extending them by focusing on the experiential dimensions shaped by AI-ETs. Unlike previous studies, which often studied technological applications separately or as isolated touchpoints (Chen, Tran-Thiem and Florence, 2021; Larivière *et al*., 2024; Liu *et al*., 2024; Orús, Ibáñez-Sánchez and Flavián, 2021), this study adopts a holistic approach by considering the entire customer journey and examining the impact of AI at an aggregate level, moving beyond the fragmented analysis of individual touchpoints in isolation.

This comprehensive perspective emphasises the interconnectedness of the customer journey and aligns with contemporary calls (De Keyser, 2015; Jaakkola and Becker, 2020; Gahler, Klein and Paul, 2023) for integrated frameworks that capture the complexity of experiences shaped by the contextual elements, here AI-ETs. In fact, introducing the umbrella term 'AI-ETs,' offers a unified lens that responds to the fragmentation in the field and the counters the tendency to label everything as AI, providing a clearer and more accurate framework for understanding its scope and applications. Another key distinction lies in the fact that this thesis foregrounded the intricate interplay between AI-ETs and customer behaviours, emotions, and expectations. In doing so, it acknowledges the transformative impact of AI-ETs and responds to calls from Hoyer *et al*. (2020) and Buhalis *et al*. (2019), who identified these technologies as drivers that would fundamentally transform the very notion of CX. The acknowledgment of AI as a transformative force aligns well with existing literature that emphasises its perceiving capabilities, enabling human-like interaction, active engagement with surroundings, and participation in shaping experiences (Aleksander, 2004; Rai, Constantinides and Sarker, 2019; Bawack, Wamba and Carillo, 2021; Schuetz and Venkatesh, 2020).

The significance of this contribution lies in its ability to bridge the gap between the rapidly evolving filed of AI and theory on CX. By introducing a comprehensive and robust framework, this study provides the foundational basis for future empirical research across diverse sectors and cultural contexts, where AI is acknowledged conceptually as a transformative force (Chaturvedi and Verma, 2023; Chen and Prentice, 2024; Ghesh, Alexander and Davis, 2024; Hollebeek *et al.*, 2024; Lv, Qiu and Cho, 2024; Peruchini, da Silva and Teixeira, 2024; Puntoni *et al.*, 2021; Verma *et al.*, 2021) reshaping industries and redefining key constructs within and beyond CX. Together, these advances offer a distinctive contribution to the field by establishing a comprehensive, adaptable framework that bridges theory and practice in the age of AI.

Positioning AICX as a new form of customer experience does not signify a departure from the foundational principles of CX. Instead, it is firmly rooted in established CX frameworks, extending them by integrating the transformative dimensions introduced by AI-ETs. Furthermore, this is not to undermine the importance of addressing AI-ETs at the touchpoint level; rather, it underscores the value of examining AI-ETs at an aggregate level to capture their broader impact. While it could be argued that the implications of AI within customer experience are still in their early stages, with its transformative potential yet to be fully realised, this study serves as a critical starting point. It lays the foundation for understanding CX in the age of AI, where AI-ETs have already begun reshaping the nature and dynamics of customer interactions.

9.1.2 The AI-ET Cube

In the process of addressing the first objective of this study, it became clear that a more comprehensive framework was needed to capture the dynamic and contextual nature of AI-ETs. Existing typologies focused primarily on technical attributes and did not fully account for the evolving roles of AI-ETs in customer experiences. This realisation led to the second key contribution of this thesis: the development of the AI-ET Cube, a typology designed to better understand and categorise the diverse roles of AI-ETs across the customer journey.

Developing the AI-ET Cube builds upon the EPI Cube (Flavián, Ibáñez-Sánchez and Orús, 2019) and extends its scope to encompass all AI-ETs, rather than being confined to extended reality applications. Existing typologies—such as those proposed by Huang and Rust (2018, 2021, 2022), Grundner and Neuhofer (2021), and Russell and Norvig (2016)—are comprehensive in their general approach but are predominantly focused on the technical aspects of AI. This narrow focus makes them limited when it comes to addressing other areas, such as social interaction and customer interactivity dynamics, which are essential for services marketing research. The AI-ET Cube, by contrast, aims to overcome these limitations by integrating these overlooked dimensions.

A key distinction of this framework is its ability to accommodate the dynamic nature of AICX by representing three key actors within the experience through its dimensions: technological embodiments, AI capabilities, and customer interactions, which collectively represent the customer, AI, and the technical device. It builds on literature highlighting the evolving roles of actors within these experiences (Larivière *et al*., 2017, McColl-Kennedy *et al*., 2015) and aligns with Actor-Network Theory (ANT) by introducing AI as an active participant in the network (Doolin and Lowe, 2002; Latour, 1987, 2005; Law, 1992).

The significance of this contribution lies in its ability to move beyond the technical attributes of AI-ETs, offering a flexible and adaptive framework that not only captures their evolving nature but also accommodates the rapid advancements within the field. By introducing a conceptual lens that enables a broader understanding of AI-ETs, this contribution provides a dynamic tool to analyse and interpret their implications across diverse contexts and applications. This adaptability ensures that the framework remains relevant as AI-ETs continue to evolve.

This is not to suggest that existing typologies are unimportant or can just be disregarded or replaced with the AI-ET Cube. Rather, it highlights the need to go beyond them and develop classifications that are accessible to non-technical audiences, offering a more experiential perspective on AI-ETs. In fact, some may argue that relative classifications, where technologies are compared as dyads along the same axis—for instance, one AI-ET being relatively more or less advanced than another within the same category—could reduce their significance. However, these classifications remain essential tools, as they offer valuable insights and enable meaningful comparisons that facilitate practical applications.

Additionally, representing the dimensions as continuums offers a flexible approach to addressing the rapid and ongoing advancements in AI-ETs, ensuring that the framework remains adaptable to new innovations and shifting trends. This dynamic representation allows for the integration of emerging developments without requiring constant restructuring of the entire framework. However, this flexibility does not entirely negate the potential need for revisiting and refining the framework in the future, as the landscape of AI-ETs evolves, and new complexities emerge that may require a more nuanced or updated approach.

9.1.3 The AICX Scale

Informed by the outcomes of the SLR, the second objective of this study was to develop a robust and reliable scale for measuring AICX. This objective was achieved through a scale development study that adopted a sequential exploratory mixed-methods design and adhered to established guidelines for scale development (e.g., Churchill, 1979; DeVellis, 2016; Netemeyer, Bearden and Sharma, 2003). The outcomes of this process resulted in the third contribution of this thesis: the AICX Scale.

A key implication of the scale lies in its contribution to advancing measurement practices within the field of CX. By providing a designated tool for measuring AICX, this thesis responds to the call for a holistic approach to measuring CX while addressing its inherently contextual and dynamic nature (Bueno *et al*., 2019; De Keyser *et al*., 2015). The resulting AICX Scale empirically validates AICX as a distinct and emerging dimension of CX, extending the conceptual foundations laid by Hoyer (2020), Buhalis (2019), and Ghesh, Alexander and Davis (2024), who highlight the transformative potential of AI. Furthermore, the scale provides a standardised lens for cross-context comparisons, enabling the analysis of AICX across diverse industries, cultural settings, and AI application forms.

The development of the AICX Scale enhances conceptual clarity by identifying its key dimensions and distinguishing it from existing CX frameworks. Its dimensions—Affinity, Affiliation, Amusement, and Advancement—capture how individuals perceive and engage with AI-ETs. These dimensions address emotional connections (Affinity), social and relational dynamics (Affiliation), enjoyment and engagement

(Amusement), and personal growth or learning (Advancement). Collectively, these dimensions might provide valuable insights into the psychological and experiential aspects of human-AI interactions, particularly through a lens that positions both AI and the customer as active participants in the co-creation of the experience. Additionally, the scale highlights dimensions that hold greater relevance in the domain of AICX. For instance, while previous CX scales prioritised sensory, social, and symbolic dimensions (e.g. Bustamante and Rubio, 2017; Gahler, Klein and Paul, 2023; Verleye, 2015) this scale demonstrates that such dimensions are less central in AI-enabled interactions. This broadens theoretical discussions by illustrating how AICX might differ from human-centric experiences or, conversely, entirely digital-free experiences.

Finally, the development of the AICX Scale contributes to advancing the understanding of how AI impacts customer satisfaction and engagement, encompassing cognitive, emotional, and behavioural dimensions. While much of the existing research has focused on conceptual explorations (Ghesh, Alexander and Davis, 2024; Hollebeek *et al*., 2024; Lv, Qiu, and Cho, 2024), this study advances the field by empirically validating these relationships, providing concrete evidence where theoretical assumptions previously dominated.

This should not be taken as a claim that the AICX Scale applies universally across all service sectors without challenges. Rather, it was developed with broad applicability in mind, recognising that in some contexts it may not be directly transferable. However, even in these situations, the scale can serve as a valuable foundation or reference point for the development of future measurement tools. Moreover, introducing the four dimensions of AICX does not suggest that these are the only important aspects to consider when evaluating AI-ETs. Instead, it highlights that, based on the scale development study and given its reflective nature, these dimensions hold the greatest weight. It could still be argued that the relative importance of these dimensions will evolve as AI-ETs become more integrated and reliance on these technologies continues to grow. This suggests the need to revisit and refine the scale periodically, ensuring that it remains relevant and accurately represents emerging advancements and shifting dynamics.

9.2 *Managerial Implications*

Beyond their theoretical significance, the contributions of this thesis hold substantial value for practice. As AI technology evolves and AI-ETs become increasingly integrated into service encounters, managers face new challenges and opportunities. The AICX construct, the AI-ET Cube, and the AICX Scale offer frameworks and tools that can guide decision-making and help practitioners adapt to these changes. Together, these contributions offer practical insights that support effective AI-ET integration across diverse service contexts.

9.2.1 The AICX construct

The introduction of AICX highlights the strategic importance of integrating AI throughout the customer journey. Managers must approach AI-ET implementation as a driver of change, not just as operational tools. AI-ETs reshape service design, delivery, and interactions, requiring thoughtful planning and investment. To navigate this transformation, managers should align AI adoption with organisational goals and adapt processes to meet new demands. This includes investing in technological infrastructure, fostering a culture of innovation, and upskilling staff to ensure readiness for AI-driven customer interactions. Managers should adopt a holistic perspective, moving beyond isolated touchpoints to consider the interconnected customer journey. By doing so, they can fully leverage AI-ETs to create seamless, customer-centric experiences. This approach empowers businesses to innovate service design and delivery, ensuring they remain competitive in a rapidly evolving industry landscape.

9.2.2 The AI-ET Cube

The AI-ET Cube offers a practical framework for navigating the complexities of AI-ET integration. Its dimensions provide insights into when customers are more open to AI, when advanced intelligence is needed, and when human interaction is essential. This helps managers allocate resources effectively, balancing technology and human roles to optimise both experiences and operations. The Cube also supports evaluating financial trade-offs, ensuring investments align with value and avoid overinvestment in features that offer little benefit. It encourages managers to consider how technology aligns with organisational identity and customer expectations, safeguarding brand reputation and satisfaction. Ultimately, the Cube equips decision-makers with a flexible tool to guide technology adoption in ways that enhance customer experience and align with strategic priorities.

9.2.3 The AICX Scale

The AICX Scale provides a robust framework to assess customers' authentic perceptions of AI-ETs. It generates insights that help managers refine service delivery and ensure alignment with customer expectations and organisational goals. As a benchmarking tool, it enables comparative assessment of AI-ET performance across roles and touchpoints, guiding best practices and informed decisions. For instance, it can compare robots versus chatbots or different uses of the same AI-ET, supporting continuous improvement. By leveraging these insights, managers can adjust strategies, improve experiences, and drive innovation across the organisation.

9.3 Limitations and Future Research Directions

This doctoral thesis is empirically grounded in the context of customer facing AI-ETs within the tourism sector. While the conceptualisation of AICX, the development of the AI-ET Cube, and the proposed measurement scale have relevance beyond tourism, the empirical findings of this thesis are situated within this specific contextual setting. As such, the generalisability of the findings to other service sectors should be regarded as theoretical rather than empirical at this stage. Future research is therefore required to validate, refine, and extend these insights across different industries, cultural contexts, and AI-enabled service environments.

Additionally, while this thesis makes significant contributions to understanding and measuring AICX, it also has certain limitations that open avenues for future exploration. Methodologically, although the SLR followed a rigorous approach, its reliance on specific databases and search terms may have constrained the comprehensiveness of the reviewed literature. Future studies could address this by broadening the scope of databases, refining search strategies, and including emerging sources such as grey literature and industry reports to capture the dynamic landscape of AI-enabled experiences more comprehensively.

The qualitative phase of the scale development process, particularly the expert reviews, also involves an element of subjectivity. While this study mitigated potential bias through anonymous and diverse expert participation, future research might benefit from combining these expert insights with in-depth interviews or ethnographic observations to enrich the qualitative understanding of AICX. Additionally, the reliance on participants' self-reported experiences, such as customer reviews in the netnography and responses in surveys, introduces challenges like recall errors and social desirability bias. Future research could adopt real-time data collection methods, capturing experiences immediately after or during interactions with AI-ETs. This would provide more accurate and spontaneous insights, reducing the distortions caused by memory decay or the tendency to present oneself in a favourable light.

Beyond these methodological considerations, the scope of this research was primarily limited to specific service contexts and demographic groups. While the selected settings offered valuable insights, they may not fully capture the diversity of experiences across industries, cultures, and customer segments. Future studies should empirically validate the applicability of the findings across a broader range of industries, such as healthcare, retail, and education, and within diverse cultural contexts. In particular, the relative importance of specific AICX dimensions and AI-ET configurations identified in this study may differ in more utilitarian or low-experiential service contexts. Therefore, future research could systematically test the boundary conditions of the findings, thereby providing a more nuanced understanding of AICX across different service ecosystems. Notably, particular attention should be given to underrepresented customer segments, including individuals with low digital literacy or accessibility challenges. Addressing these gaps would make future research more inclusive and reflective of the full spectrum of experiences in AI-enabled contexts.

Conceptually, this thesis positioned AICX as a novel and distinct experience form, contributing to the broader literature on CX. However, further research is needed to refine the boundaries of AICX and examine its interplay with other constructs, such as customer trust, satisfaction, and loyalty. For instance, how might the evolving role of AI-ETs as co-creators of the experience affect traditional customer roles?

Investigating these questions could reveal how AI-ETs influence expectations and reshape the balance of power between customers and service providers. Furthermore, while this thesis emphasised the transformative potential of AI-ETs, it is important to explore how customers' perceptions of these technologies evolve over time, particularly as AI becomes more autonomous and human-like.

A critical area for future research lies in examining negative experiences with AI-ETs. While much of the existing literature focuses on positive or neutral experiences, understanding service failures—such as a malfunctioning service robot, inaccurate chatbot information, or VR platform glitches—could reveal important insights about customer trust, satisfaction, and loyalty. Future studies should investigate how customers react to these failures, their expectations for resolution, and the long-term impacts on their relationship with the brand. These insights would not only contribute to the theoretical understanding of service recovery in AI-enabled contexts but also guide businesses in designing effective recovery processes tailored to AI-driven interactions.

Longitudinal research is also essential to capture the evolving nature of AICX. As AI-powered tools become more integrated into customer journeys, it is important to explore whether repeated interactions build trust and acceptance or, conversely, lead to fatigue or skepticism. For instance, how might customer experiences with AI-ETs differ in short-term versus long-term engagements? Examining these temporal dynamics would provide a deeper understanding of the life cycle of AICX and help service providers adapt their strategies over time.

Methodologically, future research should adopt a multimethod approach that combines qualitative depth with quantitative precision. Qualitative methods, such as in-depth interviews and ethnographic studies, could reveal nuanced customer perceptions and emotions, particularly in complex or sensitive service encounters. Quantitative approaches, including big data analytics and experimental designs, could test causal relationships and identify generalisable patterns in customer responses to AI-ETs. Mixed methods, such as customer journey mapping, would integrate these perspectives, offering a holistic view of how AI-ETs shape customer experiences across diverse touchpoints. As AI-ETs continue to evolve rapidly, this robust methodological approach will ensure that research remains relevant and adaptable.

These future research directions align closely with the three key contributions of this thesis. For the AICX construct, further exploration could examine how the integration of AI-ETs reshapes customer roles and expectations across industries and over time. For the AI-ET Cube, future work could assess how different configurations of AI-ETs perform in various service contexts and how organisations can leverage these insights for experience design and technology investments. For the AICX Scale, future studies should validate its reliability and relevance across sectors and cultures, refine its dimensions to capture the most predictive experiential aspects, and adapt it for longitudinal and cross-platform analysis. Such research would ensure that the scale remains a robust tool for benchmarking and optimising AI-enabled experiences as the technology landscape evolves.

These key directions and their alignment with the thesis contributions are summarised in Table 9-1 below. This table highlights how the identified limitations and conceptual gaps translate into actionable questions for future research, offering a clear roadmap for advancing both theoretical and practical knowledge in this emerging field.

Table 9-1 Future research directions

Contribution	Managerial Implication	Future Research Questions
AICX Construct	Helps managers reframe CX strategy around hybrid experiences where AI-ETs are active co-creators, not background tools.	• How does AICX differ between event-based experiences (e.g., tourism, entertainment) and ongoing service relationships (e.g., banking, healthcare)? • How does the integration of AI-ETs reshape customer roles across industries? • In what ways does AICX influence customer expectations and satisfaction over time? • How do cultural differences influence customer perceptions and responses to AICX? • How do negative experiences with AI-ETs (e.g., service failures) influence customer trust, satisfaction, and loyalty?
AI-ET Cube	Offers a practical tool to evaluate and map AI-ETs based on their customer-facing characteristics, guiding experience design and tech investment.	• How the relevance and salience of AICX dimensions vary across different service contexts (high vs low AI capabilities, high vs low technological embodiment, passive vs active interactivity)? • How can firms use the Cube to identify under-leveraged experiential potential in existing AI-ETs? • What configurations are most effective in different service contexts (e.g., tourism, retail, healthcare)? • How do contextual factors (such as service risk or intensity) influence which AI-ET configurations are most effective? • How can the Cube be refined to adapt to rapidly changing AI-ET capabilities and emerging technologies?
AICX Scale	Enables firms to assess the quality and impact of AI-enabled experiences from the customer's perspective, supporting benchmarking and optimisation.	• How valid and reliable is the AICX scale across different services sectors? (e.g., retail, banking, heathcare…etc.) • How valid and reliable is the AICX scale across different cultural contexts? • What dimensions of the AICX scale most strongly predict behavioural outcomes (e.g., loyalty, trust, repurchase)? • How can the AICX scale be adapted for longitudinal or cross-platform analysis? • How might the scale be extended or adapted to capture negative experiences and recovery perceptions in AI-enabled interactions?

9.4 Concluding remarks

As I bring this thesis to a close, I find myself reflecting on the journey that led me here. Delving into the world of AI-enabled experiences has been both challenging and deeply rewarding. Along the way, I have gained a renewed appreciation for the complexity of customer experience and the many ways AI is reshaping how businesses and customers interact. This process has taught me the importance of questioning assumptions, of staying curious, and of balancing technological innovation with a clear understanding of customer needs.

This journey has not only shaped my academic understanding but has also challenged me to grow as a researcher and as a person. I am deeply grateful for the mentors, colleagues, and participants whose insights and encouragement have made this work possible. I am also thankful for the countless conversations—both formal and informal—that have enriched my thinking and helped me see this field from new angles.

Looking ahead, I remain excited and curious about how AI will continue to evolve and transform customer experiences in ways we are only beginning to imagine. I hope that the insights and frameworks developed in this thesis can inspire others to explore this intersection of technology and human experience, and to do so with an open mind and a commitment to inclusivity and empathy.

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Appendices

Appendix A – Coding crosschecking session

Code	Definition
Theme 1: Behavioural	
1.1. Avoidance and neglect	Intentional disregard or disinterest in engaging with AI-ETs.
1.2. Behavioural change	Refers to shifts in actions, habits, and preferences caused by engagement with AI-ETs, prompting people to explore new behaviours or step outside their comfort zones.
1.3. Choosing or preferring the AI-ETs or AICX	Involves individuals consciously selecting or favouring AI-ETs or AICX for some reason.
1.4. Decision making	How the reliance on AI-ETs influence customer decision-making processes to choose the AICX.
1.5. Engagement and interactivity	Reflects the level of interaction and involvement individuals have with AI-ETs or AICX.
1.6. Repeat purchase	Reflects individuals' intention and willingness to repeatedly purchase or use AI-ETs.
1.7. Undesirable outcome	Negative consequences resulting from interactions with AI-ETs.
Theme 2: Cognitive	
2.1. Capabilities	Understanding the abilities and limitations of AI-ETs.
2.2. Concerns and cautiousness	Worries and carefulness regarding interactions with AI-ETs.
2.3. Customization	Tailoring AICX to personal preferences.
2.4. Errors and failure recovery	Dealing with errors occurring AICX and perception towards how mistakes are handled.
2.5. Evaluation and comparisons	Assessing AICX relative to alternatives.
2.6. Expectations	Anticipations of the AICX.
2.7. Functionality	How well AI-ETs perform their intended tasks, meeting stated promises and expectations.
2.8. Impact of AI-ETs or AICX	Influence of reliance on AI-ETs on AICX, brand or FLEs.
2.9. Informedness	How well customers understand, aware and familiar with the AI-ETs in use.
2.10. Innovation and potential	Perceived level of novelty and future possibilities of AI-ETs.
2.11. Learning and knowledge	Acquiring new information or skills through AI interactions.
2.12. Memorability	Involves the lasting impact of AI-ET interactions on individuals' memory and perception, encompassing instances where these experiences are remembered, referenced, or stand out over time.
2.13. Negative perception	Unfavourable opinions or views about AI technology.
2.14. Value enhancement and appraisal.	Involves how AI-ETs add value and dimensions to experiences, with individuals assessing their worth, cost, and impact. This theme explores perceptions of added benefits, wastefulness, and

	whether AI-ETs enhance the overall value of interactions.
2.15. Tech dominance and human-tech balance	Examines the balance between AI-ETs' influence and individuals' autonomy in interactions.
2.16. Technical considerations	Explores UX with AI-ETs through technical aspects like hardware, graphics, interface design.
2.17. Trustworthiness and scepticism	Explores customers' assessment of reliability and credibility as well as doubts and reservations regarding AI-ETs.
2.18. Upgrades and improvements	The changes of AI-ETs over time, considering both enhancements driven by competition and user feedback, and potential challenges arising from these changes.
2.19 Usability	How easily customers can interact with AI-ETs and make use of its features.
2.20. Utilization	Considers how well ideas are implemented and execuetd.
2.21. Value for money	Explores whether the cost of aligns with perceived benefits. It assesses if individuals find the price justified based on the value and features received.
Theme 3: Emotional	
3.1. Anger and frustration	Feeling upset or annoyed because of AI-ETs.
3.2. Diminished positivity	The fading or reduction of initial positive emotions and attitudes toward AI-ETs over time.
3.3. Amusement and surprise	Focuses on unexpected and captivating elements that trigger feelings of wonder and surprise.
3.4. Disappointment and regret	Feeling let down or wishing for better outcomes and interactions with AI-ETs.
3.5. Entertainment and enjoyment	Captures the fun, excitement, and entertainment aspects of interactions
3.6. Escape	AICX is a way to temporarily escape reality.
3.7. Excitement	Feeling enthusiastic or thrilled about AI-ETs and AICX.
3.8. Fear and anxiety	Covers emotions like anxiety, apprehension, and being scared or threatened by the technology.
3.9. Joy, laughter and humour	Captures instances of happiness and finding things funny or during the AICX.
3.10. Mood and wellbeing	Impact of interactions with AI-ETs on the emotional state.
3.11. Negative perception and discomfort	Unpleasant feelings arising from AI-ETs interactions.
3.12. Personal impact and connection	Focuses on customers' individual experiences and emotional connections when engaging with AI-ETs.
3.13. Positive impressions	Forming favourable opinions about AI-ETs or AICX.
3.14. Unpleasant experiences	Perceiving the AICX as unpleasant or undesirable.
3.15. Novelty and uniqueness	Perceiving AI interactions as new and distinct.
3.16. Highlight of or main feature of	Recognizing the interaction with AI-ETs as a central element in the overall experiences.
Theme 4: Sensorial	
4.1. Aesthetics	Visual attributes and design elements of AI-ETs
4.2. Authenticity	Impressions of how well AI-ETs replicate real-world experiences

4.3. Aversive sensations	Experiencing discomfort or negative sensations from AI.
4.4. Hygiene	Addressing cleanliness and hygiene-related aspects of interacting with AI-ETs.
4.5. Multisensory	Involving multiple senses in interactions with AI-ETs.
4.6. Physical comfort	Physical involvement and comfort levels during interactions with AI-ETs.
4.7. Technological embodiment	How much does AI-ETs have human-like attributes or behaviours.
Theme 5: Social	
5.1. Accessibility, diversity, and inclusivity	How AI-ETs accommodate diverse users, including different ages, cultures, languages, and needs. It focuses on breaking barriers and promoting inclusion through technology design and usage.
5.2. Advocacy and sharing	Promoting or discussing AICX or interactions with AI-ETs with others.
5.3. Human connection and social void	Impact of AI-ETs on human interaction and socialization and how these technologies can either enhance meaningful connections or create a sense of emptiness and absence of social engagement.
5.4. Social perception	How individuals' interactions with AI-ETs are perceived by others
5.5. Relation with AI-ETs	The perceived nature of the relationship between customers and AI-ETs.
5.6. Respect	The level of consideration and courtesy represented by AI-ETs.
5.5 Surroundings	How the surroundings of the AI-ETs impact the experience.

Appendix B – Content and face validity

	Item	Content Validity					Face Validity				
		R1	R2	R3	R4	R5	R1	R2	R3	R4	R5
1	Interacting with AI-ETs gives a social image of being tech savvy.	SO	SO	SO	N/A	EM	CR	SR	CR	CR	CR
2	I was active while interacting with AI-ETs.	BE	BE	BE	BE	SE	SR	CR	CR	CR	CR
3	Interacting with AI-ETs enables me to come up with new ideas.	CO	CO	CO	CO	CO	SR	CR	SR	CR	CR
4	I pay attention to how others perceive my interactions with AI-ETs.	SO	SO	SO	SO	SO	CR	CR	CR	SR	SR
5	I was attracted by the AI-ETs.*	BE	SE	EM	N/A	EM					
6	I reflected on ideas that I got during the interaction with AI-ETs and discussed with others.*	CO	N/A	CO	N/A	BE					
7	Interacting with AI-ETs creates a new world for me, and this world suddenly disappears when the interactions ends.***	CO	CO	SE	CO	CO	SR	SR	SR	SR	SR
8	I have encouraged others to try AI-ETs out.*	SO	N/A	SO	N/A	BE					
9	I perceive my interactions with AI-ET as distinct and meaningful.*	CO	EM	N/A	N/A	SE					
10	I was indulged in the interactions with AI-ETs.	SE	EM	EM	CO	EM	SR	SR	CR	CR	CR
11	I maintained a sense of autonomy and control during my interactions with AI-ET.***	CO	EM	CO	CO	CO	NR	SR	CR	CR	CR
12	I willingly interact with AI-ETs during my experience.***	BE	BE	BE	N/A	BE	NR	SR	CR	SR	CR

13	Interacting with AI-ETs has encouraged me to embrace new behaviours.***	BE	BE	BE	N/A	BE	CR	CR	NR	CR	CR
14	My privacy is assured while interacting with AI-ETs.*	CO	EM	SE	CO	N/A					
15	My actions during the interactions with AI-ETs were new.***	BE	BE	BE	N/A	CO	NR	CR	SR	CR	SR
16	Interactions with AI-ETs allowed me to tailor my experience to match my personal preferences.*	CO	BE	CO	N/A	BE					
17	Interaction with AI-ETs are marked by courtesy and politeness.*	SO	N/A	SO	CO	SE					
18	It was easy to use the features of the AI-ET.***	CO	CO	BE	CO	CO	CR	SR	CR	CR	NR
19	My feelings during the interactions with AI-ETs were positive.***	EM	EM	EM	EM	EM	SR	CR	NR	CR	CR
20	My interactions with AI-ETs were the highlight of my overall experience.*	CO	N/A	N/A	N/A	EM					
21	Interactions with AI-ETs made me feel fashionable.*	SO	SO	EM	CO	SE					
22	My interactions with AI-ETs were memorable.*	CO	N/A	EM	N/A	EM					
23	Interacting with AI-ETs is just like being in another imaginative space.***	CO	CO	CO	CO	SE	SR	SR	NR	SR	SR
24	Interacting with AI-ETs increase the likelihood I will choose a similar experience in the future.*	CO	N/A	BE	N/A	BE					
25	Interactions with AI-ETs fit well with my lifestyle.*	SO	BE	BE	N/A	EM					
26	My imagination is being stirred during the interaction with AI-ETs.	CO	CO	CO	CO	SE	SR	CR	CR	CR	CR

27	I felt a sense of adventure while interacting with AI-ETs.*	CO	EM	CO	EM	SE					
28	AI-ETs are effectively utilized within the overall experience.*	CO	N/A	CO	N/A	N/A					
29	I felt like I was having the ideal experience with AI-ETs.*	CO	N/A	N/A	CO	SE					
30	I feel playful when I interact with AI-ETs.	EM	BE	EM	EM	SE	SR	CR	CR	CR	CR
31	AI-ETs made me feel cool.	SO	SO	EM	EM	SO	CR	CR	CR	SR	SR
32	AI-ETs delight me.***	EM	EM	EM	N/A	EM	NR	CR	CR	CR	CR
33	AI-ETs gave me more control over my experience.*	CO	EM	CO	N/A	SE					
34	I engage in a lot of thinking when I interact with AI-ETs.	CO	CO	CO	CO	CO	CR	CR	CR	CR	CR
35	I felt happy while interacting with AI-ETs.	EM	EM	EM	EM	SE	CR	CR	CR	CR	CR
36	I feel good being able to use AI-ETs.	EM	EM	EM	N/A	EM	CR	SR	CR	CR	CR
37	After the interaction with AI-ETs, I felt more positive about myself.*	N/A	SO	EM	N/A	SE					
38	While interacting with AI-ETs, I have experienced a personal connection.*	SO	EM	SO	SO	SE					
39	I experienced things unknown to me while interacting with AI-ETs.***	CO	CO	CO	CO	SE	NR	SR	CR	SR	CR
40	I felt safe in my interactions with AI-ETs.	EM	EM	EM	EM	SE	CR	SR	CR	SR	CR
41	I liked how smooth it is to interact with AI-ETs.*	SE	EM	CO	CO	SE					
42	I established a personal relationship with AI-ETs.	SO	EM	SO	N/A	SO	CR	CR	CR	SR	SR
43	I have some concerns regarding my interactions with AI-ETs.***	CO	CO	CO	N/A	CO	NR	SR	CR	SR	CR

44	I have a clear understanding of the abilities of AI-ETs.*	CO	N/A	CO	N/A	CO					
45	I enjoyed the sense of freedom while interacting with AI-ETs.*	SE	EM	CO	CO	SE					
46	I felt nervous or afraid when using AI-ETs.	EM	EM	EM	EM	SE	CR	CR	CR	SR	CR
47	I have actively shared my experiences with AI-ETs with others.*	SO	N/A	SO	N/A	BE					
48	I experienced intimacy during the interactions with AI-ETs.***	SO	EM	EM	EM	EM	NR	SR	CR	NR	CR
49	I have confidence in the performance of AI-ETs.	CO	EM	CO	N/A	CO	CR	SR	CR	SR	CR
50	I felt positively connected with AI-ETs.	EM	EM	EM	SO	EM	SR	SR	CR	CR	CR
51	I have reservations about the performance of AI-ETs.***	CO	CO	CO	N/A	CO	SR	SR	SR	SR	CR
52	I felt pleased while interacting with AI-ETs.	EM	EM	EM	N/A	EM	CR	CR	CR	CR	CR
53	Overall, I have negative perception about AI-ETs.*	N/A	N/A	EM	N/A	EM					
54	My total attention was on the AI-ETs.	CO	CO	SE	CO	SE	CR	SR	CR	CR	CR
55	Resolution to conflicts with AI-ETs is easy.***	CO	CO	CO	N/A	CO	NR	SR	CR	SR	SR
56	My interactions with AI-ETs deepened the sense of connection I felt throughout the experience.	SO	EM	SO	SO	SE	SR	CR	CR	CR	SR
57	I used my intellect during the interactions with AI-ETs.	CO	CO	CO	CO	CO	CR	CR	CR	CR	CR
58	My interactions with AI-ETs brought laughter.	EM	EM	EM	EM	EM	SR	CR	CR	SR	CR
59	I value the interactivity offered by AI-ETs within the experience.*	CO	N/A	SO	N/A	CO					

60	My interactions with AI-ETs required the use of multiple senses.	SE	SE	SE	SE	SE	CR	CR	CR	CR	CR
61	My personal beliefs were confirmed during the contact with AI-ETs.*	CO	N/A	CO	N/A	CO					
62	I remember details about my interactions with AI-ETs.*	CO	N/A	CO	N/A	CO					
63	My overall experience with AI-ETs was upsetting.***	EM	EM	CO	EM	EM	CR	CR	CR	NR	SR
64	My initial positive feelings towards AI-ETs have faded with repeated use.***	EM	EM	EM	N/A	EM	SR	SR	CR	SR	SR
65	The AI-ET provide a realistic portrayal of real-world experiences.*	CO	N/A	N/A	N/A	CO					
66	I forget about my immediate surroundings when I interact with AI-ETs.***	CO	CO	SE	CO	SE	CR	SR	CR	SR	SR
67	My interactions with AI-ETs felt novel and unique.	CO	CO	CO	CO	EM	CR	CR	CR	SR	CR
68	My interactions with AI-ETs have sometimes led to unfavourable outcomes.*	CO	N/A	N/A	N/A	EM					
69	My interactions with AI-ETs impacted on my emotional state and overall mood.***	EM	EM	EM	N/A	EM	NR	CR	SR	CR	CR
70	I gave up using AI-ETs during my experience.***	BE	BE	BE	N/A	BE	SR	SR	CR	NR	SR
71	My interactions with AI-ETs did not impact on my physical comfort.*	SE	SE	SE	N/A	N/A					
72	The interactions with AI-ETs make me feel optimistic.	EM	EM	EM	EM	EM	CR	CR	CR	SR	CR
73	The interactions with AI-ETs made me feel revitalized.***	SE	EM	EM	EM	SE	SR	SR	CR	SR	SR

74	The AI-ETs had human-like attributes and behaviours.*	SO	N/A	N/A	N/A	CO					
75	I experienced negative sensations while using AI-ETs.***	SE	SE	SE	SE	SE	SR	SR	CR	NR	SR
76	I gained new knowledge while interacting with AI-ETs during my experience.	CO	CO	CO	CO	CO	CR	CR	CR	CR	CR
77	The interactions with AI-ETs made me feel vitality.***	SE	EM	EM	EM	SE	SR	SR	CR	SR	SR
78	The interactions with AI-ETs made me feel worried.	EM	EM	EM	EM	EM	CR	CR	CR	SR	SR
79	The interactions with AI-ETs caused me to feel differently about myself.*	SO	EM	N/A	N/A	SO					
80	I got emotionally recharged by interacting with AI-ETs.*	EM	EM	N/A	N/A	EM					
81	The interactions with AI-ETs positively engaged me in a variety of ways.*	N/A	BE	EM	N/A	EM					
82	The interactions with AI-ETs piqued my curiosity.	CO	CO	CO	CO	SE	CR	CR	CR	CR	CR
83	Interacting with AI-ETs is slow and tedious.***	SE	EM	CO	CO	CO	CR	SR	CR	NR	NR
84	I have experienced moments of wonder and amazement during my interactions with AI-ETs.	EM	EM	EM	CO	SE	SR	CR	CR	CR	CR
85	I have felt let down during my interactions with AI-ETs.***	SO	EM	EM	EM	EM	SR	SR	CR	NR	CR
86	I have formed favourable opinions about AI-ETs during my experience.*	CO	N/A	N/A	N/A	EM					
87	The interactions with AI-ETs made a strong impression on my senses.	SE	SE	SE	SE	SE	CR	CR	CR	CR	CR
88	The interactions with AI-ETs made me aroused.***	N/A	EM	EM	EM	SE	CR	NR	CR	NR	NR

89	Interacting with AI-ETs was useful.*	CO	N/A	CO	N/A	CO					
90	Interacting with AI-ETs provided me with a momentary escape from reality.***	CO	CO	SE	CO	SE	SR	SR	SR	CR	SR
91	Interacting with AI-ETs made my experience more complicated.***	CO	EM	CO	CO	CO	SR	SR	CR	NR	NR
92	The interactions with AI-ETs result in bodily experience.	SE	SE	BE	BE	SE	SR	CR	CR	CR	CR
93	While interacting with AI-ETs, I felt contended.	EM	EM	EM	EM	EM	CR	CR	CR	SR	CR
94	The interactions with AI-ETs were in line with my personal values.*	CO	N/A	CO	N/A	SO					
95	Understanding how AI-ETs were integrated into my service journey contributed to my overall experience.*	CO	N/A	CO	N/A	N/A					
96	When I am interacting with AI-ETs, I feel that I am in flow.	CO	CO	CO	CO	SE	CR	CR	CR	CR	CR
97	When errors occur during my interactions with AI-ETs, it negatively influences my overall service experience.*	CO	N/A	N/A	N/A	N/A					
98	The presence of AI-ETs significantly influences my decision to select this experience.*	CO	N/A	BE	N/A	BE					
99	The presence of AI-ETs allows me to be more involved during the experience.*	BE	CO	SE	N/A	SE					
100	The interactions with AI-ETs made me better educated and informed.***	CO	CO	CO	N/A	SE	NR	CR	CR	CR	CR
101	This experience with AI-ETs is action oriented.	BE	BE	BE	BE	SE	SR	CR	CR	SR	CR

102	The technical quality of the AI-ET was pivotal in shaping my overall experience.*	CO	N/A	CO	N/A	CO					
103	The resolution of problems and mistakes related to AI-ETs was handled appropriately.*	CO	N/A	CO	N/A	CO					
104	There is an element of choice in the interactions with AI-ETs.***	CO	BE	CO	N/A	CO	SR	SR	CR	SR	CR
105	The interaction with AI-ETs was socially rewarding.	SO	SO	SO	N/A	SO	CR	SR	CR	SR	CR
106	The AI-ETs in use would benefit from further technical upgrades and improvements.*	CO	N/A	N/A	N/A	N/A					
107	The interactions with AI-ETs awakened my creativity.	CO	CO	CO	CO	SE	SR	CR	CR	CR	CR
108	The functionality of AI-ETs contributed positively to my experience.*	CO	N/A	N/A	N/A	N/A					
109	The interactions with AI-ETs made me feel in a good mood.	EM	EM	EM	EM	EM	CR	CR	CR	SR	CR
110	The AI-ETs offer adaptability across age, culture, language, and needs.*	CO	N/A	N/A	N/A	N/A					
111	The interactions with AI-ETs made me feel important for a few moments.	SO	EM	SO	EM	SO	CR	CR	CR	SR	SR
112	The design of AI-ETs was important in shaping my AICX.*	CO	N/A	N/A	N/A	N/A					
113	The cost I paid for my AICX was aligned with the value I received.*	CO	N/A	N/A	N/A	N/A					
114	The interactions with AI-ETs made me feel like I belonged to a community.	SO	SO	SO	SO	SO	CR	CR	CR	SR	SR

115	My interactions with AI-ETs reduced my social engagement during the experience.	SO	SO	SO	SO	SO	SR	CR	CR	SR	SR
116	My interactions with AI-ETs made me feel angry.***	EM	EM	EM	EM	EM	CR	CR	CR	NR	SR
117	The AI-ETs has my best interests at heart.*	CO	N/A	N/A	N/A	EM					
118	I concentrate fully during my AI-ETs interaction.	CO	CO	CO	CO	CO	CR	SR	CR	CR	CR
119	My interactions with AI-ETs added value to my overall experience.*	CO	N/A	N/A	N/A	EM					
120	I consistently assess my interactions with AI-ETs in comparison to technology-free alternatives.***	CO	N/A	CO	CO	BE	NR	SR	CR	CR	CR
121	My interactions with AI-ETs added a sense of fun and excitement to my experience.	EM	EM	EM	EM	SE	CR	CR	CR	CR	CR
122	I actively seek alternatives to using AI-ETs during my experience.	CO	BE	BE	BE	BE	SR	SR	CR	CR	CR
123	AI-ETs were convenient.*	CO	N/A	N/A	N/A	N/A					
124	I appreciate having a balance between the integration of AI-ETs and the human touch.*	N/A	N/A	N/A	N/A	N/A					
125	I believe that AI-ETs have the potential to further shape future experiences.*	CO	N/A	N/A	N/A	N/A					
126	During the interactions with AI-ETs, I was explaining and interpreting things for myself.	CO	BE	CO	CO	CO	CR	CR	CR	SR	CR
127	I adopt a cautious approach in any interactions with AI-ETs.*	BE	EM	CO	N/A	BE					
128	While interacting with AI-ETs, I was absorbed intently.	CO	CO	SE	CO	SE	CR	CR	CR	SR	CR

129	I am aware of the constraints and limitations of AI-ETs.*	CO	N/A	CO	N/A	CO					
130	Using AI-ETs challenges me and tests my ability.	CO	CO	CO	CO	SE	CR	CR	CR	CR	CR

N/A=Classified as Not Applicable, CO=Classified under Cognitive Dimension, BE=Classified under Behavioural Dimension, SE=Classified under Sensorial Dimension, SO=Classified under Social Dimension, EM=Classified under Emotional Dimension, CR=Classified as Clearly Representative of the AICX construct, SR=Classified as Somewhat Representative of the AICX construct, NR=Classified as Not Representative of the AICX construct, *=item excluded based on the content validity stage results, ***=item excluded based on the face validity stage results.

Appendix C – Content Validity Survey

Disclaimer:

This survey was designed and administered using Qualtrics. To facilitate respondent navigation, it was structured into blocks and pages. The survey consisted of 11 blocks, each displayed on a separate page. It began with an introduction block, followed by 10 blocks containing potential items for classification. Each block featured 13 items, presented in a randomized order. The definition of AICX and its dimensions were repeated at the beginning of each page. However, this structure is not reflected in the exported version included in this appendix. While the original survey interface may have differed slightly, the version presented here has been reformatted for clarity and readability.

Thank you very much for participating in our project. In the upcoming sections, your task will be to categorize a series of items into different groups. If you come across any items that don't seem to fit with the provided dimensions of AICX, please list them as 'not aligned with any of the specified dimensions'. A comment box is also provided at the bottom of each page where you can provide any explanation for any of the items that you find not fit or flag any other problems that you feel are relevant.

To complete this validity task, a clear understanding of AI-enabled customer experience (AICX), AI-enabled technologies (AI-ETs), and the various dimensions of AICX, each accompanied by its respective definitions is needed. These explanations are provided below and are reiterated at the beginning of each page for your convenience.

The AI-enabled customer experience (AICX) encompasses customers' cognitive, emotional, behavioural, sensorial, and social responses to the integration of AI-enabled technologies into service encounters throughout the customer journey. This perspective examines the customer experience through the lens of AI and emphasizes the impact of AI-enabled technologies (AI-ETs) in shaping and enhancing overall experiences.

AI-ETs cover a broad spectrum of technologies, ranging from those operating behind the scenes to those directly interacting with customers. This study is focused on customer-facing AI-ETs, including virtual reality travel experiences, virtual assistants, chatbots, service robots, and augmented reality applications. The dimensions of AICX comprise the following components:

- Behavioural: captures the observable actions, behaviours, and usage patterns of customers as a result of interacting with AI-ETs.
- Cognitive: focuses on the mental processes and intellectual aspects of when interacting with AI-ETs.
- Emotional: captures the affective responses of customers as a result of interacting with AI-ETs.
- Social: centres on the interpersonal dynamics and engagements that stem from customers' interactions with AI-ETs.
- Sensorial: covers the aspects of the experience resulting from the interactions with AI-ETs that are related to the senses.

Kindly categorize the items in the list based on their respective dimensions. If any items do not seem to fit within the provided dimensions, please mark them as 'not aligned with any of the specified dimensions ' and, if possible, provide concise feedback for such items in the comments box below.

Items
• I have encouraged others to try AI-ETs out. • I maintained a sense of autonomy and control during my interactions with AI-ET. • I pay attention to how others perceive my interactions with AI-ETs. • I perceive my interactions with AI-ET as distinct and meaningful. • I reflected on ideas that I got during the interaction with AI-ETs and discussed them with others. • I was active while interacting with AI-ETs. • I was attracted by the AI-ETs. • I was indulged in the interactions with AI-ETs. • I willingly interact with AI-ETs during my experience. • Interacting with AI-ETs creates a new world for me, and this world suddenly disappears when the interaction ends. • Interacting with AI-ETs enables me to come up with new ideas. • Interacting with AI-ETs gives a social image of being tech-savvy. • Interacting with AI-ETs has encouraged me to embrace new behaviors.

Dimensions
Behavioural
Cognitive
Emotional
Sensorial
Social
Does not align with any of the specified dimensions

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items	Dimensions
• My interactions with AI-ETs were memorable. • My interactions with AI-ETs were the highlight of my overall experience. • My privacy is assured while interacting with AI-ETs. • Interacting with AI-ETs increases the likelihood I will choose a similar experience in the future. • Interacting with AI-ETs is just like being in another imaginative space. • Interactions with AI-ETs are marked by courtesy and politeness. • Interactions with AI-ETs allowed me to tailor my experience to match my personal preferences. • Interactions with AI-ETs fit well with my lifestyle. • Interactions with AI-ETs made me feel fashionable. • It was easy to use the features of the AI-ET. • My actions during the interactions with AI-ETs were new. • My feelings during the interactions with AI-ETs were positive. • My imagination was stirred during the interaction with AI-ETs.	**Behavioural** **Cognitive** **Emotional** **Sensorial** **Social** **Does not align with any of the specified dimensions**

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items		Dimensions
• After the interaction with AI-ETs, I felt more positive about myself. • While interacting with AI-ETs, I have experienced a personal connection. • AI-ETs are effectively utilized within the overall experience. • AI-ETs delight me. • I engage in a lot of thinking when I interact with AI-ETs. • I experienced things unknown to me while interacting with AI-ETs. • I feel good being able to use AI-ETs. • I feel playful when I interact with AI-ETs. • I felt a sense of adventure while interacting with AI-ETs. • I felt happy while interacting with AI-ETs. • I felt like I was having the ideal experience with AI-ETs. • AI-ETs gave me more control over my experience. • AI-ETs made me feel cool.		**Behavioural** **Cognitive** **Emotional** **Sensorial** **Social** **Does not align with any of the specified dimensions**

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items	Dimensions
• I felt nervous or afraid when using AI-ETs. • I felt pleased while interacting with AI-ETs. • I felt positively connected with AI-ETs. • I felt safe in my interactions with AI-ETs. • I enjoyed the sense of freedom while interacting with AI-ETs. • I established a personal relationship with AI-ETs. • I experienced intimacy during the interactions with AI-ETs. • I have reservations about the performance of AI-ETs. • I have some concerns regarding my interactions with AI-ETs. • I liked how smooth it is to interact with AI-ETs. • I have a clear understanding of the abilities of AI-ETs. • I have actively shared my experiences with AI-ETs with others. • I have confidence in the performance of AI-ETs.	**Behavioural** **Cognitive** **Emotional** **Sensorial** **Social** **Does not align with any of the specified dimensions**

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items
• My initial positive feelings toward AI-ETs have faded with repeated use. • My overall experience with AI-ETs was upsetting. • My personal beliefs were confirmed during the contact with AI-ETs. • My interactions with AI-ETs brought laughter. • My interactions with AI-ETs deepened the sense of connection I felt throughout the experience. • I remember details about my interactions with AI-ETs. • I used my intellect during the interactions with AI-ETs. • I value the interactivity offered by AI-ETs within the experience. • My interactions with AI-ETs required the use of multiple senses. • My total attention was on the AI-ETs. • Overall, I have negative perception about AI-ETs. • Resolution to conflicts with AI-ETs is easy. • The AI-ET provide a realistic portrayal of real-world experiences.

Dimensions
Behavioural
Cognitive
Emotional
Sensorial
Social
Does not align with any of the specified dimensions

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items	Dimensions
• The AI-ETs had human-like attributes and behaviors. • My interactions with AI-ETs did not impact my physical comfort. • My interactions with AI-ETs felt novel and unique. • My interactions with AI-ETs have sometimes led to unfavorable outcomes. • My interactions with AI-ETs impacted on my emotional state and overall mood. • The interactions with AI-ETs made me feel revitalized. • The interactions with AI-ETs made me feel vitality. • The interactions with AI-ETs made me feel worried. • The interactions with AI-ETs make me feel optimistic. • I experienced negative sensations while using AI-ETs. • I forget about my immediate surroundings when I interact with AI-ETs. • I gained new knowledge while interacting with AI-ETs during my experience. • I gave up using AI-ETs during my experience.	**Behavioural** **Cognitive** **Emotional** **Sensorial** **Social** **Does not align with any of the specified dimensions**

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items
• I got emotionally recharged by interacting with AI-ETs. • Interacting with AI-ETs is slow and tedious. • Interacting with AI-ETs made my experience more complicated. • Interacting with AI-ETs provided me with a momentary escape from reality. • Interacting with AI-ETs was useful. • I have experienced moments of wonder and amazement during my interactions with AI-ETs. • I have felt let down during my interactions with AI-ETs. • I have formed favourable opinions about AI-ETs during my experience. • The interactions with AI-ETs caused me to feel differently about myself. • The interactions with AI-ETs made a strong impression on my senses. • The interactions with AI-ETs made me aroused. • The interactions with AI-ETs piqued my curiosity. • The interactions with AI-ETs positively engaged me in a variety of ways.

Dimensions
Behavioural
Cognitive
Emotional
Sensorial
Social
Does not align with any of the specified dimensions

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items	Dimensions
• The interactions with AI-ETs result in bodily experience. • The interactions with AI-ETs were in line with my personal values. • The presence of AI-ETs allows me to be more involved during the experience. • The presence of AI-ETs significantly influences my decision to select this experience. • The resolution of problems and mistakes related to AI-ETs was handled appropriately. • The technical quality of the AI-ET was pivotal in shaping my overall experience. • There is an element of choice in the interactions with AI-ETs. • This experience with AI-ETs is action oriented. • Understanding how AI-ETs were integrated into my service journey contributed to my overall experience. • When errors occur during my interactions with AI-ETs, it negatively influences my overall service experience. • When I am interacting with AI-ETs, I feel that I am in flow. • While interacting with AI-ETs, I felt contended. • The interactions with AI-ETs made me better educated and informed.	**Behavioural** **Cognitive** **Emotional** **Sensorial** **Social** **Does not align with any of the specified dimensions**

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items	Dimensions
• The interactions with AI-ETs made me feel important for a few moments. • My interactions with AI-ETs made me feel angry. • My interactions with AI-ETs reduced my social engagement during the experience. • The AI-ETs have my best interests at heart. • The AI-ETs in use would benefit from further technical upgrades and improvements. • The AI-ETs offer adaptability across age, culture, language, and needs. • The cost I paid for my AICX was aligned with the value I received. • The design of AI-ETs was important in shaping my AICX. • The functionality of AI-ETs contributed positively to my experience. • The interaction with AI-ETs was socially rewarding. • The interactions with AI-ETs awakened my creativity. • The interactions with AI-ETs made me feel in a good mood. • The interactions with AI-ETs made me feel like I belonged to a community.	**Behavioural** **Cognitive** **Emotional** **Sensorial** **Social** **Does not align with any of the specified dimensions**

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Items
• While interacting with AI-ETs, I was absorbed intently. • AI-ETs were convenient. • Using AI-ETs challenges me and tests my ability. • During the interactions with AI-ETs, I was explaining and interpreting things for myself. • I actively seek alternatives to using AI-ETs during my experience. • I adopt a cautious approach in any interactions with AI-ETs. • I am aware of the constraints and limitations of AI-ETs. • I appreciate having a balance between the integration of AI-ETs and the human touch. • My interactions with AI-ETs added a sense of fun and excitement to my experience. • My interactions with AI-ETs added value to my overall experience. • I believe that AI-ETs have the potential to further shape future experiences. • I concentrate fully during my AI-ETs interaction. • I consistently assess my interactions with AI-ETs in comparison to technology-free alternatives.

Dimensions
Behavioural
Cognitive
Emotional
Sensorial
Social
Does not align with any of the specified dimensions

Kindly provide your feedback for any items you've pinpointed as not aligned with the provided dimensions or presenting issues:

Appendix D – Face Validity Survey

Disclaimer:

This survey was designed and administered using Qualtrics. To facilitate respondent navigation, it was structured into blocks and pages. The survey consisted of eight blocks, each displayed on a separate page. It began with an introduction block, followed by blocks containing potential items categorized under their respective dimensions and as per the content validity stage results. Each block featured items corresponding to one of the five dimensions. Due to the larger number of cognitive and emotional items, these dimensions were each divided into two separate blocks. Within each block, items were presented in a randomized order. The definition of AICX and its dimensions was repeated at the beginning of each page. However, this structure is not reflected in the exported version included in this appendix. While the original survey interface may have differed slightly, the version presented here has been reformatted for clarity and readability.

Thank you very much for participating in our project. In the following sections, your task is to rate a series of items as either 'clearly representative', 'somewhat representative', or 'not representative' of the AICX construct. A comment box is also provided at the bottom of each page where you can provide any explanation for any of the items that you find not representative or flag any other problems that you feel are relevant.

To complete this validity task, a clear understanding of AI-enabled customer experience (AICX), AI-enabled technologies (AI-ETs), and the various dimensions of AICX, each accompanied by its respective definitions is needed. These explanations are provided next and are reiterated at the beginning of each page for your convenience.

The AI-enabled customer experience (AICX) encompasses customers' cognitive, emotional, behavioural, sensorial, and social responses to the integration of AI-enabled technologies into service encounters throughout the customer journey. This perspective examines the customer experience through the lens of AI and emphasizes the impact of AI-enabled technologies (AI-ETs) in shaping and enhancing overall experiences.

AI-ETs cover a broad spectrum of technologies, ranging from those operating behind the scenes to those directly interacting with customers. This study is focused on customer-facing AI-ETs, including virtual reality travel experiences, virtual assistants, chatbots, service robots, and augmented reality applications. The dimensions of AICX comprise the following components:

- Behavioural: captures the observable actions, behaviours, and usage patterns of customers as a result of interacting with AI-ETs.
- Cognitive: focuses on the mental processes and intellectual aspects of when interacting with AI-ETs.
- Emotional: captures the affective responses of customers as a result of interacting with AI-ETs.
- Social: centres on the interpersonal dynamics and engagements that stem from customers' interactions with AI-ETs.
- Sensorial: covers the aspects of the experience resulting from the interactions with AI-ETs that are related to the senses.

Kindly rate the following items as either clearly representative, somewhat representative, or not representative, of the behavioural dimension of AICX, and, if possible, provide concise feedback for such items in the comments box below.

	Not representative	Somewhat representative	Clearly representative
I actively seek alternatives to using AI-ETs during my experience.	○	○	○
I gave up using AI-ETs during my experience.	○	○	○
I was active while interacting with AI-ETs.	○	○	○
I willingly interact with AI-ETs during my experience.	○	○	○
Interacting with AI-ETs has encouraged me to embrace new behaviours.	○	○	○
My actions during the interactions with AI-ETs were new.	○	○	○
This experience with AI-ETs is action oriented.	○	○	○

Kindly provide your feedback for any items you've found problematic or presenting issues.

Kindly rate the following items as either clearly representative, somewhat representative, or not representative, of the cognitive dimension of AICX and, if possible, provide concise feedback for such items in the comments box below.

	Not representative	Somewhat representative	Clearly representative
During the interactions with AI-ETs, I was explaining and interpreting things for myself.	○	○	○
I concentrate fully during my AI-ETs interaction.	○	○	○
I consistently assess my interactions with AI-ETs in comparison to technology-free alternatives.	○	○	○
I engage in a lot of thinking when I interact with AI-ETs.	○	○	○
I experienced things unknown to me while interacting with AI-ETs.	○	○	○
I forget about my immediate surroundings when I interact with AI-ETs.	○	○	○
I gained new knowledge while interacting with AI-ETs during my experience.	○	○	○
I have confidence in the performance of AI-ETs.	○	○	○
I have reservations about the performance of AI-ETs.	○	○	○
I have some concerns regarding my interactions with AI-ETs.	○	○	○
I maintained a sense of autonomy and control during my interactions with AI-ET.	○	○	○
I used my intellect during the interactions with AI-ETs.	○	○	○
Interacting with AI-ETs creates a new world for me, and this world suddenly disappears when the interactions ends.	○	○	○
Interacting with AI-ETs enables me to come up with new ideas.	○	○	○

Interacting with AI-ETs is just like being in another imaginative space.	○	○	○
Interacting with AI-ETs is slow and tedious.	○	○	○
Interacting with AI-ETs made my experience more complicated.	○	○	○
Interacting with AI-ETs provided me with a momentary escape from reality.	○	○	○
It was easy to use the features of the AI-ET.	○	○	○
My imagination is being stirred during the interaction with AI-ETs.	○	○	○
My interactions with AI-ETs felt novel and unique.	○	○	○
My total attention was on the AI-ETs.	○	○	○
Resolution to conflicts with AI-ETs is easy.	○	○	○
The interactions with AI-ETs awakened my creativity.	○	○	○
The interactions with AI-ETs made me better educated and informed.	○	○	○
The interactions with AI-ETs piqued my curiosity.	○	○	○
There is an element of choice in the interactions with AI-ETs.	○	○	○
Using AI-ETs challenges me and tests my ability.	○	○	○
When I am interacting with AI-ETs, I feel that I am in flow.	○	○	○
While interacting with AI-ETs, I was absorbed intently.	○	○	○

Kindly provide your feedback for any items you've found problematic or presenting issues.

Kindly rate the following items as either clearly representative, somewhat representative, or not representative, of the emotional dimension of AICX, and, if possible, provide concise feedback for such items in the comments box below.

	Not representative	Somewhat representative	Clearly representative
My initial positive feelings towards AI-ETs have faded with repeated use.	○	○	○
My interactions with AI-ETs added a sense of fun and excitement to my experience.	○	○	○
My interactions with AI-ETs brought laughter.	○	○	○
My interactions with AI-ETs impacted on my emotional state and overall mood.	○	○	○
My interactions with AI-ETs made me feel angry.	○	○	○
My overall experience with AI-ETs was upsetting.	○	○	○
The interactions with AI-ETs made me aroused.	○	○	○
The interactions with AI-ETs made me feel in a good mood.	○	○	○
The interactions with AI-ETs made me feel revitalized.	○	○	○

The interactions with AI-ETs made me feel vitality.	○	○	○
The interactions with AI-ETs made me feel worried.	○	○	○
The interactions with AI-ETs make me feel optimistic.	○	○	○
While interacting with AI-ETs, I felt contended.	○	○	○
AI-ETs delight me.	○	○	○
I experienced intimacy during the interactions with AI-ETs.	○	○	○
I feel good being able to use AI-ETs.	○	○	○
I feel playful when I interact with AI-ETs.	○	○	○
I felt happy while interacting with AI-ETs.	○	○	○
I felt nervous or afraid when using AI-ETs.	○	○	○
I felt pleased while interacting with AI-ETs.	○	○	○
I felt positively connected with AI-ETs.	○	○	○
I felt safe in my interactions with AI-ETs.	○	○	○
I have experienced moments of wonder and amazement during my interactions with AI-ETs.	○	○	○
I have felt let down during my interactions with AI-ETs.	○	○	○
I was indulged in the interactions with AI-ETs.	○	○	○
My feelings during the interactions with AI-ETs were positive.	○	○	○

Kindly provide your feedback for any items you've found problematic or presenting issues.

Kindly rate the following items as either clearly representative, somewhat representative, or not representative, of the sensorial dimension of AICX, and, if possible, provide concise feedback for such items in the comments box below.

	Not representative	Somewhat representative	Clearly representative
I experienced negative sensations while using AI-ETs.	○	○	○
My interactions with AI-ETs required the use of multiple senses.	○	○	○
The interactions with AI-ETs made a strong impression on my senses.	○	○	○
The interactions with AI-ETs result in bodily experience.	○	○	○

Kindly provide your feedback for any items you've found problematic or presenting issues.

Kindly rate the following items as either clearly representative, somewhat representative, or not representative, of the social dimension of AICX, and, if possible, provide concise feedback for such items in the comments box below.

	Not representative	Somewhat representative	Clearly representative
Interacting with AI-ETs gives a social image of being tech savvy.	○	○	○
AI-ETs made me feel cool.	○	○	○
I established a personal relationship with AI-ETs.	○	○	○
I pay attention to how others perceive my interactions with AI-ETs.	○	○	○
My interactions with AI-ETs deepened the sense of connection I felt throughout the experience.	○	○	○
My interactions with AI-ETs reduced my social engagement during the experience.	○	○	○
The interaction with AI-ETs was socially rewarding.	○	○	○
The interactions with AI-ETs made me feel important for a few moments.	○	○	○
The interactions with AI-ETs made me feel like I belonged to a community.	○	○	○

Kindly provide your feedback for any items you've found problematic or presenting issues.

Appendix E – Pilot Survey before amendments

Disclaimer

This survey was designed and administered using Qualtrics, with respondents recruited through Prolific. The questionnaire consisted of two parts: a screener, followed by the main section featuring 45 items for evaluation. To enhance navigation within Qualtrics, the questionnaire was structured into blocks, with each block displayed on a separate page. The survey comprised four blocks: an introductory block, followed by three blocks containing potential items, each featuring 15 items presented in a randomized order. For simplicity and readability, this appendix presents a condensed version of the response scale. However, in the actual survey, all seven response options were displayed in their full form and in the order shown above to ensure clarity for respondents.

Introduction and Screener

Welcome to our survey! Your valuable input is crucial for our research. Please take a moment to express your opinions by selecting the most fitting response on the 7-point Likert scale provided. Each point on the scale corresponds to a specific level of agreement or disagreement with the statements presented about interacting with AI-enabled technologies. AI-ETs cover a broad spectrum of technologies, this study however is focused on customer-facing AI-ETs during service experiences, including examples like virtual reality travel experiences, virtual assistants, chatbots, service robots, and augmented reality applications. We really appreciate your time and effort in participating in this endeavour. Your insights will greatly contribute to our research. Thank you for your participation!

Please provide your Prolific ID.

Have you ever engaged with any of the following AI-enabled technologies? Please select all that apply.

◯ Chatbots

◯ Service robots

◯ Intelligent voice assistants

◯ Virtual reality

◯ Mixed reality

◯ I've experienced engagement with another AI-enabled technology.

◯ I haven't encountered any AI-enabled technologies.

If yes, could you kindly offer more details about this interaction? When did it take place? What was the context? Anything noteworthy you recall from the experience?

Pease take a moment to express your opinions about the following statements by selecting the most fitting response on the 7-point Likert scale provided.

Items	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Agree**	**Strongly agree**
I actively seek alternatives to using AI-ETs during my experience.	○	○	○	○	○	○	○
I was active while interacting with AI-ETs.	○	○	○	○	○	○	○
This experience with AI-ETs is action oriented.	○	○	○	○	○	○	○
During the interactions with AI-ETs, I was explaining and interpreting things for myself.	○	○	○	○	○	○	○

I concentrate fully during my AI-ETs interaction.	○	○	○	○	○	○	○
I engage in a lot of thinking when I interact with AI-ETs.	○	○	○	○	○	○	○
I gained new knowledge while interacting with AI-ETs during my experience.	○	○	○	○	○	○	○
I have confidence in the performance of AI-ETs.	○	○	○	○	○	○	○
I used my intellect during the interactions with AI-ETs.	○	○	○	○	○	○	○
Interacting with AI-ETs enables me to come up with new ideas.	○	○	○	○	○	○	○
My imagination is being stirred during the interaction with AI-ETs.	○	○	○	○	○	○	○

My interactions with AI-ETs felt novel and unique.	○	○	○	○	○	○	○
My total attention was on the AI-ETs.	○	○	○	○	○	○	○
The interactions with AI-ETs awakened my creativity.	○	○	○	○	○	○	○
The interactions with AI-ETs piqued my curiosity.	○	○	○	○	○	○	○
Using AI-ETs challenges me and tests my ability.	○	○	○	○	○	○	○
When I am interacting with AI-ETs, I feel that I am in flow.	○	○	○	○	○	○	○
While interacting with AI-ETs, I was absorbed intently.	○	○	○	○	○	○	○
I feel good being able to use AI-ETs.	○	○	○	○	○	○	○

I feel playful when I interact with AI-ETs.	○	○	○	○	○	○	○
I felt happy while interacting with AI-ETs.	○	○	○	○	○	○	○
I felt nervous or afraid when using AI-ETs.	○	○	○	○	○	○	○
I felt pleased while interacting with AI-ETs.	○	○	○	○	○	○	○
I felt positively connected with AI-ETs.	○	○	○	○	○	○	○
I felt safe in my interactions with AI-ETs.	○	○	○	○	○	○	○
I have experienced moments of wonder and amazement during my interactions with AI-ETs.	○	○	○	○	○	○	○

I was indulged in the interactions with AI-ETs.	○	○	○	○	○	○	○
My interactions with AI-ETs added a sense of fun and excitement to my experience.	○	○	○	○	○	○	○
My interactions with AI-ETs brought laughter.	○	○	○	○	○	○	○
The interactions with AI-ETs made me feel in a good mood.	○	○	○	○	○	○	○
The interactions with AI-ETs made me feel worried.	○	○	○	○	○	○	○
The interactions with AI-ETs make me feel optimistic.	○	○	○	○	○	○	○
While interacting with AI-ETs, I felt contended.	○	○	○	○	○	○	○

My interactions with AI-ETs required the use of multiple senses.	○	○	○	○	○	○	○
The interactions with AI-ETs made a strong impression on my senses.	○	○	○	○	○	○	○
The interactions with AI-ETs result in bodily experience.	○	○	○	○	○	○	○
Interacting with AI-ETs gives a social image of being tech savvy.	○	○	○	○	○	○	○
AI-ETs made me feel cool.	○	○	○	○	○	○	○
I established a personal relationship with AI-ETs.	○	○	○	○	○	○	○
I pay attention to how others perceive my interactions with AI-ETs.	○	○	○	○	○	○	○

My interactions with AI-ETs deepened the sense of connection I felt throughout the experience.	◯	◯	◯	◯	◯	◯	◯
My interactions with AI-ETs reduced my social engagement during the experience.	◯	◯	◯	◯	◯	◯	◯
The interaction with AI-ETs was socially rewarding.	◯	◯	◯	◯	◯	◯	◯
The interactions with AI-ETs made me feel important for a few moments.	◯	◯	◯	◯	◯	◯	◯
The interactions with AI-ETs made me feel like I belonged to a community.	◯	◯	◯	◯	◯	◯	◯

Appendix F – Screener surveys

Disclaimer:

This survey was designed and administered using Qualtrics, with respondents recruited through Prolific. To facilitate navigation, the screening questionnaire was structured into two blocks—an introduction block and a screening block—each displayed on a separate page. While the original survey interface may have varied slightly, the version presented here has been reformatted for clarity and readability. It is also important to mention that the same screening surveys (structure and approach) were used for the three rounds of quantitative data collection.

Service robots

Introduction:

Welcome to our screening survey! We're on the lookout for individuals who have prior experience interacting with robots in a services context. Your participation in this brief survey will help us identify potential candidates for a more in-depth study delving into this specific interaction. Robots are increasingly integrated into the services sector, from providing customer service and assistance in hotels, serving as interactive exhibits in museums, to greeting and serving food at restaurants. If you've engaged with a service robot in one of these contexts (or any other similar context), we invite you to share your experience by completing this survey. Your insightful responses will play a pivotal role in determining your eligibility for our forthcoming study, where we aim to explore these interactions in greater depth. If you haven't had the opportunity to interact with a service robot in the specified context, we kindly request that you refrain from completing the survey, as the questions may not be relevant to your, and we will therefore be required to exclude your response.

Thank you.

Please provide your Prolific ID.

Screener:

Q1: Have you ever interacted with a robot in a service setting, such as a hotel, museum, airport, entertainment venue or restaurant?

◯ Yes

◯ No

Q2: How often have you interacted with service robots in total?

◯ Never

◯ Once or twice

◯ Several times

◯ Regularly

Q3: When did you last interact with a service robot?

◯ Within the past month

◯ Within the past 6 months

◯ Within the past year

◯ More than 1 year ago

Q4: Where did your most recent interaction with a service robot take place?

◯ Hotel

◯ Museum

◯ Restaurant

◯ Airport

◯ Public transportation

◯ Entertainment venues

◯ Events and conferences

◯ Tourist attraction site

◯ Other (Please specify) ___________________________________

Q5: Can you describe your most recent service robot experience in detail? What was it like? Where did it take place? What are some of the key aspects of the interaction with a service robot? Can you think of anything memorable?

Verbal and Textual Bots

Introduction:

Welcome to our screening survey! We're on the lookout for individuals who have prior experience interacting with verbal and textual bots in a services context. Your participation in this brief survey will help us identify potential candidates for a more in-depth study delving into this specific interaction. Bots are computer programs that can talk to people in text or voice and are being used more and more in the services sector. You can use bots on their own devices or on your phone or computer. For example, verbal bots (sometimes referred to as intelligent voice assistants) are providing guests at hotels with customer service, information about tourist attractions, local events, and dining recommendations for hotel guests. Text bots (sometimes referred to as chatbots) act like tour guides in some mobile apps. They also help people find and book accommodation. At airports, they help with real-time flight details like gate changes and baggage info on the website. If you've engaged with a verbal or textual bot in one of these contexts (or any other similar context), we invite you to share your experience by completing this survey. Your insightful responses will play a pivotal role in determining your eligibility for our forthcoming study, where we aim to explore these interactions in greater depth. If you haven't had the opportunity to interact with a verbal or textual bot in the specified context, we kindly request that you refrain from completing the survey, as the questions may not

be relevant to your, and we will therefore be required to exclude your response.
Thank you.

Please provide your Prolific ID.

Screener:

Q1: Have you ever interacted with a verbal or textual bot in a service setting, such as a hotel, museum, making travel arrangements, airport, entertainment venue or restaurant?

◯ Yes

◯ No

Q2: How often have you interacted with the verbal or textual bot in a services context in total?

◯ Never

◯ Once or twice

◯ Several times

◯ Regularly

Q3: When did you last interact with a verbal or textual bot in a services context?

◯ Within the past month

◯ Within the past 6 months

◯ Within the past year

◯ More than 1 year ago

Q4: Where did your most recent interaction with a verbal or textual bot take place?

◯ Hotel

◯ Museum

◯ Restaurant

◯ Airport

◯ Public transportation

◯ Entertainment venue

◯ Event or conference

◯ Tourist attraction site

◯ City tour

◯ Cruise

◯ While making travel arrangements

◯ Other (Please specify) ________________________

Q5: Can you describe your most recent verbal or textual bot experience in detail? What was it like? Where did it take place? What are some of the key aspects of the interaction with a service robot? Can you think of anything memorable?

Extended Reality Applications

Introduction:

Welcome to our screening survey! We're on the lookout for individuals who have prior experience interacting with extended reality applications in a services context. Your participation in this brief survey will help us identify potential candidates for a more in-depth study delving into this specific interaction. Extended reality is an umbrella term that includes (augmented reality, virtual reality, and mixed reality) all are being used more and more in the services sector. You can make use of these applications using wearable devices or your phone or computer. For example, some restaurants are using augmented reality for menus to allow diners to view dishes in 3D, see ingredients and nutritional information, and even play games while they wait for their food. Travel agents are using virtual reality for destination marketing, this way, potential travellers get a realistic preview of a destination, which can help them decide where to go on vacation. Museums are utilizing a variety of technologies, including augmented reality, virtual reality, and interactive displays, to create more engaging and informative exhibitions. If you've engaged with an extended reality technology in one of these contexts (or any other similar context), we invite you to share your experience by completing this survey. Your insightful responses will play a pivotal role in determining your eligibility for our forthcoming study, where we aim to explore these interactions in greater depth. If you haven't had the opportunity to interact with an extended reality technology in a services context, we kindly request that you refrain from completing the survey, as the questions may not be relevant to your, and we will therefore be required to exclude your response. Thank you.

Please provide your Prolific ID.

Screener:

Q1: Have you ever interacted with an extended reality technology in a services setting, such as a museum, making travel arrangements, airport, entertainment venue or restaurant?

◯ Yes

◯ No

Q2: How often have you interacted with an extended reality technology in a services context in total?

◯ Never

◯ Once or twice

◯ Several times

◯ Regularly

Q3: When did you last interact with an extended reality technology in a services context?

◯ Within the past month

◯ Within the past 6 months

◯ Within the past year

◯ More than 1 year ago

Q4: Where did your most recent interaction with an extended reality technology take place?

◯ Museum

◯ Restaurant

◯ Airport

◯ Entertainment venue

◯ Event or conference

◯ Tourist attraction site

◯ City Tour

◯ While making travel arrangements

◯ Other (Please specify) ____________________

Q5: Can you describe your most recent extended reality (augmented, virtual or mixed) experience in detail? What was it like? Where did it take place? What are some of the key aspects of the interaction with a service robot? Can you think of anything memorable?

Appendix G – Data collection survey – Round 1

Disclaimer

The appearance of the appendix might differ slightly here compared to how it actually appears on Qualtrics due to platform-specific formatting.

Participant information sheet

Welcome to this survey that aims to develop a scale for measuring the AI-enabled Customer Experience (AICX). Before you start, please take a moment to read this page for important information about the research, the researcher and the survey that you are about to complete.

Who am I? My name is Nada Ghesh, I am a doctoral student from the marketing department at University of Strathclyde – Glasgow, United Kingdom, and I am conducting this research as part of my PhD degree in Marketing.

What is the purpose of this research? My project explores one of the key marketing constructs, the customer experience. With AI-applications increasingly integrated across the customer journey (examples of which include augmented reality mobile apps, virtual reality assistants, chatbots, and service robots) the project aims to explore the AI-enabled customer experience and measure its impact on the resulting behavioural outcomes in the tourism sector.

Do you have to take part? Your participation in this study is voluntary and you are free to choose whether or not to participate. If you wish to take part, click the button below to continue. If you do not prefer to participate, please leave the survey by closing the browser window. If you agree to participate and then encounter any discomfort with the study, you can withdraw at any time by closing your browser. Partially completed surveys will be discarded. If you have completed the survey, you still retain the right to withdraw from the study. But in such case, and to have your response excluded, you must notify the researcher through the Prolific platform.

What will you do in the project? You are invited to participate in an online survey where you will be asked to share your perspective on your experience with AI-enabled technologies (Service robots, Verbal and textual bots, Extended reality). Your participation will be rewarded with a compensation payment through Prolific.

Who can take part and why have you been invited to take part? To qualify for this study, you must be 16 years old or older and have had at least one active interaction with an AI-enabled technology. You have been pre-qualified for this survey based on your responses to a previous screening survey. If you believe that you do not meet the criteria for this survey or there is an error with your eligibility, please withdraw from the survey and contact the researcher (contact details can be found below or alternatively you can get in touch through Prolific).

What information is being collected in the project? In this survey, we ask you to share your opinions by selecting the most appropriate response on the provided 7-point Likert scale about a previous interaction you had with an AI-enabled technology. Each point on the scale represents a specific level of agreement or disagreement with the statements presented about your interaction with AI-enabled technologies. No identifiable information will be collected from you.

Who will have access to the information? All data collected for this project will be anonymized, ensuring that your identity remains confidential at all stages of the research. No personally identifiable information will be collected from you, making it impossible to link your responses to you. Additionally, only the investigators named in this Ethics Application form will have access to the anonymized data.

Where will the information be stored and how long will it be kept for? During the investigation, all active data and related files will be kept private and saved on the university's password protected cloud storage (also backed up at the university's network drive) that is accessible through a password protected device. Upon project completion, all data and related files will be deposited in Pure (the university's data deposit system) and will be permanently restricted. Thank you for reading this information – please ask any questions if you are unsure about what is written here. All personal data will be processed in accordance with data protection legislation. Please read our Privacy Notice for Research Participants at https://www.strath.ac.uk/ethics for more information about your rights under the legislation.

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Researchers contact details:

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Chief Investigator details:

Dr. Matthew Alexander

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Consent Form

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Please enter your signature in the box below.

Introduction

This survey invites you to share your perspectives on a number of statements related to your interaction with an AI-enabled technology (Service robots, Verbal and textual bots, Extended reality). Simply select the point on the provided 7-point Likert scale that aligns with your level of agreement or disagreement with each statement.

You have been invited to participate in this survey because you indicated having experience with an AI-enabled technology in a previous screening survey. Therefore, throughout this survey, whenever you see the abbreviation **"AI-ETs" it refers to the AI-enabled technologies you interacted with during your experience**. If you've had multiple interactions with AI-ETs, please base your responses on your most recent encounter. This will enable us to gather the most relevant and up-to-date information for our research.

There are **3 attention checks** in this survey. Please answer them carefully to ensure that your response is not rejected.

Your participation in this study is greatly valued. Thank you for your time and effort.

Before we start, please provide your Prolific ID:

Please take a moment to express your opinions about the following statements by selecting the most fitting response on the 7-point Likert scale provided. Please remember that the abbreviation "AI-ETs" refer to the AI-enabled technologies you interacted with during that experience.

Items	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Agree**	**Strongly agree**
I actively seek alternatives to using AI-ETs during my experience.	○	○	○	○	○	○	○
I was active while interacting with AI-ETs.	○	○	○	○	○	○	○
This experience with AI-ETs is action oriented.	○	○	○	○	○	○	○
During the interactions with AI-ETs, I was explaining and interpreting things for myself.	○	○	○	○	○	○	○
I concentrate fully during my AI-ETs interaction.	○	○	○	○	○	○	○

I engage in a lot of thinking when I interact with AI-ETs.	○	○	○	○	○	○	○
I gained new knowledge while interacting with AI-ETs during my experience.	○	○	○	○	○	○	○
I have confidence in the performance of AI-ETs.	○	○	○	○	○	○	○
I used my intellect during the interactions with AI-ETs.	○	○	○	○	○	○	○
Interacting with AI-ETs enables me to come up with new ideas.	○	○	○	○	○	○	○
My imagination is being stirred during the interaction with AI-ETs.	○	○	○	○	○	○	○
My interactions with AI-ETs felt novel and unique.	○	○	○	○	○	○	○
My total attention was on the AI-ETs.	○	○	○	○	○	○	○

The interactions with AI-ETs awakened my creativity.	○	○	○	○	○	○	○
The interactions with AI-ETs piqued my curiosity.	○	○	○	○	○	○	○
Using AI-ETs challenges me and tests my ability.	○	○	○	○	○	○	○
When I am interacting with AI-ETs, I feel that I am in flow.	○	○	○	○	○	○	○
While interacting with AI-ETs, I was absorbed intently.	○	○	○	○	○	○	○
I feel good being able to use AI-ETs.	○	○	○	○	○	○	○
I feel playful when I interact with AI-ETs.	○	○	○	○	○	○	○
I felt happy while interacting with AI-ETs.	○	○	○	○	○	○	○

I felt nervous or afraid when using AI-ETs.	○	○	○	○	○	○	○
I felt pleased while interacting with AI-ETs.	○	○	○	○	○	○	○
I felt positively connected with AI-ETs.	○	○	○	○	○	○	○
I felt safe in my interactions with AI-ETs.	○	○	○	○	○	○	○
I have experienced moments of wonder and amazement during my interactions with AI-ETs.	○	○	○	○	○	○	○
I was indulged in the interactions with AI-ETs.	○	○	○	○	○	○	○
My interactions with AI-ETs added a sense of fun and excitement to my experience.	○	○	○	○	○	○	○

My interactions with AI-ETs brought laughter.	◯	◯	◯	◯	◯	◯	◯
The interactions with AI-ETs made me feel in a good mood.	◯	◯	◯	◯	◯	◯	◯
The interactions with AI-ETs made me feel worried.	◯	◯	◯	◯	◯	◯	◯
The interactions with AI-ETs make me feel optimistic.	◯	◯	◯	◯	◯	◯	◯
While interacting with AI-ETs, I felt contended.	◯	◯	◯	◯	◯	◯	◯
My interactions with AI-ETs required the use of multiple senses.	◯	◯	◯	◯	◯	◯	◯
The interactions with AI-ETs made a strong impression on my senses.	◯	◯	◯	◯	◯	◯	◯
The interactions with AI-ETs result in bodily experience.	◯	◯	◯	◯	◯	◯	◯

Interacting with AI-ETs gives a social image of being tech savvy.	◯	◯	◯	◯	◯	◯	◯
AI-ETs made me feel cool.	◯	◯	◯	◯	◯	◯	◯
I established a personal relationship with AI-ETs.	◯	◯	◯	◯	◯	◯	◯
I pay attention to how others perceive my interactions with AI-ETs.	◯	◯	◯	◯	◯	◯	◯
My interactions with AI-ETs deepened the sense of connection I felt throughout the experience.	◯	◯	◯	◯	◯	◯	◯
My interactions with AI-ETs reduced my social engagement during the experience.	◯	◯	◯	◯	◯	◯	◯
The interaction with AI-ETs was socially rewarding.	◯	◯	◯	◯	◯	◯	◯
The interactions with AI-ETs made me feel important for a few moments.	◯	◯	◯	◯	◯	◯	◯

The interactions with AI-ETs made me feel like I belonged to a community.	○	○	○	○	○	○	○

Demographics

What is your age?

- ◯ 18 - 25
- ◯ 26 - 35
- ◯ 36 - 45
- ◯ 46 - 55
- ◯ Above 55

What is your gender?

- ◯ Male
- ◯ Female

What is the highest level of education you have completed?

- ◯ High school diploma or equivalent
- ◯ Undergraduate degree
- ◯ Master's degree
- ◯ Doctoral degree
- ◯ Other (Please specify)

____

What is your current employment status?

- ◯ Full-time employed
- ◯ Part-time employed
- ◯ Unemployed
- ◯ Student
- ◯ Retired
- ◯ Other (please specify)

____

What is your approximate monthly income?

- ◯ Less than $1,000
- ◯ $1,000 - $2,000
- ◯ $2,001- $3,000
- ◯ $3,001 - $4,000
- ◯ $4,001 - $5,000
- ◯ $5,001 - $6,000
- ◯ Above $6,000

Appendix H – Data collection survey – Round 2

Disclaimer

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Participant information sheet

Welcome to this survey that aims to develop a scale for measuring the AI-enabled Customer Experience (AICX). Before you start, please take a moment to read this page for important information about the research, the researcher and the survey that you are about to complete.

Who am I? My name is Nada Ghesh, I am a doctoral student from the marketing department at University of Strathclyde – Glasgow, United Kingdom, and I am conducting this research as part of my PhD degree in Marketing.

What is the purpose of this research? My project explores one of the key marketing constructs, the customer experience. With AI-applications increasingly integrated across the customer journey (examples of which include augmented reality mobile apps, virtual reality assistants, chatbots, and service robots) the project aims to explore the AI-enabled customer experience and measure its impact on the resulting behavioural outcomes in the tourism sector.

Do you have to take part? Your participation in this study is voluntary and you are free to choose whether or not to participate. If you wish to take part, click the button below to continue. If you do not prefer to participate, please leave the survey by closing the browser window. If you agree to participate and then encounter any discomfort with the study, you can withdraw at any time by closing your browser. Partially completed surveys will be discarded. If you have completed the survey, you still retain the right to withdraw from the study. But in such case, and to have your response excluded, you must notify the researcher through the Prolific platform.

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Researchers contact details:

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Items	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Agree**	**Strongly agree**
			AICX Scale Items				
I felt pleased while interacting with AI-ETs.	○	○	○	○	○	○	○
I felt positively connected with AI-ETs.	○	○	○	○	○	○	○
I felt safe in my interactions with AI-ETs	○	○	○	○	○	○	○
I have experienced moments of wonder rand amazement during my interactions with AI-ETs.	○	○	○	○	○	○	○

I was indulged in the interactions with AI-ETs.	○	○	○	○	○	○	○
My interactions with AI-ETs added a sense of fun and excitement to my experience.	○	○	○	○	○	○	○
I established a personal relationship with AI-ETs.	○	○	○	○	○	○	○
The interactions with AI-ETs made me feel important for a few moments.	○	○	○	○	○	○	○
The interactions with AI-ETs made me feel like I belonged to a community	○	○	○	○	○	○	○
I gained new knowledge while interacting with AI-ETs during my experience.	○	○	○	○	○	○	○

The interactions with AI-ETs awakened my creativity	○	○	○	○	○	○	○
Interacting with AI-ETs enabled me to come up with new ideas.	○	○	○	○	○	○	○
Customer Satisfaction							
The AICX closely matched my ideal experience.	○	○	○	○	○	○	○
My AICX was better than I expected.	○	○	○	○	○	○	○
I am satisfied with the overall AICX.	○	○	○	○	○	○	○

Demographics

What is your age?

- ◯ 18 - 25
- ◯ 26 - 35
- ◯ 36 - 45
- ◯ 46 - 55
- ◯ Above 55

What is your gender?

- ◯ Male
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What is your approximate monthly income?

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Appendix I – Data collection survey – Round 3

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Before we start, please provide your Prolific ID:

Please take a moment to express your opinions about the following statements by selecting the most fitting response on the 7-point Likert scale provided. Please remember that the abbreviation "AI-ETs" refer to the AI-enabled technologies you interacted with during that experience.

Items	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Agree**	**Strongly agree**
AICX Scale Items							
I felt pleased while interacting with AI-ETs.	○	○	○	○	○	○	○
I felt positively connected with AI-ETs.	○	○	○	○	○	○	○
I felt safe in my interactions with AI-ETs	○	○	○	○	○	○	○
I have experienced moments of wonder rand amazement during my interactions with AI-ETs.	○	○	○	○	○	○	○

I was indulged in the interactions with AI-ETs.	○	○	○	○	○	○	○
My interactions with AI-ETs added a sense of fun and excitement to my experience.	○	○	○	○	○	○	○
I established a personal relationship with AI-ETs.	○	○	○	○	○	○	○
The interactions with AI-ETs made me feel important for a few moments.	○	○	○	○	○	○	○
The interactions with AI-ETs made me feel like I belonged to a community	○	○	○	○	○	○	○
I gained new knowledge while interacting with AI-ETs during my experience.	○	○	○	○	○	○	○
The interactions with AI-ETs awakened my creativity	○	○	○	○	○	○	○

Interacting with AI-ETs enabled me to come up with new ideas.	○	○	○	○	○	○	○
Customer Engagement							
During the AICX, I invested a lot of concentration.	○	○	○	○	○	○	○
During the AICX, I fully attached myself to AI-ETs.	○	○	○	○	○	○	○
During the AICX, I had difficulties to detach myself.	○	○	○	○	○	○	○
During the AICX, I forgot everything around me.	○	○	○	○	○	○	○
During the AICX, I devoted a lot of enthusiasm.	○	○	○	○	○	○	○
During the AICX, I devoted a lot of dedication.	○	○	○	○	○	○	○
During the AICX, I was emotionally attached.	○	○	○	○	○	○	○

During the AICX, I was emotionally satisfied.	○	○	○	○	○	○	○
During the AICX, I spent a lot of time seeking ideas and information from AI-ETs.	○	○	○	○	○	○	○
During the AICX, I sought help from AI-ETs.	○	○	○	○	○	○	○
During the AICX, I thought of promoting the AI-ETs.	○	○	○	○	○	○	○
During the AICX, I thought of getting others interested in the AI-ET.	○	○	○	○	○	○	○
Autonomy							
I feel like I can be myself during the AICX.	○	○	○	○	○	○	○
During the AICX, I often feel like I have to follow the AI-ETs commands.	○	○	○	○	○	○	○

If I could choose, I would do things during the AICX differently.	○	○	○	○	○	○	○
The things I do during the AICX are in line with what I really want to do.	○	○	○	○	○	○	○
During the AICX, I feel free to do things the way I think it could best be done.	○	○	○	○	○	○	○
During the AICX, I feel forced to do things I do not want to do.	○	○	○	○	○	○	○

Demographics

What is your age?

- ◯ 18 - 25
- ◯ 26 - 35
- ◯ 36 - 45
- ◯ 46 - 55
- ◯ Above 55

What is your gender?

- ◯ Male
- ◯ Female

What is the highest level of education you have completed?

- ◯ High school diploma or equivalent
- ◯ Undergraduate degree
- ◯ Master's degree
- ◯ Doctoral degree
- ◯ Other (Please specify)

____

What is your current employment status?

- ◯ Full-time employed
- ◯ Part-time employed
- ◯ Unemployed
- ◯ Student
- ◯ Retired
- ◯ Other (please specify)

____

What is your approximate monthly income?

- ◯ Less than $1,000
- ◯ $1,000 - $2,000
- ◯ $2,001- $3,000
- ◯ $3,001 - $4,000
- ◯ $4,001 - $5,000
- ◯ $5,001 - $6,000
- ◯ Above $6,000

Appendix J – Integration Table

Qualitative Phase				Quantitative Phase		
Original Scale Item	**Excerpt data from Netnography/Theme/Code**	**AICX Scale Item (Reworded or newly formulated)**	**Content And Face Validity Evaluation**	**Exploratory Factor Analysis Results**	**Shortened Scale**	**Dimension**
This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: "The two service robots – Yolanda and Yoshi – are a delight for both children and adults." — YOTEL Singapore Theme: Positive Impressions Code: Delightful	AI-ETs delight me.	Content Validity: 4 Em/ 1 NA Face Validity: 4 CR/ 1 NR	Item did not qualify for the Quantitative phase as it was removed during the face validity stage.	The item was removed for the sake of parsimony, in accordance with the criteria established in Round 1.	N/A
This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: "Don't bother with the automation though, don't always work and really, a personal experience is still what we want. No robots at check in." — YOTEL	I actively seek alternatives to using AI-ETs during my experience.	Content Validity: 1 CO/ 4 BE Face Validity: 2 SR/ 3 CR	Item did not have enough loading in the EFA so was removed during Round 1 the Quantitative Phase	The item was removed for the sake of parsimony, in accordance with the criteria	N/A

	Singapore Theme: Impact on Human Connection Code: Missing Interactions with Humans				established in Round 1.	
"I established a personal relationship with the experience partner."	This item was classified as unique during the comparison stage. No corresponding data excerpts or related themes or codes emerged from the Netnography study.	I established a personal relationship with AI-ETs.	Content Validity: 3 SO/ 1 EM/ 1 NA Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Affiliation
"While visiting the Web pages, I felt Pleased."	Data Excerpt: "I decided to give it a try and I've become a pleased user." — Wander "The interface is intuitive and snappy which makes exploring a pleasure." — Wander "Really pleasing to	I felt pleased while interacting with AI-ETs.	Content Validity: 4 EM/ 1 NA Face Validity: 5 CR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Affinity

	have the robot deliver it to our room and wish us a happy birthday." — YOTEL Singapore Theme: Positive Impressions Code: Pleasure					
"I felt positively connected with the experience partner."	Data Excerpt: "Very absorbing and tour of Machu Picchu was fascinating." — National Geographic Explorer VR Theme: Positive Impressions Code: Absorbing	I felt positively connected with AI-ETs.	Content Validity: 4 EM/ 1 SO Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Affinity
"I feel safe in my transactions with the firm's SST."	Data Excerpt: "Having Alexa in the room was a nice touch. She opened and closed the curtains, turned off the lights, adjusted the room	I felt safe in my interactions with AI-ETs.	Content Validity: 4 EM/ 1 SO Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore	The item was retained as part of the shortened AICX 12-item scale.	Affinity

	temp etc. If that sort of thing freaks you out, they have instructions on how to disable the Alexa device.” — Wynn Las Vegas Theme: Concerns Code: Privacy Concerns			retained for further analysis.		
"I gain new knowledge/expertise."	Data Excerpt: “This immersive, virtual reality experience of the Gunpowder Plot is a great way of polishing up our knowledge of the rule of James I and the torture and persecution of Catholics in 1605.” — The Gunpowder Plot Theme: Learning and Knowledge Code: Positively Redundant	I gained new knowledge while interacting with AI-ETs during my experience.	Content Validity: 5 CO Face Validity: 5 CR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Advancement

This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: “The robot that serves room service, but I would avoid the food — maybe order drinks instead.” — YOTEL Singapore “I confess to being a little sceptical. Virtual reality is another new bit of technology that you can’t seem to avoid.” — Historium Brugge Theme: Trustworthiness and Scepticism Code: Trustworthiness Code: Scepticism		Content Validity: 3 CO/ 1 EM/ 1 NA Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was removed for the sake of parsimony, in accordance with the criteria established in Round 1.	N/A

This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: "Awe and wonder is there at a click of a trigger." — Wander "The story takes you through the different scenes and flows into the virtual reality experience, which is pretty amazing!" — Historium Brugge Theme: Surprise (Distraction to Amazement) Code: Wonder Code: Amazing	I have experienced moments of wonder and amazement during my interactions with AI-ETs.	Content Validity: 3 EM/ 1 SE/ 1 CO Face Validity: 4 CR/ 1 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Amusement
This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: "They also offer a virtual reality experience as you exit the Historium (to the left of the creepy statue of a guy ringing a bell) which was pretty good and worth	I pay attention to how others perceive my interactions with AI-ETs.	Content Validity: 5 SO Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was removed for the sake of parsimony, in accordance with the criteria	N/A

	giving a go even if you look like an idiot sitting there doing it." — Historium Brugge Theme: Perception of Others Code: The Way You Look When Interacting with AI-ETs				established in Round 1.	
"Indulged in the activities."	"We loved this museum. Highly recommend. Please indulge and participate in the virtual reality experience." — Historium Brugge Theme: Entertainment and Engagement Code: Indulge	I was indulged in the interactions with AI-ETs.	Content Validity: 3 EM/ 1 SE/ 1 CO Face Validity: 3 CR / 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Amusement
"It enables me to come up with new ideas."	This item was classified as unique during the comparison stage. No corresponding data excerpts or	Interacting with AI-ETs enabled me to come up with new ideas.	Content Validity: 5 CO Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and	The item was retained as part of the shortened AICX 12-item scale.	Advancement

	related themes or codes emerged from the Netnography study.			was therefore retained for further analysis.		
This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: “Each is supplied with Alexa which makes it very easy to operate the room, i.e., curtains, lights, etc.” — Wynn Las Vegas Theme: Usability Code: Ease of Use	It was easy to use the features of AI-ETs.	Content Validity: 4 CO/ 1 BE Face Validity: 3 CR/ 1 SR/ 1 NR	Item did not qualify for the Quantitative phase as it was removed during the face validity stage.	N/A	N/A
"My imagination is being stirred."	This item was classified as unique during the comparison stage. No corresponding data excerpts or related themes or codes emerged from the Netnography study.	My imagination is being stirred during the interaction with AI-ETs.	Content Validity: 4 CO/ 1 SE Face Validity: 4 CR/ 1 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	Removed after EFA for parsimony	N/A

This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: "Leo and Cleo are so fun — who doesn't love a robot bringing you food!?" — EMC2 Autograph Collection Theme: Entertainment and Engagement Code: Fun	My interactions with AI-ETs added a sense of fun and excitement to my experience.	Content Validity: 4 EE/ 1 SE Face Validity: 5 CR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Amusement
This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: "After that we try to call room service and yee yeee ... Yolanda come!! So funny met her robot and make us laugh out loud oh ya, this hotel." — YOTEL Singapore Theme: Laughter and Humour Code: Made Us Laugh	My interactions with AI-ETs brought laughter.	Content Validity: 5 EM Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was removed for the sake of parsimony, in accordance with the criteria established in Round 1.	N/A

"Uniqueness: I thought this was unique."	Data Excerpt: “It’s definitely worth calling the front desk to ask them to send the robot up to your room with fresh towels for the novelty of it.” — EMC2, Autograph Hotel Theme: Novelty and Uniqueness Code: Novel	My interactions with AI-ETs felt novel and unique.	Content Validity: 4 CO/ 1 EM Face Validity: 4 CR/ 1 SR	Item did not have enough loading in the EFA so was removed during Round 1 the Quantitative Phase	N/A	N/A
This item was generated from netnographic data. No similar item was found in existing published scales, indicating it is non-redundant.	Data Excerpt: “Make sure you order something from room service so that the robots, Cleo and Leo, can make a delivery – it will be the highlight of your trip.” — EMC2, Autograph Collection Theme: Highlight of	My interactions with AI-ETs were the highlight of my overall experience.	Content Validity: 1 CO/ 1 EM/ 3 NA	Item did not qualify for the Quantitative phase as it was removed during the content validity stage.	N/A	N/A

	Code: Highlight of the Trip					
"Privacy is assured."	Data Excerpt: “Minor dislike: Alexa in the room. We unplugged the device.” — ACME Hotel Company Theme: Concerns and Cautiousness Code: Privacy Concern	My privacy is assured while interacting with AI-ETs	Content Validity: 2 CO/ 1 EM/ 1 SE/ 1 NA	Item did not qualify for the Quantitative phase as it was removed during the content validity stage.	N/A	N/A
"This shopping experience was socially rewarding."	Data Excerpt: “I have talked 4 people into the Oculus because of this app alone.” — Wander Theme: Impact on Human Connection Code: Drives Socialization	The interaction with AI-ETs was socially rewarding.	Content Validity: 4 SO/ 1 NA Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was removed for the sake of parsimony, in accordance with the criteria established in Round 1.	N/A

"Awaken my creativity."	Data Excerpt: "The robots were also a nice touch for creativity." — YOTEL Singapore Theme: Positive Impressions Code: Creative	The interactions with AI-ETs awakened my creativity.	Content Validity: 4 CO/ 1 SE Face Validity: 4 CR/ 1 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Advancement
"This shopping experience made me feel important for a few moments."	This item was classified as unique during the comparison stage. No corresponding data excerpts or related themes or codes emerged from the Netnography study.	The interactions with AI-ETs made me feel important for a few moments.	Content Validity: 3 SO/ 2 EM Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Affiliation
"The contact with the experience partner made me feel like I belonged to a community."	This item was classified as unique during the comparison stage. No corresponding data excerpts or related themes or codes emerged from the Netnography study.	The interactions with AI-ETs made me feel like I belonged to a community.	Content Validity: 5 SO Face Validity: 3 CR/ 2 SR	The item demonstrated a sufficiently high loading on one of the emerging dimensions and was therefore retained for further analysis.	The item was retained as part of the shortened AICX 12-item scale.	Affiliation

Appendix K – Full list of formulated items from Netnography

	Theme	Definition	Potential Item/s
Dimension 1: Behavioural			
1.1.	Avoidance	Intentional disregard or disinterest in engaging with AI-ETs.	I actively seek alternatives to using AI-ETs during my experience.
1.2.	Change in behaviour	Refers to shifts in actions, habits, and preferences caused by engagement with AI-ETs, prompting people to explore new behaviours or step outside their comfort zones.	Interacting with AI-ETs has encouraged me to embrace new behaviours.
1.3.	Selecting the AI-ETs or AICX	Involves individuals consciously selecting or favouring AI-ETs or AICX for some reason.	I willingly interact with AI-ETs during my experience.

1.4.	Decision making	How the reliance on AI-ETs influence customer decision-making processes to choose the AICX.	The presence of AI-ETs significantly influence my decision to select this experience.
1.5.	Repeat purchase	Reflects individuals' intention and willingness to repeatedly purchase or use AI-ETs.	Interacting with AI-ETs increase the likelihood I will choose a similar experience in the future.
1.6.	Negative consequences	Undesirable outcomes resulting from interactions with AI-ETs.	My interactions with AI-ETs have sometimes led to unfavourable outcomes.
1.7.	Interactivity	Reflects the level of interaction individuals have with AI-ETs or AICX.	I value the interactivity offered by AI-ETs within the experience.
1.8.	Involvement	Reflects the level of involvement individuals have with AI-ETs or AICX.	The presence of AI-ETs allows me to be more involved during the experience.
1.9.	Abandonment	Giving up on interactions with AI-ETs.	I gave up using AI-ETs during my experience.

Dimension 2: Cognitive			
2.1.	Capabilities	Perception of the capabilities of AI-ETs.	I have a clear understanding of the abilities of AI-ETs.
2.2.	Limitations	Perception of the limitations of AI-ETs.	I am aware of the constraints and limitations of AI-ETs.
2.3.	Concerns	Worries regarding interactions with AI-ETs.	I have some concerns regarding my interactions with AI-ETs.
2.4.	Cautiousness	Carefulness regarding interactions with AI-ETs.	I adopt a cautious approach in any interactions with AI-ETs.
2.5.	Customization	Tailoring AICX to personal preferences.	Interactions with AI-ETs allowed me to tailor my experience to match my personal preferences.

2.6.	Errors	Errors occurring during the AICX and how are these perceived by customers.	When errors occur during my interactions with AI-ETs, it negatively influences my overall service experience.
2.7.	Evaluation and comparisons	Assessing AICX relative to alternatives.	I consistently assess my interactions with AI-ETs in comparison to technology-free alternatives.
2.8.	Functionality	How well AI-ETs perform their intended tasks.	The functionality of AI-ETs contributed positively to my experience.
2.9.	Comprehension	How well customers understand, are aware of and are familiar with the AI-ETs in use.	Understanding how AI-ETs were integrated into my service journey contributed to my overall experience.
2.10.	Learning and knowledge	Acquiring new information or skills through AI interactions.	I gained new knowledge while interacting with AI-ETs during my experience.
2.11.	Memorability	Involves the lasting impact of AI-ET interactions on individuals' memory and	My interactions with AI-ETs were memorable.

		perception, encompassing instances where these experiences are remembered, referenced, or stand out over time.	
2.12.	Negative perception	Unfavourable opinions or views about AI technology.	Overall, I have negative perception about AI-ETs.
2.13.	Added value	Perceptions of added benefits, wastefulness, and whether AI-ETs enhance the overall value of interactions.	My interactions with AI-ETs added value to my overall experience.
2.14.	Tech dominance	Looks into individuals' autonomy in interactions.	I maintained a sense of autonomy and control during my interactions with AI-ET.
2.15.	Human-tech balance	Refers to the balance between AI-ETs' and human touch	I appreciate having a balance between the integration of AI-ETs and the human touch.
2.16.	Technical quality	Explores UX with AI-ETs through technical aspects like hardware, graphics, interface design.	The technical quality of the AI-ET was pivotal in shaping my overall experience.

2.17.	Trustworthiness	Explores customers' assessment of reliability and credibility regarding AI-ETs.	I have confidence in the performance of AI-ETs.
2.18.	Scepticism	Customers' doubts and reservations regarding AI-ETs.	I have reservations about the performance of AI-ETs.
2.19.	Upgrades and improvements	The changes of AI-ETs over time, considering both enhancements driven by competition and user feedback.	The AI-ETs in use would benefit from further technical upgrades and improvements.
2.20.	Usability	How easily customers can interact with AI-ETs and make use of its features.	It was easy to use the features of the AI-ET.
2.21.	Utilization	Considers how well ideas are implemented and executed.	AI-ETs are effectively utilized within the overall experience.
2.22.	Value for money	Explores whether the cost of the AICX aligns with perceived benefits. It assesses if individuals find the price justified based on the value and features received.	The cost I paid for my AICX was aligned with the value I received.

2.23.	Failure recovery	Perception towards how mistakes are handled.	The resolution of problems and mistakes related to AI-ETs was handled appropriately.
2.24.	Potential	Perceived level of future possibilities of AI-ETs.	I believe that AI-ETs have the potential to further shape future experiences.
Dimension 3: Emotional			
3.1.	Anger (Annoyance to Rage)	Feeling upset or annoyed because of AI-ETs.	My interactions with AI-ETs made me feel angry.
3.2.	Diminished positivity	The fading or reduction of initial positive emotions and attitudes toward AI-ETs over time.	My initial positive feelings towards AI-ETs have faded with repeated use.
3.3.	Surprise (Distraction to Amazement)	Focuses on unexpected and captivating elements that trigger feelings of wonder and surprise.	I have experienced moments of wonder and amazement during my interactions with AI-ETs.

3.4.	Disappointment and regret	Feeling let down or wishing for better outcomes and interactions with AI-ETs.	I have felt let down during my interactions with AI-ETs.
3.5.	Entertainment and enjoyment	Captures the fun, excitement, and entertainment aspects of interactions.	My interactions with AI-ETs added a sense of fun and excitement to my experience.
3.6.	Escape	AICX is a way to temporarily escape reality.	Interacting with AI-ETs provided me with a momentary escape from reality.
3.7.	Fear (Apprehension to Terror)	Covers emotions like anxiety, apprehension, and being scared or threatened by the technology.	I felt nervous or afraid when using AI-ETs.
3.8.	Joy (Serenity to Ecstasy)	Captures instances of happiness.	I felt happy while interacting with AI-ETs.
3.9.	Mood and emotional state	Impact of interactions with AI-ETs on the emotional state.	My interactions with AI-ETs impacted on my emotional state and overall mood.

3.10.	Negative perception	Unpleasant perceptions or feelings arising from AI-ETs interactions.	My overall experience with AI-ETs was upsetting.
3.11.	Personal impact and connection	Focuses on customers' individual experiences and emotional connections when engaging with AI-ETs.	While interacting with AI-ETs, I have experienced a personal connection.
3.12.	Positive impressions	Forming favourable opinions about AI-ETs or AICX.	I have formed favourable opinions about AI-ETs during my experience.
3.13.	Novelty and uniqueness	Perceiving AI interactions as new and distinct.	My interactions with AI-ETs felt novel and unique.
3.14.	Highlight of or main feature of	Recognizing the interaction with AI-ETs as a central element in the overall experiences.	My interactions with AI-ETs were the highlight of my overall experience.
3.15.	Laughter and humour	Finding things funny during the AICX.	My interactions with AI-ETs brought laughter.

Dimension 4: Sensorial			
4.1.	Aesthetics	Visual attributes and design elements of AI-ETs	The design of AI-ETs was important in shaping my AICX.
4.2.	Realism	Impressions of how well AI-ETs replicate real-world experiences	The AI-ET provide a realistic portrayal of real-world experiences.
4.3.	Negative sensations	Experiencing negative sensations from AI.	I experienced negative sensations while using AI-ETs.
4.4.	Multisensory	Involving multiple senses in interactions with AI-ETs.	My interactions with AI-ETs required the use of multiple senses.
4.5.	Physical comfort	Physical involvement and comfort levels during interactions with AI-ETs.	My interactions with AI-ETs did not impact on my physical comfort.
4.6.	Technological embodiment	How much does AI-ETs have human-like attributes or behaviours.	The AI-ETs had human-like attributes and behaviours.

Dimension 5: Social			
5.1.	Accessibility, diversity, and inclusivity	AI-ETs accommodate diverse users, including different ages, cultures, languages, and needs. It focuses on breaking barriers and promoting inclusion through technology design and usage.	The AI-ETs offer adaptability across age, culture, language, and needs.
5.2.	Sharing	Discussing the AICX with others, how they work, what do they think about the experience and so on.	I have actively shared my experiences with AI-ETs with others.
5.3.	Advocacy	Promoting interactions with AI-ETs with others and encouraging them to give it a try.	I have encouraged others to try AI-ETs out.
5.4.	Positive impact on human connection	How these technologies can create absence of social engagement.	My interactions with AI-ETs reduced my social engagement during the experience.

5.5.	Negative impact on human connection	How these technologies can enhance meaningful connections.	My interactions with AI-ETs deepened the sense of connection I felt throughout the experience.
5.6.	Perception of others	How individuals' interactions with AI-ETs are perceived by others	I pay attention to how others perceive my interactions with AI-ETs.
5.7.	Relation with AI-ETs	The perceived nature of the relationship between customers and AI-ETs.	I perceive my interactions with AI-ET as distinct and meaningful.
5.8.	Courtesy	The level of consideration and courtesy represented by AI-ETs.	Interaction with AI-ETs are marked by courtesy and politeness.

Appendix L – Directions for future research

Identified theme	Study Area	Key Research Questions
AICX Definition and Dynamics	Multidimensionality and dimensions of the AICX	What are the key dimensions that comprise AICX? How does the integration of AI-ETs contribute to the overall multidimensional nature of the experience?
	Characteristics that create value in the AICX	What are the key characteristics of AICX that contribute to value creation for customers? What is the difference in value creation between customer facing AI and behind the scenes AI? How do AI-enabled encounters differ from human-led encounters in terms of value creation?
	Dynamics within the service environment	How does AI integration impact the overall dynamics within the service environment? What is the influence on the overall CX, employee performance, and service outcomes? What impact does this have on the interactions between customers, front-line employees, and other customers and employees?
	The AI-enabled product offering and promotional elements	How does the integration of AI in product offerings and promotional elements contribute to the overall CX? What are the underlying mechanisms and dynamics involved in the utilization of AI-enabled product offerings and promotional elements within the experience?
	Emerging AI-enabled business models	What are the emerging business models that have the potential to reshape the landscape of services? How do these emerging business models impact the roles and interactions of customers, front-line employees, and AI-ETs? What are the managerial and practical implications derived by these emerging models?
AICX Implementation	AI utilisation	What is the current degree of AI utilization in the sector, and how does it vary across different sub-sectors and organizational sizes? What are the factors that influence the degree of AI utilization in the sector, such as organizational readiness, technological infrastructure, regulatory environment, and competitive pressures?
	Performance of businesses that have implemented AI	What are the critical success factors that drive positive performance outcomes for businesses that have implemented AI? How does successful AI implementation impact business performance metrics such as revenue growth, cost reduction, operational efficiency, customer satisfaction, and employee productivity? What are the KPIs that businesses can use to evaluate the performance outcomes of successful AI implementation?

	Steps and strategies to implement AI	What are the essential steps and strategies for successful AI implementation? How do different implementation approaches, such as phased adoption or full-scale deployment, impact the effectiveness and efficiency of AI implementation in organizations?
	Challenges of implementing AI	What are the key challenges and strategies to overcome them during AI implementation, ensuring a smooth and effective integration of AI-ETs into existing systems and processes? What steps were undertaken to overcome people's concerns about AI and enhancing acceptance rate?
	Balancing AI and the human-touch	How can organizations strike the right balance between AI integration and human touch in customer interactions to optimize CXs and outcomes? What are the strategies and best practices for effectively integrating AI while maintaining the human touch?
	Maximizing Business Value and Mark*et al*ignment through AI Integration	Which specific AI applications bring the most value to businesses across different industries? How do different AI-ETs impact key business outcomes? Which tourism sectors that would benefit the most from implementing AI-ETs? Which market segments exhibit the highest potential for successful integration of AI-ETs and offer significant growth opportunities for businesses? What are the most promising and impactful applications of AI across various industries and sectors that can revolutionize business processes and drive innovation?
	AICX management	How can businesses effectively manage and optimize AICX through the strategic implementation of AI-ETs? What are the key ethical considerations and guidelines that organizations should follow when managing AICX to ensure transparency, fairness, and trustworthiness? What are the most effective strategies and tools for monitoring, measuring, and optimizing AICX?
	AI integration into the CX from the perspective of FLEs	How can FLEs actively participate in the integration of AI-ETs into the CX? What are the primary challenges and concerns faced by front-line employees how can organizations address these concerns to ensure a smooth transition and collaboration? What training, support, and resources should be provided to front-line employees to effectively leverage AI-ETs, enabling them to deliver exceptional CXs while embracing the benefits of AI integration?
AICX Outcomes and Measurement	The impact of AI integration on customers' emerging emotions and behavioural intentions	How does the integration of AI-ETs into CXs impact customers' emerging emotions? What are the potential positive and negative emotional effects of AI integration on customers? In what ways can businesses effectively measure and assess the impact of AI integration on customers' emerging emotions, and how can these insights be leveraged to tailor AI-driven interactions and experiences to better align with customers' emotional needs and preferences? How does the integration of AI-ETs into CXs influence customers' behavioural intentions, such as their

		likelihood to make repeat purchases, recommend the business to others, or engage in positive word-of-mouth marketing?
	Outcomes of AI integration on the business-level	What are the key business-level outcomes and benefits that can be achieved through the successful integration of AI-ETs? How can businesses effectively measure and evaluate the impact of AI integration? What are the tangible and intangible benefits that organizations can expect to achieve through successful AICX implementation? Can businesses leverage AI-driven insights and analytics to enhance AICX outcomes?
	Variables to measure the AICX	What are the key variables that can be used to effectively measure and quantify the quality and effectiveness of AICX across different touchpoints and stages of the customer journey? What methods or tools can be employed to collect, analyse, and interpret the data associated with the identified variables to gain actionable insights and optimize the AICX? Are there any specific variables or elements that hold greater importance to customers in their evaluation of the CX?
	The dark side of AI integration in the CX	What are the potential ethical concerns and risks associated with AI integration in CXs? How might the overreliance on AI-ETs in customer interactions lead to potential customer frustration, disengagement, or a decline in trust? In what ways can biases in AI algorithms impact the fairness and inclusivity?
Consumer Perspectives of AICX	Hedonic, experiential, and social standpoints	How do consumers perceive the hedonic aspects of AICX, such as the enjoyment, pleasure, and emotional fulfilment they derive from interacting with AI-ETs? From a social standpoint, how do consumers perceive the role of AI in CXs, particularly in terms of social interactions, social influence, and social connectedness? What are the experiential dimensions that consumers associate with AI integration in CXs?
	Engagement in the AICX	How do consumers perceive and define engagement in the context of AICX and what are the key factors that contribute to their sense of engagement with AI-ETs? What are the indicators or behaviours exhibited by consumers that signify a high level of engagement during the AICX?
	Expectations, requirements, and value perceptions	What are the key expectations and requirements that customers have regarding AICX and how do these expectations vary across different industries and customer segments? How do customers perceive the value of AI integration and what factors contribute to their perception of whether AI-ETs meet or exceed their expectations? What are the potential gaps between customers' expectations, requirements, and their perceived value of AICX? What are the key elements or features that they associate with the ideal AICX?

	Motivation to choose the AICX or the digital free experience	What are the key factors that influence customers' decisions to opt for a digital-free experience instead of engaging with AI-ETs? What are the underlying motivations or preferences behind this choice? How do customers weigh the benefits and drawbacks of AICX versus digital-free experiences?
	Concerns and reluctant behaviour towards AICX	What are the primary concerns and apprehensions that customers have towards AICX? What factors contribute to customers' reluctant behaviour towards AICX? How do customers perceive the potential risks, such as privacy, security, or loss of human touch, associated with AI integration in CXs?
	Customers' reactions and resulting behaviour	How do customers' reactions to AICX influence their trust and confidence in the business?
	Preference towards specific AI forms and types	How do customers perceive the effectiveness, reliability, and user-friendliness of different AI forms or types in meeting their specific needs and preferences? What are the key considerations that customers consider when expressing a preference for certain AI forms or types in CXs?
	Level of interactivity and immersion in the optimal experience	How do customers define and conceptualize the "optimal experience" in the context of AICX in terms of interactivity and immersion? How does the level of interactivity and immersion in AICX impact customers' sense of engagement, enjoyment, and satisfaction with the overall experience?
	Customers' emotional responses for interacting with AI	What are the predominant emotional responses that customers experience when interacting with AI-ETs in CXs?
	Service failure and the resulting customer's complaint behaviour	How do customers perceive service failures within AICX, and what are the key factors that influence their decision to voice their complaints or express dissatisfaction? What are the specific channels or platforms that customers prefer to use when lodging complaints related to AICX, and how do their complaint behaviours differ compared to traditional non-AI service failures?
Contextual Lenses for AICX	Variations amongst different AI-ETs and AI applications forms	How do customers perceive and differentiate among various AI-ETs in terms of their effectiveness, reliability, and overall performance in delivering enhanced CXs? What are the specific features or capabilities of different AI-ETs that customers find most valuable and influential in shaping their preferences and satisfaction? Do customers perceive any differences in their experience and satisfaction based on the form of AI integration, such as whether it is accessible through a mobile app or another external device?
	Influence of cultural background on AICX	How does customers' cultural background influence their perceptions, expectations, and preferences regarding AICX and are there any specific cultural factors that impact their engagement and satisfaction? In what ways does cultural background shape customers' attitudes and behaviours and how can

		businesses adapt their strategies to cater to diverse cultural perspectives and preferences? Are there any cultural nuances or sensitivities that businesses need to consider when designing and implementing AICX to ensure they are culturally appropriate and resonate with customers from different cultural backgrounds?
	Tourism sector-wide receptivity of AI	What is the level of receptivity within the tourism sector towards the integration of AI-ETs? What are the key factors influencing the tourism sector's willingness to embrace AI-ETs, such as cost-effectiveness, operational efficiency, personalization capabilities, or competitive advantages? How do tourism industry professionals envision the future role of AI in transforming CX across the various tourism sector?
	Anticipatory (pre-encounter) and reflective (post-encounter) phases of the experience	How do customers' anticipatory (pre-encounter) expectations shape their overall perception and satisfaction with AICX? What are the key elements that customers reflect upon (post-encounter) after engaging in AICX? How do these reflections influence their future behaviours and decisions? How can businesses effectively manage and leverage the anticipatory and reflective phases of the CX to enhance the AICX?
	Moderating Variables (demographics, personal variables, ecological variables, aesthetic variables, and functional variables)	What is the impact of moderating variables such as demographics, personal variables, ecological variables, aesthetic variables, and functional variables? How do different customer segments perceive and engage with AI-ETs, and how are these perceptions influenced by individual characteristics and contextual factors?