Understanding Re-scheduling Decisions: Behavioural Modelling of Commuting in Disrupted Networks

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Declaration

Signed: Jingsi Li

Date: December 2025

Be Water, My Friend

- Bruce Lee

Acknowledgements

As I sit in front of my laptop on this quiet, reflective night, gathering my thoughts for this acknowledgement, I feel a sense of pride in having persevered to the final stage of this journey. Though it has taken far longer than I initially imagined, I remain determined to complete this last mile with gratitude and resolve.

This has been an incomparable period in my life. The Doctor of Philosophy signifies far more than specialised training within a research field; it represents a profound journey of personal growth that extends into life as a whole. I have learnt that it is never too late to discover what you do not know and to begin learning with curiosity. I have also come to appreciate the mindset of being grateful for whatever it comes along, recognising that life itself is a continuous process of problem-solving. No matter what happens, one must keep calm and carry on. The more knowledge one gains, the more evident it becomes how much remains unknown. It is therefore essential to remain open-minded yet critical, willing to welcome all ideas and perspectives. The only certain in life is uncertainty. This truth became particularly vivid during the COVID-19 pandemic, which brought unforeseen disruptions and significantly delayed the experimental components of my research at a critical stage. It has been a journey in which the sense of joy and accomplishment was often intertwined with solitude, and at times even tears. Despite the challenges, it is a journey I deeply cherish, certain that some of its moments will reappear before my eyes in the final montage of my life.

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I am deeply grateful to my family and friends, whose constant support has given me strength in moments of challenge. To my husband, Fulin, I offer my heartfelt thanks. After fifteen years together, I feel incredibly fortunate to still have you by my side, with your kindness, love, and care. And perhaps the most unexpectedly, I now find myself writing these final words with our little one beside me – my baby Eilean. Never could I have imagined reaching this point, holding both a thesis and a child in my arms at the graduation ceremony, an experience that brings a depth of joy and meaning far beyond anything I could have envisioned.

Last but not least, I'm profoundly grateful for the privilege of being able to live in a peaceful and safe place while completing this work. I am deeply aware that not everyone shares this fortune. Though this is the area that this thesis by no means could contribute to, but truly is my heartfelt wish - a more peaceful world.

Abstract

Modern transport systems are increasingly exposed to unexpected disruptions, often triggered by extreme weather events, introducing significant uncertainty into daily travel. In response, travellers must adopt response strategies, including altering their route, mode of transport, and/or departure time. The complexity of individual travel behaviour becomes particularly evident under dynamic and uncertain conditions. In parallel, evolving work arrangements, particularly the rise of hybrid and remote working, have added a new dimension to travel behaviour, raising new and important questions about how individuals adjust their plans in this context. In making travel decisions in these tightly constrained circumstances, time pressure frequently arises, reflecting both situational urgency and cognitive limitations. Understanding how such time pressure, and the perception of time pressure, influences rescheduling decisions is therefore critical. However, these contextual and cognitive factors remain inadequately explored in the existing transport behaviour literature, highlighting a clear research gap that this study seeks to address.

This thesis investigates how commuters reschedule their daily work-related travel in response to unexpected transport disruptions, particularly within the evolving context of post-pandemic hybrid and remote working practices. It examines the influence of perceived time pressure and varying working arrangement scenarios on decision-making when adjusting daily plans under disruption conditions. By developing empirically grounded and behaviourally realistic models, the research seeks to uncover key patterns of choice behaviour in such circumstances. In parallel, the study advances simulation capabilities by enhancing an agent-based transport simulation framework to model the effects of real-time information provision on multi-dimensional activity–

travel rescheduling within a multi-modal network subject to disruptions. This framework facilitates a deeper understanding of how individual micro-level behavioural responses aggregate to produce system-level outcomes.

To achieve the research objectives, the research is structured into two main parts. The first part extends the MATSim within-day replanning framework, an agent-based simulation model, by incorporating real-time information provision with the time-dependent transport network. Multi-dimensional rescheduling options were enabled for agents to adopt for rescheduling choices across a multimodal transport system. A decision time budget was introduced to reflect the limited window available for rescheduling decisions, thereby enhancing the behavioural realism of the simulation under time-constrained conditions. The second part of the research focusses on the design and implementation of an activity-travel stated preference (SP) experiment, aimed at capturing individual behavioural responses through a series of carefully constructed scenarios. These scenarios varied in work arrangement contexts, reflecting differences in both importance and flexibility. Respondents were asked to choose among alternative options featuring different attribute combinations, making trade-offs under imposed time pressure to simulate the limited decision-making time available when unexpected transport disruptions occur on the day. The resulting choice data were analysed using a nested logit model with heteroscedastic error structures, allowing for variations in the degree of time pressure perceived across scenarios and choice tasks to be explicitly modelled.

Findings revealed that rescheduling behaviour was shown to be highly context-dependent: individuals with more formal or group-based work commitments demonstrated stricter punctuality preferences. The incorporation of heteroscedastic error structures uncovered a non-linear relationship between perceived time pressure and decision consistency - choice behaviour was most stable under moderate time pressure but became increasingly stochastic under low or high extremes, suggesting the presence of cognitive disengagement or rushed judgement. Additionally, remote working availability emerged as a significant factor shaping rescheduling decisions. In scenarios where remote participation in the activity was permitted and widely accepted, it became a viable option, highlighting the strategic value of flexible work arrangements in sustaining activity participation while ensuring punctuality.

This research makes several novel contributions to the field of travel behaviour modelling. It advances understanding of activity-travel rescheduling under unexpected disruption, particularly in the context of evolving post-pandemic work practices. By integrating work-related contextual variables and modelling behavioural heterogeneity across varying levels of perceived time pressure, the study offers a more realistic and behaviourally grounded representation of commuter decision-making. Methodologically, this research advances the discrete choice literature by applying a heteroscedastic nested logit framework that parameterises scale heterogeneity as a function of perceived time pressure – an aspect that has been insufficiently examined in transport behaviour studies. In addition, this research contributes an enhanced MATSim Within-day Replanning module, integrated into an agent-based framework, capable of simulating the spatial-temporal impacts of real-time information on activity–travel rescheduling under multi-modal network disruptions.

The findings of this thesis have important practical implications for transport planning and disruption management. Understanding the influence of varying work context and perceived time pressure on rescheduling behaviour enables the formulation of more targeted, user-responsive policies. The demonstrated strategic role of remote work highlights the need to integrate flexible work arrangements into transport demand management frameworks. Furthermore, the extended large-scale agent-based simulation framework provides a robust analytical tool for assessing the impacts of network disruptions on travel patterns, urban mobility, and overall transport system efficiency. This capability offers transport professionals and policymakers a sound basis for designing more robust and resilient transport management strategies.

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List of Abbreviations and Symbols

List of Abbreviations

Abbreviation	Definition
AT	Arrival time
Config	Configuration
DTB	Decision time budget
DTA	Dynamic traffic assignment
ED	Early departure
Exp.	Experiment
Eexp.	Earliest expected arrive time
FIFO	First-in first-out
GEV	Generalised Extreme Value
HL	Heteroscedastic logit
HNL	Heteroscedastic nested logit model
IIA	Independence of Irrelevant Alternatives
$i.i.d$	Independently identically distributed
Lexp.	Latest expected arrive time
LL	Log-likelihood
MATSim	Multi-Agent Transport Simulation
MLE	Maximum likelihood estimation
MNL	Multinomial Logit
Mobsim	Mobility simulation
NL	Nested Logit
PAT	Preferred arrival time
PD	Preferred departure
PTP	Perceived time pressure
QSim	Queue-based traffic flow model
RP	Revealed preference
RUM	Random Utility Maximisation
SP	Stated preference
TT	Travel time
WFH	Working from home
XML	Extensible Markup Language

List of Symbol

Symbol	Definition
U_i	Utility associated the alternative i
V_i	Systematic (observable) component of utility
E	Set of directional edges
G	Abstracted directed planar graph
N	Set of nodes/vertices
dis	Disruption
DS	Day schedule
ε_i	Random (unobservable) component of alternative i
μ	Scale parameter of the logit model or the upper nest in NL model
P_i	Probability of choosing alternative i
C	A choice set
C_m	Partition of choice set C
$P_r(\cdot)$	Conditional probability function
μ_m	Scale parameter of choice set C_m
μ'_m	Scale parameter of choice set C_m with TPI_m
IV_m	Inclusive value of choice set C_m
λ_m	Dissimilarity parameter/logsum parameter
U	Utility function
β_{ASC}	Alternative specific constant
β_{TT}	Parameter of travel time
β_{SE}	Parameter of schedule earliness
β_{SL}	Parameter of schedule lateness
B_I	The ratio of μ to μ_m
t_{use}	Time used for decision making
t_{bud}	Time budget for decision making
TPI	Time pressure index for choice set 1
TPI_m	Updated TPI for choice set 2
$H_{m\_}\ H_r$	Habitual mode with habitual route
$H_{m\_}\ SP_r$	Habitual mode with shortest path route
$ALT_{m\_}\ SP_r$	Alternative mode with shortest path route
E_{dis}	Transport disruption event
Δt	Disruption time window
l_{dis}	Disrupted link(s)
I_d	Information dissemination
T_{d_s}	Strat of disruption
T_{d_e}	End of disruption
$epi_{n,tr}$	Trip of an episode
$epi_{n,act}$	Activity of an episode
t_{a_s}	Start time of an activity
t_{a_e}	End time of an activity
d_a	Duration of an activity
ty_a	Type of an activity
l_a	Location of an activity
r_o	Route of a trip

O_o	Origin of a trip
D_o	Destination of a trip
m_o	Mode of a trip
d_o	Departure time of a trip
t_o	Expected travel time of a trip
a_o	Arrive time of a trip
C_p	Physical constraint
$C_{m/c}$	Mental/cognitive constraints
r_{sp}	Available shortest path route
d^*	Earliest feasible departure time in the rescheduling logit
t^*	Updated travel time in the rescheduling logit
ReS	Rescheduling day schedule
$B(\cdot)$	Behavioural model
S_i	The severity of impact on the disrupted link
I_{int}	Interval of information notification
θ_1	Indifference band for late arrival along r_o under pre-trip conditions
γ_1	Relative indifference bands between time cost of r_o and r_{sp} under pre-trip conditions
θ_{WfH}	Likelihood of activity cancellation
θ_2	Indifference band for late arrival along r_o under en route conditions
γ_2	Relative indifference bands between time cost of r_o and r_{sp} under en route conditions
t_r^*	Perceived travel time
$\boldsymbol{c}$	Confidence level of distribution on estimated travel time
α	Random heterogeneity factor
tt.	Travel time
tc.	Travel cost
tt.var.	Travel time variability
dep.	Departure time
SE	Schedule earliness
SL	Schedule lateness
t_r	Estimated travel time
σ_r	Standard deviation of estimated travel time
T_c	Transport network condition
A_n	Pre-planned activity commission
TP_c	Time pressure perceived by an individual n
P_c	Decision-making characteristics of individual n
R_H^2	Horowitz pseudo r-square

Chapter 1 Introduction

1.1 Background

Transport networks are inherently uncertain on both demand and supply sides. It is particularly the case when transport network disruption events occur, which introduce operational uncertainty into travellers' daily activity schedules, primarily through unpredictable increases in travel time and reduced reliability. Network disruptions can be defined as a class of events which change usual conditions of traffic flows (Konduri *et al.*, 2013). A UK survey indicated that more than half of the respondents encountered different disruptive traffic events in the past month (Marsden *et al.*, 2016). Transport network disruptions can substantially extend travel times and lead to further consequences, including additional fuel costs, carbon emissions and increased accident risks (Demir *et al.*, 2015).

Transport network disruptions can be categorised from different perspectives (Mattsson and Jenelius, 2015; Kulkarni *et al.*, 2023). Some planned disruptions, such as full or partial roadway closures to work zones along a road segment or a bridge for a period of time, are normally issued with advance warning at a certain time prior to actual traffic restrictions. This provides transport users with sufficient time to re-evaluate the circumstances and adjust their actions in response. In contrast, short-term non-recurrent transport network disruptions, such as traffic crashes and bridge failures, are usually unforeseen, forcing transport users to respond within limited decision time and adapt rapidly to the changing network conditions. On top of that, adverse weather events such as floods, landslides, and heavy precipitation, which have become increasingly frequent in recent years, further highlight the importance of recognising within-day decision dynamics under uncertainty.

In response to these challenges, traffic information-related technologies including Advanced Traffic Information Systems (ATIS), Global Positioning System (GPS) and on-board navigation apps have been rapidly developed in recent decades (Ben-Elia and Shiftan, 2010). They are capable of providing transport users with real-time information of network states and route guidance in light of transport disruptions. The information provision takes within-day network dynamics into account, helping users perceive the uncertain traffic states and accordingly react to unexpected disruptions in daily travel. These technologies are widely employed and have significant impacts on activity-travel behaviour of transport users, network performance and travel safety (Dia, 2002).

In parallel, the advancement and widespread adoption of expeditious and reliable Information and Communication Technologies (ICTs), such as Zoom and Microsoft Teams, have significantly reshaped work practices over the past decade, providing opportunities of remote work to numerous employees (Messenger and Gschwind, 2016). During the COVID-19 pandemic, lockdown measures necessitated a sudden shift to home-based work. Supported by ICTs, employees adapted effectively to remote working, while employers developed greater confidence in its practicality and productivity (Beck and Hensher, 2020) (Balbontin *et al.*, 2021). This experience led to lasting behavioural changes; rather than returning to pre-pandemic norms, hybrid working patterns have become widely accepted as the 'new normal' in many labour markets (Beck, Hensher and Wei, 2020). As a result, travel demand has become more flexible, less predictable, and increasingly dependent on individual work arrangements. This transformation introduces added complexity to understanding how individuals reschedule their activity-travel plans, especially when facing short-term transport network disruptions.

Transport simulation is an indispensable tool for transport planning and management. In particular, it is crucial for the development of dynamic models that capture within-day behavioural responses under uncertain and evolving conditions. Among these, agent-based transport simulation models offer a powerful and flexible framework (Dia, 2002) (Arentze, Pelizaro and Timmermans, 2010). By representing individuals as autonomous agents, these models can realistically simulate how people adjust their travel decisions in response to real-time information, disruptions, and contextual factors such as hybrid working. They not only facilitate a detailed understanding of micro-level behaviours but also allow for the aggregation of individual responses to predict system-level outcomes (van der Gun, Pel and van Arem, 2016). This makes them highly valuable for developing responsive transport policies, infrastructure planning, and evaluating the performance and resilience of transport networks under complex and dynamic conditions.

1.2 Research Objectives

This thesis focuses specifically on unplanned, short-term, non-recurrent disruptions, as these unpredictable events are among the key triggers for dynamic changes in daily travel and activity patterns. Understanding travellers' behavioural responses to such disruptions is essential for assessing the temporal and spatial impacts of transport network disturbances. Evidence from agent-based and large-scale network simulations demonstrates that even minor individual schedule adjustments can produce substantial system-wide effect (Axhausen, 2016). These insights underscore the importance of developing transport models capable of simulating dynamic activity-travel rescheduling, where real-time user information is integrated, and both transport users' experienced and prevailing network conditions are concurrently utilised. Ideally, the transport model systems and its associated components are expected to be flexible enough and computationally efficient to accommodate multi-dimensional rescheduling options and simulate different scenarios of disruptions given the uncertain nature of the events.

Drawing on these motivations, ***the first research objectives is: to develop and implement an efficient model for simulating activity–travel rescheduling in disrupted multi-modal networks, with the provision of real-time traffic information.*** Specific research questions to answer are:

- How can transport disruption and real-time information provision be modelled within a multi-modal network?
- How do individual rescheduling decisions influence patterns of travel demand at the system level, and consequently shape the operation of the transport network?

- How can an enhanced model be implemented in a case study to demonstrate its application and test its sensitivity?

As discussed above, disruptions to the transport network constitute a critical factor in travel choice modelling. In such contexts, it is essential to recognise that activity-travel rescheduling is inherently multi-dimensional, involving interdependent decisions between activities and their associated travel components. Furthermore, the lasting impact of Covid pandemic has brought about a widespread shift towards hybrid and remote working arrangements, profoundly influencing commuting behaviours. The 'work from home' paradigm, now widely adopted across various sectors, needs to be explicitly integrated into rescheduling frameworks to reflect these transformed work patterns. The availability of remote working options amplifies the importance of the nature of intended activities, particularly work-related commitments, which play a pivotal role in shaping individuals' responses to unexpected disruptions and their corresponding rescheduling strategies.

Building on above motivations**, *the second research objective is to: understand how commuters reschedule their daily travel to work in response to unexpected transport disruptions, within the evolving context of post-pandemic hybrid and remote working practices.*** More specifically, this thesis intends to answer the following research questions:

- How do individuals evaluate and make trade-offs between rescheduling decisions when adapting their commute in response to disruption?
- How do different work arrangements influence commuters' rescheduling decision given hybrid working as a feasible option?
- To what extent do commuters consider working from home as an alternative when facing unexpected transport disruptions?

Time pressure often arises when the available time is perceived as inadequate relative to the time required for decision-making. It is particularly the case when unexpected disruption events occur, introducing uncertainties both temporal and spatial. While some studies have account for limited time budgets for activities during schedule execution processes (Arentze, Pelizaro and Timmermans, 2010), few have explicitly examined the role of perceived time pressure in decision-making under such conditions.

The idea of time pressure is important since it constrains an individual's ability to evaluate all options fully in line with general assumptions of utility theory. The effect of time pressure on rescheduling decision making is worthy of attention since it is very likely to influence choice behaviour by altering perceptions of travel time, reliability and trade-offs between alternatives.

Consequently, ***the third research objective of this thesis is to: examine how perceived time pressure influences travellers' decision-making when adapting their commute in response to transport disruptions.*** This leads to the formulation of the ensuing research questions:

- How can perceived time pressure be quantified and measured?
- What strategies do individuals take to cope with perceived time pressure?
- How do travellers exhibit behavioural adaptations under different levels of time pressure?
- How does perceived time pressure influence commuters' rescheduling behaviour in response to unexpected transport disruptions?

To clarify the scope of this research, the analysis focuses on commuters' responses involving two primary transport modes: private car and public transport. These modes represent the dominant forms of commuting travel and are most directly affected by transport network disruptions. While public transport options are included in the data collection and experimental design, the behavioural analysis primarily focuses on private car users, reflecting the emphasis of the modelling framework on road network disruptions. Other travel modes, such as walking and cycling, are not explicitly considered in the modelling framework.

In addition, the study considers a defined set of behavioural responses to disruption, examined through the two methodological components of the research. These responses include adjustments to departure time, route, and travel mode, as well as the option of working from home, reflecting the key rescheduling strategies available to commuters when unexpected disruptions occur.

1.3 Expected Contributions

This research makes four principal scientific contributions towards the research objectives, primarily focusing on *methodological contributions*:

Firstly, this research will enhance the existing within-day replanning in the Multi-Agent Transport Simulation (MATSim) to model the impacts of real-time information provision on multi-dimensional activity-travel reschedules within a multi-modal network, which is subjected to the unexpected transport network disruption. The enhanced module is integrated within the agent-based simulator, forming a modelling framework which has the capability of simulating transport network disruptions, traffic information provision and activity-travel rescheduling decisions in both space and time dimensions. Such a framework will provide transportation professionals with a powerful tool to devise and improve real-time information systems and mitigate the adverse effects of such disruptions.

Secondly, this research expected to provide empirical evidence on how transport users adjust their travel plans in response to unexpected disruptions. The analysis emphasises the trade-offs commuters make when considering multiple rescheduling alternatives, including the option of working from home. The study will contribute to a deeper understanding of how commuters respond to disruptions, especially in situations that require the assessment of provided traffic information, thereby enriching the knowledge of behavioural adaptation under such scenarios.

Thirdly, this research will contribute to the understanding of how the evolving nature of work in the post-pandemic era, characterised by increased flexibility and the prevalence of hybrid working arrangements, influences commuters' decision-making processes. In particular, it will show how the characteristics of subsequent workplace activities influence rescheduling choices. By addressing the decision dynamics within the context of hybrid and flexible working practices, the study will provide a more realistic representation of contemporary commuter responses and extend the field of travel behaviour modelling.

Lastly, this research will contribute to the investigation of how perceived time pressure influences individuals' rescheduling behaviour in the context of transport disruptions. Particular emphasis is placed on the intensity of time pressure as a psychological factor, examining how it shapes decision-making when unexpected increases in travel time risk causing substantial delays in arriving at work. By incorporating the perceived time pressure into the behavioural model, the study will provide valuable insights into how urgency and cognitive load influence the interpretation of information and subsequent behavioural responses to unplanned disruptions.

In addition, this thesis is expected to provide the following *practical contributions*:

This study will provide a more accurate representation of real-world transport disruption scenarios by simulating the complex interplay between travellers' behaviour and the evolving traffic conditions. The extended large-scale agent-based simulation framework will provide policymakers and transport planners with a powerful tool to assess the implications of network disruptions on travel patterns, and overall efficiency of transportation system. In doing so, these insights will support the development of more robust and resilient management strategies for future transportation networks.

Furthermore, this research will generate insights into the multifaceted changes in commute travel patterns that have emerged in the wake of the pandemic, particularly under the wide acceptance of the flexible and hybrid working arrangements. By examining the impacts of these evolving work practices on rescheduling behaviour, the research will clarify the interactive relationship between workplace dynamics and commuter rescheduling behaviours. The findings will also support the development of resilient, adaptive, and user-centred transport systems that respond effectively to the needs of a dynamic post-pandemic workforce.

1.4 Research Outline

To address the research objectives, the thesis is structured into two parts, providing a comprehensive investigation of rescheduling under disruption. The first part enhances an agent-based simulation to reflect how real-time information and travellers' rescheduling decisions influence outcomes at the system level. The second part focuses on individual decision-making through an empirical stated preference experiment, offering insights into behavioural mechanisms that shape rescheduling choices. While addressing closely related aspects of disruption-induced rescheduling, the two parts were developed independently using different methodological approaches. Together, these parts address the problem from both system-level and individual-level perspectives, enabling a comprehensive examination of network-wide performance impacts as well as detailed behavioural responses to disruption. The outline of the thesis is plotted in Figure 1-1.

Chapter 2 Literature Review. This chapter begins with a review of literature on decision-making behaviour and choice modelling approaches. It then examines the development of dynamic activity-travel rescheduling decision with agent-based micro-simulation framework, followed by a review of studies on the influence of time pressure and the impacts of the COVID pandemic on work and travel patterns.

Part I. Simulating Commuters' Response to Transport Disruption

Chapter 3 provides a brief introduction to the Multi-Agent Transport Simulation (MATSim) framework. **Chapter 4** presents the enhancements made to the MATSim's Within-Day Replanning module, detailing four enhanced components and their mechanism for simulating transport disruption. **Chapter 5** applies the enhanced model to the Cottbus case study to simulate short-term transport disruptions and commuters' activity-travel rescheduling behaviour, thereby demonstrating the model's applicability and effectiveness.

Part II. Modelling Commuters' Rescheduling Behaviour Under Time Pressure

Chapter 6 outlines the experimental design and data collection, including the development of stated preference experiment, the specification of key variables, participants' task, execution of the survey, data collection and subsequent data processing. **Chapter 7** details the development of the research methodology, including the formulation of key assumptions, the construction of the modelling framework, and the specification of the model. Together, these components establish the foundation for investigation of specific research objectives of the study. **Chapter 8** presents the results of the data analysis, including descriptive statistics, comparative evaluation of model performance based on estimation results and behavioural relevance, and insights derived from the estimation of alternative models.

Chapter 9 Synthesis of Findings and Implications for Future Research and Practice. This chapter synthesises the findings and implications from the two parts of the studies and offers recommendations for further research directions.

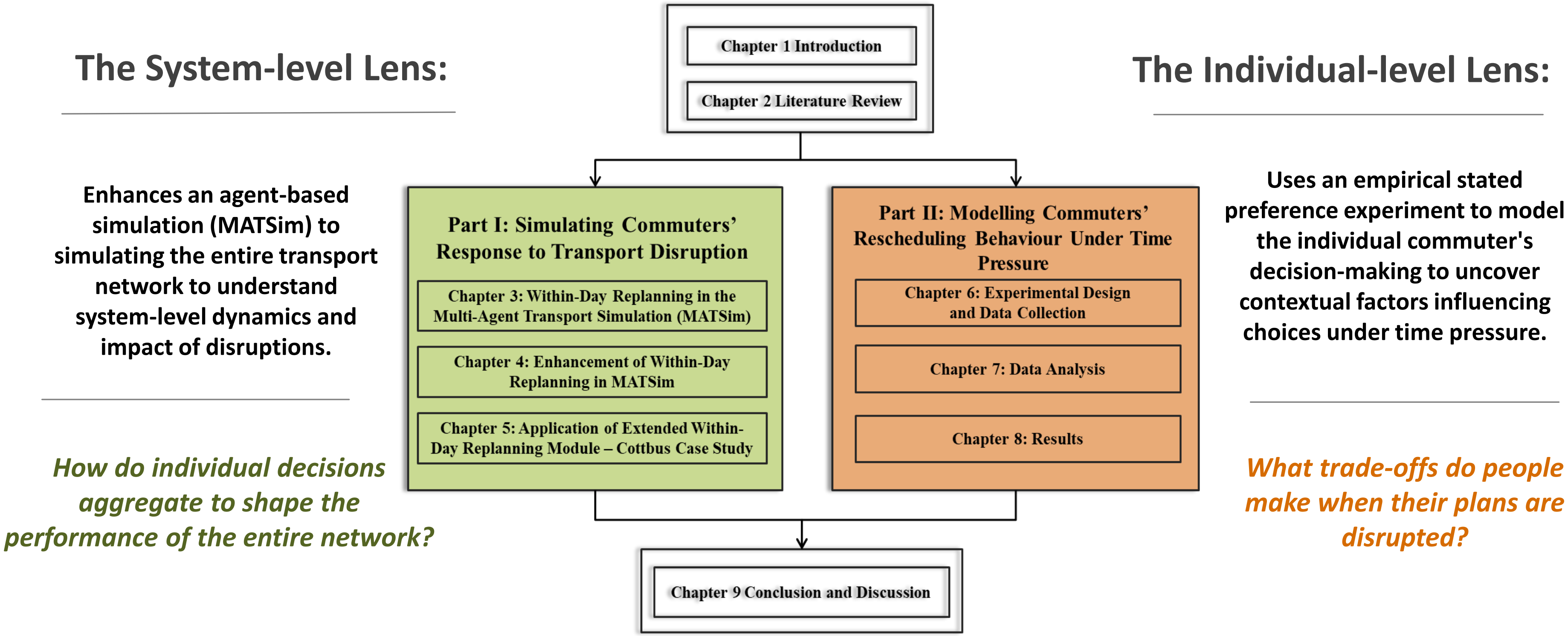


Figure 1 - 1 Thesis Outline

Chapter 2 Literature Review

The persistence of unexpected transport disruptions continues to introduce considerable uncertainties into commuters' daily routines, making it difficult to maintain reliable travel plans. These challenges are further compounded by the evolving nature of work arrangements, where hybrid and flexible patterns have become increasingly common. Emerging in the aftermath of the COVID-19 pandemic, these new working norms have fundamentally reshaped traditional commuting behaviour, adding new layers of complexity onto how individuals respond to disruptions and reschedule their travel plans.

Against this backdrop, understanding the mechanisms by which individuals adjust their travel and work arrangements in response to such disruptions has become a critical area of inquiry. This literature review synthesises several interrelated strands of research to support this investigation. These include: 1) decision-making behaviour and choice modelling, which provide insights into how commuters interpret and respond to available travel information when adjusting their daily plans in the face of disruptions; 2) the role of time pressure, which introduces psychological dimensions that can distort decision-making processes when rapid responses are required; 3) the influence of diverse work arrangements, which sheds light on how the purpose, flexibility and modality of work arrangements shape rescheduling behaviour—particularly relevant in labour markets where hybrid and remote working have become widely accepted alternatives. In addition, the literature review considers developments in simulation-based approaches, with a particular focus on agent-based models. These models have emerged as powerful tools for linking micro-level behavioural responses with macrolevel system performance, offering a means to analyse the complex interactions between individual decisions and broader network outcomes.

This Chapter is structured as follows. Section 2.1 reviews existing approaches to decision-making behaviour and choice modelling, with an emphasis on the contexts involving risk and uncertainty in transportation. Section 2.2 presents recent advances in modelling techniques, particularly dynamic models of activity-travel behaviour under disruptions and the role of information provision. Special attention is given to the agent-based microsimulation as a means of capturing individual-level adaptation within complex transport systems. Section 2.3 examines time pressure as a behavioural factor arising from uncertainty, and its implications for activity-travel rescheduling. Section 2.4 explores the effects of the COVID-19 pandemic on commuting and teleworking patterns, highlighting shifts in travel behaviour during the transition to hybrid work. Conclusions are presented in Section 2.5.

2.1 Decision-Making Behaviour and Choice Modelling in Transport

A number of theoretical methods have been employed to investigate decision-making behaviour and choice modelling in transport under uncertain contexts. Transport theory has been historically developed with strong behavioural connections to neoclassical economics and its core decision-making paradigm – rational choice which assumes a choice maker to behave rationally. Given the attributes of all the relevant alternatives in a choice set, a choice maker would choose the option that maximises the utility. Economists such as Friedman (2009) have adopted rational choices as a suitable depiction of human decision-making, contributing to a significant corpus of empirical behavioural studies (Chater *et al.*, 2003). However, decision-making theories developed in the cognitive psychology and behavioural economics literature imply that they are not flawless. Rational choices have been frequently criticised in transportation research (Gärling & Young, 2001) for offering a limited account of reasoning in travel behaviour. In particular, some evidence including laboratory-based trials has unveiled breaches of the fundamental axioms of rational decisions.

The transportation system is a choice environment involved with uncertainties since passengers are unable to predict the actual travel time for certain. Uncertainty, by its definition, implies that travellers are dealing with imperfect information. In response to this uncertainty, travellers may adopt either reactive or proactive strategies. As a result, a substantial body of literature has emerged in transport research, exploring a range of theoretical frameworks to understand and explain the behavioural responses under the uncertainty. This section comprehensively and concisely reviews different approaches, including their theoretical assumptions and their ability to behaviour in the uncertain context.

2.1.1 Utility-based discrete choice models

Utility-based discrete choice models view a choice situation as a mathematical optimisation problem. A proper decision is reached by interpreting the choice outcomes as random variables, casting the choice problem in the way of expectations, and deriving the solution that maximises the expected utility of a pre-determined objective function based on probability distributions of outcomes generated by different alternatives. The assumption of purely deterministic decision-making is impractical due to the fact that the utility an individual assigns to an alternative is not deterministic, but instead has a random component induced by imperfect information, unobservable factors or individual differences. For instance, individuals in reality may make different choices when presented with the same choice problem. Therefore, McFadden (1974) proposed the approach of combining the expected utility theory with the **random utility theory**, which introduced an error term into the utility prospect and as a result, replacing the deterministic choice assumption with the probabilistic choice assumption.

McFadden's random utility model is particularly influential in the development of discrete choice models, including the logit model which is essential for modelling discrete choices (e.g., route selection or mode choice) in transportation. De Palma et al. (2008) explored the integration of random utility models with decision-making under risk and uncertainty, providing insights into how individuals make choices in uncertain environments. The authors discussed various models, including expected utility theory and its deviations, as well as the applications in discrete choice contexts. Sun et al. (2012) developed a decision model based on the random utility theory to investigate activity-travel reschedules under multiple uncertain events and information acquisition.

A case study conducted in Delft employed linear-additive utility functions to examine pre-trip and en route decision-making during an emergency evacuation, where households' route choices were modelled based on random utility maximisation (van der Gun, Pel and van Arem, 2016).

The significant advancements in theoretical development and application of discrete choice models have later been seen to transportation. Ben-Akiva and Lerman (1985) synthesised their earlier work on random utility theory and introduced a range of practical modelling techniques, including the **multinomial logit (MNL) model** which was then widely applied in transportation studies to examine the effects of unexpected network disruptions on dynamic adaptation of travel behaviour. Khattak et al. (1993) applied a MNL model to investigate drivers' diverting and return choices under advanced traveller information systems (ATIS) in the context of unexpected congestion. Roorda and Andre (2007) adopted an MNL model to investigate the factors that determine the choices of respondents among several rescheduling options when a well-defined unexpected delay was presented to the respondents. Small (1982) provided an early example of departure time choice modelling by applying the MNL model to analyse commuting departure times. Similarly, Hendrickson and Plank (1984) utilised MNL models to examine departure time interval choices alongside mode choices, exploring the relative impacts of various factors on these decisions. Chin (1990) also employed the MNL model to study morning commuting departure times in Singapore.

MNL models rely on three fundamental assumptions: (a) the random components of alternative utilities are independently and identically distributed (IID), following a Type I extreme-value (Gumbel) distribution; (b) the responses to the attributes of alternatives are homogeneous across individuals (i.e., the attribute coefficients are identical for all the individuals); and (c) the error variance-covariance of alternatives are homogeneous across individuals. These assumptions are essential since other discrete choice models for random utility maximisation generally focus on relaxing one or more of these assumptions.

While the MNL model has been a valuable framework in transportation research, its property of Independence of Irrelevant Alternatives (IIA) presents a significant limitation. The IIA property arising from the IID assumption implies that the relative odds of the choice between any two alternatives are unaffected by the presence or characteristics of other alternatives. Even though the IIA property makes the model computationally efficient, it fails to accurately reflect the real-world transport choices where alternatives might be correlated. This limitation has driven the development of more flexible models to better cope with such complexities.

To overcome the IIA property of the MNL model in specific contexts, a **nested logit model** (Ben-Akiva and Lerman, 1985) has been introduced to capture correlations between alternatives in the same nest. The nested logit (NL) model has proven useful for applications such as mode choice, where alternatives with similarities can be grouped into nests. In addition, by considering the nesting of alternatives in the form of hierarchical decisions, the NL model is suitable for modelling departure time choices (Sasic and Habib, 2013). Polak and Jones (1993) investigated the role of pre-trip information on travellers' departure time choices, employing a NL model to analyse stated preference data and assess the impact of information on decision-making. Yang et al. (2012) developed NL models to analyse travellers' joint choices of travel mode and departure time and demonstrate the applicability of NL models in understanding commuter behaviour based on Beijing scenarios.

Researchers also sought to relax the restrictive assumption of the IIA by accounting for differences in error variances across alternatives, leading to the development of the **heteroscedastic logit (HL) model**. Unlike the MNL model, the HL model allows error terms of utilities to have different variances across alternatives, which can represent the unobserved heterogeneity or inherent variability in decision-making related to specific alternatives. The model was first introduced by Bhat (1995) who developed a new heteroscedastic extreme value model to overcome the IIA property inherent in the commonly used multinomial logit model. This extension was applied to the analysis of intercity mode choice and was pivotal in enhancing the flexibility of discrete choice models and their applicability to real-world scenarios. Bhat (1997) further proposed the COVNL model, an extension of the nested logit framework that accommodates covariance heterogeneity across decision-makers in the correlation structure of alternatives within a nest. In the standard nested logit, the logsum parameter, which determines the degree of correlation between alternatives in a nest, is assumed constant across individuals. Bhat relaxed this restriction by allowing the logsum parameter to vary systematically with observed individual characteristics through a transformation function. This specification effectively introduces a heteroscedastic formulation across individuals, such that the variance–covariance of the unobserved components differs by traveller attributes.

Sasic and Habib (2013) addressed heteroscedasticity at the level of groups of alternatives by modelling departure time as overlapping clusters of adjacent intervals. Their framework, referred to as Heteroscedastic Generalized Logit (Het-GenL) model in general, or more specifically, a heteroscedastic Paired Combinatorial Logit Model (Het-PCL), employed a scale parameterisation approach in which each cluster of adjacent departure times was associated with its own scale parameter, parameterised as a function of explanatory variables such as level-of-service attributes. This enables the strength of correlation/substitution between time intervals (e.g., 7:55 vs 8:05 vs 8:30) to vary systematically across contexts. The empirical application demonstrated the effectiveness of this approach in modelling home-based commuting trips in the Greater Toronto and Hamilton Area (GTHA). Chen et al. (2016), on the other hand, focuses on contextual heteroscedasticity within individuals, capturing the impacts of task complexity and time pressure on activity-travel decision-making. In their resulting heteroscedastic logit model, the scale parameter was no longer considered to be identical as a constant but was parameterised as a function of task complexity and time pressure. Subsequent integration with mixed logit have further enhanced its applicability to account for unobserved taste heterogeneity alongside situational heteroscedasticity.

A trend towards incorporating behavioural and psychological aspects into choice models was witnessed later, with a focus on more accurate capture of heterogeneity in preferences and reflection of unobserved preferences. Train (1998) advanced RUM theory by introducing the mixed logit model to simulate random taste variations and correlations across alternatives and account for random taste heterogeneity in individual preferences. The model was a major improvement over the traditional logit models, offering greater flexibility and better empirical performance, particularly in the contexts where individual preferences vary across the population. The mixed logit model is highly versatile and widely used in transport modelling given its capability of representing complex decision-making processes. However, the model is generally computationally intensive and requires more data for reliable estimation of additional parameters and careful specification of the distribution of random coefficients. Another major contribution was the development of hybrid choice models, which extend discrete choice models by incorporating latent variables and psychological constructs. Hensher and Greene (2003) were instrumental in extending mixed logit models for their application in transportation contexts such as mode and route choices. Their work emphasised the importance of incorporating latent variables to reflect unobserved preferences. A similar but more advanced research conducted by Tsirimpa et al. (2010) developed a combined choice and latent model which utilised the MNL model and latent variable model to examine the impacts of information acquisition on travellers' switching travel behaviour (departure time and route choice).

2.1.2 Heuristics and rule-based approaches

Although the assumptions of pure rationality and utility maximisation are useful, the research relying on utility functions assumes that people are capable of examining all alternatives and all attributes across all choice tasks in the same fully compensatory manner (Leong and Hensher, 2012). However, it is not always the case in reality and the actual decision-making processes deviate greatly from the ideal utility maximisation framework (Chen and Kai, 2001) (Pinjari, 2013)(Xiong *et al.*, 2018a)(Zhang, 2006)(Di and Liu, 2016). It is especially noted for short-term dynamics, as Guo (2012) stated that economic models are not suitable for within-day rescheduling. Specifically, it is found that people are not completely irrational but have a contingency plan which depends on the context, conditions, accumulated experience, knowledge, and their abilities to cope with incomplete and biased information (Gärling, Kwan and Golledge, 1994). The attempt to address some of these deficiencies has been conducted.

Rather beginning with utility maximisation in economic discrete choice models and then modifying as needed to reflect observed human decisions, such as Prospect Theory (Kahneman and Tversky, 1979), Cumulative Prospect Theory (CPT) (Tversky and Kahneman, 1992), and Regret Theory (Loomes and Sugden, 1982), a branch of studies have been built directly from cognitive and emotion processing assumptions. Those approaches focus on sequential decision-making processes, seeking to understand the underline cognitive and emotional processes that produce the observable actions. A wide range of decision rules have been documented in the behavioural and cognitive sciences literature. However, full-fledged theory explaining individuals' responses to information has not been established (Ben-Elia and Avineri, 2015). Nevertheless, several theoretical frameworks, such as heuristic and rule-based approaches, have been explored and applied in transport research.

Heuristics is widely regarded as one of the most intuitive techniques for decision-making, offering simplified procedures to facilitate problem-solving. These techniques are typically articulated in the form of verbalisation rules or flowcharts, which outline discrete processes to achieve a solution. It generates adequate results rather than exploring all potential possibilities for an optimal solution (Shah and Oppenheimer, 2008). Decisions are made by evaluating heuristic functions subject to time and resource availability.

Threshold is a widely referred concept by several heuristics such as satisficing, eliminate-by-aspect (EBA), etc. The concept itself is not a heuristic but relevant to understanding many of them. The threshold or cut-off specifies the range of an attribute level (value) that defines if an alternative is acceptable or not. Many heuristics utilise this idea to express that attitude (decision) may change contingent upon the degree of the attribute. The value which triggers the attitude change is called the critical value or tipping point and is determined by the threshold or cut-off. Moreover, the critical value or tipping point can be presumed to be consistent for the whole population or to vary from person to person (Balbontin, 2018).

Traditional discrete choice models assess all possibilities before making decisions. However, options are frequently considered sequentially in human decision-making. In order to ensure a unique answer, Satisficing (Simon, 1955) suggested that an individual would select the first alternative that met its imposed requirements. If a satisfactory solution was not found, the individual would adjust the pay-off conditions to ensure the existence of a solution. A stochastic satisficing model (González-Valdés and Ortúzar, 2018) was proposed for transport mode choices in Santiago de Chile with the choice heuristic considering two attribute acceptability functions. One of the two functions analysed the mode costs, while the other examined flying time and stop time, attempting to estimate the marginal rate of substitution. A mixed heuristic model (Gonzalez-Valdes and Raveau, 2018) was proposed and tested on simulation data before being applied to simulate air travel from survey. The results demonstrated that the mixed heuristic model can accurately detect the existence and structure of heuristics in simulation data. More specifically, the model identified the random utility maximisation and stochastic satisficing behaviour of individuals based on real-world data. The boundedly rational user equilibrium (BRUE) (Mahmassani and Chang, 1987) was proposed based on the bounded rationality theory, positing that individuals would apply “satisficing” criteria to seek or achieve a satisfactory outcome rather than the best possible outcome. A dynamic behavioural user equilibrium (BUE) arose from a positive travel behaviour theory - SILK (Zhang, 2006) that emphasised search, information, learning and knowledge in wayfinding, which employed an empirical ‘satisficing’ to search route and utilised the Bayesian learning process to update a traveller’s knowledge and subjective beliefs.

Elimination by Aspects (EBA) was proposed by Tversky (1972) as a probabilistic elimination model. This heuristic explains the uncertain and inconsistent responses that violate the axioms of rational choice behaviour. EBA states that the significance of each alternative’s attributes could be determined by the respondent in a probabilistic or deterministic way. The key point is the rank of the attributes to consider. A threshold or cut-off is assigned to each attribute which determines the acceptance of an alternative. At that point, an individual eliminates the choices that fail to meet the specified threshold. Then, the individual employs this procedure onto the second most significant attribute until just a single option is left. It is viewed as a useful heuristic when a large number of attributes and alternatives being presented in a choice set makes the experiment complex (Cantillo, Heydecker and de Dios Ortúzar, 2006)(Williams and Ortuzar, 1982). However, as pointed by Hensher (2006), what matters is the relevance rather than the complexity of choice experiments, which is subjective in the perspective of the decision maker. This heuristic is included in the research of Gigerenzer and Todd (2008) which employed the most general and common heuristics in decision making. In the research conducted by Hess et al. (2012), the choice experiment involved rail travel behaviour. Four specifications indicating different rules (e.g., eliminating the worst for the considered attribute of any alternative at a given stage) have been assumed to eliminate towards three alternatives (i.e., the guarantee of reserved seats, the availability of free Wi-Fi, and the flexibility of ticket rescheduling) so as to reveal their influences and implications.

Lexicography was introduced by Tversky (1969). This heuristic states that a respondent selects the most important attribute based on previous knowledge and experience and evaluates all alternatives based on the deemed most important attribute. The alternative with the best level on that attribute will be chosen. If more than one alternative possesses the attribute of the best level, then these alternatives are compared based on the second most important attribute, and so on. The orders of attributes in terms of importance potentially vary across individuals. Hess et al. (2012) utilised the knowledge of lexicographic behaviour and assumed those who always chose the shortest travel time or the cheapest alternative were lexicographic on travel time or cost, respectively. Furthermore, the inclusion of lexicographic classes within models reduces the random taste heterogeneity, leading to an improved fitting compared to the simple MNL model and mixed MNL models. Non-trading behaviour and extreme sensitivity of respondents appear to be better modelled by explicitly specifying a lexicographic structure rather than a random taste parameter to explain non-trading impacts via an extreme tail on its distribution.

Beyond various specific applicable heuristics, Gigerenzer and Selten (2001) proposed an adaptive toolbox, aiming to reflect the actual decision-making process of people with practically limited time, knowledge, memory and other finite resources. The adaptive toolbox concept provides a framework for non-optimal vision of bounded rationality based on the psychological plausibility, domain specificity and ecological rationality. The building blocks specify searching, searching termination, and decision making. Heuristics in the adaptive toolbox are based on actual cognitive abilities and are made up of cognitive and emotional building blocks which can be part of more than one heuristic and may also be combined to form new heuristics. The building blocks are broader in scope than the heuristics. In addition, agents can be environmentally rational by using heuristics that are tailored to certain environmental structures. The ecological rationality entails examining the structure of environments, the structure of heuristics, and the matches between the two. The adaptive toolbox is a flexible and powerful tool in modelling actual decision making with bounded rationality. However, it has seldom been explored given the transportation environment, leaving a research gap worth to be investigated.

Another main group of activity-based travel demand models is the rule-based computational process models (CPMs) (Arentze and Timmermans, 2004), which use various sets of condition-action rules to implement daily travels and arrangements in order to imitate individual behaviour of daily plan scheduling. To date, several pieces of research have attempted to investigate the rescheduling process via the computational approach paradigm. For instance, Pendyala et al. (1997) developed an activity-based microsimulation (AMOS) to simulate changes of individual travel patterns in response to a transportation control measure by using a neural network approach. The behaviour rules fed into the neural network are extracted from a designed activity-based time use survey. Its application in Washington DC area implied that AMOS is a capable tool to cope with transport policy analysis. ALBATROSS (Arentze and Timmermans, 2004) is another example in modelling choice behaviour of individuals using rule-based approaches. ALBATROSS uses decision trees as a formalism to model choice behaviour. The learning algorithm is continuously adapted through learning while an individual interacts with the environment (i.e., reinforcement learning) or communicates with others (i.e., social learning). Another machine learning algorithm, i.e., Bayesian network, was later introduced into ALBATROSS to enhance the stability of induced rules (Janssens *et al.*, 2006). According to Sasaki (2011), a computational theory was proposed to cope with the dynamic selection of strategies in decision-making processes between collaboration and competition.

Zhang (2006) proposed a coherent positive behavioural model SILK to analyse travel behaviour and travel demand. Instead of assuming complete information and perfect rationale, the proposed SILK explored how travel behaviour was formed and adapted as the result of the subjective factor interaction, including spatial knowledge, perception updates, information acquisition, learning and heuristics. In the model, the RIPPER algorithm was utilised along with the if-then rules to model route choices on a real-world transportation network in Twin Cities, Minnesota. Departure time searching and switching have been further explored by Xiong and Zhang (2013) in the SILK framework. The framework has further been applied to joint choices of mode and departure time by Zou (2016). Based on the same framework along with the aforementioned theoretical and practical investigations, Xiong at el. (2018b) developed an agent-based approach to model travel behaviour under uncertainty and different information provision strategies. The routing algorithms in the model for dynamic traffic assignments (DTA) were adapted, and the dynamic user equilibrium condition was replaced by behavioural equilibrium.

2.2 Dynamic Activity-travel Rescheduling Decision with Agent-based Micro-simulation

Transport demand is derived from how individuals and households schedule their daily lives subject to the constraints imposed by their physical contexts and institutional environments. The major focus in terms of application has been put on forecasting and analysing the impact of travel demands as part of transportation policy measures. The effectiveness of these programmes is determined by how people plan and adapt their activity-travel patterns. However, most activity-based models assume a static activity scheduling procedure, i.e., activity plans being fixed without attempts to rescheduling (Bladel, Bellemans and Janssens, 2009). It is not the case in reality but a dynamic combination of (re)scheduling decisions. Recognising this limitation of most existing activity-based models, many research seeks to push the activity-based travel demand modelling to new development.

A recent interest in the field concerns the development of multi-agent systems for micro-simulation. Agent-based modelling is a powerful tool for its flexibility to accommodate complex systems with microscopic granularity. It has a long history, dating back to Von Neumann's (1966) book on self-reproducing automata. Modern agent-based modelling employs methodologies from a variety of disciplines, including genetic algorithms, cellular automata, cybernetics, cognitive science, social science, and more recently artificial intelligence. There are three basic elements for the agent-based models, i.e., agents, environment and rules. As the basic units of activity performance, agents have their socioeconomic attributes, desires and behaviours. The environment offers agents the space to reside and travel. Behavioural rules specify how agents behave and interact with each other, as well as how the environment changes as a result of agents' interactions. In this sense, it would be more reasonable to view the agent-based approach as an integrated modelling framework rather than a specific modelling method.

When applying the agent-based theory to transportation demand modelling, an agent is the basic unit which represents an individual or traveller with its associated demographic and travel characteristics. Given the transport network that is the physical context or environment, agents behave, learn and interact with each other according to certain rules. The transportation system will then evolve to a pattern, not necessarily an equilibrium, from which useful information might be derived. In this respect, travel demand would be the consequence of an evolutionary process (Zhang, 2006).

The microscopic traffic simulation can be viewed as a form of agent-based models. Most of the published studies related to agent-based transportation systems generally integrate three components, i.e., the travel demand or activity travel plan for each agent with demographic characteristics; the production of network-wide transportation results through micro-simulation which activity travel plans are fed into; and the utilisation of feedback among these components. Among a range of approaches to traffic simulation, agent-based ones have shown their capability of capturing necessary information at individual level and regenerating relevant realistic situations. Agent-based approaches represent agents as active entities with heterogeneity in the road network, in which these agents could present complex information processing and decision making.

The combination of activity-based approaches and agents can deal with complex socio-economic properties and heterogeneity of decision makers. In addition, their combination enables users to adapt individual daily agendas to obtain realistic and optimised activity schedules. Furthermore, activity-based approaches that are combined with agents can take account of the interactions among agents (e.g., members of a household), the decision-making (e.g., selections related to travel mode and route) and the actual travelling with potential delays. This will give immediate evaluations on the feasibility of the schedules of remaining activities.

Recent progress in activity-based analysis has attempted to push the development of dynamic models to the realm of activity-travel scheduling. One of the perspectives concerns the dynamics of scheduling adaptation with dynamic traffic assignment, i.e., rescheduling behaviour. The Aurora model was developed by Joh et al. (2004) to generate activity-travel schedules and provide dynamic rescheduling decisions by assuming individuals to be of bounded rationality and using S-shaped utility functions, in which the maximum value of utility assigned to a given activity is determined as the product of specific functions that estimate the attenuation in terms of start time, activity location, position in activity plan and time gap from the last execution of the activity. It is then developed into a comprehensive Aurora model (Arentze, Pelizaro and Timmermans, 2005) in which people were represented by individual agents, enabling the generation of schedules and simulation of activity-travel rescheduling decisions in space and time while considering a number of reschedule options. They specified the comprehensive Aurora model with a description of changes of activities such as their insertion, re-positioning, removal, and replacement, as well as variations in locations, travel modes and trip chaining options. The model has been implemented in a dynamic micro-simulation system to assess green-space recreation activities while capturing time pressure (Arentze, Pelizaro and Timmermans, 2010).

As an extended version of Aurora, FEATHERS (Arentze *et al.*, 2006) was developed as an activity-based micro-simulation framework to model short-term transport dynamics for the Flanders region of Belgium. A learning-based transportation oriented simulation system ALBATROSS (Arentze and Timmermans, 2004) was embedded in FEATHERS to incorporate the learning process along with activity re-scheduling and re-routing. WIDRS (Knapen *et al.*, 2014) model was developed to deal with the activity rescheduling under unexpected events. It utilised FEATHERS to produce an initial micro-simulated schedule with TransCAD taking the macroscopic traffic assignment. Information on network conditions was fed back to transport users, whose response actions were determined by their perception on the state of the network.

Pendyala et al. (2012) developed a prototype system SimTRAVEL by integrating the micro-simulation-based travel demand model OpenAMOS (an open-source activity-based travel demand modelling system) and the microscopic traffic simulator MALTA (Multi-Resolution Assignment and Loading of Traffic Activities). In order to accurately capture interactions and constraints of individuals' activity-travel agendas, the prototype has been enhanced to incorporate additional feedback between the model systems and update the travel time matrices used in the simulation process. The travel demand model was run sequentially with the dynamic traffic assignment model until road network conditions were converged. Three information provision scenarios have been examined to investigate the impacts of unexpected network disruptions. Further research has been conducted by Pendyala (2012) with major enhancements being made in rescheduling activities compared to the SimTRAVEL model. It was expected to overcome the limitations of integrated sequential models and accomplish a dynamic integration of an activity-based travel demand model and a dynamic traffic assignment model. Travellers' learning effects were also taken into consideration, though it was not applicable to the simulation of expected incidents.

Jha et al. (1998) proposed a simulation framework that integrated a driver behaviour model with a mesoscopic dynamic traffic network simulator DYNASMART to study day-to-day dynamics. An Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) (Auld and Mohammadian, 2012) model was also developed to simulate activity planning, scheduling and execution for households and individuals. The ADAPTS model assumed that activity planning and scheduling were time-dependent processes so that its general idea tended to reflect the opportunistic and context-dependent nature of activity rescheduling dynamics.

In general, most of the approaches have been proposed by combining the activity-based demand simulator with a dynamic traffic assignment model in a loosely coupled fashion. The implementation of a fully integrated simulation system has remained a major challenge to the field, which has been explored in a few pieces of research. A hybrid simulation mechanism SimMobility (Adnan *et al.*, 2015) moves a step further in model integration. Besides comprising short-term and mid-term planning, SimMobility has a long-term planning module where the demand and supply at each level and interactions between different levels are simulated simultaneously. The simulation at the middle-term level is a full-fledged activity-based model which integrates the pre-day activity-scheduling together with rescheduling and re-routing during the day on a multi-modal network. TRANSIM (Smith *et al.*, 1995) is an another example of such effort. There is an Activity Generator module in TRANSIMS which uses household survey data to work out almost all the scheduling dimensions of activity patterns for synthetic population. Furthermore, there is a feedback mechanism introduced between router and micro-simulator within the TRANSIMS, which attempts to bring the system into equilibrium. However, during that process, individuals can only change their routes with no flexibility of changing other dimensions of their activity patterns.

Like TRANSIMS, MATSim-T (Michael, 2007) (Balmer *et al.*, 2009) enables the application of an activity-based approach to large-scale simulation. Each daily plan elaborated for each agent includes detailed information of both activities and associated travels. A queueing simulation is used to execute the schedules of all agents, leading to a more realistic simulation of travel behaviour on traffic networks. Daily plans are iteratively adapted by using genetic algorithms to optimise travel times and costs, evaluated through utility functions. A multinomial logit formulation is commonly applied as one of the strategies for plan innovation, after which one plan is selected for execution in the next iteration. The later named MATSim framework uses an agent-based stochastic user equilibrium (SUE) formulation, which relies on a co-evolutionary iterative learning process and a utility-based approach to model behaviour at individual levels. A follow-on series of research (Axhausen, 2016) regarding the framework lead to a mature and relative comprehensive stage.

2.3 Effects of Time Pressure on Activity-travel Rescheduling Behaviour

2.3.1 Why does time pressure matter on travel behaviour

The activity-based approach, which offers insights into a traveller's decision-making process, is widely recognised as significant in the management of travel demand. When navigating in a complex environment where uncertainties encountered disrupt original schedules, an individual is required to rearrange their remaining schedule accordingly. The time pressure that arises from these uncertainties emerges as a critical factor that affects decision-making processes in the context of activity-travel rescheduling.

Time pressure influencing decision-making in varying contexts has been witnessed by a wide range of domains. The evidence from mental science research on brain neurons highlighted that the humans' capability of information processing is limited and the bounded neuron firing frequency triggers the adoption of heuristics. On top of that, the heuristics could be very rudimentary when the decision was made under time pressure (Miller, 1956)(Kalat, 1995). More observations have been discussed from the psychology research perspective, finding out how time pressure affects strategy choices and cognitive processes in terms of not only problem solving in dealing with particular problems or tasks (Alison *et al.*, 2013)(Caviola *et al.*, 2017), but also cognitive creativity (Amabile *et al.*, 2002)(Amabile *et al.*, 1996) and decision-making (Payne, Bettman and Johnson, 1988; Edland and Svenson, 1993; Ariely and Zakay, 2001; Young *et al.*, 2012; Ordóñez, Benson and Pittarello, 2015). The results suggested that people would have shifted from complex to simpler strategies when they were under pressure (Chesney *et al.*, 2013)(McNeil and Alibali, 2005).

So far, the impacts of time pressure on transport-related decision-making have not been given adequate attention. Rescheduling is typically initiated by unexpected events. Time pressure emerges as the remaining time to fulfil existing activity commitments is constrained by the time required for schedule revision (Gärling, Gillholm and Montgomery, 1999). Time pressure can significantly influence choice behaviour by altering perceptions of travel time, reliability and trade-offs between alternatives. However, less research has been conducted to explicitly capture the impacts of time pressure on activity-travel decision making. The idea of time pressure is important since the decision-making mechanism reflected in the travel behaviour will potentially change when decision time is limited. Travellers are unable to evaluate all possible options and outcomes to make an optimal choice, which challenges the assumptions of traditional utility-maximisation paradigms.

2.3.2 Impacts of time pressure on decision-making

Time pressure has been mostly investigated in the psychology and cognitive stream fields. The literature in relation to time pressure consequences and coping strategies is reviewed in terms of information processing and decision making.

Miller (1960) highlighted three information processing strategies in response to time pressure: accelerating, filtering and changing information processing strategies. Accelerating means speeding up the decision process, i.e., individuals interpreting the same amount of information with less time consumption. Filtering indicates a decline in the amount of information processed. It is further recognised by two different aspects: selection and filtration (Lallement, 2010). Individuals making choices based on certain attributes is identified as selection where decision makers tend to screen items out of the choice set under time constraints (Ordóñez, Benson and Beach, 1999). The similar screening strategies were also discovered by Weening and Maarleveld (2002). Acceleration and filtration of information are also confirmed by Ben's research which investigated the risky choice behaviour under different time pressure intensities (Ben Zur and Breznitz, 1981). Changing information processing strategies (also known as variation in (Batool, 2017)) is referred to the situation where individuals might change their behaviour rules which they used to rely on for decision-making when facing a complex choice task. Two associated sub-strategies are often discussed: behaviour shifting and avoidance. According to Bettman et al., (1998), an individual would switch from more compensatory strategies to a simpler non-compensatory mode when time pressure becomes greater. Besides, the time pressure increases difficulties in making decisions such that an individual appears to postpone or defer, influencing the attractiveness of the options (Dhar and Nowlis, 1999). Payne et al. (1988) concluded that people adapted to time pressure in a progressive manner. First, they accelerated their processing speed; if that was insufficient, then they increased the selectivity of processing; finally, they would consider a more attribute wise information search and processing.

Inspired by Miller's research (1960), Lallement (2010) proposed six hypothesis on how respondents processed information under time pressure. Not only the strategies revealed by previous researchers have been confirmed, but also new contributions were made in exploring richer evidence on time pressure intensity. Regarding accelerating, it was further found that less time would be spent on each piece of information in the time pressure situation compared to the situation without time pressure. Furthermore, a curvilinear relationship was discovered between the effect of time pressure intensity on acceleration and the threshold effect. Selection effect became stronger when time pressure became more intense due to an increasing number of information/attributes/alternatives to be processed.

Other researchers investigated time pressure from the perspective of decision-making optimality. By summarising various related studies, Svenson (1990) concluded that decision makers under time constraints used fewer but more important attributes, less complex and mainly non-compensatory decision rules. In addition, they weighted more on negative aspects and showed less satisfaction with decisions made under time constraints than those made without time constraints. Zakay (1993) demonstrated that the decision-making under time stress would rely on simple, nonlinear decision strategies, leading to a suboptimal decision. It further reviewed some homogeneous results on the side effects of time pressure on decision making that have been proved by psychologists, such as forgetting important data, incorrect judgment, and evaluation in consequence. However, the adverse effect may not exist in all circumstances. There are some signs indicating that time pressure can have a positive impact on decision making in some way. Many investigations have indicated that moderate time pressure can increase productivity and efficiency in some conditions. Isenbery (1981) found that time constraints initially had a positive impact on group decision making through helping groups focus on making decisions. In light of the time limitation, groups tended to filter out less significant information so as to accelerate the decision-making procedure without yielding choice quality (Kelly and Loving, 2004). Some other research is related to time constraints caused by deadlines. Moore and Tenney (2012) argued that an appropriate deadline could maximise the productivity since spending more time on a task actually decreased the marginal return to performance. A moderate time limit that induced feelings of time pressure might prompt decision makers to stop the decision paralysis and switch to another strategy if the choice task was not easy to handle using a specific strategy. In this way, time pressure may actually promote individuals to take action rather than suffering from paralysis and procrastination (Ariely and Zakay, 2001).

Other investigators have looked into the behavioural models that individuals apply to make a decision. It is found that the lexicographic heuristic which takes the most important variable to truncate a decision is more likely to be employed when time constraints are imposed or information costs are high (Payne, Bettman and Johnson, 1988) (Rieskamp and Hoffrage, 2008). Other decision heuristics may be used by an adaptive decision maker when time constraints increase. Hilbig et al. (2012) found that participants facing time constraints inclined to use the recognition heuristic where probabilistic inferences were determined based on whether options were recognised or not. Gigerenzer and Brighton (2009) proposed a "fast and frugal" heuristic which used less information, computation and time, and can interestingly lead to a higher decision accuracy if the right heuristic was chosen. As Lallement (2010) claimed, the effects of time pressure on acceleration and filtering have been commonly confirmed in a large number of research. Whereas the impacts of time pressure on changes in decision-making strategies are increasingly disputable.

There have been many attempts to study the relationship between time constraints and risk attitudes, focusing on how a decision maker weighs between losses and gains. The initial study carried out by Ben-Zur and Breznitz (1981) indicated that compared to those who did not face time constraints, time-constrained decision makers tended to focus on the probability of loss and increase risk aversion, becoming more or less conservative in their risk-taking proclivity. However, Young et al. (2012) found that the time pressure increased the sensitivity to selecting the "safe alternative" and reduced the probability discriminability, leading to severe risk-seeking behaviour in the domain of losses. According to research on the influence of time pressure on human judgement and decision making (Maule and Svenson, 1993), time pressure increases risk taking when the expected outcome of an action is negative and decreased risk taking when the expected outcome is favourable (Stern, 1999). Nursimulu and Bossaerts (2014) found that time pressure increases probability distortions and diminished risk aversion for gains. Kocher et.al (2013) conducted a study from the economic perspective, demonstrating that time constraints did not affect risk attitudes for gains but increased risk aversion for losses. Given these findings, the impacts of time pressure on decision making is yet to be adequately resolved and needs further exploration for better explanation (Ordóñez, Benson and Pittarello, 2015).

2.3.3 Impacts of time pressure on activity-travel rescheduling

The aforementioned studies have examined the impacts of time pressure on information processing and decision making. However, these investigations were primarily situated within the psychology paradigm, focusing on general human reactions to time pressure. Research specific to the transportation field remains insufficiently explored. Current models generally lack an adequate explanatory mechanism for the choice process, especially when time pressure is a significant influential factor (Stern and Richardson, 2005). In addition, limited attempts were made to explicitly capture the impacts of time pressure on activity-travel scheduling and rescheduling decision processes in the fields adjacent to transportation.

Arentze and Timmermans (2009) (2011) introduced a need-based theory to generate activity agendas which was scarce evidence that considered time pressure in the process of agenda production. The theory suggested that the utility of an activity was a dynamic function of the need of an individual at person and household levels. Every single activity performed by an individual intended to satisfy a certain need. A decision rule was introduced to generate the activity agenda with an aim to maximise the utility in terms of timing and duration decisions. In the model, an individual adopted a utility-of-time threshold parameter to determine the time of adding an activity into its agenda. The threshold parameter representing an individual's perception of time pressure was constantly adapted during the learning process. If the value of utility-of-time exceeded the threshold, then the activity was included in the agenda; otherwise, the activity would be excluded or postponed. This rule was implemented for all the available activities.

The total time pressure on an individual’s activity agenda depends on its need and time required to implement mandatory activities. The model took day-varying time budgets into account, meaning that different weekdays could differ in thresholds. Furthermore, in the context of household activities, needs at the household level were shared by individuals within the household. Household activities conducted by more than one individual could cut the time budget for individual activities. If several individuals were expected to conduct a certain household activity, its utility-of-time would be examined against the smallest threshold of all the relevant individuals. The joint and individual decision rules were specified to satisfy their particular needs, considering influences of perception, selfishness–altruism, joint activity participation and competences of individuals.

Rescheduling actions would happen due to the time pressure and unexpected events. From an application perspective, the problem of how individuals reschedule their activity-travel plans in response to unexpected events under time pressure is even more relevant. For example, traffic congestion may force people to adjust their activities, which in turn changes spatial-temporal distributions of traffic. According to Stern (1999), time pressure could be the most prominent effect of congestion, which not only impacted the deliberative process in decision making, but also affected the threshold controlling the selected action, either in a direct way or through the mediation of risk taking. Figure 2-1 depicts the causal link between time pressure and the deliberative mechanism or the threshold, leading to a direct relationship between time pressure and the frequency of reaction to congestion. Deliberation is a time-consuming cognitive process that requires gathering knowledge on the consequences of observable actions. Deliberation is characterised by vacillation until a decision is reached and an action is taken (Svenson, 1992). Edland and Svenson (1993) demonstrated that when time pressure affected travelling during congestion, the following were the primary changes in deliberation: 1) increasing the selectivity of retrieved information; 2) assigning greater weights to salient features; 3) decreasing the precision of decision making; and 4) increasing the usage of non-compensatory decision rules. Stern (1999) also examined the influences of time pressure on route choices under congestion by employing the decision field theory (DFT) model. The results proved the second and forth changes concluded by Edland and Svenson (1993).

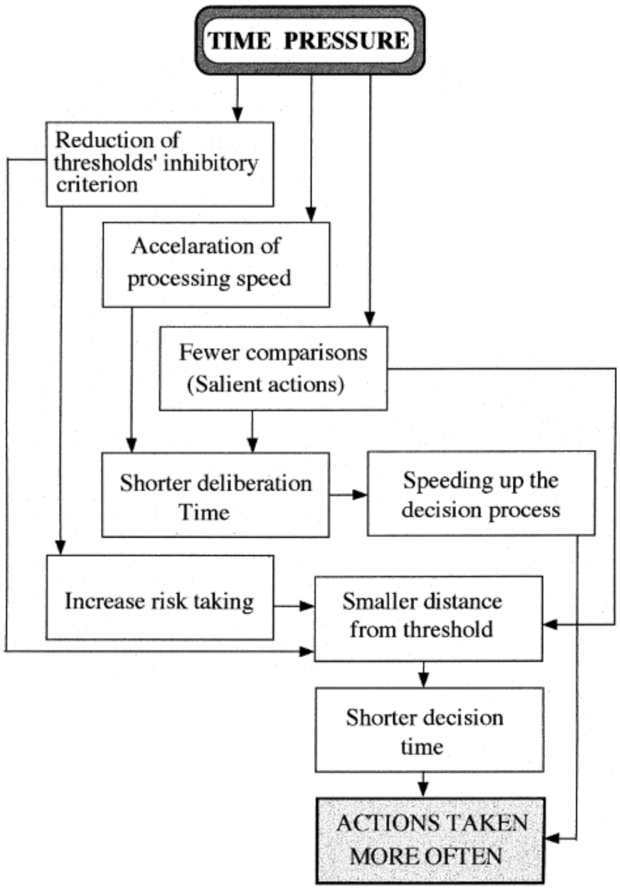


Figure 2 - 1 The assumed impacts of time pressure on an individual's decision-making process (Stern, 1999).

Garling et al. (1998) proposed a model for the short-term household activity scheduling, named SCHEDULER, in which time pressure could be mitigated by dynamic responses such as compressing activity durations, switching to faster travel modes, changing the sequence of activities or postponing activities according to their priorities. If the short-term plan cannot alleviate time pressure, the long-term planning would be applied to change demands and commitments by adjusting the number and frequency of activities. In their follow-on study, a descriptive analysis of activity-travel scheduling was proposed (Gärling, Gillholm and Montgomery, 1999), discussing the role of anticipated time pressure in daily activity rescheduling and indicating that time pressure would stimulate the planning of routine activities. When being faced with time pressure, individuals would try to first shorten durations of activities and then reschedule them. If this was insufficient, individuals were assumed to prioritise certain activities and eliminate the one with the lowest priority. This process was continued until the total duration was reduced below a particular threshold.

The more recent progress of dynamic rescheduling in activity-travel patterns is the development of Aurora (Agent for utility-driven rescheduling of routinised activities) model. The foundations of the model were laid in the research of Timmermans et al. (2001), which developed a comprehensive theory and model for activity rescheduling. The model conceptualised and specified the process of individuals adjusting their activity programs as a function of anticipated time pressure during the execution of the programs. Then, Joh et al. (2002)(2004) carried out numerical experiments and empirically estimated the proposed theory and model, focusing on the formulation of a comprehensive theory and model for activity rescheduling and reprogramming decisions. The Aurora model enables the schedule generation and dynamic decisions on activity-travel rescheduling which are meant to simulate how travellers react to time pressure and unexpected events by dynamically adjusting an existing schedule. The core of the Aurora model is S-shaped utility functions. The maximum utility achievable by a particular activity is determined by the product of the functions that model various factors: the start time, locations and positions of activities within an agenda, as well as the time gap since the completion of the last activity. Aurora suggested that time pressure was an essential factor affecting the activity rescheduling procedure where decisions were made with bounded rationality. This means that an individual would select an acceptable option when taking into account external constraints or having incomplete information. Further research conducted by Arentze et al. (2005) (2010) presented a comprehensive description of Aurora where people were simulated as individual agents. A comprehensive model was developed to include more activity-travel rescheduling options such as activity insertion, re-positioning, deletion, etc. The models developed in their works successfully integrated with the agent-based simulator which enabled the simulation of activity-travel scheduling decisions, rescheduling and learning processes in space and time. Furthermore, the experimental setup of Aurora has been presented in various scenarios to investigate the schedules consisting of work activities and green recreation activities.

Chen et al. (2016) captured time pressure in a discrete choice model by utilising a HL model to measure potential impacts of task complexity and time pressure on activity-travel choices. To evaluate the impact of time pressure on activity-travel rescheduling, a survey was conducted to observe and collect respondents' behaviour in decision-making experiments with unlimited or limited time budgets, respectively. The experimental results evidenced that high task complexity and time pressure would lead to less pronounced differences in choice probabilities, i.e., an increased randomness in choice behaviour. Inspired by Chen's research, Batool (2017) investigated the relevancy between the time pressure perceived and daily agenda rescheduling. "Satisfying" which belongs to the bounded rationality has been proved to be a strategy that could cope with time pressure in the research where most people were prone to this strategy for time scheduling. It was assumed that time pressure was especially related to the decision of travel mode in daily agenda, making it possible to predict travel mode choices from measurements of constrains. Hui (Hui *et al.*, 2020) established a model to simulate the individual decision behaviour under perceived time pressure. As shown in Figure 2-2, individuals would choose from three different strategies (optimal, salient and experience) to make rescheduling decisions with respect to different levels of perceived time pressure.

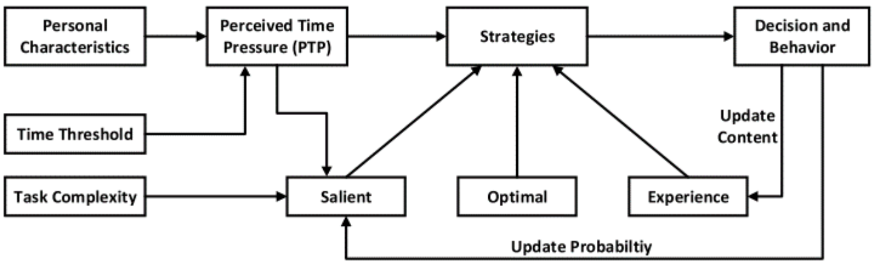


Figure 2 - 2 Decision strategies under time pressure (Hui et al., 2020)

Instead of capturing time pressure in model specification, some research considers it as a factor in the experiment design. Sun (2005) modelled the impacts of travel information on activity-travel rescheduling decisions under the events with multiple sources of uncertainty by using a distributed myopic decision heuristics. Individuals were assumed to switch from a depth-based strategy to a simpler, breadth-based strategy given insufficient time to fully examine information and all the attributes. When there existed a large number of alternatives, it would be difficult to accurately judge all possibilities. The efficiency and accuracy of judgment would also degrade due to time pressure. Therefore, heuristics were employed to reduce the decision tree to a manageable scale in an intelligent way. The proposed model specified how an individual made scheduling decisions with uncertainty. Then, the potential scheduling decisions were assessed based on presumed rational behaviour under each possible scenario. Ultimately, the scheduling decision that maximised the expected utility was finally selected.

Another research conducted by Sun (2012) considered time pressure in the design of activity scheduling. In the web-based interactive experiment, a particular scenario consisting of uncertain events was designed to investigate the behaviour of activity/travel rescheduling. Respondents had to make decisions on activity/travel reschedules at designed time points when facing the adverse effect of the uncertain events. Since the time slot of the planned activity has been specified, respondents had to make a quick decision in advance, otherwise the risk of being late for the next activity would be increased. In the experiment, respondents in one of the comparative groups faced time pressure when deciding how to adapt the next activity or element of travel. In the other comparative group, the activity schedules were adjusted without time pressure. Since activity cancellation was also an option for respondents, the activity scheduling was more flexible.

2.4 Commuting Travel and Telecommuting under COVID Pandemic

Our lives underwent significant changes when the COVID-19 virus began to spread and persisted longer than most people anticipated. Daily work and travel patterns of most people were notably impacted. Consequently, many transport researchers have conducted studies to analyse the effects of the pandemic on transport, among which commuter travel and teleworking behaviour have received more interests.

2.4.1 Telecommuting through the COVID pandemic

Since COVID-19 has spread over the world, many nations have issued national lock downs, which pushed commuting into an ever more difficult position. Most people were allowed to work from home except for essential workers. Researchers have investigated the characteristics of this situation, its possible pros and cons, as well as the resulting impacts.

- Telecommuting and related terms

The discussions on the term ‘telecommuting’ have emerged in the United States around 1970s as a feasible way of reducing commuting trips to alleviate social challenges such as traffic congestion and air pollution (Nilles and Gray, 1975). A similar concept ‘telework’ comparability refers to an innovative way of working which employs information and communication technologies to enable working remotely from main office (Hynes, 2016)(Nguyen, 2021). In such cases, part of the traffic flows created by commuting for work can be substituted by continuous flows of information exchange via telecommunication networks. This working pattern quickly gained acceptance and implementation all around the world especially in the United States and some European countries (Mokhtarian, 1991). In addition to ‘telecommuting’ and ‘telework’, there are other different terms describing similar situations such as remote work, distant work, e-work, virtual work, flexible-location work, etc. (Andreev, Salomon and Pliskin, 2010).

Due to national lockdown policies implemented during the Covid-19, working from home became the most common and feasible alternative for many workplaces. Consequently, researchers have mostly referred to this context using terms such as home-working, home-based telework (Nguyen, 2021) or simply ‘work from home’ (Moeckel, 2017; Balbontin *et al.*, 2021; Balbontin, Hensher and Beck, 2022) as most media coverage and research papers do.

- Influencing characteristics to telecommuting

There is a volume of research investigating the characteristics of telecommuting and its determining factors such as sociodemographic characteristics, job properties and commute trip features. It is generally shown that women are more likely to work from home than men because of the family responsibilities such as childcare (Bernardino and Ben-Akiva, 1996). However, it has become a paradox as evidenced by other studies – childcare could reduce the productivity of employees at home, resulting in a decreased willingness to continue telecommuting during the Covid pandemic (Nguyen, 2021; Nguyen and Armoogum, 2021).

In terms of age, the frequency of telecommuting is found to be favourably connected with Generation Y or millennials aged 25 to 40 as a result of being more familiar with information and communication technologies in their lives (Mohammadi *et al.*, 2022). Young people are generally more likely to telecommute compared to middle-aged or elderly people (Popuri and Bhat, 2003). This may be in part because elderly people are more likely to hold in management roles that require them to be present in workplaces or to set a role model effect (Sener and Reeder, 2012).

Education and income are the other important demographic factors that positively and directly contribute to the frequency of telecommuting (Mohammadi *et al.*, 2022) (Loo and Wang, 2018). It is conceivable that the well-educated, and attractive-wages paid employees within knowledge-intensive industries largely rely on technologies in their work. Therefore, they are more feasible to adapt to teleworking, compared to those in labour-intensive industries where teleworking is fairly hard.

The characteristics of commuting itself have also been explored in relation to its impacts on telecommuting. Data indicated a favourable relationship between long-distance commutes (greater than 30 minutes) and the frequency of telecommuting (Mohammadi *et al.*, 2022). This trend was particularly evident during the pandemic when commuters were wary of being infected along long trips on public transport. Evidence suggested that employees who drove their own cars to work were less likely to telecommute frequently (Shabanpour *et al.*, 2018) (Mohammadi *et al.*, 2022). This was possibly because owning private vehicles made commuting simpler and less exposed to the potential risk of infection.

2.4.2 Impacts of COVID on commute travel

Commuting behaviours have also been changed as a result of the variations in working patterns. Many studies have been carried out to investigate the impacts of pandemic on domestic commute travels and on cross-border commuters (Novotný, 2022). Over the past two years, many countries have experienced different waves or phases of virus spreading at certain time points, each involving its own characteristics due to distinct national conditions and implemented policies. However, there are still some commonly shared changes which have been presented by many case studies across states.

- Public transport

Travel patterns of public transport users were generally more disrupted by the pandemic than the other transport modes. A general decrease in public transport usage has been witnessed across the world, particularly for the commute travel of bus and train.

The data collected on the mode share in Australia reported that the COVID-19 led to a considerable decrease in the usage of public transport from 29% to 19% (Balbontin *et al.*, 2021), including a significant decline in train use from nearly 19% to slightly more than 12% and a reduction from nearly 10% to almost 7% in bus use (Balbontin, Hensher and Beck, 2022). However, for longer-distance trips to work, people tended to remain on trains because it allowed them to work onboard while travelling (Campisi *et al.*, 2022). Similar to the circumstance in Australia, samples collected in New Zealand also reported negative attitudes to public transport use when restrictions were eased. When travel restrictions were all removed, the usage of public transport was slightly improved but remained notable less than the level prior to the Covid-19 (Thomas *et al.*, 2021). The drops of public transport usage have also been observed in five South American countries where public transport was the most frequently used transport mode, falling from 79% to 45% in Argentina, 67% to 40% in Chile, 74% to 60% in Colombia, 61% to 40% to Ecuador, and 61% to 53% in Peru (Balbontin *et al.*, 2021). By translating the GPS traced smartphone data into the metrics of weekly average number of trips and travel distances prior to and after the pandemic, it was reported that about 75% of public transport users took less public transport since the outbreak of pandemic. This was most likely to be induced by public transport service changes, concerns on infectious risks and stay-at-home rules. It was also noted that the lower-income public transport users showed significantly less reductions on the weekly average number of trips and travel distances compared to the higher-income group, implying that these lower-income households held less flexibility over the amount of trips that they had to conduct during the period of pandemic (Parker *et al.*, 2021).

As the country where the pandemic outbroke and was mitigated at the earliest time, China presents different picture. The data collected in Qingdao during the second wave in October 2020 (after the city had remained stable at zero cases since 2nd March, 2020) showed that travellers without access to private vehicles relied on public transport for work trips and maintained positive attitudes towards public transport (Luan *et al.*, 2022). This is different from the findings of most case studies in other countries. The reason behind is likely to be the sense of security gained from the strictly compulsory mask policy and the dynamic zero-Covid policy implemented by the government from central to local levels.

- Other shared transportation

Apart from public transport, other shared transport modes have also drawn attention to some studies. Commuting travel behaviour was investigated in the wake of Covid-19 pandemic and during the Tokyo Olympics, focusing on the role of shared transportation options such as car-sharing, bike-sharing and kickboard-sharing. A survey was carried out to find out the perception of shared transport and whether the commute travel behaviour has changed (Yoshida and Ye, 2021). The attitude towards car-pooling on commuting has also been examined in studies carried out in Australia and New Zealand. Compared to the circumstance prior to the pandemic, there was a significant decline of positive attitude on car-pooling when pandemic restrictions were first eased, followed by some recovery once restrictions were completely lifted (Thomas *et al.*, 2021).

- Private vehicle

Recent data has witnessed an increase of private vehicle use due to the fact that people avoided the use of public transport to reduce infection risks over the pandemic, and/or public transport operation was suspended as a mitigation strategy (Campisi *et al.*, 2022). The findings of an Australian case study also reflected a growth in the use of motorised private vehicles (Balbontin, Hensher and Beck, 2022), from around 63% to 68% (Balbontin et al., 2021). Among the motorised private vehicles, the most notable change was seen in car drivers, which could be explained by the health concerns associated with shared modes (Balbontin, Hensher and Beck, 2022). Similar trend has also been observed in South American countries. Car/motorcycle use increased from 9% to 17% in Argentina, 34% to 50% in Chile, 14% to 16% in Colombia, 28% to 38% in Ecuador, and 15% to 19% in Peru (Balbontin et al., 2021). A research in Israel concluded that commuters using public transport were more likely to captive whereas drivers reflected greater adaptiveness in response to COVID-19 since they were more easily to change their ridership so as to lower the risk of being exposed to viruses (Soria *et al.*, 2022).

- Active modes

It does not appear that the travellers who stopped using public transport have switched to motorised vehicles since active mode usages showed a general upward trend across the case studies. In Australia, the usage of active modes has increased from nearly 8% to 12% (Balbontin *et al.*, 2021), with walking increasing from 5.9% to 9.7%

and bicycle remaining almost at the same scale (Balbontin, Hensher and Beck, 2022). A potential behaviour switch from transit rider to active mode has also exhibited in the United States, i.e., an reported increase in walking (Parker *et al.*, 2021). Campisi et al., (2022) analysed the impacts of teleworking on travel habit of walking based on a case study in Sicily, Italy. Various factors conducive to walking were assessed throughout the pre-pandemic, during-pandemic and post-pandemic phases. Similar situation has also been revealed in the five South American counties. The greatest shift was observed in Argentina, where the active mode share rose from 11% prior to COVID-19 and to 32% in middle of 2020 (Balbontin *et al.*, 2021).

2.5 Discussions

Transportation is fundamental to the mobility of people and the delivery of goods, yet transport networks are inherently vulnerable to unexpected disruptions, such as accidents, adverse weather, etc. These non-recurrent events demand rapid traveller responses and adaptive planning, underscoring the importance of understanding and predicting travellers' decision-making behaviours under such conditions. Improved behavioural insights are crucial for transport planners and managers to design strategies that mitigate disruption impacts and enhance the reliability of transport networks.

Unplanned disruptions highlight the need for robust scenario simulation in transport planning and traffic management. Simulation models are ideally capable of capturing the dynamic and multimodal nature of transport network, incorporating interactions among individual travellers, and representing behavioural mechanisms underlying individual decision-making. The agent-based models have emerged as powerful tools in this regard, offering the ability to represent heterogeneous individuals and their interactions within complex, evolving network contexts.

Among such models, MATSim (Multi-Agent Transport Simulation), has gained wide adoption. However, as this review highlights a critical gap remains in its Within-day Replanning module, which is limited in simulating integration of real-time information with multi-dimensional behavioural adaptation in a multi-modal network. Existing implementations predominantly focus on route choice using utility-based formulations, whereas a broader presentation of adaptive behaviour is required to develop more realistic simulations of commuter rescheduling behaviour during unexpected events. Bridging these gaps will provide valuable insights for both academic research and practical transport planning applications.

In the broader field of behavioural research within transportation, random utility-based discrete choice models have long served as a dominant framework for analysing individual travel behaviour. However, conventional formulations of utility maximisation exhibit limitations when applied to real-world conditions of uncertainty and time pressure (Bailenson, Shum and Uttal, 2000). This limitation is particularly evident in short-term dynamics, where travellers are not entirely irrational but instead rely on contingency plans shaped by circumstances, prior experience, knowledge and bounded information-processing capacities (Guo, Nandam and Adams, 2012).

Recent methodological advances have sought to overcome these shortcomings by incorporating heterogeneity, perception biases, and psychological factors into utility-based frameworks, thereby enhancing behavioural realism. Parallel to these developments, heuristic and rule-based approaches grounded in cognitive and psychological theories, have gained attention as intuitive and computationally efficient alternatives. These approaches forgo strict optimisation in favour of adaptive, sequential decision-making, offering efficient approaches to capture behavioural responses in dynamic complex, real-world travel environments.

Nevertheless, a significant knowledge gap persists in explicitly modelling the role of time pressure in shaping the decision-making. While prior research has demonstrated its influence in contexts of limited time trade-offs such as traffic congestion (Stern, 1999), little attention has been devoted to its impact on rescheduling behaviour during network disruptions. Given the inherently disruptive and time-sensitive nature of such events, this omission is critical. Travellers benefit from timely information not only through potential travel time savings but also by avoiding delays in decision-making, as protracted deliberation under disruption can result in suboptimal or missed opportunities. Understanding how perceived time pressure influences behavioural adaptation is therefore important to developing realistic models of rescheduling behaviour.

A further gap arises from the changing context of travel following the COVID-19 pandemic, which has added an additional layer of complexity onto the commuter behaviour. The widespread adoption of remote and hybrid working arrangements has significantly altered commuting patterns, becoming established either routinely or on an ad hoc basis. This shift underscores the importance of re-evaluating commuters' travel behaviour in the face of transport disruptions under the emerging 'new normal'. This shift introduces new dimensions of flexibility and variability into commuter behaviour, which must be accounted for when modelling responses to transport disruptions.

Taken together, these gaps underscore the need to advance understanding of commuter's rescheduling behaviour under disruption in three key directions: (i) extending agent-based simulations to integrate real-time information with multi-dimensional rescheduling options within a multimodal network setting; (ii) explicitly modelling the influence of perceived time pressure on the decision-making during disruptions; and (iii) accounting for the behavioural implications of hybrid working arrangements in the post-pandemic era. The subsequent chapters of this thesis are structured to address these issues by enhancing MATSim, an agent-based simulation to capture both traveller's responses and systems performance; and developing advanced model that incorporates time pressure into discrete choice analysis, applying experimental methods to investigate behavioural mechanisms under disruption. In doing so, this research contributes both to the methodological foundations of travel behaviour modelling and to the practical design of more resilient and responsive transport systems.

Part I Simulating Commuters' Response to Transport Disruption

MATSim (Multi-Agent Transport Simulation) (Axhausen, 2016), as one of the widely applied agent-based transport simulation platforms, has demonstrated strong capabilities for simulating individual-level decision-making and interactions within a dynamic network context, while aggregating these behaviours into system-level travel demand. Such features make it particularly suitable for examining the impacts of disruptions on transport networks. This part of the thesis focuses on extending and testing MATSim by enhancing its Within-Day Replanning Module through the development of a more flexible framework capable of accommodating multi-dimensional rescheduling choices within a multi-modal network. This enhancement improves the model's capacity to represent adaptive travel rescheduling behaviours and to assess their system-wide effects, thereby enabling more rigorous scenario-based analyses to support resilience planning in urban transport systems.

Chapter 3 Within-Day Replanning in the Multi-Agent Transport Simulation (MATSim)

Transportation simulation software programs enable traffic to be modelled and predicted through simulating the interaction between dynamic travel demand and transportation infrastructure in various levels of aggregation. The microscopic transportation simulation model focuses on disaggregate elements of transportation systems, such as the individual vehicle or user. MATSim (Axhausen, 2016), as one of the open-source agent-based microscopic transport simulation software, combines the activity-based demand simulator with a dynamic traffic assignment model in a fully tight integrated fashion. Therefore, it is considered as a suitable simulation platform to facilitate examining the impact of disruptions on the transport network, by effectively aggregates individual behaviours into system-level demand. This chapter introduces the MATSim framework and its main components to establish the foundation for the work undertaken in Chapters 4 and 5, where its within-day replanning model is extended to simulate system responses to network disruptions.

Section 3.1 introduces the overall MATSim framework including the basics of the framework. Section 3.2 and 3.3 then present the traffic flow model (Mobility Simulation, Mobsim), and the co-evolutionary optimisation algorithm. Another important module – Scoring/the utility function will be described in Section 3.4. Lastly, an extension module – Within-day Replanning Module, and rationale behind the enhancement will be introduced in Sections 3.5 and 3.6.

3.1 Overall Framework of MATSim

3.1.1 Overview

MATSim is a large-scale micro-simulation framework developed in Java. It was initially developed by Kai Nagel at ETH Zurich, with his research interest in improving TRANSIMS (TRansportation ANalysis and SIMulation System) (Smith *et al.*, 1995), and subsequently in collaboration with Kay W. Axhausen. MATSim has been widely used for diverse research topics and has been applied to many scenarios across the globe, for instance, Switzerland (Axhausen *et al.*, 2010), Gauteng, South Africa (Joubert, Fourie and Axhausen, 2010), and TelAviv, Israel (Bekhor, Dobler and Axhausen, 2011). In the MATSim framework, an agent represents an individual traveller characterised by a set of socio-demographic attributes and a daily activity–travel plan. Each agent is assumed to act autonomously and seeks to execute and adapt their activity schedule in response to changing transport network conditions.

MATSim offers a framework to simulate the travel and activity behaviour of individual agents within a transport network. There are several main modules within the framework as shown in Figure 3-1. An initial demand module selects an activity plan for each agent from a set of feasible plans. The selected plan is then executed in the network mobility simulation module (Mobsim). The scoring module evaluates the utility of the simulated plans in each iteration, and the experienced utilities of the plans are then optimised through a re-planning process which uses co-evolutionary adaptive algorithms (i.e., replanning within the iterative process). The utility of feasible plans within the set for an agent is therefore improved with each iteration until converging to a state that is an analogue to a (stochastic) user equilibrium (Rieser *et al.*, 2015).

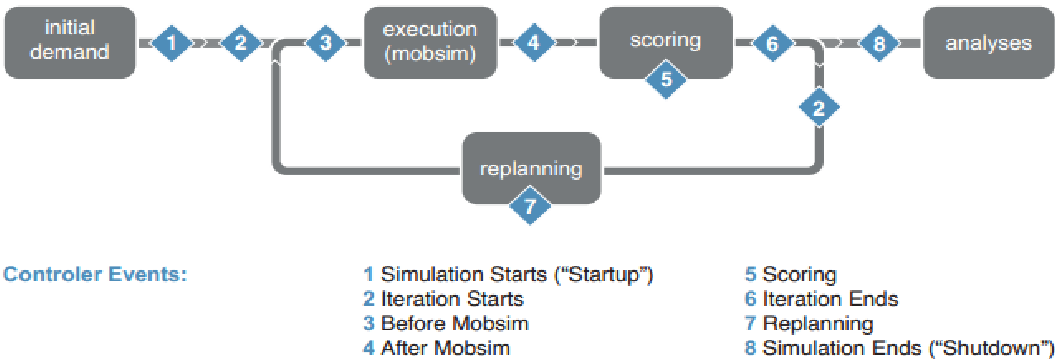


Figure 3 - 1 MATSim controller events (Zilske, 2016)

3.1.2 Building the simulation

In this section, the typical required input data for a MATSim experiment, along with the expected output files are briefly presented. More detailed description can be found in MATSim guide book (Rieser, Horni and Nagel, 2016).

General Input

The following bullets describe the input data to support a MATSim simulation. The files containing information on the network, the travel demand and the simulation configuration is the minimum required for a basic experiment. All the input files must be prepared in the format of XML (Extensible Markup Language).

- Network *network.xml* defines the network constraints that the simulation has to comply with. Graph theory is employed which presents roads as links and intersections as nodes. Each link and node contain the attributes including a unique ID and corresponding coordinates. Additional attributes are given for each link such as free flow speed, length, capacity, and accessible vehicle type, an example is illustrated in Figure 3-2. In addition, MATSim links are uni-directional, therefore, instead of having node A and node B, it is presented as from- and to- node.

```
<network name= "example network file ">
        <nodes >
                <node id="1" x="-20000" y="0"/>
                <node id="2" x="-15000" y="0"/>
                <node id="3" x="-865" y="5925"/>
                 ……
                <node id="15" x="-20000" y="-10000"/>
        </ nodes >

        <links >
                <link id="1" from="1" to="2" length="10000.00" capacity="36000" freespeed="27.78" permlanes="1"  modes= " car " />
                <link id="2" from="2" to="3" length="10000.00" capacity="3600" freespeed="27.78" permlanes="1" modes= " car "  />
                 ……
                <link id="23" from="15" to="1" length="10000.00" capacity="36000" freespeed="27.78" permlanes="1"  modes= " car,
               pt" />
        </ links >
</ network>
```

Figure 3 - 2 Example of a network file

MATSim supports time dependent/varying network, which offers an opportunity to simulate cases like accidents and disasters etc., where some lanes or multiple links have to face movement restriction or accidental closure. It is simulated by changing the attribute such as free flow speed, flow capacity or number of lanes in a defined *NetworkChangeEvent.xml* file (as shown in Figure 3-3 an example), which works together with the network file achieving a time dependent network.

```
<networkChangeEvents>
        <networkChangeEvent  startTime="06:00:00">
                <link refId="5"/>
                <link refId="6"/>
                <freespeed type="absolute" value="0.0"/>
        </networkChangeEvent>

        <networkChangeEvent startTime="9:00:00">
                <link refId="5"/ >
                <link refId="6"/ >
                <freespeed type="absolute" value=" 27.78 "/>
        </networkChangeEvent>
</networkChangeEvents>
```

Figure 3 - 3 Example of a network change event file, specifying that links 5 and 6 are fully closed between 06:00–09:00.

- Travel demand: *population.xml/plans.xml* represents travel demand. Since MATSim is an agent-based framework, each person is modelled as an individual agent with its social-demographic characteristics (such as gender, age and income, etc.), mode availability and scheduled day plan. The data is organised in a hierarchical structure where each population entry comprises a list of individuals; within each individual's record, there exists a list of plans, and each plan is composed of a sequence of activities and legs (representing the mode of travel between locations). The population file provides all simulated agents and their typical plan for a day. Figure 3-4 depicts an example of a population file including essential information.

```
<population >
        <person id= "1" sex= "f" age= "28" license="yes" employed="yes">
                <plan>
                              <act type="home" x="-25000" y="0" link="1" end_time="07:45" />
                          <leg mode="car">
                                  <route type= " links ">2 7 12</route>
                              </leg>
                              <act type="work" x="10000" y="0" link="20" dur="07:30" />
                              <leg mode="car">
                                      <route type= " links ">13 14 15 1</route>
                              </leg>
                              <act type="home" x="-25000" y="0" link="1" />
                </ plan >
        </ person >

        <person id= "2" sex= “m" age= “40" license="yes" employed="yes" >
                <plan>
                  ……
                </ plan >
        </ person >
               ……
</ population >
```

Figure 3 - 4 Example of a population file, specifying the socio-demographics of Person ID = 1, engaged in a Home–Work–Home activity chain.

- Config: *config.xml* file sets the rules for MATSim on managing the simulation. As shown in Figure 3-5, several essential configurations are defined, for example, the storage paths of input files, output files, parameter configuration for mobility simulation, scoring module, and replanning module (discussed in more detail in Section 0).

```
<module name= " network ">
        <param name= " inputNetworkFile " value= "<path -to - network -file >" / >
</ module >

<module name= " plans ">
        <param name= " inputPlansFile " value= "<path -to -plans – file> " / >
</ module >

<module name= " controler ">
        <param name="outputDirectory" value="< path -to -output - file >" />
        <param name= " firstIteration " value= "0" / >
        <param name= " lastIteration " value= “100" / >
</ module >

<module name="qsim">
        <param name="startTime" value="00:00:00" />
        <param name="endTime" value=“00:00:00" />
</module>

<module name= " planCalcScore " >
        < parameterset type= " activityParams “
                <param name= " activityType " value= "home" / >
                <param name= " typicalDuration " value= " 12:00:00 " / >
        </ parameterset >
        < parameterset type= " activityParams " >
                <param name= " activityType " value= "work" / >
                <param name= " typicalDuration " value= " 08:00:00 " / >
        </ parameterset >
</ module >
```

Figure 3 - 5 Example of a configuration file

A wider range of input data could be implemented for a broader range of simulation purpose. For example, to simulate public transport, additional data is required to define transit vehicles and transit schedule. Traffic lights and parking information can also be applied to MATSim model to make the transport model closer to real life situations.

General Output

The outcome results created by MATSim can be utilised to monitor the current simulation progress as the output files are built ‘on the fly’. The outcome can be further analysed when the simulation is completed. In default, some of the given results summarise the entire MATSim run, whereas other files are generated for individual iterations.

To summarise the complete simulation, a *log* file is generated to print detailed message on module settings and the detailed records on each simulation step. The output plan file is another critical output which contains the state of agents’ plan, which is compared to the plan in the input file, with more detailed information such as leg start time, travel time, leg route and leg mode, and normally more than one plan for a person because of the iteration processing. As one of the main outputs of MATSim running, ‘Events’ is an essential basis for visualisation and post-analysis, which is recorded in the *events.xml* file. Figure 3-6 presents the Events file which protocols routes of all vehicles and records the locations where an agent’s activity starts and ends on the precise link. Since the Mobsim is time-based, the Events are structured by the timeline of the Mobsim process (an example is shown in Figure 3-7). Further analysis can be customised with code writing in Java interpreting more information from Events for own research purpose.

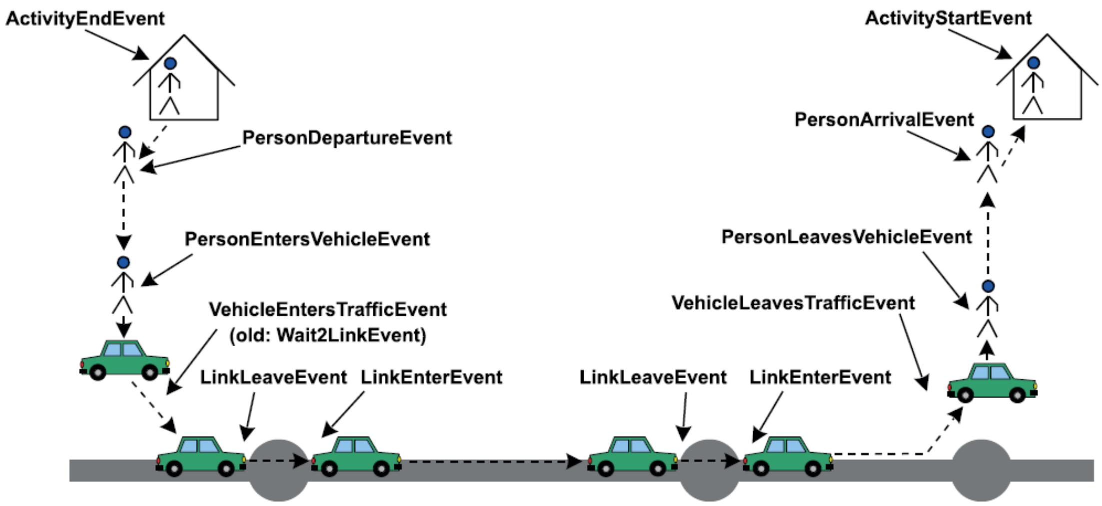


Figure 3 - 6 Typical events file (Rieser, Horni and Nagel, 2016)

```
<events version="1.0">
        ......
    <event time="29838.0" type="left link" vehicle="6" link="4162"  />
    <event time="29838.0" type="entered link" vehicle="6" link="4774"  />
    <event time="29838.0" type="left link" vehicle="810" link="149"  />
    <event time="29838.0" type="entered link" vehicle="810" link="211"  />
    <event time="29838.0" type="vehicle leaves traffic" person="75" link="855" vehicle="75" networkMode="car" />
    <event time="29838.0" type="PersonLeavesVehicle" person="75" vehicle="75"  />
    <event time="29838.0" type="arrival" person="75" link="855" legMode="car"  />
    <event time="29838.0" type="actstart" person="75" link="855" actType="work"  />
    <event time="29839.0" type="left link" vehicle="640" link="7539"  />
    <event time="29839.0" type="entered link" vehicle="640" link="7541"  />
        ......
</events>
```

Figure 3 - 7 Example of an event file

Some simulation results are produced in iteration-specific folders. For each iteration, the leg histogram is summarised describing the number of agents who depart, arrive and are en route in each time unit with every transport mode. In addition, a summary of trip duration is provided for different travel patterns, with duration classified by a time bin. Also, the average trip duration for all trips is provided. The simulated and collected volume can be compared if traffic count data is available, which is important for model validation. The output plan and events produced by the specific iteration are created in default at intervals of ten times and are printed along with other output files.

3.2 Mobility Simulation

To complete the simulation for a large number of agents with an acceptable computation time, an efficient traffic flow model is required. Several mobility simulations have been developed over the years each having unique features (Dobler, 2013). QSim (Rieser, Nagel and Horni, 2016), which is a single queue-based, multi-threaded approach, is employed as the default traffic flow modelling method of the Mobsim.

3.2.1 Dynamic agents in MATSim

QSim regards each link in the network as a first-in first-out (FIFO) queue as shown in Figure 3-8. That is, an agent that just drives into a link will wait at the last place of the queue and is not allowed to leave until it reaches the first place of the queue. As a result, the time of an agent staying at the link is greater than or equal to the travel time that is estimated under the free speed of the link. In addition, the outflow capacity and the storage capacity of a link will determine the maximum rate that vehicles can leave the link and the maximum number of vehicles being permitted to stay on the link respectively. This means that an agent cannot leave the current link and enter the next link when the next link's maximum allowable storage capacity is reached. It is noted that the parameters of each link, i.e., the outflow and storage capacities, may need to be scaled down accordingly when only a small number of agents are sampled from the entire population for a simulation. For example, for a 10% sample of the population, the flow capacity factor is suggested to set at 0.1; the storage capacity is advised to set a little greater than flow capacity, e.g., 0.15. QSim is also able to handle the time-variant and multi-model networks. Multiple vehicular modes can share the same network links with the premise of defining link attributes in the network file. The interactions between the modes are consequently captured by the simulation. All modes not registered with the QSim as “main modes” are “teleported”, which means the vehicles are moved from origin to destination at a predefined speed or as (expected) travel times and (expected) travel distances, without considering interactions with the network.

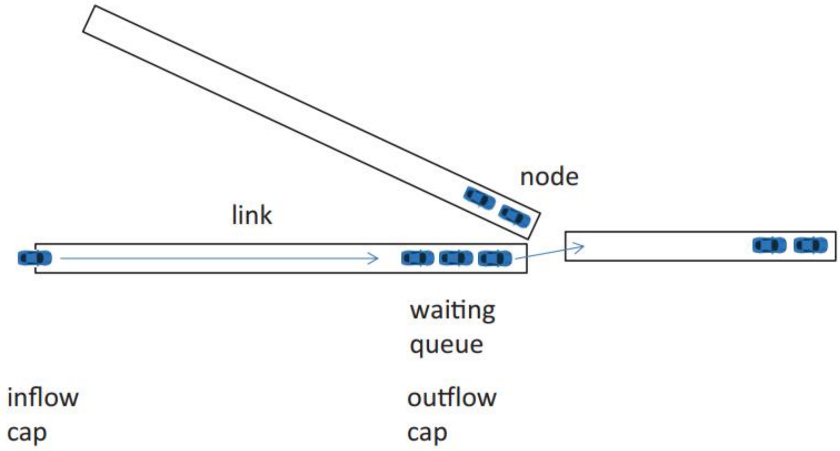


Figure 3 - 8 Queue-based traffic flow model (Horni, Nagel and Axhausen, 2016)

3.2.2 Multimodal mobility

In MATSim, transit vehicles move along the defined transit network as specified, picking up and dropping off passengers at stop stations (Rieser and Nagel, 2010). There are four sets of data that need to be specified to simulate the public transport in MATSim.

- Transit network - Apart from the road network where cars could move around, the multi-modal network also needs to be defined before simulation initialisation. To achieve this, an additional attribute is included for each link in the network file, indicating the transport modes that are permitted for the link. Therefore, cars, buses and trams could share the same link whereas train transit is distinguished independently.
- Transit vehicles - This dataset describes the vehicles serving the transit lines. Public transport vehicles are specified with characteristics such as vehicle type, passenger serving capacity, etc. This set of data will normally be stored in a file named *transitVehicles.xml.*
- Stop facilities - Transit stops where passenger boarding and alighting are also defined. Each stop has a unique identifier and the associated coordinate reference to the network, so that the walking distance and the nearest stops from one location can be estimated. A link reference to the network is utilised to specify the connecting link that the transit vehicle could dock. Additionally, it is possible to specify a name for the stop for identification, and its status can be identified on whether the stop is currently blocked by other transit vehicles.

- Transit services - The transit service describes the transit line, which corresponds to a type of transit system with an associated number or name, such as: Bus 501 or Victoria Line. A transit line commonly consists of multiple transit routes with each for one direction. Each transit route is specified with its route profile (specifying a list of ordered serving stops and its relative departure and arrival offset); network route (an ordered list of all links that vehicle traverses); and scheduled departure (the information on what time and which vehicle should start the service). The data defining the transit line is structured hierarchically, along with the defined stop facilities. A file called *transitSchedule.xml* is used to store the data.

All transit vehicles moving on the transit network are simulated by the Mobsim. The transit vehicles move along the predefined transit route, taking care of transit stops while offering service to passengers. A vehicle starts from its first transit stop at the given departure time, and keeps interacting with passengers boarding and alighting at each stop. Transit related events are generated during the simulation process. Whenever a vehicle arrives and departs from a stop, a passenger enters and leaves a vehicle, the action is recorded as an event.

Based on the generated topology of transit network (Rieser and Nagel, 2010), the transit router calculates the best route for an agent on the graph representing the least cost transit route to the desired destination with a given departure time. A time-dependent disutility function is utilised to calculate the cost of the network. The total cost of the path C_{path} is given by the sum of cost of in-vehicle links $C_{iv}(t^*)$, cost of a boarding links $C_{bo}(t^*)$, cost of a alighting links $C_{al}(t^*)$, and cost of a walking links $C_{wk}(t^*)$. In-vehicle link disutility is given by travel time t_{iv}, travel distance d_{iv} and fare $\beta_{ivf} * d_{iv}$; boarding link disutility depend on waiting times t_{wait} and transfer cost c_{tf}; alighting cost normally specified as zero while cost of walking links is described by walking time t_{wk} and distance d_{wk}.

$$C_{path} = \sum C_{iv}(t^*) + \sum C_{bo}(t^*) + \sum C_{al}(t^*) + \sum C_{wk}(t^*) \quad (3\text{-}1)$$

where:

$$C_{iv}(t) = \beta_{ivt} * t_{iv} + \beta_{ivd} * d_{iv} + \beta_{ivf} * d_{iv} \quad (3\text{-}1a)$$

$$C_{bo}(t) = \beta_{waitT} * t_{wait} + c_{tf} \quad (3\text{-}1b)$$

$$C_{al}(t) = 0 \tag{3-1c}$$

$$C_{wk}(t) = \beta_{wkt} * t_{wk} + \beta_{wkd} * d_{wk} \tag{3-1d}$$

where:

t_{iv}: in-vehicle travel time.

d_{iv}:in-vehicle travel distance.

t_{wait}: waiting time.

t_{wk}: walking time.

d_{wk}: walking distance.

c_{tf}: cost of making a transit line transfer.

β_{ivt}: cost per unit of travel time in a vehicle.

β_{ivd}: cost per unit of travel distance in a vehicle.

β_{ivf}: cost per unit of travel fare in a vehicle.

β_{waitT}: cost per unit of waiting in a stop.

β_{wkt}: cost per unit of walking time.

β_{wkd}: cost per unit of walking distance

While agents make decisions independently based on the utility of alternative actions, they are interdependent through their shared use of the transport network. The actions of individual agents collectively determine network performance, and in turn influence the experienced travel conditions of others. This interaction between agents is a fundamental characteristic of the agent-based modelling approach and is essential for capturing emergent system-level behaviour under disrupted network conditions.

3.3 The Co-evolutionary Algorithm

The co-evolutionary algorithm (Popovici *et al.*, 2012) implemented in MATSim is utilised to simulate plan choice. In MATSim's standard iterative framework, plan innovations are introduced at the end of the simulated day, during the replanning phase. The approach allocates changes in a random manner to the individual agent, and efficiently identifies the optimum of each individual's day plan. MATSim is an agent-based approach, which means each agent represents a person in the simulation and the agents are represented by their plans in the simulation. The co-evolutionary algorithm approaches every agent's daily planning problem as a population-based search algorithm, i.e. the entire agent population explores and improves their travel plans through repeated simulation and adaptation.

Structure of the Population-based Evolutionary Algorithm

- **Initiation:** Generate a collection of candidate solutions for a problem instance.
- **Iterations:** Repeat the following steps many times as defined.
  - ❑ **Scoring:** Evaluate every candidate solution's score.
  - ❑ **Selection:** The solution that owns the highest score is normally selected. Therefore, decrease the occurrence of "bad" solutions.
  - ❑ **Construction of new solutions (plan innovation):** Construct new solutions and add them to the candidate solutions collection.

Figure 3 - 9 Structure of population-based evolutionary algorithm

Figure 3-9 depicts the structure of the evolutionary algorithm. An agent has several plans stored in its memory, whereas an agent can only hold a single plan in the simulation. Therefore, a plan has to be selected from the collection to be executed (selection). New solutions/plans can be created by cloning and recombination and/or mutation on an existing one (plan innovation). The scoring (to be described in section 3.4) is utilised to evaluate the fitness of the executed plans. The simulation iterates until agents cannot improve their plan scores anymore. Thus, the optimisation ends and (stochastic) user equilibrium achieved, where the agents cannot further improve their plans unilaterally (Rieser *et al.*, 2015).

Plan Selection

There are several selection algorithms available for selecting plans from the collection. For instance, the *SelectExpBeta* implements the multinomial logit model to perform selection between plans. *SelectRandom* randomly chooses one from the specified plans. *BestScore* selects the plan having the best score from the previous iterations. However, the *BestScore* selector is likely to get stuck in sub-optimal plans. For example, plans receiving a low rating because of a random fluctuation (such as rare traffic congestion) in a single iteration will never be put to the test again. Therefore, it is recommended to combine the *BestScore* selector with the S*electRandom* selector, so the selection is based on the score difference of two plans. More options and descriptions are described in guide book (Horni and Nagel, 2016).

Plan Innovation

The “Innovation” in MATSim terminology is applied as continuously choice set generation between iterations. Several strategies are available when creating a new plan. For example, the time innovation shifts the end time of the plan’s activity randomly within a configured range (e.g. postpone by 30mins), leading to activity duration changes. Route innovation calculates and generates a new route using a shortest path route algorithm, with generalised link costs computed as time-dependent values. The mode innovation strategies can alternate the transport mode for all legs, sub-tour, or single leg of a randomly picked agent’s plan. More innovation options can be found in (Horni and Nagel, 2016).

```
<module name= " strategy " >
        < parameterset type= " strategysettings " >
                <param name= " strategyName " value= " ChangeLegMode " />
                <param name= " weight " value= " 0.1 " />
        </ parameterset >
        < parameterset type= " strategysettings " >
                <param name= " strategyName " value= " TimeAllocationMutator "/>
                <param name= " weight " value= " 0.2 " />
        </ parameterset >
        < parameterset type= " strategysettings " >
                <param name= " strategyName " value= " SelectExpBeta " />
                <param name= " weight " value= " 0.7 " />
        </ parameterset >
</ module >
```

Figure 3 - 10 Example of plan innovation in a Config file

An example of the evolutionary strategics invoked by configuration file is illustrated above in Figure 3-10. This strategy defines the rules governing how plan innovation operates. Each sub-strategy is assigned a weight that determines the probability of its defined action being executed. The strategy modules’ weights are normalised in case they do not sum to one. In the example given above, each agent changes their leg mode with probability of 0.1 and time plan with probability of 0.2. Otherwise, the agent would choose a plan from the choice set according to a logit model.

The model incorporates stochastic elements in both plan selection and replanning processes. As a result, simulation outcomes are not strictly deterministic; repeated runs with different random seeds may produce variations in individual-level results, although aggregate patterns are generally stable. This stochasticity reflects the variability in individual decision-making and the uncertainty inherent in the simulation of dynamic transport systems.

3.4 Mathematical Formulation of the MATSim Scoring Function

The MATSim equilibrium is achieved by a co-evolutionary algorithm. Optimisation considers agents' whole day plans. The optimisation within an agent's set of plans is performed subject to constraints that are defined in scoring function. The current scoring function in MATSim is called Charypar-Nagel utility function (Charypar and Nagel, 2005). The two terms "score" and "utility" are normally interchangeable in the context of MATSim. The term "utility" will be used mostly in this section since the concept of a marginal utility is employed here.

The plans executed by the agents are evaluated by a scoring function comprising two major components, i.e. the sum of positive scores for activity participation S_{act} and the sum of travel-related negative scores S_{trav}:

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,q} \tag{3-2}$$

where the term S_{plan} is the total or accumulated score of a plan and q represents an activity among N activities in the plan. A higher score will be assigned to a plan having more activity participation and shorter traveling time. The score $S_{act,q}$ for a particular activity q is defined as:

$$S_{act,q} = S_{dur,q} + S_{wait,q} + S_{lateArr,q} + S_{earlyDep,q} + S_{shortDur,q} \tag{3-3}$$

where the score $S_{dur,q}$ for performing the activity q at a marginal utility $\beta_{dur,q}$ over a time period $t_{dur,q}$ is calculated as:

$$S_{dur,q} = \beta_{dur,q} t_{typ,q} \ln\left(\frac{t_{dur,q}}{t_{0,q}}\right) \tag{3-4}$$

where $t_{typ,q}$ and $t_{0,q}$ represent the typical duration for the activity q and the minimum duration, respectively. A negative value of $S_{dur,q}$ will be obtained for $t_{dur,q} < t_{0,q}$.

When an agent arrives before the open time $t_{open,q}$ of the activity q, a waiting-related score $S_{wait,q}$ is generated as the product of the marginal utility of waiting β_{wait} and the duration $t_{wait,q}$ from $t_{open,q}$ to the time $t_{start,q}$ at which the agent arrives the activity q.

$$S_{wait,q} = \beta_{wait} \cdot t_{wait,q} \tag{3-5}$$

The terms $S_{lateArr,q}$ and $S_{earlyDep,q}$ in equation 3-3 are the penalties assigned to an agent who starts the activity after the latest start time $t_{latestArr,q}$ and ends the activity at $t_{end,q}$ prior to the earliest end time $t_{earliestDep,q}$ respectively:

$$S_{lateArr,q} = \beta_{lateArr} \cdot max\left(t_{start,q} - t_{latestArr,q}, 0\right) \tag{3-6}$$

$$S_{earlyDep,q} = \beta_{earlyDep} \cdot max\left(t_{earliestDep,q} - t_{end,q}, 0\right) \tag{3-7}$$

where parameters $\beta_{lateArr}$ and $\beta_{earlyDep}$ describe the levels of punishment on late arrivals and early leaves, respectively. An agent may also be punished provided that the shortest duration required $t_{shortDur,q}$ for the activity q is not fulfilled:

$$S_{shortDur,q} = \beta_{shortDur,q} \cdot max\left(t_{shortDur,q} - t_{tur,q}, 0\right) \tag{3-8}$$

where the level of the punishment is indicated by the parameter $\beta_{shortDur,q}$.

The travel-related score $S_{trav,q}$ following an activity q is defined as:

$$\begin{aligned} S_{trav,q} = {} & C_{mode(q)} + \beta_{trav,mode(q)} \cdot t_{trav,q} + \beta_c \cdot c_q \\ & + \left(\beta_{d,mode(q)} + \beta_c \cdot \gamma_{d,mode(q)}\right) \cdot d_{trav,q} + V_{transf,q} \end{aligned} \tag{3-9}$$

where $C_{mode(q)}$ is a constant specified for the travel $mode(q)$ from an activity q to the next activity $q+1$. The term $\beta_{trav,mode(q)}$ is the marginal utility of time spent for $mode(q)$ and $t_{trav,q}$ is the travel time from the activity q to $q+1$. The term c_q represents the leg's cost which is then adjusted by the marginal utility of money β_c. The term $\beta_{d,mode(q)}$ is the marginal utility for travelling distance $d_{trav,q}$ which costs at a mode-specific monetary distance rate $\gamma_{d,mode(q)}$. The penalty for a transfer in public transport is denoted by $V_{transf,q}$.

The standard scoring formulation assumes that agents evaluate alternatives through a fully compensatory utility calculation. In real disruption contexts, travellers often face limited decision time and cognitive constraints, which may trigger fast-and-frugal decision strategies rather than exhaustive evaluation of all alternatives. Recognising these behavioural realities highlights the importance of extending the modelling framework to better represent simplified or heuristic rescheduling decisions under time pressure, which motivates the enhancements developed later in this thesis.

3.5 Within-day Replanning Module

The iterative simulation approach, which introduces the plan innovation at the end of a simulated day, generally presumes that agents expect the occurrence of recurring congestion during peak hours and then manage to avoid it or bear with it. In situations where unexpected transport disruption cannot be anticipated by travellers (e.g., traffic incidents or adverse weather conditions), the iterative approach is not an appropriate option since the achievement of equilibrium is not relevant in this context. Therefore, an alternative simulation method without an iterative optimisation process is required. To overcome this challenge, one of the MATSim extensions, the within-day replanning approach (Dobler *et al.*, 2012) uses a different strategy. It is designed to simulate unpredictable, dynamic scenarios with changes in the network structure and capacities of the links, desires of the people, and amount of available capacity. Therefore, it is essential that agents are able to reschedule their plans during a single iteration (a simulation day) without relying on the outcome from previous iterations, but by continuously collecting information in response to the unexpected event.

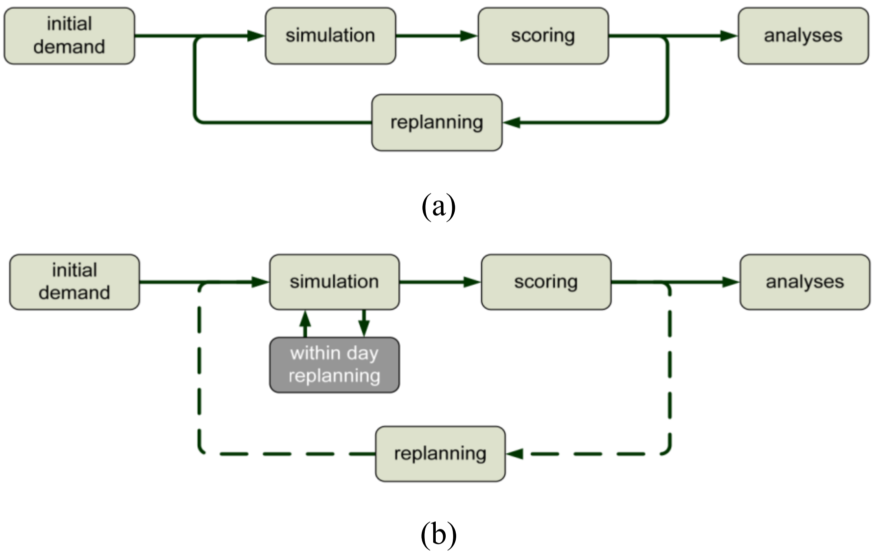


Figure 3 - 11 Structure of MATSim loop: (a) iterative MATSim loop and (b) (iterative) within day replanning MATSim loop (Dobler et al., 2012)

In order to implement Within Day Replanning in MATSim, the previously described iteration loop is adapted. As shown in Figure 3-11, the additional within-day replanning module is added, which interacts with the mobility simulation. The within-day replanning logic (also called WithinDayEngine) does not take responsibility on simulating traffic flow, it is designed to track agents and adapt their plans in certain circumstances. Since the QSim uses a time-step based approach, the Within-day Engine can interact with it whenever key events occur within a time-step, enabling dynamic plan adjustments during the simulation.

The Travel Time Collector calculates the average travel time for each link based on agents that have recently used within a given time period and then provides these actual travel times to the agents in the form of real-time travel information. This information is available to agents allowing them to replan their schedules where permissible. By default, link travel times are updated every 15 minutes.

3.6 Limitations of the Current Within-Day Replanning Module

Travel choices are inherently interdependent, and behavioural adaptation in one dimension often influences decisions in others. In practice, travellers may exercise multi-dimensional rescheduling options, such as adjusting their departure time or changing their mode of transport to achieve more desirable or reliable travel outcomes. Under more constrained conditions, they may even decide to cancel or postpone planned activities. However, in its current state of development, the Within-Day Replanning module in MATSim provides limited behavioural adaptation. It is not yet multi-dimensional and lacks the flexibility required to fully capture how individuals adjust their plans in response to transport network disruptions and real-time information.

Present applications of the within-day re-planning module have mainly focussed on route choice and route switching behaviour. Illenberger et al. (2007) presented a model framework which focused on en route replanning under different types of prescriptive information. Based on real-world traffic incident data, Kaddoura and Nagel (2018) investigated the impacts of long-term and short-term incidents on transport systems respectively; the latter was simulated in the MATSim Within-day Replanning Module where users reconsidered their route choices just before departure and at the moment of becoming aware of an incident during their travels. The Within-Day Replanning has also been applied to car parking (Bischoff and Nagel, 2017), taxi dispatching (Maciejewski, Bischoff and Nagel, 2016) and evacuation research (Zhu *et al.*, 2018), which generally utilise independent re-routing functionality in different topics.

In their review of rescheduling model packages, Zhao et al. (2018) pointed out that MATSim, as an agent-based simulation model, could not yet reschedule a plan during the process of a simulation iteration, nor consider all the rescheduling possibilities and choices. Though the presence of Within-Day Replanning Module addresses the former argument, the latter is still the case. Dobler (2013) also highlighted that the variability in the agents' plans is worth being examined in more details. In addition, Mads et al. (2018) noted that Within-Day Replanning was originally developed for car traffic only, and incorporating multi-modal transit would represent a methodological advancement.

All together, these studies highlight a research gap: enhance the existing model to comprehensively represent the behavioural complexity of agent's adaptive responses to transport disruptions. In practice, agents confronted with such disruptions may adopt a variety of replanning strategies, often involve multiple and interdependent adaptations, including changes in route, mode, departure time, or even activity participation, depending on their current state and constraints. The current model provides only a partial representation of those adaptive behaviours.

The objective of this research is therefore to enhance the existing Within-Day Replanning Module so that it can capture multi-dimensional rescheduling options within a multimodal network environment, and to create the flexibility to integrate alternative replanning behavioural models.

Chapter 4 Enhancement of Within-Day Replanning in MATSim

Preface *- This chapter is based on a conference paper presented at the 11th International Conference on Ambient Systems, Networks and Technologies (ANT-2020) in Warsaw, Poland* (Li and Ferguson, 2020). *Most of the following sections are excerpts from the published conference paper, with more details fulfilled and extended to better integrate into the thesis.*

4.1 Introduction

Building upon the rationale and necessity established in the preceding chapter, this chapter seeks to enhance the existing Within-Day Replanning Module in MATSim by developing a more flexible framework capable of accommodating multi-dimensional rescheduling choices within a multi-modal network. The proposed enhancement comprises four specific extensions, and the interrelationships among these components are also examined.

This chapter is structured as follows: Section 4.2 defines the research context, followed by an overview of the enhanced framework in Section 4.3. The components of the enhancement are detailed in Section 4.4, where each major element is explained in depth. Finally, Section 4.5 presents the conclusion and discussion, summarising the chapter.

4.2 Context

In this section, the general context of this research is defined. The classification of the transport network disruption is first discussed. Then the definition of several terms regarding an agent's daily plan and its rescheduling is specified. The disruption notification and information dissemination mechanism are presented in the last subsection.

4.2.1 Transport network disruption

The transport network disruption is caused by one or more events that reduce the capacity of the transport system. It has a significant impact on travellers and those who rely on the transport system. Classifying disruptive events is challenging, however, to establish a clear context for this research, disruptions are categorised according to key characteristics, with examples provided for each category. As shown in Figure 4-1, network disruption is commonly classified into two main types depending on whether the event is **planned** or **unplanned** (Pendyala, Hickman and Waddell, 2012). In addition, events can be divided into **short-term** and **long-term** events subject to their duration.

Long-term events result in habitual behaviour changes in transport users. The transport policy interventions, such as the introduction of a Low Emission Zone, can be seen as planned permanent disruptions to the normal course of transport activity. One example of long-term unplanned event is the unexpected collapse of I-35W Bridge over the Mississippi River in Minneapolis, Minnesota (Danczyk *et al.*, 2017) which resulted in the closure of the crossing for over a year.

With regard to short-term disruption, it is noted that some events may recur whereas other events do not. Short-term recurring disruption can be either planned or unplanned. For instance, the annual maintenance of a bridge is a planned recurring event and traffic congestion on critical links at peak time is an unplanned recurring event. They are, however, to some extent, predictable due to their recurring character which means that travellers may be able to anticipate disruption in these cases. In comparison, short-term, non-recurring transport disruption causes greater inconvenience for commuters due to their unpredictability.

A particular type of unforeseen disruption is emergencies. These can be either short-term or long-term disaster events, from major storm, flooding, volcano eruptions or industrial catastrophes to the nuclear plants' explosion or even war, where evacuation is often required followed by or with the warning of the emergency.

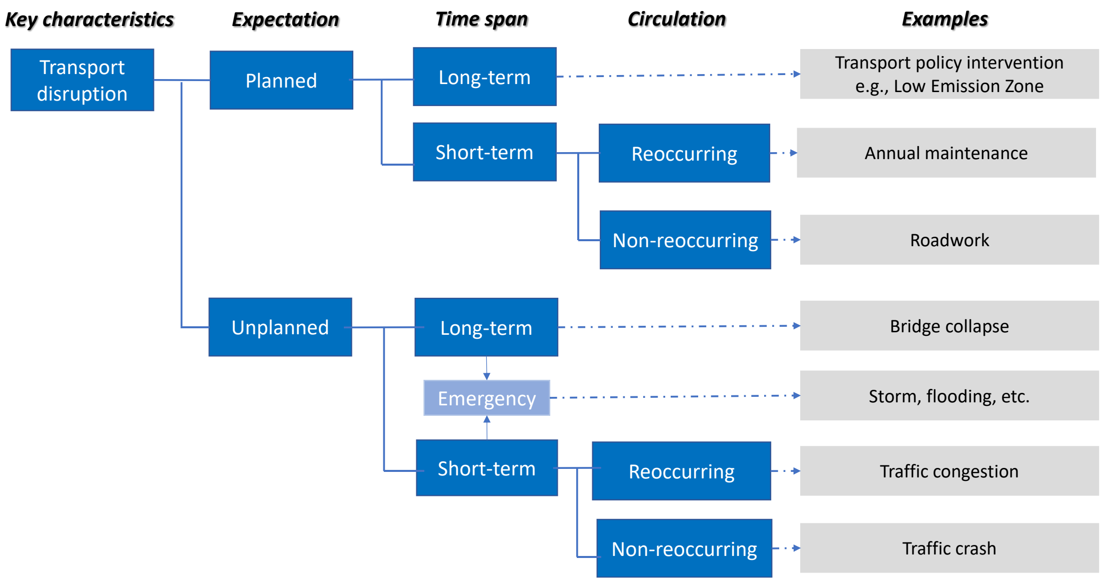


Figure 4 - 1 Classification of transport disruption and examples

The focus of this research is on the unplanned, short-term, non-recurring events. Such events are interesting to investigate due to their uncertain nature, and it is a major trigger for dynamic activity-travel patterns. When unexpected disruptions occur, travellers face uncertainty regarding future network conditions, particularly travel times and route availability. Modelling the impact of network disruptions allows the estimation of changes in travel demand along both spatial and time dimensions.

The configuration of a road network is commonly represented as an abstracted directed planar graph denoted by G= {N, E}, where N denotes a set of nodes (vertices) interconnected by directional edges (links) E. It is noteworthy that a bi-directional link in the real world is represented by two links – e.g. one travelling from node R to S and the other travelling from node S to R. As shown in equations 4-1a and 4-1b, an unexpected transport disruption event E_{dis} can be characterised by: *scale* of disturbance to transport supply and the *duration* of the disrupted time window Δt, with its impacts $\psi_{Event_{dis}}$ being conditional on the information dissemination I_d and the day schedule DS of affected travellers.

$$E_{dis}: \{scale, \Delta t\} \tag{4-1a}$$

$$\psi_{Event_{dis}}: \{E_{dis}|I_d, DS\} \tag{4-1b}$$

As defined in equation 4-2, the $scale$ of the disruption is characterised by the spatial extent of the disruption l_{dis}, i.e., whether it affects a single link or multiple links across a broader area, and the severity of impact on the disrupted links S_i. The *duration* of the transport disruption occurrence Δt is the time difference between the start T_{d_s} and the end T_{d_e} of disruption, as defined in equation 4-3. The implementation of this time-dependent in multimodal network will be represented in later section.

$$scale = \sum_{l_{dis} \in E} l_{dis} \cdot S_i \tag{4-2}$$

$$\Delta t = T_{d\_e} - T_{d\_s} \tag{4-3}$$

The definition of the information notification and dissemination, along with the definition of day schedule and rescheduling will be discussed in detail in the following sections.

4.2.2 Traveller information dissemination

Information exchanges via Advanced Traffic Information System, navigation apps, and on-board GPS publish travel information to the transport users. The dissemination mechanism of real-time traffic information to some extent determines the level of information assimilation, time and frequency of information provision and the level of perceived information credibility. There are two widely considered dissemination models (Knapen *et al.*, 2014); One is an eruptive mechanism-based broadcast model where an information sender proactively posts information at a relatively fixed broadcast time. Traffic information disseminated in this way has a high chance of being missed by the audience. The other model is a publishing model in which information is distributed to (subscribed) users often based on a certain route or service. Compared to the broadcast model, the publishing model reflects enhanced precision and greater flexibility. Users can access subscribed information anytime and anywhere, and may further query the information provider or consult other services, such as navigation apps.

In the simulation context of this study, a publishing model was adopted for travel information dissemination. Agents in MATSim follow daily schedules comprising multiple trips. Accordingly, agents could receive disruption notifications while engaged in an activity (prior to their next departure) or during a trip already in progress. In both cases, affected subscribers were able to reassess their situation and adapt their schedules in line with the prevailing network conditions.

4.2.3 Definition of day schedule and rescheduling action

The generation of a trip originates from the intention of pursuing an activity. The decision to perform an activity or not determines the need to travel. Given this high symbiotic relationship, a day schedule (DS) is defined as a series of N episodes.

The activity episode $epi_{n,act}$, $n \in N$, is characterised by its start time t_{a_s}, end time t_{a_e}, the determined duration of d_a which is given by activity end and start time, $d_a = t_{a\_e} - t_{a\_s}$, the location l_a of where the activity takes place and also the type of the activity ty_a.

$$epi_{n,act} = \begin{pmatrix} t_{a_s} \\ t_{a_e} \\ d_a \\ l_a \\ ty_a \end{pmatrix}, \ n \in N \tag{4-4}$$

The travel episode $epi_{n,tr}$ $n \in N$ that satisfies the need to perform the activity $epi_{n,act}$, $n \in N$, can be expressed as a joint choice of route r_o from origin O_o to destination D_o, with mode m_o, with preferred departure time d_o and expected travel time t_o, expected to arrive at a_o:

$$epi_{n,tr} = \begin{pmatrix} O_0 \\ D_o \\ r_o \\ m_o \\ d_o \\ t_o \\ a_o \end{pmatrix}, \ n \in N \tag{4-5}$$

The episodes forming a DS are connected in time and space. For instance, the arrival time a_o of the $epi_{n,tr}$ equals the start time t_{a_s} of $epi_{n+1,act}$; also, the destination D_o of the $epi_{n,tr}$ shares the same location of $epi_{n+1,act}$, l_a of the next episode.

Uncertainty may arise from inherent randomness or variability within the system, referred to as aleatory uncertainty, as well as from incomplete knowledge or limited information about the system state, referred to as epistemic uncertainty (Der Kiureghian and Ditlevsen (2009). In the modelling framework adopted in this research, uncertainty is operationalised through the occurrence of disruption events that dynamically alter network conditions. Travellers are assumed not to have perfect foresight of these changes; instead, they respond to evolving network states and available information through within-day replanning mechanisms in the MATSim simulation environment.

In response to an unplanned, non-recurring, short-term transport disruption, the rescheduling action $\boldsymbol{ReS}$ refers to how travellers adapt their planned DS by accounting for the changed conditions caused by the disruption event (dis). This adjustment is shaped by both physical constraints C_p, such as spatial-temporal factors including opening hours and travel distances, and mental or cognitive constraints $C_{m/c}$, such as habit, familiarity, and perceived factor. The rescheduling action is therefore represented as a behavioural function $B(\cdot)$ of how agents process episodic inputs under a set of governing constraints $C = \{C_p, C_{m/c}\}$ in response to a disruption event.

$$ReS = B\left(epi_1, epi_2, \dots\ epi_n \,\middle|\, C_p, C_m, dis\right), n \in N \tag{4-6}$$

4.3 Enhancement of Within-day Replanning Module

The MATSim Within-day Replanning Module differs from the iterative approach in the way that it involves agents modifying their plans during a day rather than at the end of an iteration (representing a day of travel execution). As described in Section 3.5 of previous chapter, the process is executed as a single iteration within the simulation run, rather through the iterative loop used in standard MATSim. Agents are enabled to gather real-time traffic data to make $\boldsymbol{ReS}$ decisions continuously during the execution.

This work aims to enhance the existing Within-Day Replanning Module in MATSim (Dobler *et al.*, 2012) by developing and testing a more flexible module capable of handling multi-dimensional rescheduling choice options in response to network disruptions affecting both car and public transport, while incorporating decision-making models based on utility and non-utility-based approaches. The building blocks of the enhanced Within-Day Replanning Module are presented in Figure 4-2.

To launch the enhanced simulation model requires a set of input files containing the time-dependent network, population, and simulation configuration. The enhanced simulation employs a time-dependent multi-modal network that captures the spatial and temporal impact of disruption on both the private and public transport system (as detailed in Section 4.4.1). The agents execute their planned activities and trips, initially defined in the demand data. Within Mobsim (as introduced in Section 3.2 of the previous chapter), where traffic flow is simulated, Mobsim can interact with the Within-Day Replanning module at each discrete time step. Between these interactions, the Travel Time Collector gathers and computes the average travel times for each network link over a specific time period and subsequently provides agents with real-time traffic data to support a range of rescheduling possibilities. Depending on their current circumstances, whether travelling or engaged in an activity, agents are capable to make diverse travel decisions. A behavioural model is therefore required to govern and represent agents' rescheduling behaviour under this enhanced mechanism.

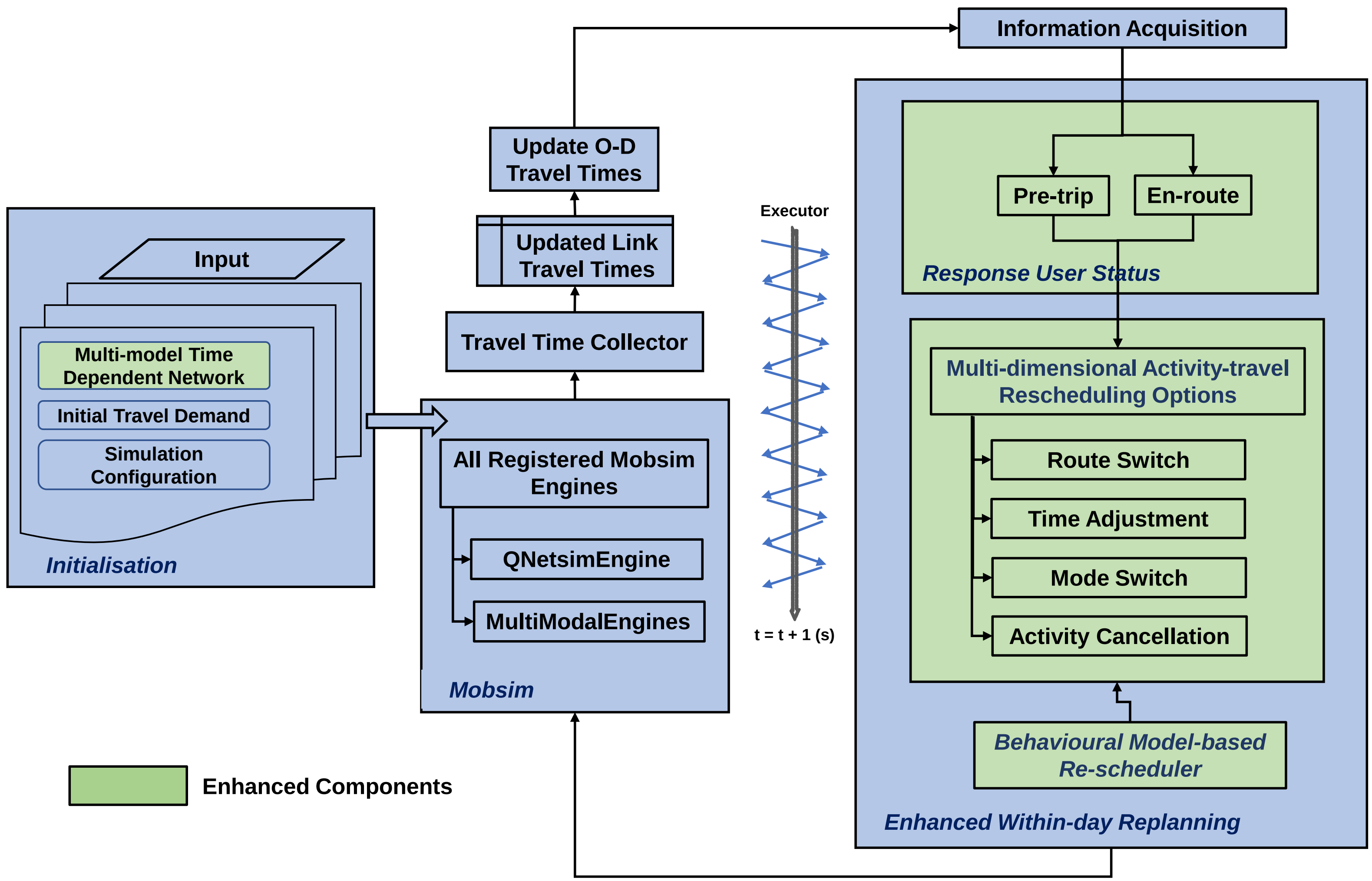


Figure 4 - 2 Building blocks of Enhanced Within-Day Replanning Module

The green shaded sections in Figure 4-2 highlight the following four enhancements to the MATSim Within-day Replanning Module:

1 **Multi-modal time-dependent transport network:** The impacts of transport disruption on both private vehicles and public transport services were addressed by extending the model to simulate the impact on scheduled public transport services within the disrupted network circumstance.

2 **Response user information status:** A feature was developed to disseminate real-time traffic information to both en route travellers and agents engaged in activities (pre-trip travellers). This allows agents to access current network conditions regardless of their state, enabling those already travelling to adjust their travel and those still at activities to reconsider upcoming plans in response to prevailing conditions.

3 **Multi-dimensional activity-travel rescheduling options:** Upon receiving traffic information about a disruption, en route agents reconsider their ongoing travel. Agents prior to departure, on the other hand, evaluate a range of multi-dimensional rescheduling alternatives to their current schedule, including route switching, departure time adjustment, mode change, or even cancelling subsequent activities and associated trips.

4 **Flexible behavioural model supported re-scheduler:** The re-scheduler was enhanced to model agents' choice-making behaviour in the event of a disruption, accounting for the attributes of alternative schedules and employing multiple decision-making approaches to evaluate and select among these alternatives.

These extensions enable agents to evaluate and consider alternative choices dynamically. The activity-travel demand model and the dynamic traffic assignment model communicate with each other continuously over the time axis, allowing travellers to respond to real-time changes in traffic conditions. As a result, the enhanced features require more frequent state updates and behavioural evaluations for agents, increasing both memory usage and processing time. The overall computational cost is influenced by the complexity of the network and the size of the simulated population, with larger-scale and more detailed scenarios leading to substantially longer runtimes. Section 4.4 details each of the enhanced components within the MATSim Within-day Replanning framework.

To activate the enhanced Within-Day Replanning components, a customised *EnhancedWithinDayMobsimListener* was developed and implemented in Java. This listener extended MATSim's default WithinDayMobsimListener[1] functionality. The customised listener was registered within the Main function, which overrides MATSim's default execution workflow to ensure that the enhanced replanning procedures were initialised and executed during the simulation runtime.

To represent multi-modal disruption scenarios, the time-dependent networks for both private cars and public transport services are specified in the configuration file, together with the parameters governing simulation operation and the invocation of replanning modules. During initialisation in the Main function, the configuration file was loaded together with the customised classes in the *EnhancedWithinDayMobsimListener*, ensuring that the simulation run with the specified disruption settings and enhanced replanning capabilities. All required resources, including the customised Java code, the configuration file, and the associated input datasets, have been deposited in the University PURE system.

4.4 Components of Enhanced MATSim Within-day Replanning Module

4.4.1 Multi-modal time-dependent transport network

As introduced in Section 3.5, MATSim's Within-day Replanning functionality enables the simulation of time-dependent networks where links may be subject to volume restrictions or closure. However, the current implementation does not account for the impact of such disruptions on public transport services, leading to an incomplete representation of transport performance during disruptive events.

As illustrated in Figure 4-3, the enhancement enables the simulation to capture the dynamics introduced by the unforeseen transport disruption affecting both private and public transport service. The routing algorithm accounts for these evolving network

[1] For the default package documentation of **org.matsim.withinday**, see: MATSim Doxygen – WithinDay Package. An illustrative implementation of the code examples can be found in the MATSim GitHub repository: Within-Day Replanning from Plans.

conditions and can update agents with routings. Consequently, the activity–travel demand model and dynamic traffic assignment adapt continuously to these updated network conditions. This enhancement to the MATSim's Within-day Replanning provides a more comprehensive presentation of real-world transport scenarios.

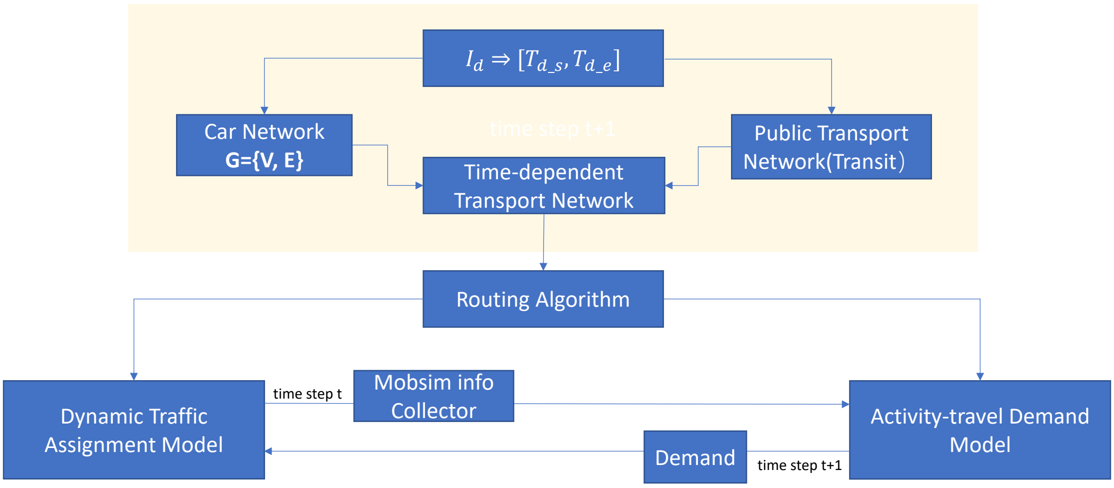


Figure 4 - 3 Framework in Within-day Replanning for modelling impacts of network disruptions under user information provision

The impact of disruption on public transport was modelled through service availability, specifically by cancelling services on affected transit lines within the defined time window of disruption. Transit services not affected by the disruption continued to operate in accordance with the scheduled timetable, with public transport vehicles adhering to planned boarding and stopping times at each station and offering sufficient passenger capacity.

As described in Section 3.2.2, there are two files defining the transit service in MATSim, one describing the transit vehicle *transitVehicles.xml* (as shown in Figure 4-4) and the other one explaining the transit service *transitSchedule.xml* (as shown in Figure 4-5). The structure of the dataset is demonstrated below:

```xml
<?xml version="1.0" encoding="UTF-8"?>
<vehicleDefinitions xmlns="http://www.matsim.org/files/dtd" xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
xsi:schemaLocation="http://www.matsim.org/files/dtd http://www.matsim.org/files/dtd/vehicleDefinitions_v1.0.xsd">
	<vehicleType id="bus_90pax">
		<capacity>
			<seats persons="52"/>
			<standingRoom persons="90"/>
		</capacity>
		<length meter="18.0"/>
		<width meter="1.0"/>
		<accessTime secondsPerPerson="1.0"/>
		<egressTime secondsPerPerson="1.0"/>
		<doorOperation mode="serial"/>
		<passengerCarEquivalents pce="1.0"/>
	</vehicleType>

	<vehicleType id="tram_93pax">
		…
	</vehicleType>

	…

	<vehicle id="1_0" type="bus_90pax"/>
	<vehicle id="1_1" type="bus_90pax"/>
	<vehicle id="1_2" type="bus_90pax"/>
	<vehicle id="1_3" type="bus_90pax"/>
	<vehicle id="1_4" type="bus_90pax"/>
	…

</vehicleDefinitions>
```

Figure 4 - 4 An example of transitVehicles file specifying vehicle type settings and associated IDs

```xml
<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE transitSchedule SYSTEM "http://www.matsim.org/files/dtd/transitSchedule_v1.dtd">
<transitSchedule>
	<transitStops>
		<stopFacility id="9445451_a" x="455551.5822241595" y="5728935.910032587" linkRefId="6050" isBlocking="false"/>
		<stopFacility id="9445451_b" x="455551.5822241595" y="5728935.910032587" linkRefId="6051" isBlocking="false"/>
		…
	</transitStops>

	<transitLine id="10">
		<transitRoute id="10">
			<transportMode>pt</transportMode>
			<routeProfile>
				<stop refId="9470168_a" arrivalOffset="00:00:00" departureOffset="00:00:00" awaitDeparture="true"/>
				<stop refId="9470294_b" arrivalOffset="00:03:00" departureOffset="00:03:20" awaitDeparture="true"/>
				…
			</routeProfile>

			<route>
				<link refId="3503"/>
				<link refId="9962"/>
				…
			</route>

			<departures>
				<departure id="10_18240.0" departureTime="05:04:00" vehicleRefId="10_0"/>
				<departure id="10_20040.0" departureTime="05:34:00" vehicleRefId="10_1"/>
				…
			</departures>
		</transitRoute>
	</transitLine>

	<transitLine id="12">
		…
	</transitLine>

	…

</transitSchedule>
```

Figure 4 - 5 An example of transitSchedule file specifying transit stops, routes, and timetables for transit lines

A process was implemented to capture the impact of network disruptions on public transport services. Based on the predefined disrupted links specified in the *network event* file, the affected public transport services were identified by referencing the *transitSchedule* file, which maps transit routes to the corresponding road network links. Public transport services operating within the disrupted time window were subsequently withdrawn from availability to users.

The specific steps applied to the original *transitSchedule* are outlined below, and Figure 4-6 illustrates the workflow of simulating the transit network event:

Step 1:

Identify disrupted link(s) l_{dis} from the links E on transport network G.

Step 2:

Identify disruptive time window $[T_{d\_e} - T_{d\_s}]$.

Step 3:

Locate the affected transit line(s).

Search if any transit line overlaps with any link in the set of disrupted links in the expected disruptive time window $[T_{d\_e} - T_{d\_s}]$.

$\forall\{route_i\} \subseteq \{transitLine_{1,} \dots\ transitLine_n\}$,

$\forall\ link\ refId\ \in \{route_i\}\text{:}\ link\ refId \cap l_{dis}$,

If $\exists\ link\ refId \cap l_{dis} \notin$ null,

Locate the identified $transitLine_i$

Step 4:

Locate affected service on the identified $transitLine_i$

Search if any transit service on the $transitLine_i$ is affected during the disruptive time window $[T_{d\_e} - T_{d\_s}]$.

$\forall\{departureTime_j\} \in transitLine_i$,

If $T_{d\_s} \leq departureTime_j \leq T_{d\_e}$

Locate $departureTime_j, j = 1, \dots n$.

Step 5:

Cancel the transit service by removing the identified departures from the *transitSchedule*.

$$departureTime_j \notin transitLine_i, \ i, j = 1, \dots n.$$

Step 6:

Publish the adapted *transitSchedule* dataset.

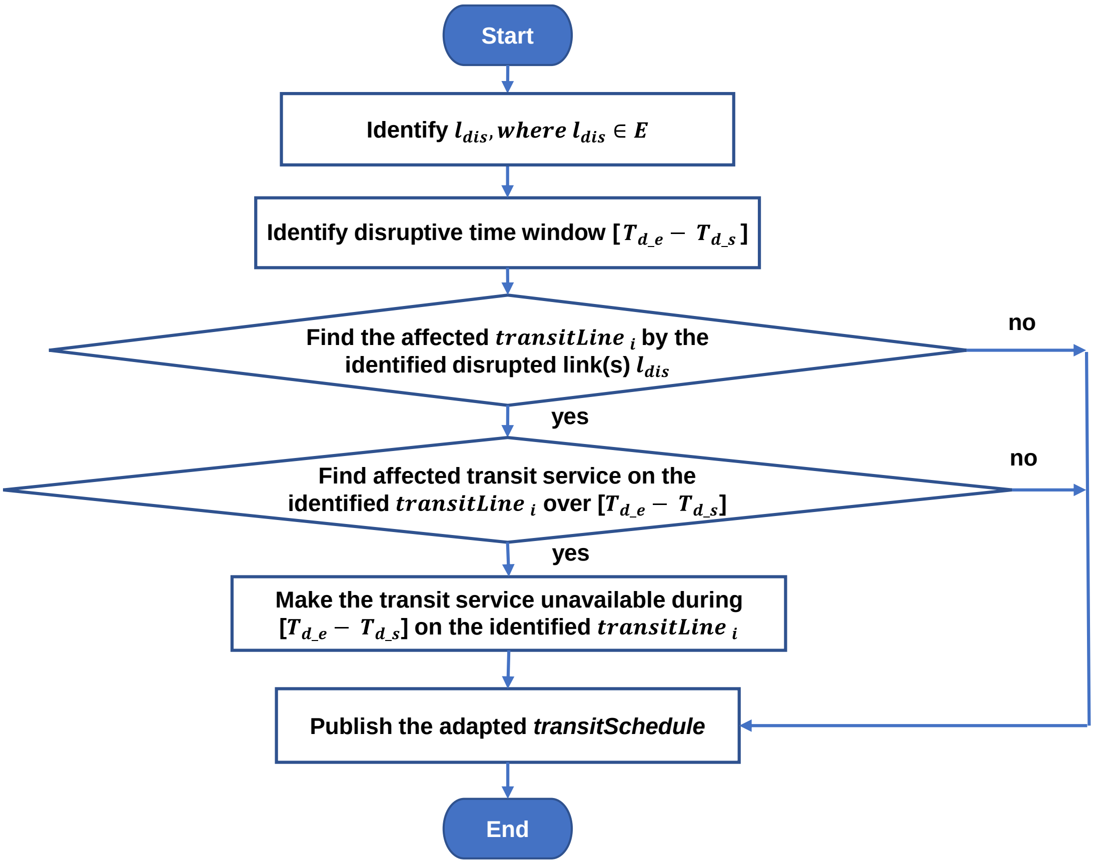


Figure 4 - 6 Process of simulating the public transport NetworkChangeEvent

Through the process outlined above, a time-dependent representation of public transport services is established, enabling the simulation to reflect variations in service availability across different temporal windows. Depending on the scale and complexity of the transport network, this procedure may be undertaken manually in relatively simple or small-scale systems, whereas for larger or more intricate networks it is more appropriately implemented as an automated workflow through coding.

4.4.2 User response to travel information

Travellers vary in their awareness of disruptions and access to traffic information directly shape their ability to adapt travel plans. This enhancement aims to address this dimension by identifying agents, whether pre-trip or en route, whose plans are affected by a disruption, and providing them with up-to-date travel information to support the replanning of their daily schedules. By integrating varying states of information accessibility into the model, the enhancement captures heterogeneity in travellers' situational awareness and adaptive decision-making, both at the pre-trip stage, when route and mode choices are formulated, and en route, when adjustments are made in response to evolving network conditions. This is crucial for realistically representing behavioural responses to disruptions and for improving the model's capacity to simulate dynamic, real-world transport scenarios.

Three different categories of access to user information provision states were defined. The first category ($C1$) comprises all agents who rely solely on their personal experiences of network conditions to make activity-travel engagement decisions. These individuals have their initial plan comprising the activities, destinations, activity durations, and transportation modes which is based on their understanding of network conditions in the past. Agents in this category may respond to disruptions differently when additional information states, as defined in C2 or C3, become available. The second category ($C2$) includes individuals who use real-time information about current network conditions to make pre-trip decisions on their activity-travel choices. These individuals consider the network conditions to plan their activity and transportation before they embark on their trip. The third category ($C3$) comprises individuals who are already en route and have access to real-time traveller information via in-vehicle navigation systems or smartphone applications (such as Google Maps (Google, 2023)), enabling them to adjust their route or make further choices in response to evolving network conditions. It is essential that categories of $C2$ and $C3$ are sub-sets of $C1$, from which the corresponding replanning actions originated. If no replanning actions are taken, agents will continue to execute their original daily schedule as initially planned. The relationship between these categories of agents is illustrated in Figure 4-7.

During a given timestep in the simulation period, notified agents whose original plan was affected by disruption (subsets of $C2$ and $C3$) evaluated whether to adjust their schedule or not. It's worth noting that $C2$ and $C3$ are not mutually exclusive, they are dynamic sets that vary at each replanning time step, producing different subsets over time. The range of rescheduling options available depends on agent's state, i.e., whether currently traveling on the network or engaged in an activity, which will be explored further in the subsequent section. The updated plan is then incorporated and executed in the Mobsim alongside agents whose original schedules remain unaffected, before the simulation moves to the next time step. To optimise computational efficiency, this process is activated only during periods of transport network disruption. Outside of the disruption time window, agents rely on their habitual understanding of network conditions and execute their day schedule as planned.

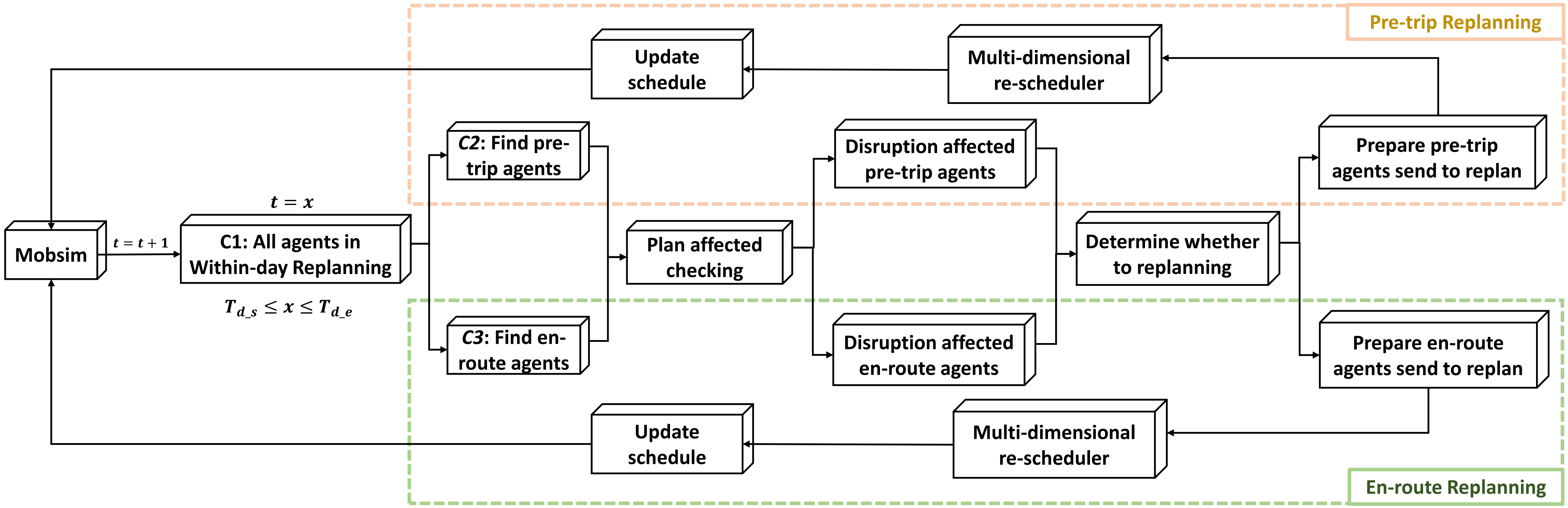


Figure 4 - 7 Process flow of user information provision state

Pre-trip Rescheduling Implementation

```
@Find pre-trip agents
    For all agents in the population
    If currentTime = t
    If agents.currentState is instance of activity
        Get currentActivity i
        Get nextLeg with index(i+1)
        Get nextLeg.getRoute
        If (DisruptedLinks.contains(nextLeg.getRoute())
                Get agentID
                New container for disruptionAffectedPretripAgents
                Add agentID to disruptionAffectedPretripAgents
    @Implementing pre-trip rescheduling
    For all agents in disruptionAffectedPretripAgents container
      Get agent's executedPlan
      Get currentActivity
      Get nextTrip
      Get nextActivity
      MakeReschedulingDecisions(agent, currentNetworkStates)
      Update agents' Plan
```

Figure 4 - 8 The implementation of pre-trip rescheduling

<u>**En-route Rescheduling Implementation**</u>

```
@Find en-route agents
    For all agents in the population
    If currentTime = t
        For links on NetsimNetwork
            For vehicles on links
                For MobsimDriverAgents on vehicles
                    Get enRouteAgents
                    If (DisruptedLinks.contains(enRouteAgents.getRoute())
                        Get agentID
                        New container for disruptionAffectedEnrouteAgents
                        Add agentID to disruptionAffectedEnrouteAgents
    @Implementing en-route rescheduling
    For all agents in disruptionAffectedEnrouteAgents container
            Get agent's executedPlan
            If currentPlanElement instanceof Leg
            Get currentTrip
            Get nextActivity
            MakeReschedulingDecisions(agent, currentNetworkStates)
            Update agents' Plan
```

Figure 4 - 9 The implementation of en route rescheduling

The implementation of pre-trip and en route rescheduling is illustrated in Figure 4-8 and Figure 4-9. For each agent category, the process involves two main steps: identifying the targeted agents and executing the corresponding rescheduling actions. A key input to this process is the set of multi-dimensional alternatives available to agents at different states, together with the rescheduling decision-making mechanism that evaluates these options. The details of these components are elaborated in the following sections.

4.4.3 Multidimensional activity-travel rescheduling

In practice, travellers adopt a range of within-day rescheduling options when confronted with unexpected disruptions. However, as reviewed in Section 3.6, the existing Within-day Replanning module has focussed on route choice behaviour. This gap highlights the need to extend dynamic activity–travel model to capture the bidirectional interactions between transport network conditions and a wider spectrum of rescheduling behaviours.

Travellers who are already en route have fewer options at their disposal. With access to real-time information via smartphone applications or in-vehicle navigation, they can engage in en route rescheduling. Although other adjustments may be possible, this simulation focuses on en route choice, as it represents the most essential and immediate response to evolving network conditions.

Pre-trip rescheduling occurs when individuals are informed of disruptions prior to departing from their current activity location. In such circumstance, travellers who are still engaged in an activity and has not yet commenced their travel can consider a broader range of strategic adjustments across multiple dimensions, including route, departure time, mode choice. In the post-pandemic era, the widespread adoption of remote working, supported by Information and Communication Technologies (ICTs), has introduced an additional feasible alternative: working from home, in response to disruption. This option may replace the need to undertake the commute altogether, and therefore leading to the cancellation of the planned activity and associated travel.

Figure 4-10 presents a flowchart illustrating the logic underlying multi-dimensional rescheduling options for pre-trip agents when network disruptions occur and real-time traveller information is available. Depending on the activity context, such as the type, timing constraints, and priority of the planned activity, travellers upon receiving updated network information assess the situation and consider a set of possible responses. This includes maintaining the original route, switching to an alternative route, changing to a different mode. For any of these options, agents then evaluate potential departure times, which are further assessed against the available time budget to determine their feasibility. Alternatively, agents may choose to cancel the planned activity and its associated trip. This process continues until a rescheduling decision is reached, at which point the agent's activity–travel plan is updated to reflect the chosen adjustments. To facilitate the selection among these enhanced multi-dimensional rescheduling options, a behavioural modelling framework is required, operationalised through a re-scheduler, which will be introduced in the following section.

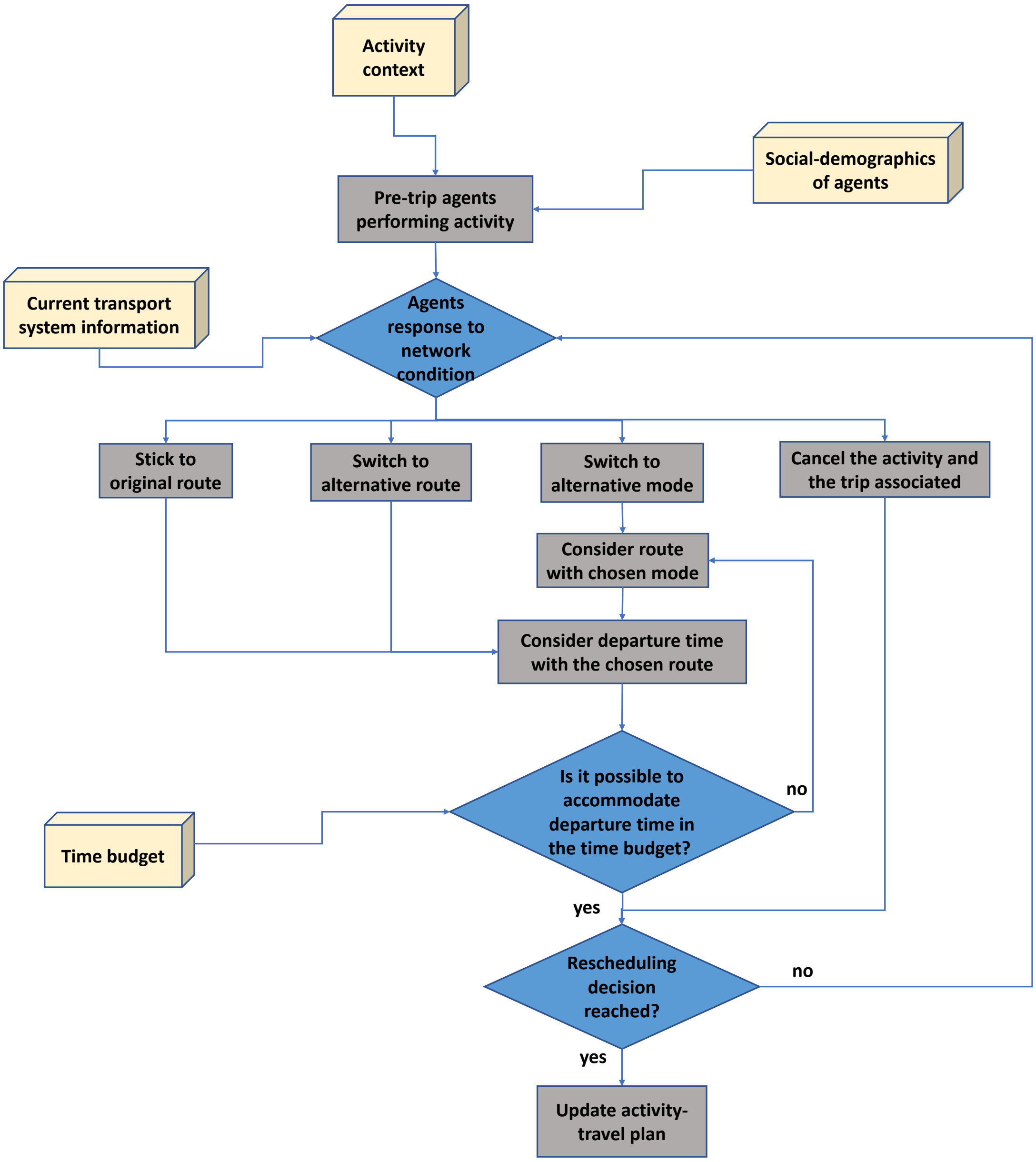


Figure 4 - 10 A flowchart *depicting the decision-making process for pre-trip agents' activity-travel rescheduling in response to network delay events, with consideration for real-time traveller information*

The mode switch behaviour in this enhancement is limited to private vehicle users opting to switch to public transport. This reflects a key element of pre-trip adaptation, particularly relevant for commuting trips on regular weekdays. By contrast, mode shifts in the opposite direction - switching from public transport to private vehicle, depends on car availability and parking constraints. These factors fall outside the scope of this research.

4.4.4 Flexible behavioural model supported re-scheduler

The behavioural model embedded within the existing Within-day Replanning module in MATSim facilitates route switching through deterministic shortest-path selection. However, such approach overlooks critical behavioural dimensions, including cognitive constraints and psychological influences on decision-making. In the context of within-day replanning it is essential that the modelling framework allows sufficient flexibility to account for how individuals dynamically respond to disruption-induced uncertainties via multi-dimensional rescheduling strategies. This requires extending MATSim's Within-day Replanning to incorporate alternative paradigms, such as heuristic-based and situational decision-making models, particularly under conditions of uncertainty and associated time pressure.

The enhanced Within-day Replanning module extends beyond deterministic shortest-path selection by incorporating a more adaptable behavioural architecture. To operationalise this, a heuristic decision-making rule was implemented following the 'adaptive toolbox' framework proposed by Gigerenzer and Holbrook (2001), which characterises decision-making as a set of cognitive heuristics comprising search, stopping, and decision rules, grounded in core capacities such as recognition memory. The operational implementation of these heuristic rules, including the detailed rescheduling logic and condition–action structures governing agent behaviour, is further specified in Section 5.3.2. By moving beyond conventional utility-based assumptions, this framework enables the representation of a broader spectrum of decision-making processes in response to network disruption and real-time information provision, thereby facilitating a more behaviourally grounded simulation of activity–travel rescheduling.

4.5 Conclusions and Discussions

Capturing travellers' adaptive responses to unexpected transport network disruptions is essential for realistically evaluating system performance and behavioural dynamics under real-world circumstance. A critical enabler of such adaptability is the provision of real-time traffic information, which allows individuals to modify their travel plans in response to the evolving network conditions. To support this objective, the Within-day

Replanning framework in MATSim was enhanced to enable a more comprehensive and realistic representation of traveller decision-making under disrupted network scenarios, thereby improving the overall precision of the simulation.

The enhanced Within-day Replanning framework integrates several key extensions to better capture travellers' adaptive responses under network disruption. It incorporates a multi-modal, time-dependent transport network that accounts for both private and public transport services, enabling realistic simulation of disrupted conditions. Real-time traffic information is modelled across different user states, allowing agents to receive updates either en route or before departure. A wide range of rescheduling options is supported, including changes to route, departure time, travel mode, and even activity cancellation. In addition, the replanning behavioural model is enabled to accommodate diverse decision-making paradigms, extending beyond traditional utility-based theory to incorporate other behavioural approaches.

Altogether, these enhancements strengthen the behavioural realism and methodological flexibility of the Within-day Replanning module, allowing it to more accurately reflect the complexities of real-world activity-travel decisions under uncertainty. This development not only contributes to the refinement of agent-based transport modelling but also provides valuable insights for the design of responsive transport policies and information strategies in increasingly dynamic urban environments.

To illustrate the application and potential of this enhanced framework, a demonstration model has been developed and will be presented in Chapter 5. This example serves to present how the enhanced module can be operationalised within MATSim and evaluated under experimental conditions.

Chapter 5 Application of Extended Within-Day Replanning Module – Cottbus Case Study

5.1 Introduction

This chapter presents a case study to demonstrate and test the capabilities of the enhanced Within-day Replanning module in MATSim. Building upon the methodological advancements introduced in Chapter 4, the study illustrates how these enhanced features are implemented and assessed within a realistic urban context. Through the simulation of disruption and corresponding user responses in a metropolitan setting, the case study highlights the responsiveness and adaptability of the improved replanning module. Therefore, it demonstrates the framework's potential to support more dynamic and inform urban mobility and transport planning. This case study serves as a valuable reference for researchers and practitioners seeking to apply MATSim's Within-day Replanning functionality in empirical transport studies.

The chapter begins with an overview of research area for the case study in section 5.2, followed by the development of simulation scenarios in section 5.3. Section 5.4 to 5.6 present a detailed analysis of the simulation outcomes across different scenarios including a sensitivity analysis of network performance. Finally, Section 5.7 concludes the chapter by summarising the key insights.

5.2 Case Study

Building on the extended functionality described in the previous chapter, the enhanced within-day replanning module was applied to a real-world scenario to evaluate its performance. This section introduces the process of scenario setup, including the multi-modal transportation networks, as well as the population dataset.

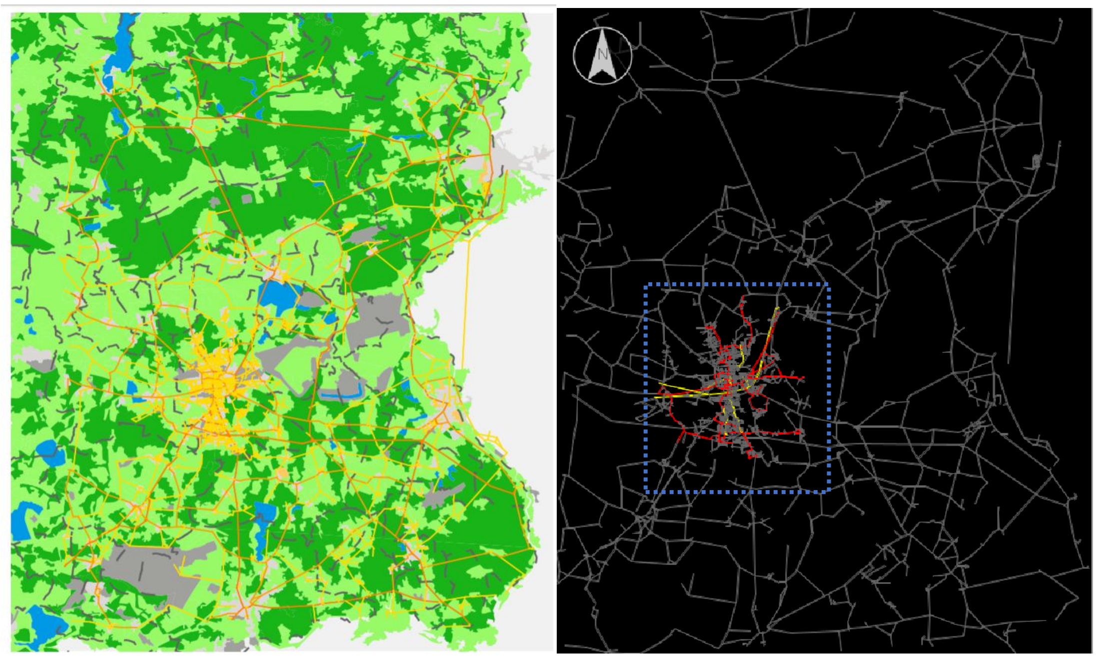
The case study was carried out in Cottbus, which is located in the south of the federal state of Brandenburg, Germany. The full Cottbus scenario covers the area of the "Spree-Neiße" administrative district which encloses the city of Cottbus. There are approximately 114,429 people dwelling in the administrative area of Spree-Neiße, including 100,219 people living in the Cottbus to date 31/12/2018 (*Cottbus Population Statistics*, 2019). The input data of the Cottbus scenario including network and travel demand were created by Grether (2014) in a previous study. The scenario has been applied in many MATSim studies on different topics, for example traffic signal control (Grether, 2014)(Thunig, Kühnel and Nagel, 2019) and Demand Responsive Transport (DRT) (Bischoff, Führer and Maciejewski, 2018). The data employed in this research was an excerpt of the full Cottbus scenario, which only depicts core urban areas in terms of the geographic scope. The scenario data are available to the public on MATSim webpage and GitHub[2], where it can be downloaded for research purposes.

5.2.1 Network and travel demand

The map of Cottbus traffic network was derived from OpenStreetMap (*OpenStreetMap*, 2019), depicting the real-world network with given coordinates. The network comprises all streets within the Cottbus city boundary and only the main roads in the wider administrative district. The network contains 4096 nodes and 8192 links with each link containing the attributes of coordinate, capacity, and free speed. Figure 5-1(a) shows the network on top of the map of land use. Figure 5-1(b) depicts the Cottbus' road network with the blue rectangle showing the inner-city transport network. The traffic network is denoted by the grey lines, public transport as red lines and other modes (e.g.

[2] Data used in this study were downloaded from MATSim webpage http://matsim.org/datasets, Access date: 03/2018. It is currently can be found from GitHub: matsim-maas/scenarios/cottbus https://github.com/matsim-org/matsim-maas/tree/master/scenarios/cottbus.

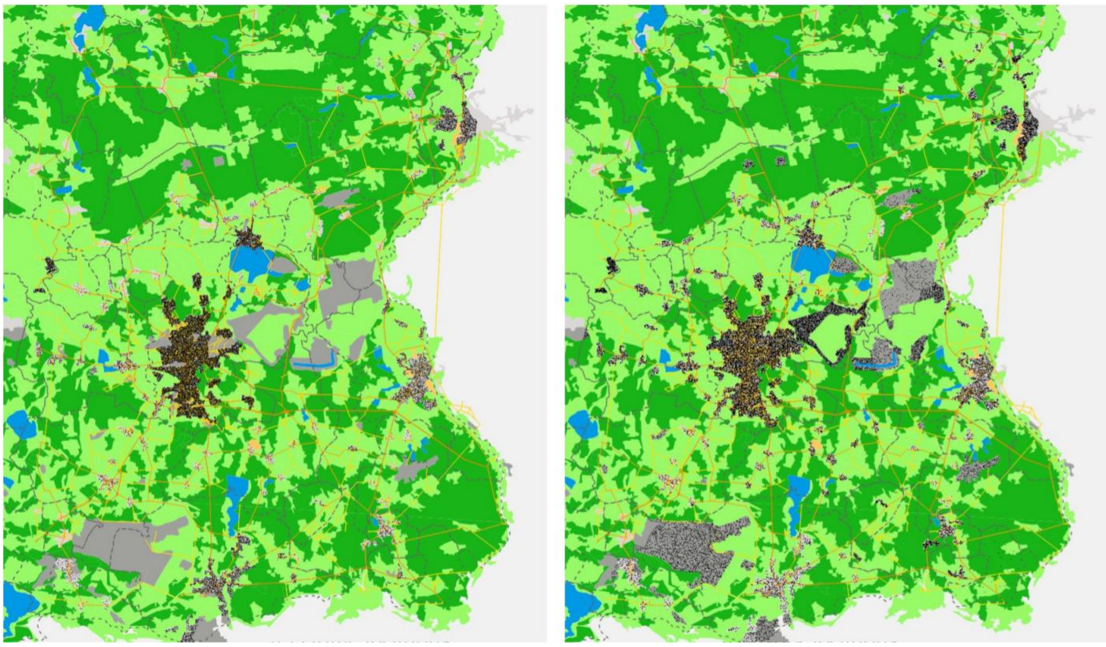
train) marked with yellow lines. The public transport options considered in this study including buses, trams, and trains.



(a) (b)

Figure 5 - 1 Cottbus network (a) covering the land use with municipality borders, source: (Grether, 2014) (b) showing inner-city traffic within the blue square

The synthetic population was produced by Grether using data from the German employment agency (Grether, 2014). Each commuter has an independent daily plan containing their activities during a typical working day as well as the connecting trip and mode. In the simulation, 6813 commuters, representing approximately 7% of the total Cottbus population were modelled as employed. Transport mode of both car and public transport were available to the commuters. Figure 5-2 (a) and 5-2 (b) shows the geospatial distribution of home and work locations, respectively, with locations represented by black dots. Activity locations were randomly assigned in accordance with the land use data, i.e., home activities were restricted to urban residential areas, while work activities were located within designated industrial or commercial zones.



(a) (b)

Figure 5 - 2 Synthetic population for the Cottbus scenario, geospatial locations of (a) home and (b) work. Source: (Grether, 2014)

It should be noted that the Cottbus case study was designed as a simplified and illustrative representation of an urban transport system, rather than a fully calibrated real-world model. These simplifications are intentionally introduced to ensure computational feasibility and to allow the analysis to focus on the behavioural mechanisms of rescheduling and system responses to disruption, thereby demonstrating the implementation and performance of the enhanced modelling framework.

5.2.2 Modelling transport network disruption

As described in the previous chapter, the enhanced MATSim Within-day Replanning module supports the simulation of time-dependent networks for both road traffic and public transport. This capability enables the modelling of scenarios involving accidents or disruptions that lead to volume restrictions or complete closures of major link or multiple network links.

In the case study, the network disruptions occurred between 6:00 am and 10:00 am on four major bridges that connect the west and east sides of the city, serving as key commuting corridors. During the defined time window, the capacity of the links in both directions on the affected bridges was reduced by 50%, with full capacity restored thereafter. As shown in Figure 5-3, the disrupted bridge links are highlighted with the colour of orange arrows indicating the route direction. To assess the impact of network disruption on commuters' rescheduling choice, four monitoring points (indicated by green lines with arrows) located on alternative routes to the disrupted major bridges connecting the west and east sides of the city, were established to observe changes in traffic volume.

As for the public transport event, nine scheduled departures of a particular bus service were cancelled. These cancellations affected the morning peak period and was expected to lead to increased waiting times and reduced service availability for passengers along the route. The adjustment reflects temporary changes in public transport service operations due to network disruptions.

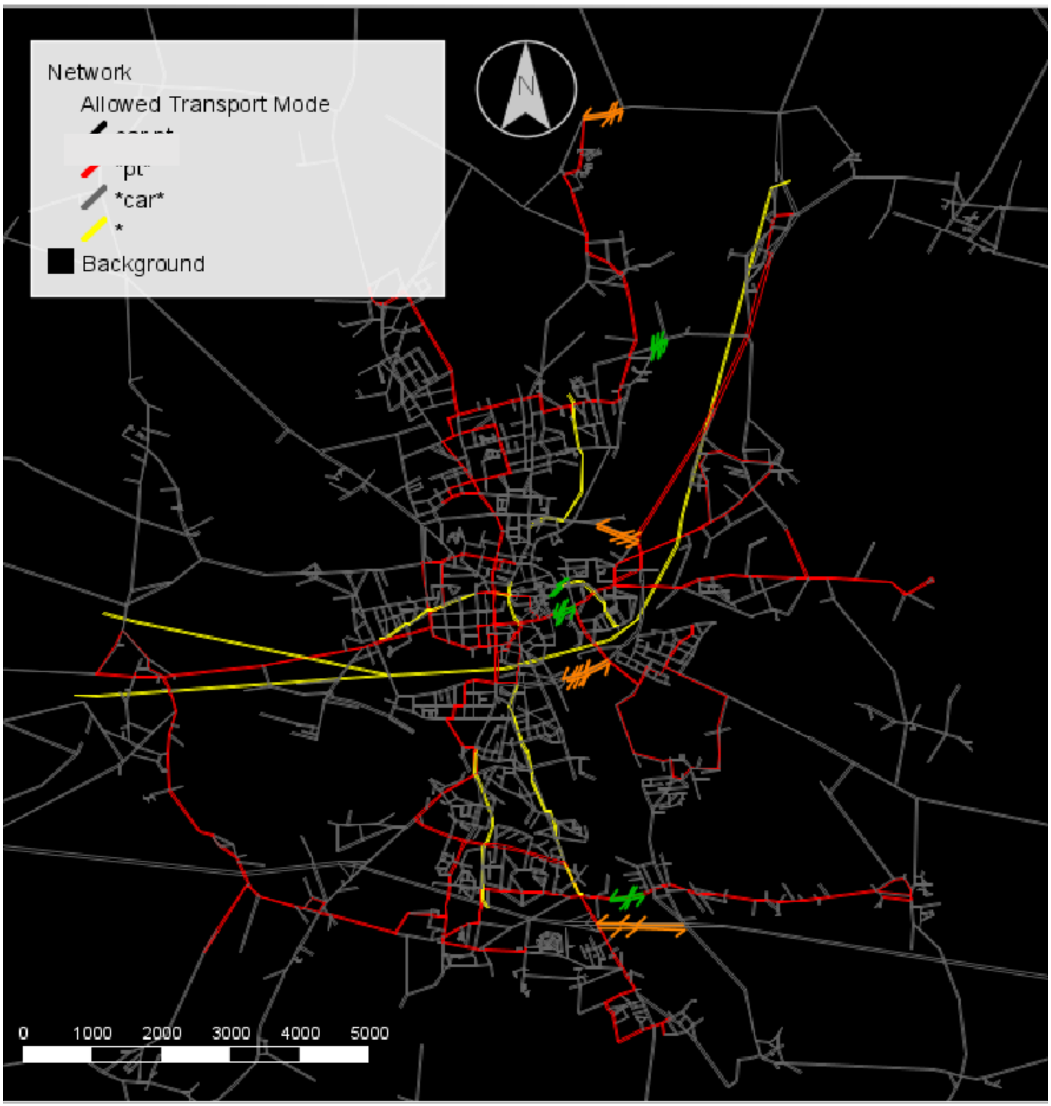


Figure 5 - 3 A map of network zooms in Cottbus inner-city traffic. Line colour description: traffic network - grey lines; public transport - red lines; other modes - yellow lines; disrupted bridges - orange line with arrows; watch points- green line with arrows

5.3 Simulation Scenario Development

The primary objective of the scenario development is to demonstrate the applicability of the enhanced Within-day Replanning model in evaluating the impacts of disruptive network scenarios on traveller behaviour. This section specifically examines the role of real-time traffic information in facilitating travellers' rescheduling decisions under such conditions. The analysis aims to provide insights into the extent to which information-aided rescheduling can enhance the operational efficiency and robustness of urban transport networks, as well as improve overall system resilience during periods of disruption.

5.3.1 Simulation scenarios

The three experimental scenarios simulated and compared in this study are detailed below.

- Experiment (Exp.) A: The baseline scenario.

The baseline simulation was implemented utilising the input data of network and synthetic population with the simulation configuration. The baseline scenario represents the normal demand pattern without any network disruption occurrence. All the agents have the opportunity to adjust their travel plans at the end of the day. To ensure that the simulation results converge to a stable state, the model was run for 100 iterations, representing day-to-day learning and adaptation. In the first 80 iterations, agents generated, scored, and retained alternative plans through iterative learning, while in the final 20 iterations they probabilistically selected among the retained plans based on their relative performance.

- Exp. B. The disruption scenario without information provision.

In this scenario, the planned network disruptions were introduced as outlined in the preceding section. It is assumed that individuals have no access to information either prior to departure or during their journey, implying that the dynamic changes in the network are entirely unknown to them. Travellers are presumed to remain unaware of the disruptions and proceed with their schedules based on habitual behaviour, following their routine travel patterns as established in the baseline scenario.

- Exp. C. The rescheduling scenario with information provision.

This scenario aims to investigate the influences of short-term transport disruption on the transport system with the provision of real-time traffic information. The transport network was configured to reflect the same disruptions as described in the preceding disruption scenario. Agents' daily plans were derived from the output of the baseline scenario. Affected agents were modelled to make multi-dimensional rescheduling decisions, guided by the specified rescheduling logic and supported by real-time traffic information. A sensitivity analysis of 10 cases was conducted as a pre-cursor to Experiment C to test how different assumptions on traveller responsiveness shaped network-level outcomes. The results informed the choice of parameter settings applied in Experiment C.

5.3.2 Rescheduling behavioural assumptions input

- Rescheduling Logic

Agents were modelled to respond adaptively to disruptions through multi-dimensional rescheduling decisions, including route switch, departure time adjustments, mode switch, and trip cancellation. These behavioural responses were governed by a simplified rule-based model embedded within the Within-day Replanning module, based on the adaptive toolbox framework proposed by Gigerenzer and Holbrook (2001).

To clarify the implementation of heuristics within the Re-scheduler, adaptive toolbox framework was operationalised through three key components: search, stopping, and decision rules. The search rule is represented by the generation of a limited set of feasible rescheduling alternatives (e.g. route change, departure time adjustment, mode switch, or activity cancellation), conditioned by the agent's current state, activity context, and available information. The stopping rule is governed by constraints such as the decision time budget and feasibility conditions (e.g. temporal constraints on departure), which restrict the extent of alternative exploration. The decision rule is implemented through condition–action logic, where agents evaluate these alternatives and select an acceptable option based on disruption severity, perceived travel conditions, and behavioural parameters.

This framework provides a flexible representation of choice behaviour, capturing how individuals make decisions in real-world context. It offers greater explanatory power than approaches based solely on a single heuristic or full rational optimisation. Rather than performing exhaustive optimisation, agents follow simplified, context-dependent decision processes consistent with bounded rationality.

Within this adaptive decision-making framework, arrival time emerges as a critical factor in daily commuting. Commuters are generally insensitive to minor fluctuations in arrival time, as long as they fall within a tolerable 'indifference band', defined as the condition where the difference between actual and preferred arrival time (PAT) is below a specified threshold (Mahmassani and Herman, 1990; Srinivasan and Mahamassani, 2002). When outcomes deviate beyond this threshold, travellers are likely to adapt their routines through heuristic adjustments.

The rescheduling process assumed that options requiring greater behavioural change encounter stronger resistance. Car users are more likely to adjust route or departure time than to switch to public transport, while activity cancellation is considered a last resort (Marsden *et al.*, 2016). Agents sequentially evaluate available options and either select the first acceptable one or forgo rescheduling altogether. Pre-trip travellers engaged in activities may adopt multi-dimensional rescheduling, while en route travellers can only adjust their route choice. As summarised in Table 5-1, an overview of the logic guiding agents' pre-trip multi-dimensional rescheduling decisions is presented. Further details, including a graphical illustration, are provided in Appendix A. This rescheduling logic, under the above assumptions, is introduced as an input to support travellers' choice behaviour among alternative schedules and enable network dynamics within the simulation, rather than as a subject of detailed analysis in its own right.

As the logic outlined in Table 5-1, upon receiving traffic information at time T, travellers scheduled to depart at d_o via the original route r_o with travel time t_o may reconsider their schedules if the disruption causes t_{r_o} to exceed a predefined tolerance. Parameters θ_1 and θ_2 denotes the indifference band for late arrival along the original route r_o under pre-trip and en route conditions. Parameters γ_1 and γ_2 capture the relative indifference bands between the cost of the original route r_o and that of the available shortest path r_{sp} in each case. The parameter θ_{WfH} governs the likelihood of activity cancellation.

Table 5 - 1 Rescheduling logic of rescheduling options (for agents in activity)

Reschedule Option	Searching Rules	Stopping Rules	Decision Rules
Route Switch	• Search for alternative route, if: $t_{r_o} - t_o \geq \theta_1$ • Stick to the original route and consider departure time choice, otherwise.	• Stop searching if: r_{sp} between the specific OD is found.	• Change to the shortest path first, if: $t_{r_o} - t_{r_{sp}} \geq \gamma_1$ • Stick to original route and consider departure time choice, otherwise.
Departure Time	• Search for an earlier departure time, if: $d_o + t^* \geq PAT + \theta_1$ • Departure at original time, otherwise.	• Stop searching if: $d^* = min\ (PAT + \theta_1 - t^*, d_o - t_{bud}{}^*)$ is found	• Change to earlier departure time if: $d^* + t^* \leq PAT + \theta_1$ • Consider mode switch, otherwise.
Mode Switch	• Search for available public transport, if: $d^* + t^* > PAT + \theta_1$ • Keep the current mode of car, otherwise.	• Stop searching if: $r_{sp,bus}$ with $t_{r_{sp,bus}}$ and $d_{bus}$are found.	• Change to public transport if: $d_{bus} + t_{r_{sp,bus}} \leq PAT + \theta_1$ • Consider trip cancellation, otherwise.
Trip Cancellation	• Consider trip cancellation, if: $d_{bus} + t_{r_{sp,bus}} > PAT + \theta_1$ • Stick to the trip, otherwise.	• Stop searching if: no satisfactory option is reached.	• Cancel the next trip if: $d_{bus} + t_{r_{sp,bus}} > PAT + \theta_{WfH}$ and $d^* + t^* > PAT + \theta_{WfH}$ • Chooses the mode with the earlier time to arrival.

PAT: preferred arrival time; d^*: earliest feasible departure time; t^*: updated travel time.

Refer to the List of Notation for full symbol definitions and to Appendix A for a detailed explanation of the rescheduling logic.

While the applied indifference band reflects the general attitude towards a given origin–destination (OD) pair, an additional parameter was introduced to capture heterogeneity in travel time perception at the individual level. The perceived travel time t_r^* was modelled for the travel time evaluating on a new route or mode, as a function of the estimated travel time t_r, its standard deviation σ_r, specified confidence level c, and a random heterogeneity factor α[3].

$$t_r^* = t_r + c \times \alpha \times \sigma_r. \tag{5-1}$$

In addition to the behavioural rules, the ReS actions were also influenced by several contextual attributes. These include: S_i, representing the severity of impact on each disrupted link; T_{d_s} and T_{d_e}, denoting the start and end time of the transport disruption; I_{int}, the interval at which information notifications are provided; and t_{bud}, the assumed time required for evaluating and making decisions across the available rescheduling options[4]. These parameters collectively shape the timing and likelihood of adaptive responses within the simulation.

- Sensitivity analysis of behavioural assumptions and parameter settings

To examine how behavioural assumptions affect network performance, a sensitivity analysis was conducted by varying key parameters within the behavioural model across ten distinct cases. Table 5-2 tabulates the parameter ranges of the adaptive behavioural model used in different cases for the sensitivity analysis. The variations in parameters, including the indifference band values across cases, were informed by independent datasets reported in existing literature. The rationale for the specified parameter values is provided in Appendix A.

Specifically, Case 2 builds upon Case 1 to examine whether the time consumed in decision-making influences agents' rescheduling outcomes. Cases 3 and 4 explore the

[3] Where α is a random variable sampled from a uniform distribution over $(-1, 0)$ or $(0, 1)$, as determined by the case setup to capture individual heterogeneity in risk attitudes, corresponding to risk-averse and risk-seeking behaviours, respectively. The constant c is estimated here based on an assumption that t_r^* is within a particular confidence level of a normal distribution $N(t_r, \sigma_r)$. For example, c equalling 1, 2 or 3 means a 68%, 95% or 99% confidence level.

[4] Most rescheduling studies overlook the decision-making time budget (t_{bud}), i.e., the time available to make a rescheduling decision at a time point. This parameter accounts for the temporal constraint during decision-making and may influence the strategy adopted—e.g., limited t_{bud} increases the likelihood of fast, heuristic-based choices. Moreover, time consumed at each step reduces the time available for subsequent decisions.

effects of varying lateness tolerances and indifference bands on route choice behaviour. Case 5 investigates the influence of en route replanning on decision outcomes. Cases 6, 7, and 8 capture individual heterogeneity in travel time perception. Case 9 introduces a shorter interval for information provision, while Case 10 examines the impact of delayed information delivery to assess the role of provision frequency.

To mitigate the effects of stochastic variability in the simulation, each scenario, along with its respective cases, was run five times, with the average results used in subsequent analysis. The outcomes of these simulations are presented in the following sections.

While the model parameters were varied to examine their effectiveness and influence on network performance, the rescheduling logic itself is not the focus of this chapter. Rather, it serves as an input to generate plausible traveller responses and enable network dynamics through the simulation.

Table 5 - 2 The values of parameter settings for testing cases

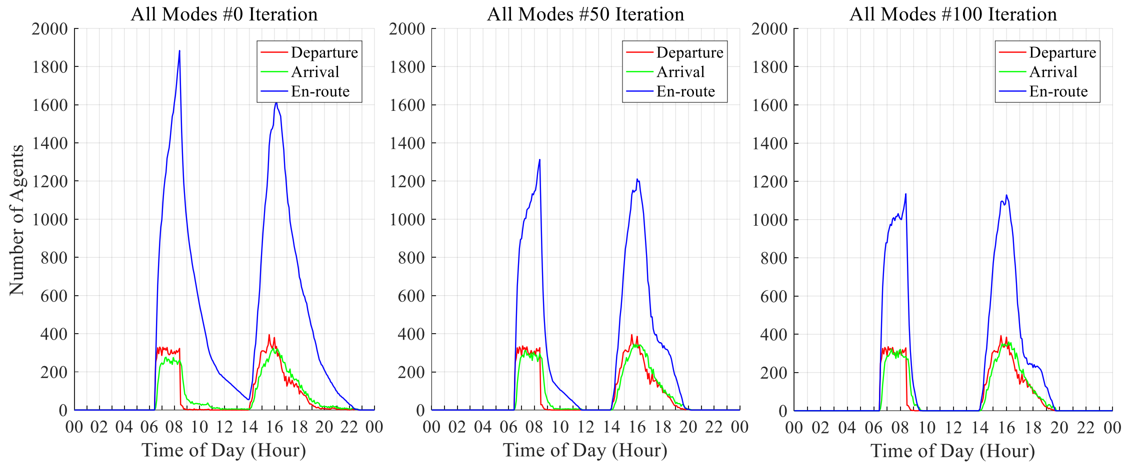
Parameter	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
S_i	-50%	-50%	-50%	-50%	-50%	-50%	-50%	-50%	-50%	-50%
T_{d_s}	6:30	6:30	6:30	6:30	6:30	6:30	6:30	6:30	6:30	8:00
T_{d_e}	10:00	10:00	10:00	10:00	10:00	10:00	10:00	10:00	10:00	10:00
I_{int}	15 min	15 min	15 min	15 min	15 min	15 min	15 min	15 min	5 min	15 min
t_{bud}	120 s	0	120 s	120 s	120 s	120 s	120 s	120 s	120 s	120 s
θ_1	$U(0, 9.18\text{mins})$	$U(0, 9.18\text{mins})$	0	$U(0, 9.18\text{mins})$	$U(0, 9.18\text{mins})$	$U(0, 9.18\text{mins})$	$U(0, 9.18\text{mins})$	$U(0, 9.18\text{mins})$	$U(0, 9.18\text{mins})$	$U(0, 9.18\text{mins})$
γ_1	$N\ (0.19, 0.048)$	$N\ (0.19, 0.048))$	$N\ (0.19, 0.048)$	$N\ (0.0967, 0.024)$	$N\ (0.19, 0.048)$	$N\ (0.19, 0.048)$	$N\ (0.19, 0.048)$	$N\ (0.19, 0.048)$	$N\ (0.19, 0.048)$	$N\ (0.19, 0.048)$
θ_{WfH}	30 min	30 min	30 min	30 min	30 min	30 min	30 min	30 min	30 min	30 min
θ_2	/	/	/	/	$U(0, 9.18\text{mins})$	/	/	/	/	/
γ_2	/	/	/	/	$N\ (0.18, 0.035)$	/	/	/	/	/
c	1	1	1	1	1	3	1	1	1	1
α	(-1, 1)	(-1, 1)	(-1, 1)	(-1, 1)	(-1, 1)	(-1, 1)	(-1, 0)	(0, 1)	(-1, 1)	(-1, 1)

S_i : The severity of impact on the disrupted link
T_{d_s}: Start of disruption
T_{d_e}: End of disruption
I_{int}: Interval of information notification
t_{bud}: Time budget for decision making
θ_1: Indifference band for late arrival along r_o under pre-trip
γ_1: Relative indifference bands between time cost of r_o and r_{sp} under pre-trip
θ_{WfH}: Likelihood of activity cancellation
θ_2: Indifference band for late arrival along r_o under en route
γ_2: Relative indifference bands between time cost of r_o and r_{sp} under en route
c: Confidence level of distribution on estimated travel time
α: Random heterogeneity factor

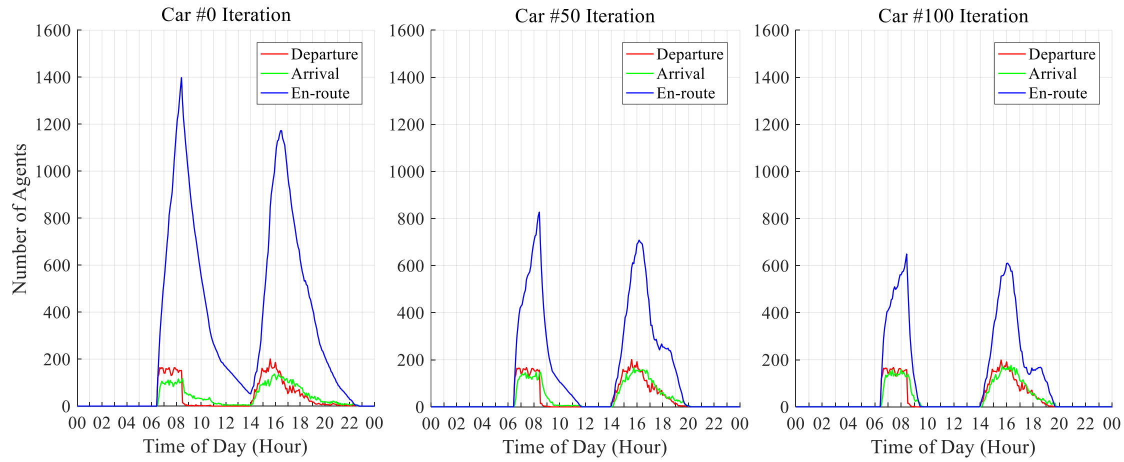
5.4 Results of Experiment A - Baseline Scenario

A standard MATSim simulation was iteratively executed to obtain a stable and converged set of baseline day plans, which were subsequently used as inputs for the following experimental scenarios. In the baseline scenario, 6,813 agents residing in Cottbus inner-city executed their day plans based on the initial synthetic population. Both car and public transport were available for reaching activity destinations. Travellers adhered to their stated preferred transport modes throughout the iterative process. They were permitted to adjust their travel at the end of the day, with 30% of car users allowed to divert to a new route. The number of iterations was set to be 100 to ensure that the simulation converged to the (stochastic) user equilibrium, i.e., no traveller can improve their score by switching to a different route, which efficiently identified the optimum of each agent's daily schedule.

During the simulation, MATSim optimised the experienced utilities in order to search for the equilibrium. Figure 5-4 depicts the number of travellers departing, arriving, or travelling over time of day for the first, 50^{th}, and 100^{th} iteration. The number of agents in the en route state represents the accumulation of travellers within the network at a given time. Higher en route values indicate longer travel times and greater congestion. The number of en route agents peaks at Iteration 0, decreased by Iteration 50, and shows further stabilisation by Iteration 100, indicating that congestion is progressively mitigated over the iterations. During the iterative process, only car users were able to explore alternative routes, whereas public transport routes remained fixed and followed predefined schedules. As a result, changes observed in the leg histogram primarily reflected route adjustments within the car mode, with limited impact from the public transport.



(a)



(b)

Figure 5 - 4 Leg histogram analysis for (a) overall agents and (b) car users only at iteration 0th, 50th and 100th throughout the simulation.

The level of convergence was evaluated by visual inspection. An approximate equilibrium state was considered to have been reached when the average score of all simulated agents' executed plans (represented by the blue line in Figure 5-5) stabilised and no longer increased with additional iterations. As shown in Figure 5-5, the simulation results tended to stabilise after 80 iterations, beyond which the average score of executed plans showed no further improvement.

The results show that the average trip duration for all users was approximately 15 minutes. As illustrated in Figure 5-6, the home–work–home activity pattern was the most common daily schedule, performed by 6,171 commuters, accounting for approximately 91% of the simulated population sample. Most of these commuters spent around 20 minutes commuting. An additional 642 commuters included child drop-off and pick-up activities before and after work. For leisure activities, represented by shopping in this simulation, the travel time tended to be constrained to within 10 minutes, which is both reasonable and consistent with typical human behavioural patterns (Axhausen *et al.*, 2002).

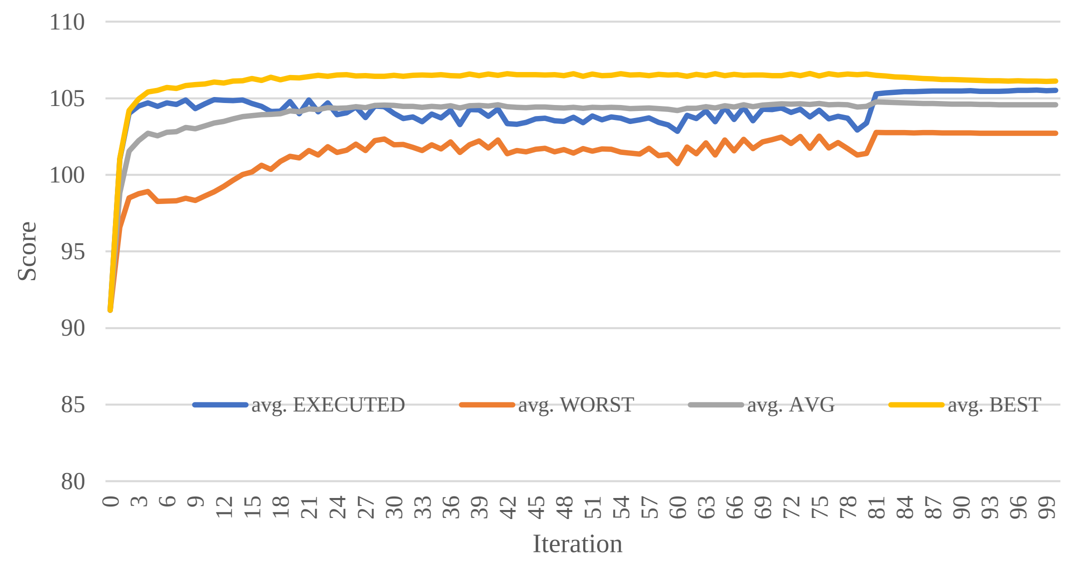


Figure 5 - 5 The score statistics of the plan execution in the baseline

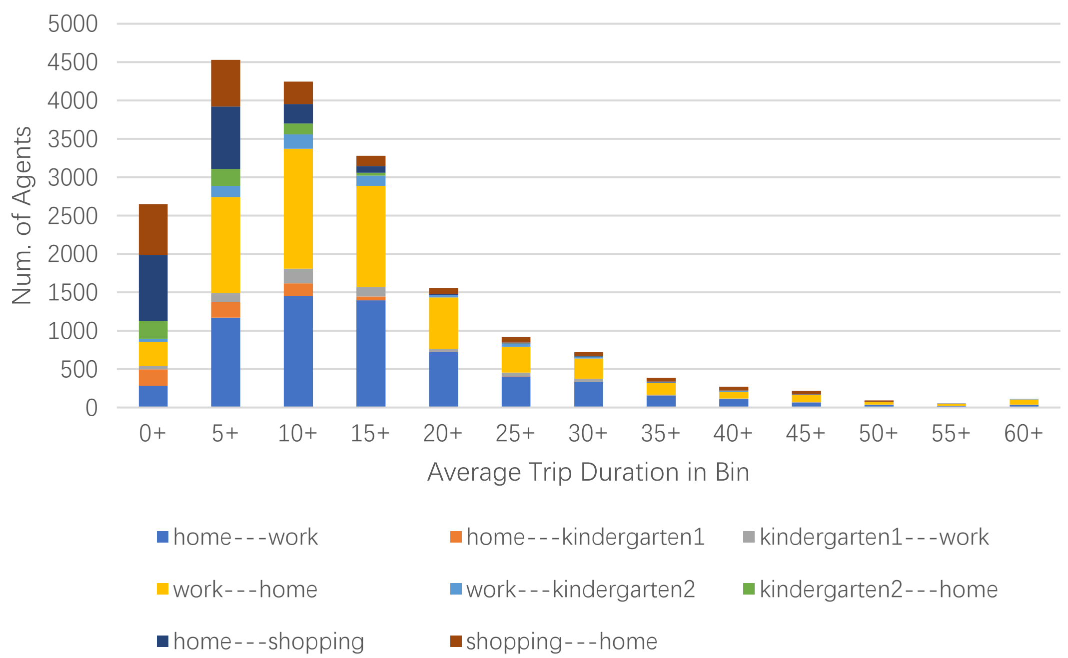
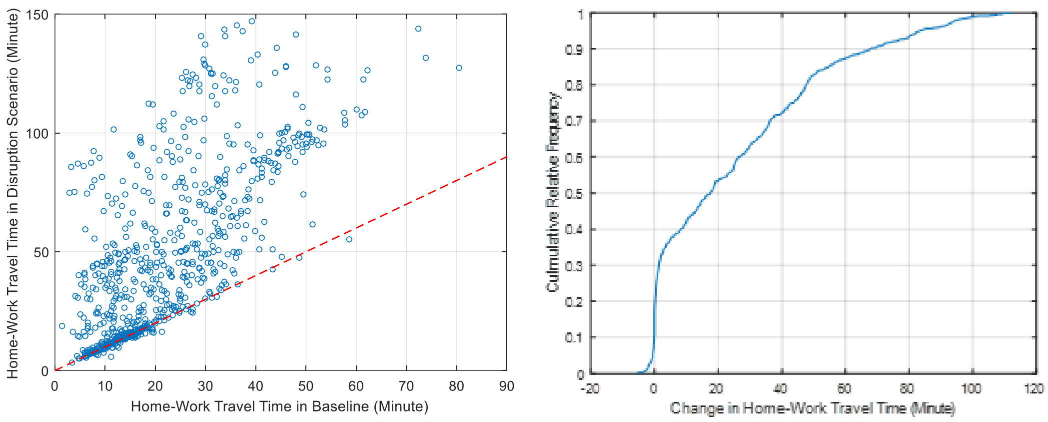


Figure 5 - 6 Distribution of the duration of trips by activity with y-axis representing the average number of agents in each time bin calculated from 100 runs.

5.5 Results of Experiment B - Disruption Scenario without Information Provision or Schedule Adaptation

In this scenario, the network disruption was introduced as described in section 5.2.2. The disruption started at 6:00 am and ended at 10:00 am. Commuters depart at the same time as usual and commit to their habit route with daily preferred transport mode. The input activity-travel pattern is taken from the output of baseline scenario. No information was provided to the commuters. Therefore, people are presumed to execute trips and select routes without any knowledge about the incident. As a result, they experience higher travel time delays and spend more time on the network.

The simulation results show that the average trip duration per trip increases from 15.17 mins in the baseline (Exp.A) to 16.32 mins in the disruption scenario (Exp.B). A number of private vehicle commuters whose routine route passes through the disrupted links, thus were identified as directly affected commuters. The impact of the unexpected network disruptions on this group is further examined by comparing their home–work travel times during the morning peak between the baseline and disruption scenarios. Figure 5-7(a) presents a scatter plot of Home-Work travel time in both scenarios. It is obvious that the time cost to reach the work location in the disruption scenario shows a significant increase compared to the baseline. The distribution of the difference in travel time between two scenarios is further illustrated in Figure 5-7(b), indicating that 50% of directly affected car commuters experienced an increase more than 20 minutes while 13% endure severe delays exceeding 60 minutes.



(a) (b)

Figure 5 - 7 (a) Data pairs of the home-work travel time in the morning peak and (b) the distribution of the travel time difference, comparing between the baseline scenario (Exp.A) with the disruption scenario (Exp. B) of directly affected private car users

5.6 Results of Experiment C - Within-day Replanning

A sensitivity analysis comprising 10 cases was carried out as a pre-cursor to Experiment C, designed to evaluate how assumptions about traveller responsiveness influence emergent network-level outcomes. Within the simulations, agents were permitted to adopt multi-dimensional rescheduling strategies in response to the assumed disruptions, following the behavioural assumptions embedded in the rescheduling logic. The insights gained from this analysis guided the selection of the appropriate parameter combination for Experiment C, whose performance is subsequently examined in Section 5.6.2.

5.6.1 Sensitivity analysis of network performance – pre-cursor to Experiment C

5.6.1.1 Sensitivity to information provision and agent behaviour

Various features of behavioural parameters were analysed on the impacts of defined transport network failures. Figure 5-8 presents a boxplot that summarises the distribution of average trip durations using key statistical markers. The central red line indicates the median, while the box edges represent the 25th (Q1) and 75th (Q3) percentiles, defining the interquartile range (IQR) that captures the middle 50% of values. Whiskers extend to the furthest points within 1.5×IQR, and any points beyond are plotted as outliers.

Case 1 served as the basis against which Cases 2 to 9 were compared, each involving a systematic variation of a single behavioural parameter to assess the sensitivity of network performance to that specific assumption. Compared to the disruption scenario without information provision (Exp. B), represented by the green dashed line in Figure 5-8, where the average trip duration was 16.32 minutes, the incorporation of traffic information enabled agents to replan their trips, leading to varying degrees of reduction in average trip durations across all simulated cases. This demonstrated the potential of information-aided rescheduling to alleviate the adverse impacts of network disruptions and improved overall system efficiency.

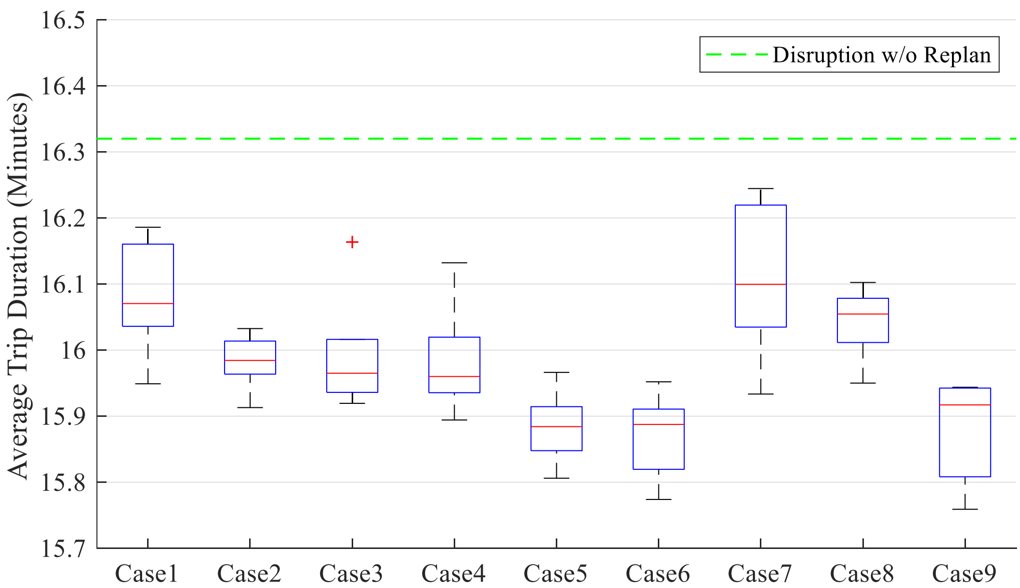


Figure 5 - 8 Boxplots of average travel time (minutes) based on five runs under each case.

Much of the existing literature overlooks the time required for processing information and making decisions, which can result in agents being modelled as departing earlier than realistically possible (Wong and Farooq, 2019). Moreover, longer decision-making times may increase the likelihood of missing better alternatives, as the side effects of disruptions tend to intensify during peak periods due to rising demand. The influence of the decision time budget (t_{bud}) was primarily reflected in agents' departure time choices. As demonstrated in Case 2, where t_{bud} was omitted, compared with Case 1, the observed reductions in average trip duration suggest that disregarding the time required for decision-making can lead to an underestimation of trip durations and thus result in biased travel demand estimates.

The variations in indifference band were examined in Cases 3 and 4. In Case 3, travellers were specified to strictly adhere to on-time arrival, by the late-side tolerance parameter (θ_1) set to zero. In Case 4, the indifference band between the original and shortest paths (γ_1) was reduced, reflecting a diminished tolerance for additional lateness before abandoning the original disrupted route. In both cases, travellers became more likely to explore alternative routes and make route-switching decisions. As shown in Figure 5-9, a greater number of agents adjusted their schedules, either by switching routes or departing earlier, compared to Case 1, with the effect being particularly pronounced in Case 3. In Case 5, where en route switching was enabled alongside pre-trip rescheduling, a greater number of agents opted for improved routes, resulting in a substantial reduction in average trip duration compared to Case 1. The median of average trip duration decreased to approximately 15.86 minutes.

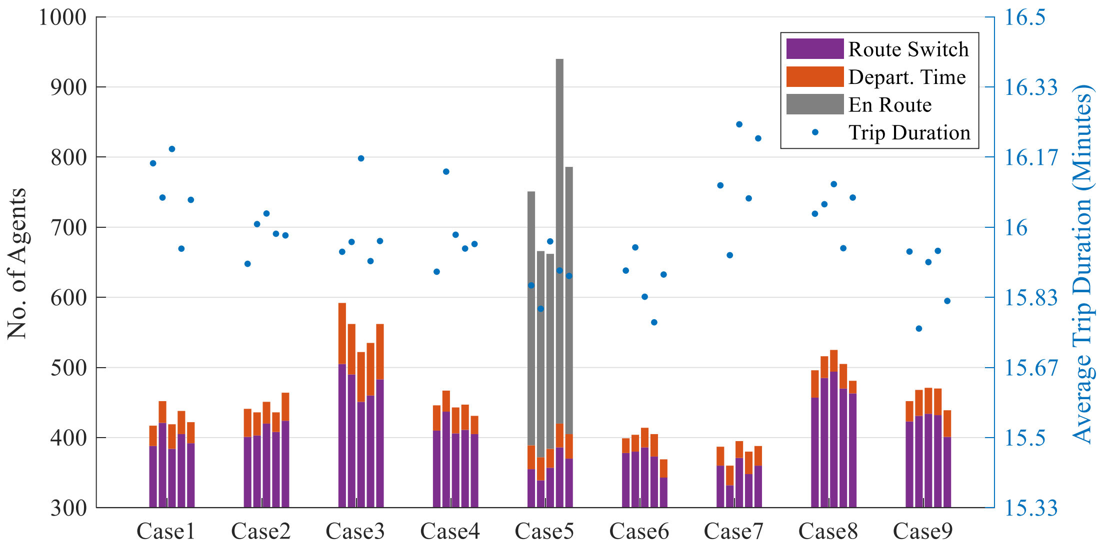


Figure 5 - 9 Numbers of agents switching their routes and/or changing their departure time in each of five runs under each case.

Cases 6, 7, and 8 examine the influence of parameters governing how agents perceive travel time along their routine routes, that is, the heterogeneity in travel time perception. In Case 6, a broader diversity in perceived travel time among agents is assumed by setting a constant $c = 3$, which corresponds to a 99% confidence interval under the normal distribution $N(t_r, \sigma_r)$ specified for the routine route. Such parameter settings amplify individuals' perception of travel time, thereby increasing the likelihood of agents undertaking rescheduling. In Cases 7 and 8, heterogeneity in risk attitudes is explored by assigning the random variable α from a uniform distribution over $(-1, 0)$ or (0, 1), representing risk-seeking and risk-averse behaviours, respectively. As shown in Figure 5-9, risk-averse agents in Case 8 tend to reschedule their original plans more readily than risk-seeking agents in Case 7, leading to shorter average trip durations.

In Case 9, reducing the interval of information provision from 15 minutes to 5 minutes led to a marked improvement in network performance compared to Case 1, as illustrated in Figure 5-8. This finding underscores the critical role of timely and continuous information updates in enhancing the responsiveness and efficiency of the transport system under disruption conditions.

In summary, the results across the nine simulated cases show that the incorporation of traveller rescheduling significantly reduced average trip durations and improved overall network performance compared to the scenario without traffic information provision (Exp. B). In particular, the combined implementation of pre-trip and en route replanning (as in Case 5), along with shorter information dissemination intervals (as in Case 9), proved particularly effective in mitigating disruption-induced congestion.

5.6.1.2 Sensitivity to disruption severity and information provision

Disruption severity was another factor influencing travellers' rescheduling behaviour. In this section, network performance was compared across different levels of disruption severity and varying information provision strategies. In Case 1, information provision commenced almost simultaneously with the onset of the disruption and continued from 6:30 to 10:00 am. In contrast, Case 10 assumed a 1.5-hour delay relative to Case 1, with the dissemination starting at 8:00 am during the morning peak. Both cases were simulated under three levels of disruption severity, with the capacity of the affected bridge links reduced by 20%, 50%, and 80%, respectively. This yielded Case 1(20), Case 1(50), and Case 1(80), as well as Case 10(20), Case 10(50), and Case 10(80).

As shown in Figure 5-10, a greater number of agents opted for rescheduling as the severity of the disruption increased in both cases. The effect was more pronounced when information was disseminated earlier, as in the Case 1 scenarios. When real-time information was provided to agents both pre-trip and en route, more substantial link-capacity reductions prompted greater behavioural adjustments. These rescheduling responses helped to alleviate delays, resulting in a larger relative reduction in average trip duration, as illustrated in Figure 5-11.

Overall, the results indicate that timely information provision can play a critical role in mitigating network congestion. By enabling travellers to reschedule in response to updated traffic conditions, such strategies enhance the operational efficiency of the transport system under disruption.

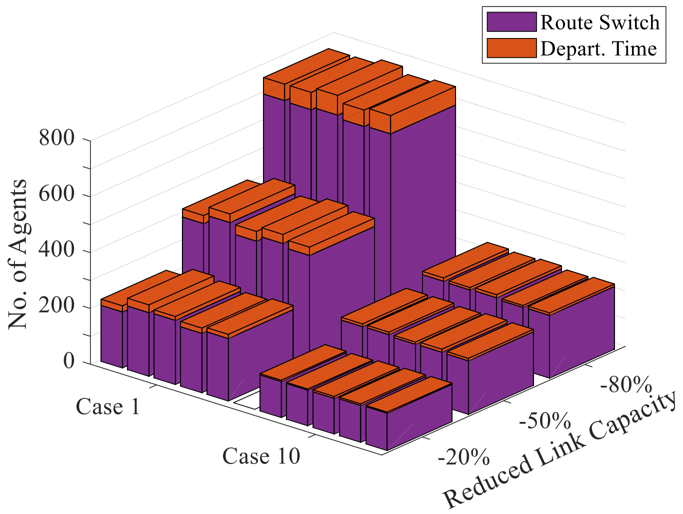


Figure 5 - 10 Numbers of replanned agents given varying severity levels of network disruptions in Cases 1 and 10.

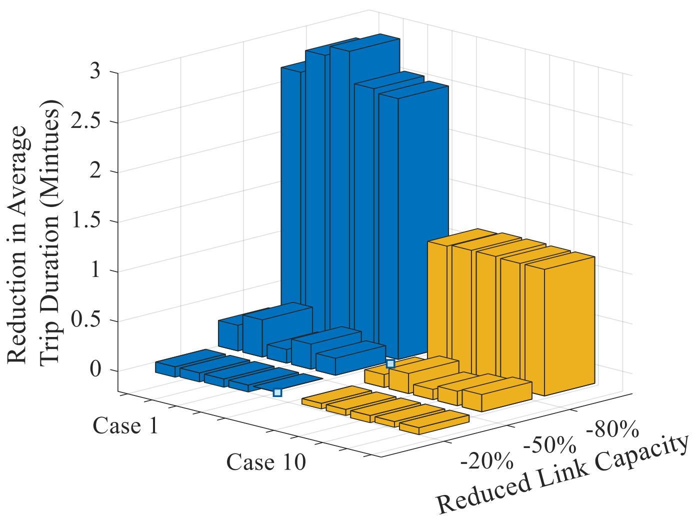


Figure 5 - 11 Reductions in average trip durations under varying severity levels of disruptions in Cases 1 and 10, relative to the disruption scenario without information provision

5.6.2 System performance analysis of Experiment C

The sensitivity analysis indicated that the most effective strategy for reducing average trip duration and improving overall network efficiency was the combined application of pre-trip and en route rescheduling, supported by more frequent real-time information provision. Building on these findings, Experiment C was designed to further examine the effectiveness of the enhanced Within-day Replanning Module and to examine system performance in greater detail. In this experiment, traffic information I_{int} was provided at 5-minute intervals, and agents were allowed to reschedule their original plans both before departure and during the trip (with θ_2 and γ_2 enabled) based on their evaluation and perception of the current network conditions. All other parameter settings were kept identical to those in Case 1.

5.6.2.1 Agents rescheduling behaviour and resulting network performance.

In the simulation, the same disruptions as those in the disruption scenario were introduced during the morning peak period (6:00 AM–10:00 AM), a time window in which commuters are typically more sensitive to travel delays due to the risk of being late for time-critical commitments, such as workplace meetings or client appointments. In the Experiment C, among the 3,405 simulated car commuters, 1,114 agents experienced disruption-affected trips. Of these, 401 travellers engaged in pre-trip route switching. An additional 330 agents diverted en route, some of whom may have initially rescheduled prior to departure but subsequently adapted their routes in response to real-time network updates. No agents were observed to change their travel mode or cancel their upcoming activities, suggesting that the disruption effects could be mitigated through route adjustments and/or earlier departures without necessitating more disruptive behavioural changes in this case. This outcome can be explained by the relatively low congestion levels of network in the study area and the fact that the disruption reduced link capacity rather than causing a complete closure.

To better understand the behavioural dynamics of en route agents across different Experiments, the number of agents on the move during each 15-minute interval between in a simulation day (5:00-21:00) was recorded and compared, as illustrated in Figure 5-12. In baseline scenario (Experiment A), represented by the red solid line with evenly spaced dots, the number of en route agents gradually declined, with the system stabilising around 09:35 AM.

In contrast, in the disruption without replanning scenario (Experiment B), represented by the blue solid line with evenly spaced cross marks, a significantly higher number of agents remained on the network during the morning peak, indicating prolonged trip durations. The system in this scenario only returned to a stable state at approximately 10:25 AM, roughly 50 minutes later than in the baseline, highlighting the impact of unmitigated disruptions.

In Experiment C, where replanning was enabled, the result was represented by the green line with dotted squares. As is shown in the plot, both the green and blue lines peaked higher than the red baseline during the disruption period, with the blue line reaching the highest level. While the initial post-peak decline was broadly similar for the blue and green lines, the number of en route agents in Experiment C subsequently decreased more rapidly, enabling the system to reach normalisation by 09:45 AM. This reflects a substantially earlier recovery compared to Experiment B, where stabilisation occurred considerably later. These observations suggest that rescheduling options adopted by agents, both pre-trip and en route, effectively alleviating congestion and accelerating system recovery.

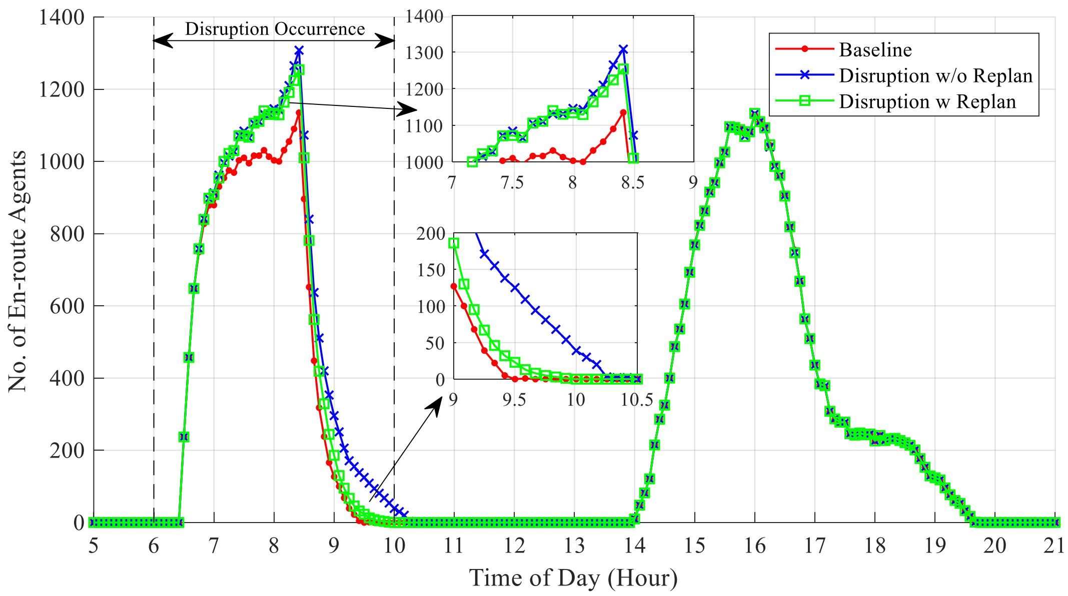


Figure 5 - 12 Numbers of en route agents over each 15-minute time window in three scenarios (Baseline: Experiment A; Disruption w/o Replan: Experiment B; Disruption w/ Replan: Experiment C).

5.6.2.2 Network performance analysis

The effectiveness of information provision and adaptive rescheduling in mitigating network disruptions is further evaluated in this section. In the disruption scenario without replanning (Experiment B), travellers had no prior knowledge of the incident and consequently experienced longer delays, with the average trip duration rising from 15.17 minutes in the baseline scenario (Experiment A) to 16.32 minutes. By contrast, when real-time traffic information was provided and travellers were allowed to reschedule their daily plans using replanning logic (Experiment C), the impact of the disruption was significantly alleviated. The average trip duration decreased to 15.75 minutes, indicating that the integration of dynamic information and adaptive rescheduling can effectively mitigate congestion and therefore enhance network performance under disruption conditions.

Figure 5-13 illustrates the changes in average trip duration in Experiment C compared to Experiment B. Following the introduction of replanning in Experiment C, the number of agents with trip durations exceeding 40 minutes decreased significantly in Experiment C relative to Experiment B, particularly in the 60+ minute time bin. Correspondingly, a greater proportion of agents experienced travel times within the 10 to 40 minute range, indicating a substantial improvement in overall network efficiency.

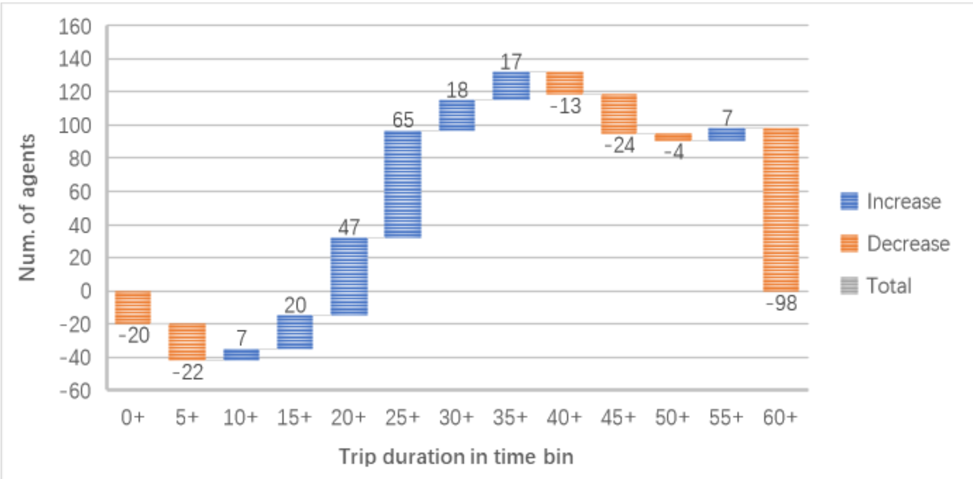


Figure 5 - 13 Average trip duration in replanning scenario (Exp. C) compared to disruption scenario (Exp. B)

Zooming into the home-work travel pattern, a similar trend was observed. Figure 5-14 illustrates the travel times of car commuters directly affected by the disruptions across the three scenarios. In Experiment B, where no replanning mechanism was incorporated, the disruptions resulted in noticeably longer travel times compared to the baseline scenario (Experiment A). While the majority of travel time increases remained under one hour, a subset of agents experienced delays exceeding 90 minutes. In contrast, when replanning was introduced in Experiment C, the impact of the disruption was substantially mitigated, with significantly fewer agents experiencing travel time increases greater than 30 minutes. These results highlight the effectiveness of adaptive rescheduling in reducing excessive delays during disruptive events.

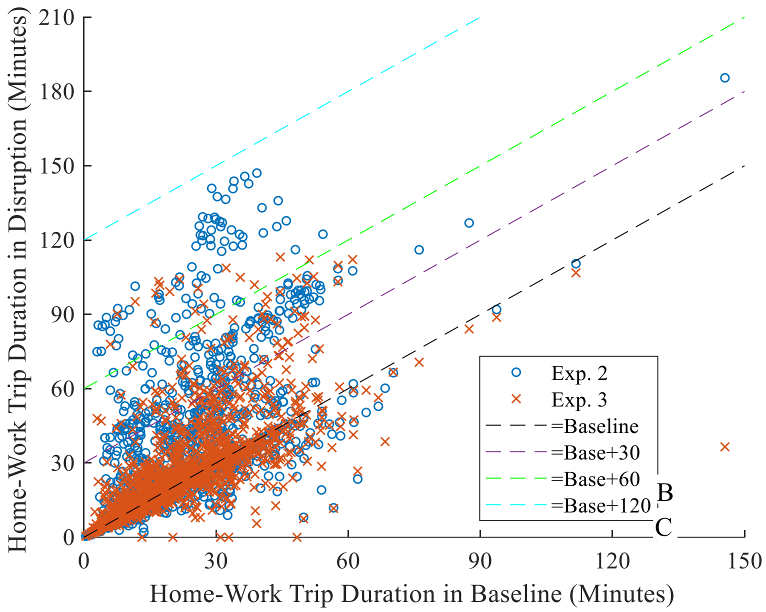


Figure 5 - 14 The home-work travel time comparison for direct disruption affected car commuters in three scenarios

A summary of network performance across the three scenarios is presented in Table 5-3. In addition to the average trip duration and the average travel time for the home-to-work (H_W) travel pattern discussed above, other performance metrics are also included. The total travel time decreased from 145,172 minutes in Experiment B to 132,266 minutes in Experiment C, representing a cumulative time saving of 12,9076 minutes for the population during the morning peak. Regarding travel distance, agents in Experiment B followed the same routes and plans as those in the baseline scenario; consequently, the distance metrics remained identical between the two. As the replanning mechanism was primarily driven by travel time considerations. As a result, agents in Experiment C were willing to travel slightly longer distances in exchange for shorter travel times. This led to a modest increase in average travel distance compared to the baseline and Experiment B.

Table 5 - 3 Summary of network performance on three scenarios

	Average trip duration (mins/person/trip)	Average travel time (m/person/H_W)	Total travel time (mins-H_W)	Average trip distance (m/person/trip)	Average travel distance (m/person/H_W)	Total travel distance (km-H_W)
Exp.A	15.17	17.52	123,107	6,893	12,373	84,299
Exp.B	16.32	20.62	145,172	6,893	12,373	84,299
Exp.C	15.75	19.41	132,266	6,903	12,413	84,569

5.6.2.3 Analysis on the volume/capacity over the experiments

To further evaluate the level of congestion and link-level performance within the transport network, the volume-to-capacity (v/c) ratio was calculated for the Cottbus inner-city network during the morning peak period (7:00 AM–9:00 AM). The results are illustrated in Figures 5-15a to 5-15f for the three scenarios, respectively. The v/c ratio was computed based on the maximum simulated traffic volumes within each one-hour interval. Links with v/c ratios exceeding 0.95, indicative of severe congestion, are highlighted in red. Those with ratios between 0.75 and 0.95 are classified as congested and displayed in orange. Links with v/c ratios below 0.75, suggesting relatively free-flowing conditions, are shown in green.

Although the Cottbus network was not particularly busy under typical conditions, the comparison of volume-to-capacity (v/c) ratios across the three scenarios still effectively illustrates both the impact of disruptions and the benefits of replanning. The black dashed rectangles on the plot c-f of Figure 5-15 denote the areas to illustrate the notable changes. As shown in Figure 5-15 c and Figure 5-15 d, in disruption scenario, two of the four bridges experienced severe congestion due to the assumed network disruptions with the northern bridge exhibiting more pronounced congestion. While other congested segments gradually eased as the morning progressed toward 8:00–9:00 AM, the bridge-related congestion induced by the disruptions persisted. In contrast, Figure 5-15 e and Figure 5-15 f demonstrate how the v/c ratios evolved over time when rescheduling actions were incorporated in Experiment C. With the provision of real-time traffic information, travellers were able to gain awareness of the disruptions and their associated impacts. Upon recognising the anticipated delays, commuters engaged in various rescheduling strategies, including route switching or/and departure time adjustments, which contributed significantly to the alleviation of congestion, as clearly reflected in Figure 5-15 f.

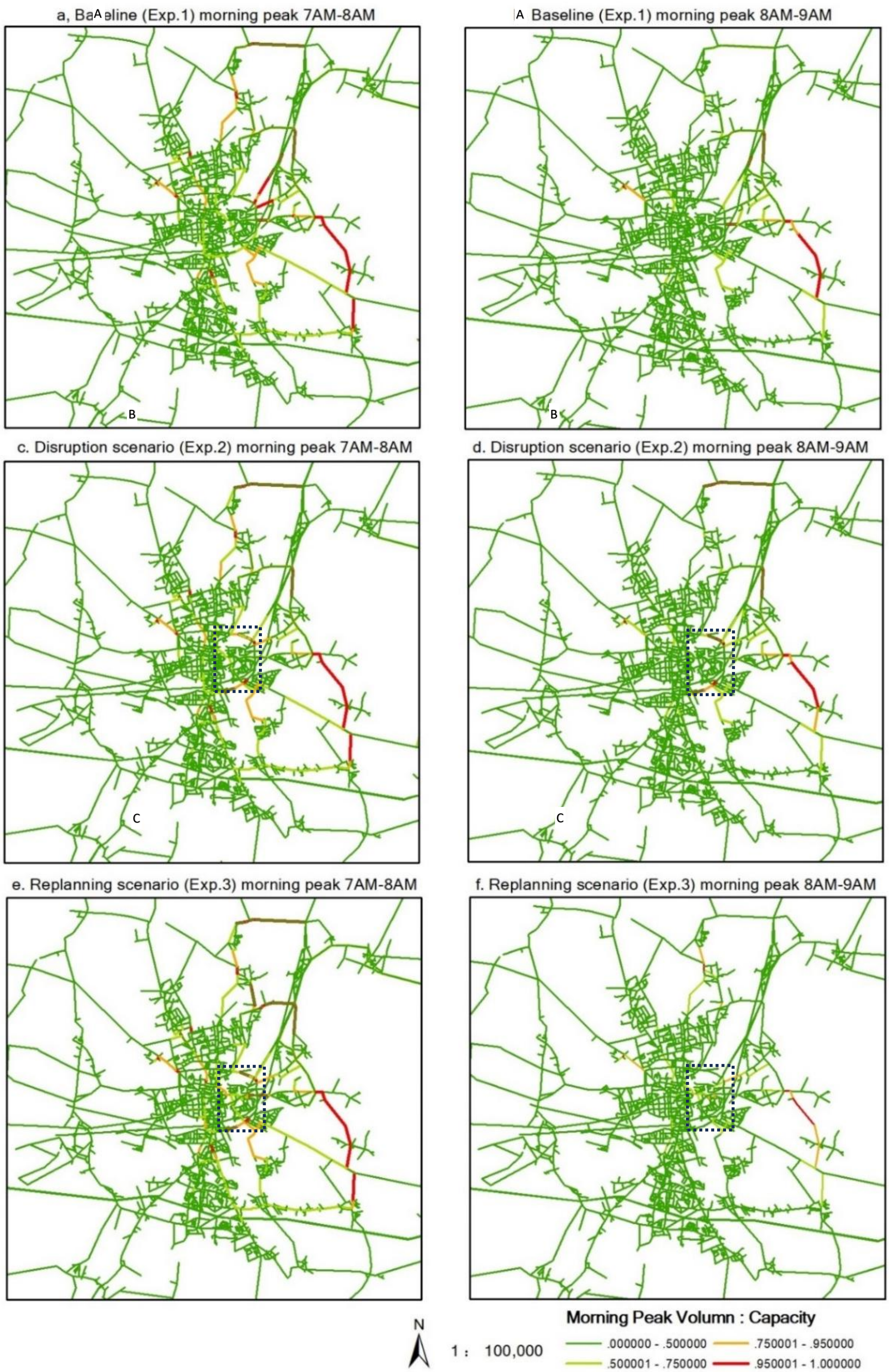


Figure 5 - 15 Map of morning peak congestion on Cottbus inner-city network

5.6.2.4 Investigation on disrupted bridges and monitor bridges

In Experiment C, car users whose habitual routes were affected by the network disruption were permitted to reconsider their committed routes. As a result, the volume distribution across network links deviated from the typical pattern, most notably on the bridges that serve as key commuting corridors between the western and eastern parts of the city. Figures 5-16 and 5-17 present the volume changes on both the disrupted bridges and the unaffected monitoring bridges, the latter located over the same river but not subjected to simulated disruptions.

To maintain clarity and focus, the analysis did not cover all affected links in detail, instead, a subset of representative links is selected for illustrative purposes. As shown in the figures, the disruptions prompted travellers to reroute and avoid the affected links, leading to a noticeable reduction in traffic volumes on those links during the disruption period. For instance, links 10236, 10299, 10300, and 4591 exhibited higher vehicle volumes in the disruption scenario (Exp. B) compared to the scenario where rescheduling was enabled (Exp. C). In contrast, the monitoring bridges, such as links 2513, 8746, 8747, and 4527 as plotted, exhibited a clear increase in traffic volumes in Exp. C, indicating that commuters diverted to these alternative routes in response to the disruption.

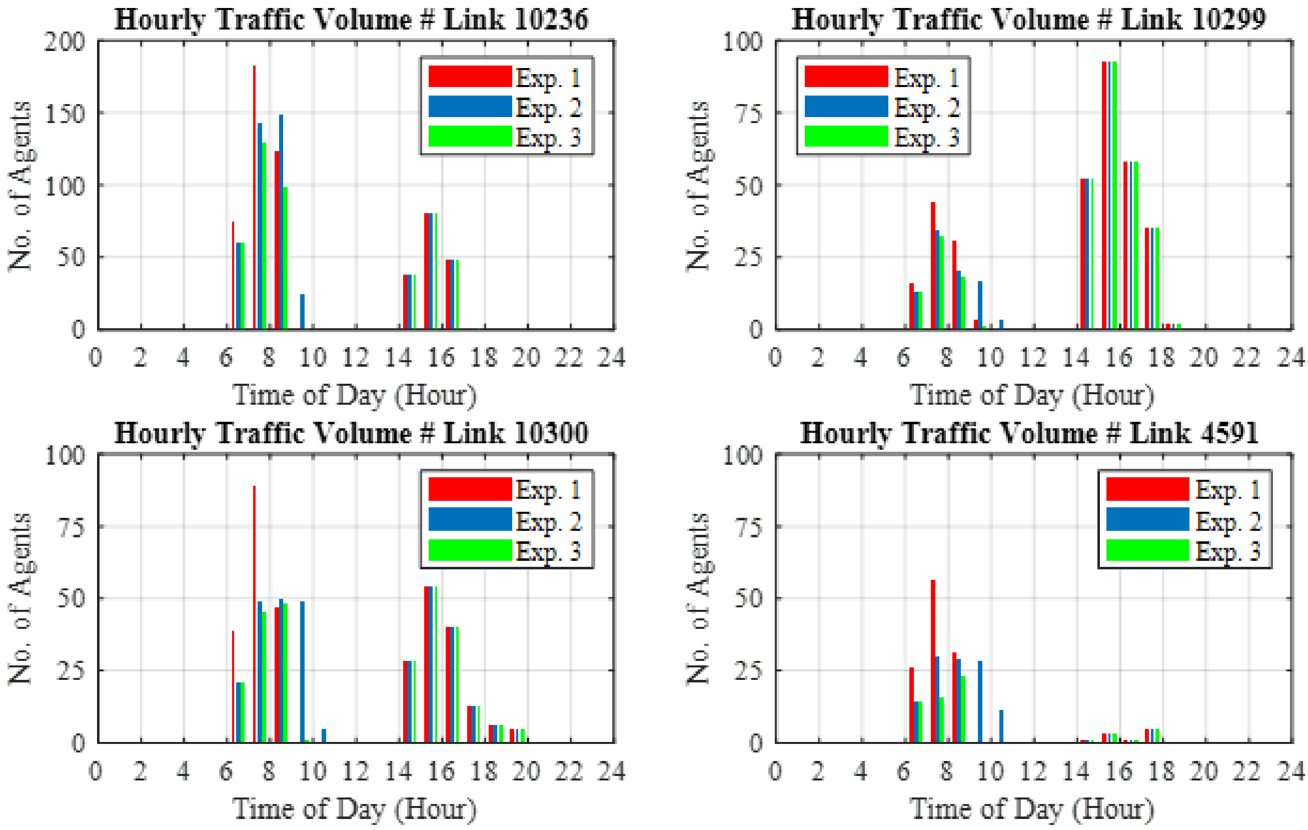


Figure 5 - 16 Traffic flow changes of disrupted links

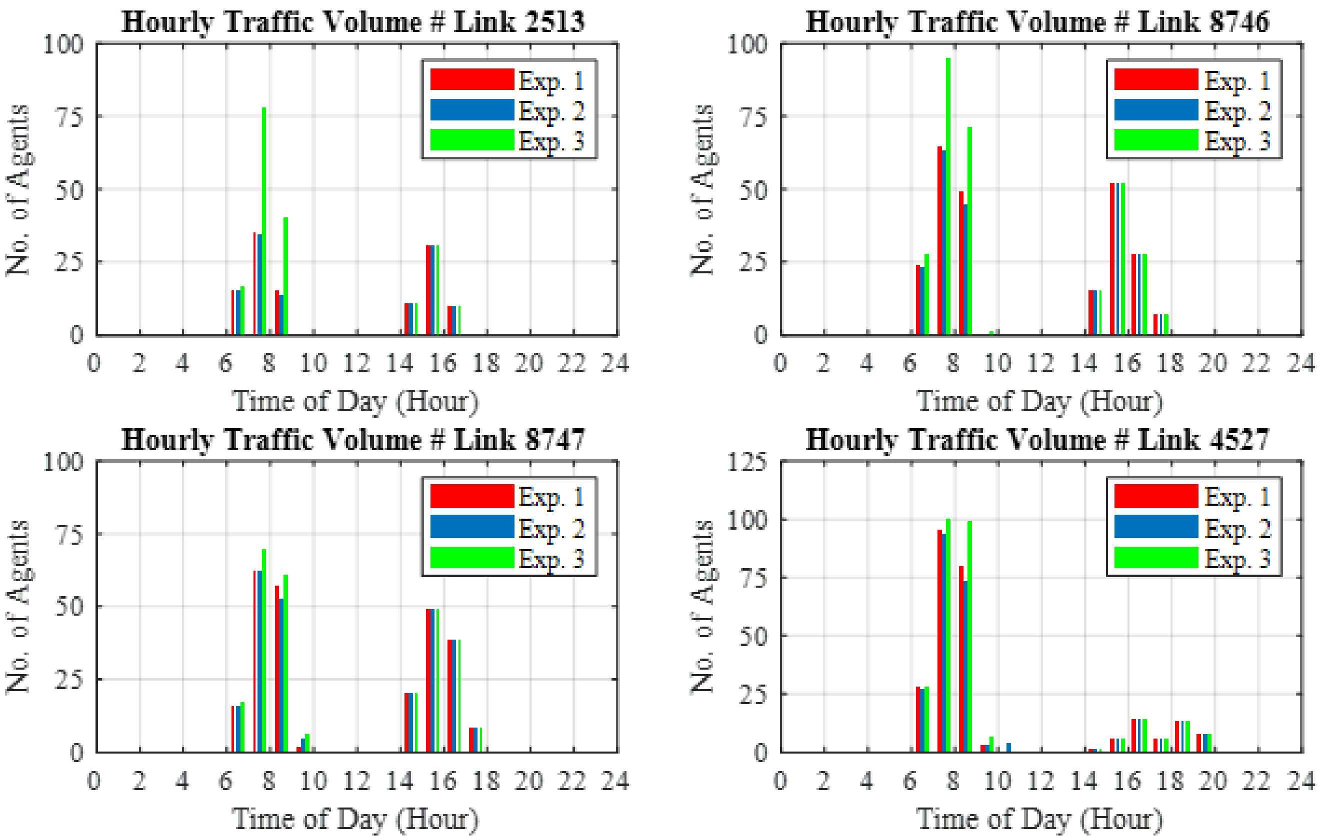


Figure 5 - 17 Traffic flow changes of monitored links

5.7 Conclusions

This chapter has demonstrated the effectiveness of the enhanced Within-day Replanning model in simulating travellers' rescheduling behaviour under transport network disruptions. A simple heuristic rule-based rescheduling logic was developed and incorporated with the multiple rescheduling dimensions.

Applied to the urban transport context of Cottbus, Germany, the enhanced model yielded several key insights. Simulation results revealed that road bridge failures significantly increased travel costs, whereas the provision of real-time traffic information enabled travellers to adapt their plans and mitigate the resulting congestion. The rescheduling behaviour model, developed primarily to test the simulation framework, was based on adaptive heuristics and supported the dynamic responses of travellers under disruption scenarios, demonstrating the enhanced model's capability to represent such behaviours. The model further accounted for individual heterogeneity in perceived travel time and the time consumed during the decision-making process. By introducing a decision time budget – an aspect often overlooked in previous research, the results highlighted its critical role in shaping rescheduling outcomes.

Moreover, sensitivity analyses showed that variations in key parameter values lead to expected changes in system performance, thereby supporting the internal consistency and practical relevance of the assumed rescheduling logic used for model testing. By integrating both pre-trip and en route rescheduling mechanisms, dynamically updated with traffic information, the model effectively reduced recovery time from disruption-induced congestion, and therefore enhancing network resilience. In sum, this case study reinforces the utility of the enhanced Within-day Replanning module as a valuable tool for urban transport modelling and planning. It offers meaningful insights into traveller adaptation behaviours and supports the development of more responsive and robust transport systems capable of managing unexpected network disturbances.

The Cottbus case study is presented as a simplified and illustrative representation of an urban transport system, rather than a fully calibrated real-world model. These simplifications are intentionally introduced to ensure computational feasibility and to allow the analysis to focus on the behavioural mechanisms of rescheduling and system responses to disruption, thereby demonstrating the implementation and performance of the enhanced modelling framework. Due to the limited availability of empirical data on within-day rescheduling behaviour, particularly in relation to real-time information and multi-modal adaptation, the model was not validated against observed data. Instead, the case study serves as a methodological demonstration, providing an illustration to the implementation and performance of the enhanced Within-day Replanning model. As such, its value lies in demonstrating a flexible and computationally efficient approach for modelling adaptive travel behaviour, offering insights into behavioural plausibility and system response, while providing a foundation for future applications with richer empirical data.

Part II Modelling Commuters' Rescheduling Behaviour Under Time Pressure

While the MATSim extension developed in this study offers a valuable framework for simulating within-day rescheduling, the assumptions underlying behavioural responses are not data-driven, and may therefore fall short in reflecting the full complexity of decision-making mechanism. Besides, the simulation results implies that time pressure, a condition that arises when the time available for making travel-related decisions is constrained, may play a critical role in shaping both the likelihood and quality of rescheduling actions. However, its behavioural implications remain insufficiently explored in transport models, underscoring the need for further empirical investigation. Therefore, Part II of this thesis aims to address these gaps by collecting and analysing empirical evidence on travellers' responses under disrupted conditions, with particular emphasis on how perceived time pressure influences rescheduling behaviour across varying contextual circumstances.

Chapter 6 Experimental Design and Data Collection

Preface *- This chapter is based on the conference paper presented at the 26th International Conference of Hong Kong Society for Transportation Studies (GREAT TRANSPORTATION - Green, Resilient, Empowering, Adaptable, and Transformative) in Hong Kong (2022). Most of the following sections are excerpts from the presented paper, with more details and extensions provided to better integrate into the thesis.*

6.1 Introduction

Unexpected transport network disruptions often lead to increased travel times and introduce greater uncertainty. As these events typically occur with little advance warning, travellers are left with limited time to evaluate options and adjust their plans accordingly. Such constrained decision-making time windows can have an impact on both rescheduling strategies and the outcome of travel decisions. In parallel, working from home (WfH) has emerged as a viable and increasingly accepted alternative following the COVID-19 pandemic, offering flexibility to respond to the immediate impacts of disruption. For many individuals, particularly commuters, the feasibility of adapting daily plans is closely tied to the nature, importance, and flexibility of their work-related activities.

In order to investigate how individuals respond under these context-dependent and time-pressured conditions, a stated preference (SP) experiment was developed and embedded within an online survey to collect empirical data on travellers' rescheduling behaviour. The survey was delivered through a structured questionnaire, which presented the SP choice tasks alongside supplementary questions on respondents' characteristics and travel behaviour. Understanding these behavioural responses is crucial for strengthening the resilience of transport systems and for informing the development of user-centred policy interventions.

This chapter provides a detailed explanation of the data collection methodology, covering the design of the study (Section 6.2), the survey instrument (Section 6.3), the sampling and data collection (Section 6.4). The implementation of the data processing is also presented in Section 6.5, followed by concluding remarks in the last section of the chapter.

6.2 Study Design

6.2.1 Stated preference choice experiment

Choice responses are typically derived from two primary sources of data: revealed preference (RP) data and stated preference (SP) data (Ben-Akiva and Lerman, 1985). The RP data refers to situations where a decision has been made in a real situation. In comparison, the SP data is collected when a decision is made by respondents in a hypothetical situation. The hypothetical situation is presented to respondents in a stated preference survey which is designed to replicate a real-world situation and that data is collected when respondents are asked to choose between alternatives that are characterised by attributes. Additionally, alternatives in SP may incorporate supplementary attributes that are either absent from or challenging to extract from the collected RP data. SP data are particularly valuable for examining choices not only within existing contexts but also in relation to new phenomena arising from emerging conditions, as well as to examine the factors that potentially influence the choice made but are not observed in the RP data.

In order to capture individuals' activity–travel rescheduling decisions within the contextual realism of post-pandemic daily life, this research aims to examine a spectrum of workplace scenarios, incorporating a travel objective (i.e., arriving at work on time) and considering these choices in the context of unexpected short-term transport disruption and the time pressure they impose. Collecting such detailed behavioural data through revealed preference methods is challenging, as real-world disruptions and individual-level responses under time pressure are often unobservable, irregular, or conpounded by external factors. Therefore, a stated preference (SP) approach was adopted to systematically obtain decision-making patterns within controlled, yet contextually realistic, hypothetical scenarios that reflect the complexities of commuting behaviour.

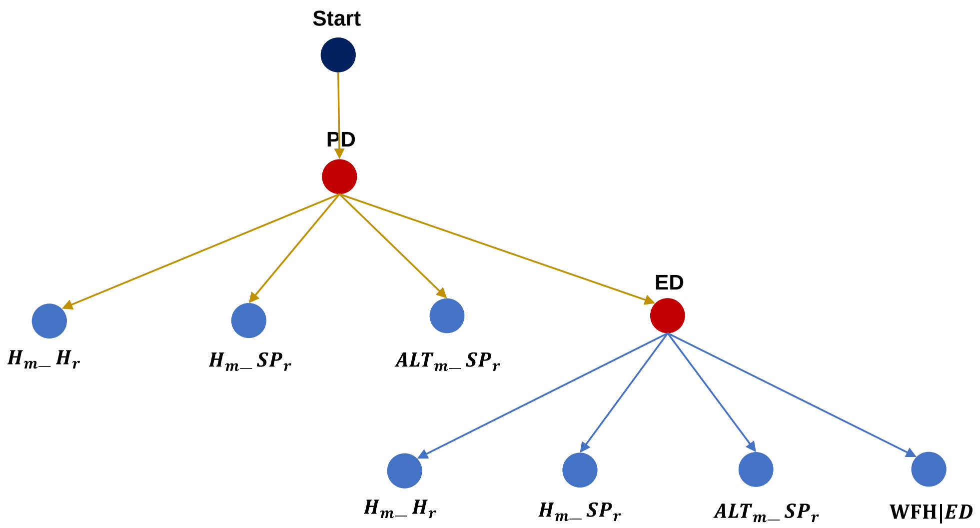
6.2.2 Stated preference terminology

In a stated preference experiment, the *choice set* contains two or more *alternatives* (or options) over which respondents are asked to express a preference within the given hypothetical scenario. Each alternative is typically characterised by several *attributes*, such as expected travel time, with the values (or *levels*) of attributes being selected to enable the researcher to explore the trade-offs made by respondents when choosing between alternatives. For example, expected travel time could have three *attribute levels* e.g., 10, 15 and 20 minutes. A single *choice task* may comprise multiple sub-choice sets; in this study, each choice task included two such choice sets, referred to as, *choice set 1* and *choice set 2*. These tasks represent the decisions participants were asked to make in response to the constructed *scenarios*. The specific design of these scenarios is outlined in the following section.

6.2.3 Representing the rescheduling choice tasks

The need to perform an activity is the fundamental driver of travel demand, whereas prevailing traffic conditions can impose constraints on the set of feasible travel choices. Upon encountering unexpected events or disruptions, commuters are required to make a sequence of rescheduling decisions, including the selection of route, departure time, mode, and potentially, the cancellation of the trip to work from home. These decisions are inherently interdependent and reflect a joint decision-making process, in which individuals assess and adopt integrated alternatives that involve consideration of spatial, temporal, and modal aspects of travel behaviour.

It is conceivable that most people have a morning routine, for instance, a personal routine such as washing up, getting changed and having breakfast, while some others may have household commitments, for example, walking the dogs and taking care of children or elderly people. These cases were included as home constraints, which lead to a preferred departure time for travel to work. In addition, the preferred departure time is scheduled based on the anticipated travel time from home to work, ensuring a timely arrival at work. In light of becoming aware of unexpected disruption, commuters assess the potential delay with departure at their preferred departure time. If arrival lateness is anticipated, the commuter must consider whether the habitual route remains a feasible choice, whether an alternative route or mode of transport might serve as a better option, whether an earlier departure is necessary and practical, or whether cancelling the trip and working from home constitutes a viable alternative. With unlimited time to make a decision, the commuter can be expected to make trade-offs between attributes such as travel time, late (or early) arrival etc.



Note: $\boldsymbol{PD}$: preferred departure time; $\boldsymbol{ED}$: earlier departure time; $\boldsymbol{H_m}$: habitual mode; $\boldsymbol{H_r}$: habitual route; $\boldsymbol{SP_r}$: shortest path route; $\boldsymbol{ALT_m}$: alternative mode

Figure 6 - 1 Nested structure (grouped under departure time)

Figure 6-1 shows a nested structure in which travel alternatives are grouped under preferred departure (PD) time and early departure (ED) time. Within each nest, alternatives are ‘habitual mode with habitual route’ ($H_{m\_}\ H_r$), ‘habitual mode with dynamically updated shortest path route’ ($H_{m\_}\ SP_r$), and ‘alternative mode with shortest path route’ ($ALT_{m\_}\ SP_r$). Commuters are assumed to explore alternatives – route switch, mode switch, and departure time adjustment – before considering cancelling a trip entirely. Abandoning the trip and its associated activity is usually regarded as a “last resort”, given the considerable disruption it causes to daily routines. Notwithstanding the impact of post-Covid working-from-home practices, the option 'Work from Home' (WfH) is categorised under the sub-choice set of early departure.

In such condition, a choice task (organised as a *block* of stated preference question) would consist of two sub choice sets. The red dot shown in Figure 6-1 represents the point at which the respondent makes a decision when faced with the set of alternatives, which are denoted by the light blue dots.

6.2.4 Incorporating time pressure in the stated preference experiment

Unforeseen transport disruptions introduce uncertainty in the commuter’s mind that arrival at scheduled activities may be delayed. Anticipating such delays often creates a sense of time pressure, prompting individuals to make rapid rescheduling decisions to stay on track with their planned itinerary. In the stated preference experiment, this notion of time pressure was operationalised by requiring participants to make choices under explicit time constraints, thereby simulating decision-making under time pressure.

Alongside the choice set presented to the respondents, a countdown timer was also displayed, indicating a predefined time budget for making the decision. Participants were required to make a preferred choice within the allotted time; otherwise, the survey automatically proceeded to the next question. This approach allowed for the precise recording of time each respondent spent on completing each choice set. The imposed time budget constraints varied across choice tasks, with the specific limits informed by findings from the pilot study described in Section 6.3.2. It should be noted that the imposed time constraints were designed to simulate decision-making under time pressure within a controlled experimental setting, they do not necessarily represent exact real-world decision times. Instead, they provide a structured mechanism to examine behavioural responses under constrained decision conditions.

6.2.5 Experimental design

6.2.5.1 Stated preference experiment

The event-based stated preference experiment was designed to place respondents in a context of uncertainty, where the delay in travel time is anticipated in the event of a disruption. The content enclosed in the box was presented to respondents at the outset of the survey to establish the context for their subsequent choices.

> You wake up in the morning and discover that there has been bad weather overnight which has disrupted your normal route to work due to flooding. The time is currently 8:00 am. You have a busy day at work. Your planned schedule is as follows:
>
> - 8:30 Leave home to travel to work.
> - 9:00 Start the day with a planned diary engagement.
> - 17:00 Leave work.
>
> Before leaving for work, you had planned to prepare your diary for the day ahead and respond to important emails. If you choose to leave for work earlier than the planned you will lose the opportunity to do this, although you could deal with some straightforward tasks if you choose to travel by public transport.

Three hypothetical scenarios, each reflecting a distinct type of work arrangement, were specified and sequentially presented to respondents as the survey progressed, as illustrated in Figure 6-2 (a) (b) and (c). These scenarios were designed to capture variations commonly experienced in hybrid working contexts, differing in meeting type, level of involvement, and schedule flexibility (Appel-Meulenbroek *et al.*, 2022; Munnich *et al.*, 2025). By doing so, it provided a structured way to elicit how respondents adapt their travel and rescheduling choices under different work commitments. The scenarios thus not only ensured comparability across responses but also reflected realistic conditions that commuters are likely to encounter in practice.

- ***Scenario 1: Team meeting to plan a new project***

Schedule: *9:00 to 10:00 am, with some flexibility over the start and end times.*

Attendees: *Five colleagues who you work with on a daily basis.*

Involvement: *The meeting will involve referring to multiple documents and figures and using a flip chart or whiteboard to work together on the plan.*

Flexibility: *You can join the meeting remotely if absolutely necessary.*

(a)

- ***Scenario 2: Meeting with senior management***

Schedule: *9:00 to 10:00 am, with no flexibility over the start and end times.*

Attendees: *Your manager and other senior colleagues.*

Involvement: *Formal meeting with fixed agenda. You will be asked to give a brief verbal update on a current project.*

Flexibility: *You can join the meeting remotely if necessary.*

(b)

- ***Scenario 3: Breakfast meeting hosted by your employer***

Schedule: *9:00 to 9:30 am, networking over tea/coffee*

9:30 to 10:00 am. panel discussion on your highly interest topics

No flexibility over the start and end times

Attendees: *Individuals from within and outside your organization.*

Involvement: *Opportunity to chat informally with attendees before the panel discussion.*

Flexibility: *The panel discussion will be live streamed for those unable to attend the event.*

(c)

Figure 6 - 2 Three hypothetical scenarios; (a) Scenario 1; (b) Scenario 2; (c) Scenario 3

6.2.5.2 Selected attributes and levels

This section introduces the set of attributes incorporated in the stated preference choice experiment, which were carefully selected to capture the key factors influencing individuals' rescheduling decisions under disruption scenarios. In addition to travel time and travel cost, the survey also incorporated predicted travel time variability.

In previous research, travel time reliability has often been introduced by specifying a range of possible travel times and their associated probabilities (e.g. Li, Hensher and Rose, 2010). Within this framework, travellers were assumed to select the alternative with the highest expected utility based on these probabilistic outcomes. While theoretically sound and analytically tractable, this assumption may not accurately reflect real-world behaviour, as travellers generally lack knowledge of the precise probability distributions of travel times. Instead, they are more likely to rely on real-time navigation tools, such as Google Maps (2023), which provide an expected travel time as well as optimistic and pessimistic estimates derived from historical traffic data.

To enhance the realism of the experimental setting and promote respondent engagement, a similar approach was adopted in this study. Specifically, each alternative was characterised not only by its expected travel time but also by upper and lower bounds representing the earliest and latest likely arrival times. This representation of travel time reliability offers a more intuitive and contextually grounded measure, aligning with how commuters' access and interpret travel-related uncertainty. The attributes and levels used in the experiment are presented in Table 6-1 to Table 6-2 for habitual private vehicle commuters and habitual public transport (PT) commuters respectively. Table 6-3 shows derived attributes for both categories of commuter.

Table 6 - 1 Attributes and level for habitual private vehicle commuters

	Attribute	Choice set 1 (PD - 8:30am fixed)			Choice set 2 (ED - 8:30am relaxed)			
		CAR_Hr|PD	CAR_SPr|PD	PT|PD	CAR_Hr|ED	CAR_SPr|ED	PT|ED	WfH
Internal	Departure Time (dep.)	8:30	8:30	8:30	8:00	8:00, 8:10, 8:20	8:00, 8:10, 8:20	-
	Expected travel time (tt.)	50, 70	Randomly sampled from [60%, 80%] with a resolution of 5% on the habitual route travel time	41+7 (inc. walking)	50, 70	Randomly sampled from [60%, 80%] with a resolution of 5% of the habitual travel time	41+7 (inc. walking)	-
	Reliability (tt.var.)	[-5,15]	[-5, 5], [-5, 15]	[-5, 5]	[-5,15]	[-5, 5], [-5, 15]	[-5, 5]	-
	Monetary cost (tc.)	£5.6, £6.8	£4.4, £5.6, £6.8	£4.9	£5.6, £6.8	£4.4, £5.6, £6.8	£4.9	-
External	Scenario	[1,2,3]						
	Time pressure	None, 0.6, 0.8, 1.0 (relative to the 20 s)						

Table 6 - 2 Attributes and levels for habitual public transport commuters

	Attribute	Choice set 1 (PD - 8:30am fixed)			Choice set 2 (ED - 8:30am relaxed)			
		PT_H|PD	PT_SP|PD	CAR|PD	PT_H|ED	PT_SP|ED	CAR|ED	WfH
Internal	Departure Time (dep.)	8:30	8:30	8:30	8:00	8:00, 8:10, 8:20	8:00, 8:10, 8:20	-
	Expected travel time (tt.)	43+7, 63+7 (inc. walking)	Randomly sampled from [60%, 80%] with a resolution of 10% on the habitual route travel time +12 (inc. walking)	37	43+7, 63+7 (inc. walking)	Randomly sampled from [60%, 80%] with a resolution of 10% of the habitual travel time +12(inc. walking)	37	-
	Reliability (tt.var)	[-5,15]	[-5, 5]	[-5, 5], [-5,15],	[-5,15]	[-5, 5]	[-5, 5], [-5,15],	-
	Monetary cost (tc.)	£4.9	£4.4, £5.6	£6.8	£4.9	£4.4, £5.6	£6.8	-
External	Scenario	[1,2,3]						
	Time pressure	None, 0.6, 0.8, 1.0 (relative to the 20 s)						

Table 6 - 3 Derived attributes of both private vehicle and habitual public transport user

	Attributes	Levels	Description
Internal	Expected arrival time	/	Equal to dep. + tt.
	Earliest expected time of arrival (Eexp.)	/	Equal to dep. + tt. + tt.var. lower bond
	Latest expected time of arrival (Lexp.)	/	Equal to dep. + tt. + tt.var. upper bond

6.2.5.3 Creating candidate choice sets

- Why not orthogonal or optimal experiment design?

In conventional stated preference/choice experiments, orthogonal or Bayesian-efficient designs using D-error are used to systematically vary the experimental factors. In this study, however, such approaches were not feasible due to the presence of multiple interactions both across choice sets and among the choice attributes of alternatives, as outlined below.

<u>Interactions between choice sets:</u>

- In each choice task, Choice Set 2 was conditional on the response to Choice Set 1 and was presented only if the respondent selected the early departure option in Choice Set 1. It was specifically designed to examine early departure decisions, with its expected travel times aligned to those in the corresponding conditions of Choice Set 1.
- For the same reason, the travel time variability affecting the earliest and latest arrival time of the alternatives in choice set 2 should be kept smaller or at least consistent to their corresponding ones in choice set 1. In addition, it is conceivable that the level of travel time variability is to some extent dependent on the expected travel time of the alternatives, i.e., the longer the expected travel time due to the unexpected disruption, the greater the uncertainty and hence the greater variability in travel time.

<u>Interactions between choice attributes:</u>

- The expected travel time of the shortest path should not exceed that of the habitual route affected by the disruption.
- It is inevitable that the longer a private vehicle is stuck on the street, the greater the fuel cost will be. Therefore, the travel cost is relevant to the expected travel time for the private vehicle[5]. In addition, the parking fee, which is included in

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[5] The monetary cost (fuel and parking) of habitual private vehicle user is dependent on its travel time (tt). Consequently, if tt. CAR ∈ [30, 40) mins, monetary cost = £4.4; if tt. CAR ∈ [40, 50) mins, monetary cost = £5.6; if tt. CAR ∈ [50, 60] mins, then monetary cost = £6.8. The monetary cost of public transport is £4.9, which allows comparing the costs between modes.

In order to boost the trade-off while maintaining a reasonable size of combination, two levels of label on monetary the travel cost, is identical among the private vehicle alternatives since taking a different route to work would not affect the choice of where to park.

The complicated dependency and restrictions between choice sets and the alternatives in the choice set make part of the experimental design contradict assumptions in classical design. Therefore, the experiment was constructed through applying attribute-level permutations that remained consistent with these constraints.

- Eliminating dominated alternatives

Choice tasks containing dominated alternatives offer limited insight into participants' preferences, as they fail to introduce meaningful trade-offs. Moreover, their presence can undermine the credibility of the survey and reduce participants' motivation to complete it. Therefore, such tasks should be excluded. In this study, the elimination of dominated choice tasks was conducted by comparing internal attributes across alternatives within each choice set.

The dominated rule was applied to remove the choice task where an alternative excels in all internal attributes over one of its accompanying alternatives within the same choice set. For habitual private vehicle users, the dominated alternatives were identified in 432 out of 2160 possible permutations of choice task (leading to 1728 choice tasks left) where the shortest path having a travel time of 30-38 mins with a variability of [-5, 5] was a dominating alternative over the alternatives. No dominated alternatives were screened out from the choice tasks of habitual public transport users, leading to 1296 possible combinations. However, it was still a large combination size, which would make the fulfilment of the sample size challenging.

- Boost the trade-off in arrival time between alternatives

The number of potential choice tasks in the experiment would become extremely large when considering all levels of attributes of both internal and external attributes. To maintain a manageable set of choice tasks that could be effectively implemented within the survey platform, the design was carefully processed to enhance the trade-offs between alternatives while reducing unnecessary complexity.

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cost were set to PT_SP for habitual public transport users, i.e., the monetary cost equalling £4.4 if tt. PT_SP <= 30 mins, and £5.6 otherwise. The monetary cost for the car was set to £6.8 for the trade-off between options. A relatively higher cost of private vehicles can partially explain why public transport has been chosen as the habitual mode.

Taking the survey for habitual car users for instance, the ideal design would involve permuting all possible combinations of attribute levels to capture trade-offs in expected travel time between the habitual route and the shortest path route, therefore identifying the threshold at which individuals consider switching routes. In practice, however, the expected travel time difference between these two alternatives was sometimes minimal, for example, approximately 3 minutes, which, under the assumption of same departure time, results in a similarly small difference in expected arrival time. If a public transport (PT) option were included for all three departure times (08:00, 08:10, and 08:20) across each combination of the habitual route and the shortest path, a total of nine distinct choice sets would be generated. However, given the marginal differences in arrival times among these combinations, a more efficient design was adopted. In this design, each public transport departure time was assigned to one specific combination of the habitual route and the shortest path. For example, the 08:00 departure was paired with the case where the shortest path required 30 minutes, the 08:10 departure with the 33-minute shortest path, and the 08:20 departure with the 35–minute shortest path. This approach reduced the number of choice tasks from nine to three, without substantially diminishing the ability to capture differences between the habitual route, the shortest path, and public transport. As a result, the overall number of choice sets in the experimental design was reduced from 1,728 to 576, while preserving meaningful variation in the trade-offs presented to participants.

6.2.5.4 Task of the stated choice experiment

In the stated choice experiment, the full task was divided into two sub-tasks and assigned to participants consecutively, in order to manage participants' workload and minimise respondent fatigue. For each participant, a series of six choice tasks were assigned. Each choice set in the choice task contained the same number of alternatives, as presented in Figure 6-3. The alternatives were displayed in four columns, with the rows indicating the different attributes and their corresponding levels. Participants were advised that each choice task was independent, with circumstances varying across tasks. Each of the two choice sets per task included at least three alternatives, enabling the exploration of behavioural dynamics that binary choices may fail to reveal.

The following example illustrates that the stated preference experiment adopted a sequential (two-stage) choice structure. Respondents were first presented with a baseline choice scenario (e.g. departing as planned) and then a follow-up scenario (e.g. considering an earlier departure), with each stage presented as a separate but related choice task. In this design, respondents were guided by the contextual framing of each scenario rather than being presented with all possible attributes simultaneously. The attributes associated with the alternative strategy (e.g. early departure) were therefore introduced in the subsequent task. This approach was adopted to reduce cognitive burden and to reflect a more realistic decision-making process, whereby individuals first consider a general adjustment strategy before evaluating specific alternatives in detail.

[Scenario description: …]

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

[Timer]

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Private car	Private car	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	…	…	…	
Expected Arrival Time [Earliest, Latest]	X:XX [X:XX, X:XX]	X:XX [X:XX, X:XX]	X:XX [X:XX, X:XX]	
Monetary Cost	£X	£X	£X	

O Option 1 O Option 2 O Option 3 O Option 4

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

[Timer]

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Private car	Private car	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	…	…	…	
Departure time	…	…	…	
Expected Arrival Time [Earliest, Latest]	X:XX [X:XX, X:XX]	X:XX [X:XX, X:XX]	X:XX [X:XX, X:XX]	
Monetary cost	£X	£X	£X	

O Option 1 O Option 2 O Option 3 O Option 4

Figure 6 - 3 Illustration of choice sets and corresponding alternatives in a choice task

In addition to the implementation of internal attributes, external attributes define the context of the choice tasks and shape respondents' decision outcomes. Figure 6-4 illustrates the assignment of choice tasks across these attributes. The same scenarios applied to two consecutive choice tasks: in the first, respondents made their choice without any time constraint, whereas in the second, the decision had to be made within a limited time. In a choice task, the timer would reset when respondents proceeded to a new choice set, and the value of the decision time budget t_{bud} was kept consistent across the choice sets in a choice task. All three scenarios were presented to respondents, with the numbers in blue parentheses indicating the number of choice tasks assigned to each participant. The intensity of imposed time pressure, randomly selected for each respondent, ranged from 60% to 100% of the general time budget (20 seconds), as estimated from the pilot study.

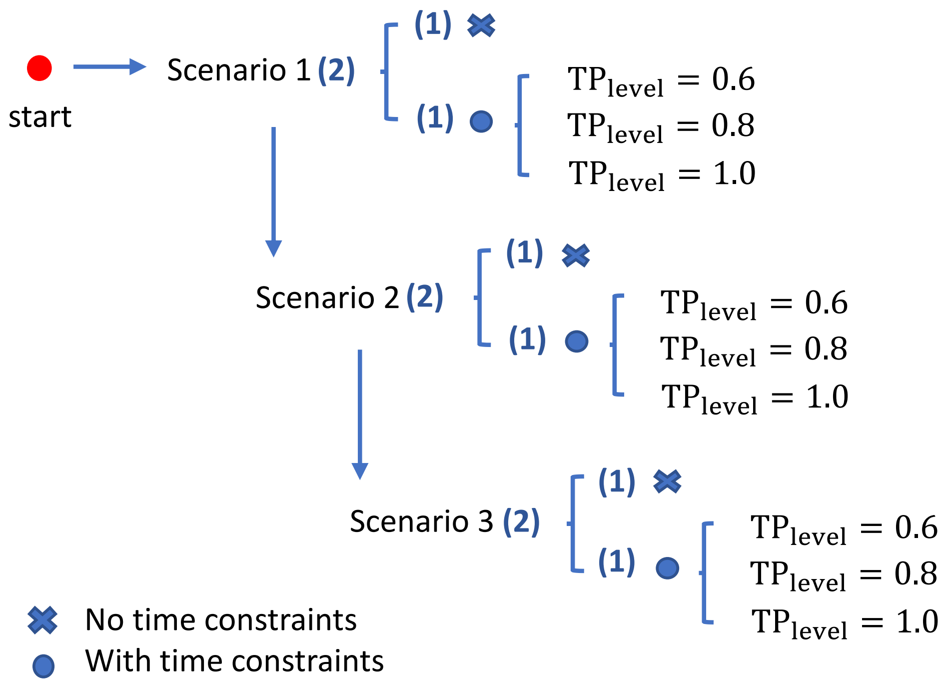


Figure 6 - 4 Structure of choice task presentation. Bracketed numbers denote the number of choice tasks per participant under each scenario, reflecting varying time pressure conditions.

6.3 Survey Instrument

6.3.1 Structure of questionnaire

The questionnaire consisted of three main sections. The first section of the questionnaire introduced the stated preference (SP) experiment, in which participants were presented with hypothetical commuting scenarios designed to capture their rescheduling behaviour. To tailor the experiment to individual contexts, participants were first asked about their habitual travel modes and commuting patterns. Their responses determined which version of the choice tasks they received. At the end of this section, follow-up questions were included to explore the reasoning behind their rescheduling decisions. The second section presented questions on attitudes towards activity cancellation and remote working during the pre-, mid-, and post Covid phases. The final section gathered socio-economic background information, including gender, age, employment, nature of work, etc. Participant feedback was also collected at the end to assess overall satisfaction to the survey. The estimated completion time was provided at the outset, and a dynamic progress bar was displayed throughout to indicate the proportion completed. The survey was administered via two separate web links, distinguishing between habitual private vehicle users and habitual public transport users. Two sample questionnaires are provided in Appendix B for reference.

6.3.2 Survey pilot

Following the creation of the questionnaire, it was important to conduct a pilot as a preliminary step before the survey distribution so as to make sure that the technical setup works well in every aspect and the questions in the survey can be correctly understood by respondents. Given the complexity of the stated preference experiment, combining the structured design of choice tasks with the introduction of time pressure, conducting adequate pilot work was necessary.

Two rounds of pilot were conducted. One pilot was carried out to investigate the appropriate time constraints set for each choice task which were then applied to the survey and incorporated into the choice tasks. The second pilot was conducted following the internal review of the survey design. The pilot was conducted by staff within the Department of Civil and Environmental Engineering who completed and commented on the survey. A section of rating and comments was designed to collect feedback from the respondents at the end of the survey. A total of 29 pilot surveys were distributed, collected, and analysed, based on which the scenario design and the functionality of display and skip logic were examined and the value of time pressure setting was adjusted to be most effective. A comment regarding the aversion to being late for pre-scheduled meetings prompted a re-examination of the experiment design, ensuring that the considerations for both arriving early and arriving late were carefully addressed. The pilot responses also provided an opportunity for a preliminary data analysis as prior information before the main survey was launched based on the final design.

6.4 Sampling and Data Collection

6.4.1 Target population and survey mode

The target population for this survey comprised working-age individuals who regularly engage in weekday commuting and are habitual users of either private vehicles or public transport. Specifically, the focus was on those who routinely travel to fixed workplaces during weekday peak hours, as their travel behaviour are more likely to be affected by disruptions, schedule constraints, and time-sensitive decisions. This population was considered most relevant for exploring rescheduling behaviours to different work arrangement scenarios in response to short-term unexpected transport disruption.

To reach this population effectively, an online stated preference survey was administered using the Qualtrics (2022) platform. Qualtrics was selected for its flexibility in survey design, enabling the implementation of complex choice tasks, embedded logic, and time-limited responses to simulate realistic decision-making conditions. The survey was distributed via the social media channels (twitter, Facebook, and LinkedIn) of the University of Strathclyde's Civil and Environmental Engineering Departmental account. Data collection was conducted in October 2022, following approval from the University's Ethics Committee. To encourage participation, respondents were offered the opportunity to enter a prize draw to win one of five £20 Amazon vouchers upon completing the survey.

6.4.2 Sampling strategy

A non-probability sampling strategy was employed in this study. The survey was distributed online and shared through social media platforms to reach a broad outreach to working-age individuals with diverse commuting backgrounds. Interested participants self-screened based on their primary commuting mode, ensuring relevance to the study context. As participation was voluntary and unrestricted, the sample was subject to self-selection bias and may not fully guarantee the demographic balance observed in census statistics. Nevertheless, this approach was considered appropriate for stated preference research, where the primary objective was to engage a more targeted population to examine their behavioural responses to hypothetical scenarios.

6.4.3 Response rate

Table 6 - 4 Summary of survey responses

	Total	Private Vehicle	Public Transport
Started survey	2226	995	1231
Private or public transport mode users	1372	615	757
Completed survey responses	1152	557	595
Response rate (%)	84.6%	90.6%	78.6%

Due to the restriction on the permitted number of blocks in Qualtrics, the survey was split into two separate links for private vehicle users and public transport users, respectively. 995 participants entered the private vehicle link, and 1231 participants entered the public transport link. However, the participants would have the opportunity to be redirected to the right/corresponding link if the link entered was not their habitual mode. A total of 162 participants were redirected from the private vehicle user link to the public transport link, while 167 participants were redirected from the public transport link to the private vehicle link. In addition, it was noted that some participants, who use a mode of transport other than private vehicles or public transport, also expressed interest and participated in the survey. For these respondents, the activity-travel rescheduling choice experiment was not presented, as it was not relevant to their travel context. However, their responses were still recorded and retained for the remaining sections of the survey.

The response rate was calculated as the proportion of completed surveys relative to the number of eligible participants who initiated the survey through the link corresponding to their habitual transport mode. As shown in Table 6-4, a total of 557 out of 615 habitual private vehicle commuters completed the survey, resulting in a response rate of 90.6%. Similarly, 595 out of 757 habitual public transport commuters completed the survey, yielding a response rate of 78.6%. Overall, the number of completed responses exceeded initial expectations.

As to the sample size, it was suggested that "As a rule of thumb, sample sizes which yield less than thirty responses per alternative produce estimators which cannot be analysed reliably by asymptotic methods" (McFadden, 1984). In this study, the final sample size ensured that each alternative received more than 30 responses, which was sufficient representation to capture the necessary variability in choice responses across alternatives and to support asymptotically efficient parameter estimation, particularly given the repeated-measures design of the choice tasks.

6.4.4 Participants' feedback on the survey

The feedback on the survey was reflected in the satisfaction questions included at the end of the survey "Q - How were you satisfied with the experience of completing this survey?" and "Have you experienced any confusion or unclear expression during completing the survey? If any, please specify".

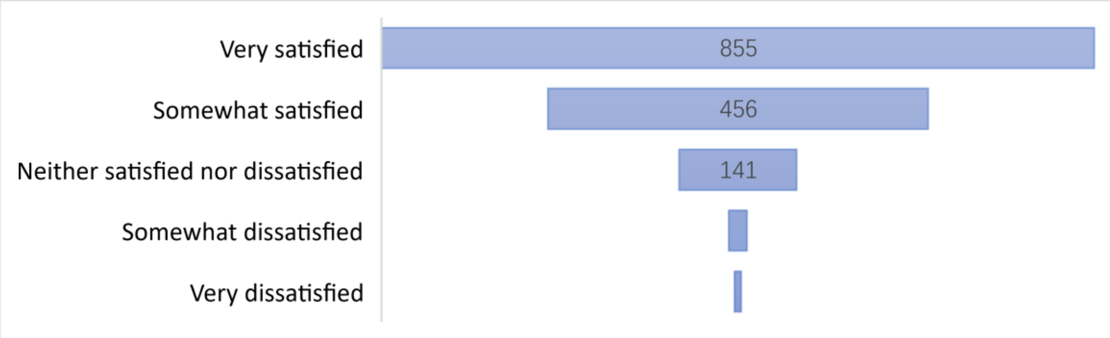


Figure 6 - 5 Feedback on satisfaction of the survey

As shown in Figure 6-5, 855 (57.69%) of respondents were' Very satisfied' and 456 (30.77%) were 'Somewhat satisfied with the survey, leading to a Satisfaction rate of 88.46%. Most of the comments didn't claim to have experienced any confusion in the survey and some thought the survey was comprehensive. Apart from 141 (9.51%) who claimed a neutral attitude to the survey, in the meantime, there were 22 (1.48%) 'Somewhat dissatisfied' and 8 (0.54%) 'Very dissatisfied' reported. The criticism was mainly a result of repetitive questions in the rescheduling choice-making section and the stress imposed by the time constraint. Some people also expected some practical solutions from taking part in this survey.

6.5 Data Processing

Data processing is the series of operations that transform raw data into useable information. After collecting data in the survey, the following steps were taken in data processing: data entry, data cleaning, and data transformation. Data processing was performed using MATLAB-based programming (MATLAB, 2023). The working flow is shown in Figure 6-6.

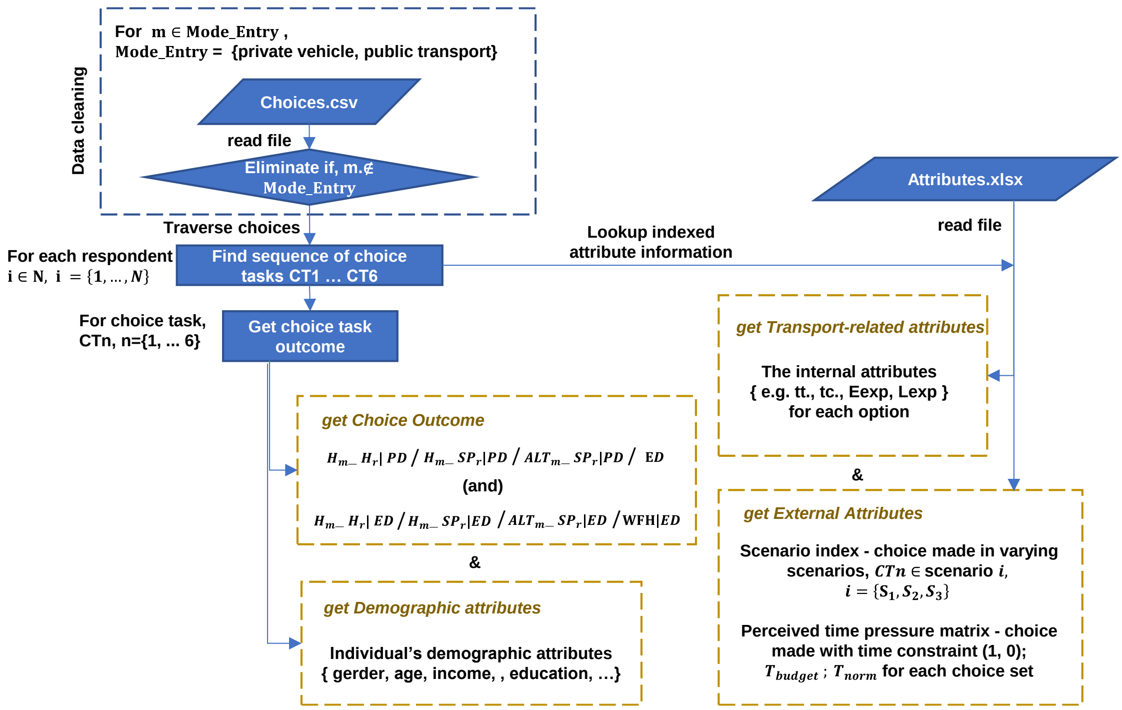


Figure 6 - 6 Data processing and outcomes

The collected data from the online survey tool Qualtrics was saved in comma separated variable (CSV) format. As the choice set presented to respondents was shown in the form of a 'picture', a data transformation was required to link the corresponding attribute values stored in an output table to the presented alternatives of choice sets. For each respondent i characterised by a series of social demographics, a sequence of choice tasks CT_n was made, with each CT_n charactersed by certain scenario and time pressure level. The choice outcome was recorded, which represents the preference among all alternatives in a given choice set. The involved attributes of all alternatives in one choice set allows a thorough analysis of the respondent's decision-making behaviour and preferences.

To ensure the reliability and quality of data for modelling purposes, thorough data cleaning was conducted. The general principle to data cleaning was removing only those records that were absolutely necessary and minimise bias. In general, the most common cleaning factors were missing responses and partial completion, as well as exclusions on suspected thoughtless choice (e.g. took less than 1 second in completing a choice), which would make the stated preference choice outcome unreliable. In addition, a basic diagnostic test was conducted to avoid adverse effects on the model estimation. For example, the non-trading behaviour – those who always choose the option presented on the same side/position in the choice set across all stated preference choice tasks. Although their number was negligible, such cases were detected and removed from the dataset.

6.6 Conclusions and Discussions

This chapter outlines the survey design, survey instrument, data collection, as well as the data processing conducted on the designated activity-travel stated preference survey. This survey was developed to collect data on activity-travel rescheduling choices in the context of short-term unexpected transport disruptions, enabling the modelling of potential impacts associated with perceived time pressure.

The limitations of stated preference (SP) experiments, particularly limited cognitive load and lack of contextual realism are widely acknowledged in the literature (Louviere *et al.*, 2000). In this research, these challenges were attempted to be addressed through thoughtful experiment design. To mitigate the risk of bias associated with cognitive burden from repeated choices, the number of attributes and alternatives per choice set were restricted, and the total number of choice tasks were also limited. In addition, a progress bar was incorporated and kept visible throughout the survey to support expectation management, helping to sustain respondent engagement. To improve contextual realism, scenarios were grounded in realistic commuting situations and, where possible, tailored to reflect common work arrangement patterns that respondents could readily relate to. These measures enhanced the behavioural validity of the responses by making the choice tasks more relatable and the decision context more reflective of real-life conditions.

Although the survey covered both private vehicle users and public transport users, the latter dataset, while valuable, was set aside for future research. The substantial analysis will primarily focus on private vehicle sample.

Chapter 7 Data Analysis

7.1 Introduction

Travel behaviour in the real-world often exhibits substantial complexity. Short-term unexpected transport disruptions, the time pressure generated, and the evolving work patterns of the post-pandemic time further compound this complexity, presenting new challenges for travel behaviour modelling. While the heuristic models capture aspects of bounded rationality under uncertainty, they are often weak in providing a systematic formulation (Hensher, Rose and Greene, 2015). The Random Utility Maximisation (RUM) framework, which offers a rigorous framework for capturing utility-driven decision-making, remains the dominant approach for modelling travel behaviour. As reviewed in Chapter 2, while a substantial body of literature has advanced traditional utility-maximisation models, the way in which individuals adapt under uncertainty and time pressure remains not well understood and are inadequately represented in current approaches (Gärling, Gillholm and Montgomery, 1999)(Chen *et al.*, 2016). This is particularly evident in short-term dynamics, where individuals are not entirely irrational but rely on contingency strategies shaped by prior experience, contextual knowledge, and their capacity to cope with available information (Guo, Nandam and Adams, 2012). In response to these limitations, this chapter proposes a modelling framework grounded in random utility theory, designed to better capture decision-making under bounded travel time uncertainty, with particular attention to reschedule related trade-offs, the influence of work arrangements, and the role of perceived time pressure in light of transport disruptions.

The chapter is organised into six subsections. Section 7.2 introduces the Random Utility Maximisation (RUM) and its application – NL (nested logit) model. Section 7.2 explores the scheduling models and the specification of the utility function. Section 7.3 presents the heteroscedastic model developed to capture the effects of perceived time pressure on choice modelling. Section 7.4 outlines the approaches for model comparison and estimation. In Section 7.5, the chapter concludes with a summary of key points.

7.2 Multinomial Logit and Nested Logit Models

Random Utility Theory offers a foundational framework for modelling choice behaviour in transportation, grounded in the assumption that individuals select the alternative that yields the highest utility. This utility is typically represented as a function of the observable attributes of each alternative, along with an unobserved random component. As reviewed in Chapter 2, a widely used implementation of this framework is the Multinomial Logit (MNL) model. According to the RUM-based decision rule, individuals evaluate all available alternatives and choose the one with the greatest perceived utility, where the total utility comprises a systematic (deterministic) part and a stochastic (random) component accounting for unobserved factors: $U_i = V_i + \varepsilon_i$, Here, U_i represents the utility of the alternative i; V_i is the systematic component of the utility; ε_i is a random component of alternative i. It is commonly assumed that the random component ε_i is independently identically distributed (IID) Extreme value type I, then the well-known multinomial logit model (MNL) specifies that probability of choosing each alternative is proportional to the sum of the exponentiated utilities of all alternatives (Train, 2009b). A decision-maker labelled n, faces a choice among j alternatives, $i = 1,2, \dots, j$. The probability of choosing alternative i can be expressed as follows:

$$P_i = \frac{e^{\mu * V_i}}{\sum_{j \in C} e^{\mu * V_j}} \tag{7-1}$$

Where P_i is the probability of choosing alternative i; V_i is the systematic utility of alternative i, which can be specified by alternative-specific attributes and the individual-specific characteristics; μ is the scale parameter which is commonly normalised to 1.

In addition, the MNL relies on the Independence of Irrelevant Alternatives (IIA) assumption, which may be violated in cases where correlations exist between choice alternatives. The nested logit (NL) model extends the MNL model by allowing for correlations between alternatives within the same nest. The nested logit model provides a more flexible way of modelling decision-making behaviour, allowing for the incorporation of substitutability among alternatives within nest.

To implement the nested logit procedure, a nesting hierarchy is first imposed, and the probability of choosing a particular alternative is calculated as the product of the probability of choosing its nest and the conditional probability of selecting the alternative within that nest. Let C_m be a partition of choice set C, the probability of choosing alternative i among choice set C, is equal to the probability of choosing alternatives in the nest, $P_r(C_m|C)$, and the conditional probability of choosing exactly alternative i given some alternative in the same nest, $P_r(i|C_m, C)$, that is:

$$Pr(i|C) = \sum_{m=1}^{M} Pr(i|C_m, C) \cdot Pr(C_m|C)\,, \quad i \subseteq C_m \subseteq C \tag{7-2}$$

The utilities of the lower-level alternatives within a nest are aggregated into an inclusive value (also known as log-sum)(Train, 2009a), which enters the utility function of the corresponding upper-level nest. For each nest m, the inclusive value captures the overall attractiveness of that nest by aggregating the utilities of all alternatives it contains. Behaviourally, it represents the expected maximum utility that an individual can attain from alternatives within nest m. The expected maximum utility of the nest m is written as (Bierlaire, 1997):

$$IV_m = \frac{1}{\mu_m} \ln \sum_{i \in m} e^{\mu_m \cdot V_i} \tag{7-3}$$

Where μ_m denotes the nest-specific dissimilarity parameter scale parameter of the lower nest m. To ensure consistency with random utility theory since, these parameters should satisfy $\mu_m \geq \mu$, if nest $C_m \subseteq C$. This condition reflects the requirement that the variance of the unobserved components decrease as the choice set is narrowed going down the choice tree.

Therefore, the probability of an individual choosing the alternative i within the nest m, $(i \in m)$ is formulated by:

$$\Pr(i|C_m) = \frac{e^{\mu_m V_i}}{\sum_{j \in C_m} e^{\mu_m V_j}}. \quad (7\text{-}4)$$

To that end, the probability of an individual choosing the lower nest m from the upper nest, i.e., the probability across nests is given by:

$$\Pr(C_m|C) = \frac{e^{\mu IV_m}}{\sum_{p=1}^{M} e^{\mu IV_p}}. \quad (7\text{-}5)$$

The nested logit can be fitted by plugging them into Equation 7-2.

7.3 Utility Function Specification for Early and Late Arrivals

Building on the RUM framework, the scheduling model incorporates temporal aspects of travel decisions, specifically by accounting for penalties associated with deviations from preferred arrive time. The choice behaviour model proposed in this research builds upon the schedule delay framework developed by Small (1982) which simulates the disutility of an individual not arriving at its destination at a specific 'preferred arrival time (PAT)' subject to the unreliability of travel time (TT). The schedule delay is defined by the deviation of an expected arrival time (AT) from PAT, with positive or negative (PAT–AT) indicating arriving earlier or later than desired, which is assumed to result in respective disutility.

Motivated by the objective of understanding rescheduling decision-making under travel time uncertainty induced by transport disruptions, this study examines alternative specifications of rescheduling-related attributes within travel choice models. In contrast to approaches that assume a known statistical distribution of arrival times, a bounded uncertainty approach was adopted in which actual arrival times fell within a range defined by earliest and latest possible arrival times, a representation that aligns with estimates commonly provided by navigation applications, such as Google Map (Google, 2023). The representation was incorporated into the utility function, allowing for a systematic evaluation of how different specifications captures the travel choice behaviour.

In light of disruption with delay anticipated, it is reasonable to assume that travellers aim to arrive in time for the start of their pre-scheduled work activities, and thus the preferred arrival time (PAT) is set equal to the activity start time. Based on this, schedule earliness (SE) and schedule lateness (SL) were defined by comparing the expected arrival time with the PAT:

$$SE = \max(PAT - AT, 0) \tag{7-6a}$$

$$SL = \max(AT - PAT, 0) \tag{7-6b}$$

The systematic utility function U of an alternative was thus defined as a linear additive combination of attributes:

$$U = \beta_{ASC} + \beta_{TT} \cdot TT + \beta_{SE} \cdot SE + \beta_{SL} \cdot SL \tag{7-7}$$

where β_{TT}, β_E, and β_L represent the sensitivities of utility to attributes travel time (TT), SE and SL, respectively. The parameters β_{ASC} is associated with the alternative specific constant (ASC). A normalisation technique was applied to the ASC, in which one of the alternatives was designated as the reference point, with its ASC set to zero. This allowed for the estimation of relative preference weights associated with unobserved factors not captured by the explanatory variables.

Investigating the influence of different work-related activities on travel behaviour is especially relevant in the post-COVID era, where flexible working patterns are of common practice in the labour market (Aksoy *et al.*, 2025). To examine this aspect, dummy variables were used to capture the effects of different scenarios of work commitments. These variables were incorporated into the utility function by interacting each purpose-specific dummy variable with the travel attributes, allowing selected coefficients to vary across purposes. The utility function is specified as:

$$U_i = \beta_{ASC} + \beta_{TT} \cdot TT + \beta_{SE}^{S_i} \cdot SE + \beta_{SL}^{S_i} \cdot SL, \qquad i = 1,2, \dots k \tag{7-8}$$

Where, S_1, S_2, … S_k are dummy variables representing each purpose, such that $S_i = 1$ if the observation corresponds to the purpose i, and 0 otherwise. Three dummy variables were introduced rather than two because the primary interest lies in the purpose-specific sensitivities of the parameters, rather than in comparing the relative weights between purposes.

7.4 Including Perceived Time Pressure in the Logit Model

The error term in RUM theory captures the unobserved or stochastic component of utility, reflecting factors influencing individual choice that are not explicitly represented by the observed attributes of the alternatives. According to MNL model, the error terms ε_i are assumed to be independently and identically distributed (i.i.d.) across alternatives, following an Extreme Value distribution with the same parameters for each alternative, $\varepsilon_i \sim EV(0, \mu)$. The variance of the error term reflects the scale of unobserved utility - the part of individuals' decision-making that is not explained by the observed attributes in the utility function. The scale parameter μ in a standard logit model is inversely related to the variance of the random component ε, i.e., $var(\varepsilon) = \pi^2/(6\mu^2)$ (Bierlaire, 1997). A higher value of μ corresponds to a lower variance of the error term, indicating that choices are more consistently explained by the modelled attributes and thus exhibit more deterministic choice behaviour. Conversely, a lower value of μ reflects a higher variance, implying that the choices are influenced more by unobserved factors and therefore appear more random (Ben-Akiva and Lerman, 1985). The standard approach to normalising the scale of utility is by fixing the variance of the error terms. A common normalisation is to set the scale parameter μ to 1, which implies that the variance of the random error equals $\pi^2/6$.

In the NL model where multi-level decision processes or nests exist, the scale parameter associated with the utility of alternatives in the upper nest must be smaller than or equal to the scale parameter for the lower nest, reflecting the greater variance of random error terms at upper levels of the decision hierarchy. This relationship can be expressed by normalising μ to 1 and introducing a variable B_I, defined as the ratio of μ to μ_m. The variable B_I must be estimated from the data, and satisfies $0 < B_I \leq 1(\text{Train}, 2009\text{a})$:

$$B_I = \mu/\mu_m \tag{7-9}$$

The assumption that the error terms associated with all alternatives within a nest share the same variance is known as homoscedasticity. However, in some situations, the variance of the error terms can be different for different segments across the population considering the factors such as geographic regions, data sets, time, etc, which gives rise to a more flexible model, called heteroscedastic logit (HL)(Bhat, 1995)(Train, 2009b).

Time pressure refers to an insufficiency of available time to complete a given task within a constrained time budget. In the context of unexpected transport disruptions, such constraints are commonly encountered and constitute a critical factor that may significantly influence decision-making behaviour in activity-travel rescheduling. The process of making a choice inherently requires cognitive effort and time, and these demands vary across individuals and decision contexts. In situations confronted with time pressure, individuals may accelerate their decision-making by reducing the depth of comparative evaluation, disregarding information they perceive as less relevant, and focusing more narrowly on selected attributes of alternatives deemed most comparable. Such behavioural adjustments suggest that the variance of the unobserved utility components, captured by the error term, may not remain constant across tasks, but instead vary according to the level of time pressure perceived by the individual in each task.

Given the relationship between random error variances and scale parameters explained above, the non-identical variances of random error terms can be translated into an task-dependent scale parameter which can be described through a function of perceived time pressure (PTP). The time pressure is incorporated in a heteroscedastic model:

$$\mu = e^{f(PTP)} \tag{7-10}$$

The exponential function is utilised to ensure a non-negativity value, where $f(PTP)$ is a linear function of the explanatory parameter on the measurement of perceived time pressure PTP on a task.

In this study, it was expected that increasing levels of time pressure impose significant challenges to decision-makers, hindering their ability to make trade-offs between attributes and to select the alternative that maximises the utility. Consequently, under tight time constraints, a higher degree of randomness is expected in observed choices compared to the situation where there is no time pressure, reflecting reduced consistency in decision-making. Building upon this reasoning, the study hypothesises that an increase in perceived time pressure is associated with a decrease in the scale parameter, indicating greater variance in the unobserved utility components.

In order to reflect the heterogeneity of time pressure levels perceived by individuals and to model the resulting effects on their choice behaviour, this study proposes a time pressure index (TPI), following (Chen *et al.*, 2016). The TPI is defined as the ratio of the actual decision-making time t_{use} to the decision time budget t_{bud}:

$$TPI = t_{use}/t_{bud} \tag{7-11}$$

Importantly, a very short decision time may lead to a low TPI, but this does not necessarily indicate the absence of perceived time pressure; rather, it may reflect a lack of engagement with the task. In such cases, the reduced cognitive effort is more likely to result in random choice behaviour, reflected by a smaller scale parameter. This implies that the relationship between the effect of perceived time pressure to the scale parameter is unlikely to be monotonic.

As described in Section 6.2.5.4, given the structure of a choice task, the timer is reset for each choice set within a task. Consequently, the actual decision time (t_{use}) varied between choice set 1 and choice set 2, leading to corresponding variations in the TPI, which was modelled for each choice set separately. For the upper nest, the time pressure index of a particular individual is denoted by TPI, and the corresponding scale parameter μ, is formulated by (7-12a). The scale parameter μ_m of the lower nest m was then derived through the cross-nest relationship parameter B_I, as shown in Equation (7-12b). Thus, the choice probability of the individual in the upper nest under time pressure is calculated by the TPI-based μ and μ_m, in accordance with Equations (7-3) and (7-5).

$$\mu = \exp(a \cdot TPI^2 + b \cdot TPI) \tag{7-12a}$$

$$\mu_m = \mu/B_I \tag{7-12b}$$

For an individual who chose ‘early departure’ in the upper nest and subsequently selected an alternative (grouped under early departure) from the lower nest m, the decision-making within the lower nest was governed by an updated TPI. This updated index, denoted as TPI_m, incorporated the information from choice set 2 relevant to that nest. The corresponding scale parameter of the nest m, denoted as $\mu_m^{'}$, is defined in Equation (7-13). The probability of the individual selecting alternative j from the nest m under time pressure was then computed using the TPI_m-based $\mu_m^{'}$, as specified in Equation (7-4).

$$\mu_m^{'} = \exp(a_m \cdot TPI_m^2 + b_m \cdot TPI_m) \quad (7\text{-}13)$$

7.5 Model Comparison and Estimation

To ensure the reliability and quality of data for modelling purposes, the sample obtained from the survey was thoroughly examined and cleaned (as described in Chapter 6) to remove the records which would otherwise create significant bias.

Three models were developed to capture the rescheduling behaviour of participants and were subsequently compared to examine preferences for arrival times, the effects of working commitment purposes and perceived time pressure on travel choices. These models were: 1) a basic Nested Logit (NL) model; 2) a commitment-sensitive NL model, which incorporated dummy variables to distinguish between different working commitment purposes (referred to as NL-dummy); and 3) a heteroscedastic NL (HNL) model that integrated perceived time pressure by allowing the scale parameter of alternative utilities to vary accordingly. For each of the proposed models, the vector of model parameters X were estimated to maximise the overall log-likelihood (LL) of individuals' choices using the maximum likelihood estimation (MLE) method:

$$\hat{X} = \arg\max \sum_n \sum_s \ln\left(P_{n,s}(X)\right) \quad (7\text{-}15)$$

where $P_{n,s}(X)$ is the choice probability of an individual n in a task s ($s = 1, \dots, S$) depicted by the model parameter vector X. To mitigate the risk of model parameters converging to a local optimum, 1,000 randomly initialised starting points were generated using MATLAB's (2023a) global search, which identified the solution with the potentially best log-likelihood within the search space. As global search sacrifices some precision to ensure broader coverage, the resulting solution was treated as a candidate for the global optimum. Then, a local optimiser 'fminunc' was further employed to refine this solution. The process of parameter estimation was carried out multiple times, and the same solutions were obtained between different runs, suggesting that the global optimum was found in the search space.

In addition to the overall LL, the model performance was also be evaluated by the Horowitz pseudo r-squared (R_H^2) that takes into account the improvement in the overall LL over a null model (i.e., the one without any predictor) and the number of model parameters, as formulated by (7-16).

$$R_H^2 = 1 - \frac{LL_{NL} - M/2}{LL_0} \tag{7-16}$$

where LL_{NL} and LL_0 denote the overall LL values of the proposed model and the null model respectively, and M is the number of model parameters. The Horowitz pseudo r-squared adopted in this work measures the trade-off between the goodness-of-fit of choice behaviour modelling and the number of model parameters. In addition, the statistical significance of the estimated model parameters was assessed through the t-test, as formulated by (7-17) and (7-18).

$$t_{\hat{X}_i} = \frac{\hat{X}_i}{\sigma(\hat{X}_i)} \tag{7-17}$$

$$p_{\hat{X}_i} = 2 * \left(1 - \Phi\left(\left|t_{\hat{X}_i}\right|\right)\right) \tag{7-18}$$

where $t_{\hat{X}_i}$ and $p_{\hat{X}_i}$ are the t-statistic and the p-value of the model parameter estimate $\hat{X}_i$, respectively, and terms $\sigma(\cdot)$ and $\Phi(\cdot)$ denote the SD and CDF of the standard normal distribution, respectively. When $p_{\hat{X}_i}$ is very low or less than a pre-determined significance level (e.g., up to 0.05 which corresponds to $\left|t_{\hat{X}_i}\right| \geq 1.96$), it suggests that the null hypothesis of the model parameter X_i being equal to 0 can be rejected in favour of the alternative hypothesis of $X_i = \hat{X}_i$, indicating a statistically significant difference between the two hypotheses. In other words, the t-statistics and the p-value reflect the significance of an estimated model parameter along with its associated attribute to the model performance.

In this work, all calculations, including the formulation of probability equations, and the evaluation of the statistical significance of the estimated parameters, were all accomplished using codes written in MATLAB (2023a).

7.6 Conclusions

This chapter has outlined the methodological framework adopted in this study, with particular emphasis on the data analysis procedures. Building upon the Random Utility Theory (RUT), the study extends into scheduling models and commitment-sensitive choice modelling to gain better insights into travel behaviour in response to disruption. Scheduling models emphasise temporal aspects such as preferred arrival times and highlight how scheduled commitments shape choices through individual preferences within specific contexts, thereby revealing the multi-layered nature of travel decision-making. Furthermore, this chapter introduces the concept of heteroscedasticity in relation to perceived time pressure. The discussion centres on how differences in the perception of time constraints influence the variance of unobserved factors, thereby generating distinct decision-making patterns under varying levels of time pressure.

By establishing these procedures, the chapter provides the foundation for the subsequent estimation and interpretation of behavioural models. The next chapter applies the proposed methodology to the empirical data, presenting the results and discussing their implications in the context of travel behaviour under time pressure.

Chapter 8 Results

8.1 Introduction

This chapter begins with an analysis of dataset using descriptive statistics, followed by the presentation of model estimation results to reveal the underlying behavioural patterns. This chapter is structured as follows: Section 8.2 provides a thorough analysis of the sample data collected from respondents; Section 8.3 presents the model estimation results and provides empirical insights into the hypotheses of this work; and Section 8.4 concludes with a discussion of findings.

8.2 Descriptive Statistics

8.2.1 Socio-demographic characteristics

Table 8-1 presents a summary of participants' key characteristics. The first and second columns of the table represent the variables related to respondents and their categories, and the number and percentage of respondents in the sample who fall into each category are listed in the last two columns.

Table 8- 1 Socio-demographic and commute characteristics of respondents

Variable	Category	NO.	%
Gender	Male	320	57.97%
	Female	218	39.50%
	Non-binary	12	2.17%
	Prefer not to say	2	0.36%
Age	18-24 years	67	12.14%
	25-34 years	311	56.34%
	35-44 years	160	28.99%
	45-54 years	14	2.54%
	55-64 years	0	0.00%
	above 65 years	0	0.00%
Educatiton	Secondary school	6	1.09%
	Vocational or similar	35	6.33%
	Some University but no degree	110	19.89%
	University - Bachelor's degree	236	42.68%
	University - Master's degree	152	27.49%
	University - Doctorate	12	2.17%
	Prefer not to say	2	0.36%
Income	Less than £10.000	19	3.44%
	£10,000 - £29,999	149	26.94%
	£30,000 - £49,999	181	32.73%
	above £50,001	197	35.62%
	Prefer not to say	7	1.27%
Caring responsibility^	Children	351	48.55%
	Elderly people	189	26.14%
	Pets	161	22.27%
	No caring responsibiltiy	22	3.04%
Job status^	Working full-time	588	93.63%
	Working part-time	24	3.82%
	On maternity or paternity leave	1	0.16%
	Unemployed and looking for work	2	0.32%
	Not currently working, and not looking for work	1	0.16%
	Student	4	0.64%
	Retired	0	0.00%
	Other	8	1.27%
Instant work resehcdule flexibility (one hour before departure)	Very easy – I could do nearly all of my work from home if necessary.	113	20.29%
	Generally easy – although there are some days when I would need to go to work.	219	39.32%
	It depends what I have on – it would be easy some days but difficult on others.	158	28.37%
	Generally difficult – although there are some days when I could work from home.	45	8.08%
	Very difficult – nearly all of my work requires me to go to work.	22	3.95%
Short-term work from home flexibility (on the day)	Very easy – I could do nearly all of my work from home if necessary.	136	24.42%
	Generally easy – although there are some days when I would need to go to work.	209	37.52%
	It depends what I have on – it would be easy some days but difficult on others.	153	27.47%
	Generally difficult – although there are some days when I could work from home.	41	7.36%
	Very difficult – nearly all of my work requires me to go to work.	18	3.23%
long-term work from home flexibility (three consecutive days)	It would be very easy for me to work from home on three consecutive days.	84	15.14%
	Most of the time it would be easy for me to work from home on three consecutive days.	216	39.28%
	It depends what I have on – sometimes it would be easy, other times it would be difficult.	164	29.55%
	Most of the time it would be difficult for me to work from home on three consecutive days.	69	12.43%
	It would be very difficult for me to work from home on three consecutive days.	20	3.60%
	Commute feature	**Mean (std.)**	
	Time spend on travelling to work one-way (mins)	35.67(17.73)	
	Days of travelling to work before Covid (days)	4.86(0.86)	
	Days of travelling to work currently (days)	4.51(0.95)	

^ refers to question allows multiple choices

The socio-economic profile of the survey participants reveals a moderate male majority, with 57.97% of the total sample being identified as male, and that the most common age group falls between 25 and 34 years. As the recruitment was carried out through engineering-oriented social media platforms, the resulting distributions are likely to reflect the demographic characteristics of these online communities. Nevertheless, it is worth noting that 42.03% of the participants did not identify as male, and 31.53% were above the age of 34. These figures indicate that the sample is not exclusively composed of young males, but instead encompasses a certain degree of gender and age diversity.

In terms of educational background, participants holding bachelor's degrees constituted the largest proportion of the sample, followed by those with master's degrees and those who had attended some university education. Income was mainly reported in three discrete categories: £10,000–£29,999, £30,000–£49,999, and above £50,001. The distribution across these brackets was relatively even, with a maximum difference of no more than ten percentage points between adjacent levels. Additionally, a significant portion of respondents reported caregiving responsibilities, most commonly children, followed by elderly dependents and pets. Regarding employment status, the majority of participants were engaged in full-time work, reflecting a relatively stable working population within the sample.

8.2.2 Commute characteristics

This section presents an overview of the commute characteristics of the surveyed respondents. On average, private vehicle users report an average commute time of 35.67 minutes, with a standard deviation (SD) of 17.73 minutes. Figure 8-1 illustrates the distribution of one-way commute times among the survey participants. The distribution is unimodal, with the most frequently reported commute duration falling within 20–30 minutes. The distribution of commute durations is right-skewed, indicating that a longer tail of respondents experiences higher commute durations.

Furthermore, the average number of commute days per week in the sample was found to decline following the pandemic, decreasing from 4.86 days per week (SD = 0.86 days per week) to 4.51 days per week (SD = 0.95 days per week). This shift demonstrates a trend toward reduced commuting frequency, reflecting increased remote or hybrid working arrangements.

The summary of commuting characteristics indicates that flexible working is widely adopted among respondents, with approximately half reporting either high or moderate degrees of flexibility in their working arrangements. However, the data also indicates that sustained remote working posed greater challenges: 16.03% of the respondents found it generally difficult or very difficult to work from home for three consecutive days. This proportion is higher than the 10.59% who found short-term (on the day) rescheduling flexibility difficult or very difficult, and the 12.03% who reported similar difficulty with instant rescheduling flexibility.

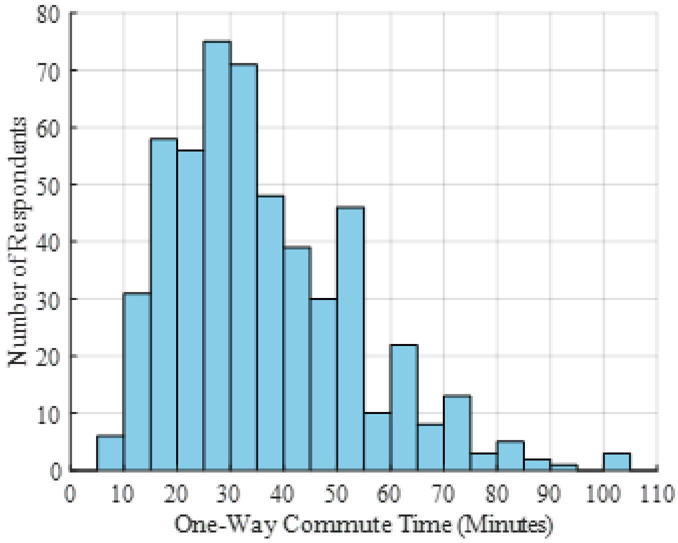


Figure 8- 1 Histogram of the distribution of one-way commute times from sample

8.2.3 Association between socio-demographics and participants' chosen options

The association between various socio-demographic characteristics and chosen options in the stated preference experiment was explored using a combination of cross-tabulation (Pearson *et al.*, 1930) and chi-square analysis (Agresti and Finlay, 1998). Although choice behaviour might be influenced by multiple socio-demographic factors simultaneously, associations between choice and individual socio-demographic variables were examined separately so as to assess their respective significance.

The impacts of socio-demographics factors, including gender, age, education background, and annual income on individual choices were examined. To ensure the reliability of the chi-square test[6] for each socio-demographic, the cross-tabulation was first implemented. These cross-tabulation tables illustrate how the observed frequencies were distributed across categories. Cross-tabulations covering all combinations of choice options and demographic categories for different choice sets were examined, with the results presented in the Appendix C. In order to satisfy the validity assumptions of the chi-square test, cells with counts below five were excluded. The analysis therefore focuses on the main socio-demographic categories in combination with the choice options. Subsequently, the significance of the differences between observed and expected counts was assessed, both under conditions with (w/) or without (w/o) time pressure (TP). The deviation of the number of observations from the expected number can be described by the chi-square χ^2 which is defined by:

$$\chi^2 = \sum_x \sum_y \frac{\left(N_{Cx,Oy}^{exp} - N_{Cx,Oy}^{obs}\right)^2}{N_{Cx,Oy}^{exp}} \tag{8-1}$$

where $N_{Cx,Oy}^{exp}$ and $N_{Cx,Oy}^{obs}$ represent the expected and observed numbers of the participants which belonged to the category C_x $(x = 1, \dots, X)$ of the socio-demographic and selected the choice option O_y $(y = 1 \dots, Y)$. Given X categorites for the socio-demographic and Y choice options, the degree of freedom (k) of the chi-square distribution is determined by:

$$k = (X - 1) \cdot (Y - 1) \tag{8-2}$$

which was then used to calculate the p-value (p) associated with χ^2:

$$p = 1 - F_{Chi2}(\chi^2, k) \tag{8-3}$$

where $F_{Chi2}(\cdot)$ represents the cumulative distribution function (CDF) of a chi-square distribution. A p-value associated with χ^2 statistic below 0.05 indicates that the observed frequency differs significantly from the expected frequency under the null hypothesis of independence. In such cases, the socio-demographic factor under

[6] The chi-square test is an approximate method that becomes more accurate as the counts in the table cells increase. Therefore, it is important to ensure that the counts are sufficiently large to produce a reliable p-value. To meet the requirements for the chi-square test, no more than 20% of the expected counts should be less than 5, and all individual expected counts should be 1 or greater. Specifically, in a 2x2 table, all four expected counts should be 5 or greater.

investigation is deemed to have a significant impact on the individual's choice behaviour.

Table 8-2 reports the chi-square and corresponding p-value estimated for the main socio-demographic variable across the full sample, as well as separately for with TP and without TP. The results indicate that age, education and income were significantly associated with the individual choice behaviour, with the exception of gender (which shows p-values above 0.05 across all the cases). Notably, the strength and significance of these associations varied between the TP and non-TP subgroups. For age, a significant association was observed in all cases and in the TP subgroup. Although there was a lack of statistical significance in the non-TP subgroup, the descriptive statistics remain informative: the p-value decreased from 0.1765 (w/o TP) to 0.0095 (w/ TP), suggesting that TP strengthens the statistical association between age and choice behaviour. This implies that time pressure may amplify underlying age-related differences in decision-making. Furthermore, the analysis revealed a highly significant relationship between education level and choice in both the overall sample and the non-TP subgroup, while a slightly weaker yet still statistically significant association was observed in the TP subgroup. Similarly, income demonstrated a significant association with choice behaviour across all cases and within both TP and non-TP subgroups.

Table 8- 2 Chi-square values and p-values of individual choices for different socio-demographics under all cases, cases with TP or without TP.

Socio-Demographic	Degree of Freedom	All Cases		Cases with TP		Cases w/o TP	
		χ^2	p	χ^2	p	χ^2	p
Gender	3	6.7756*	0.0794	7.1080*	0.0685	3.4421	0.3283
Age	6	19.9574***	0.0028	16.9304***	0.0095	8.9481	0.1765
Education	6	47.0288***	0.0000	15.7440**	0.0152	44.7493***	0.0000
Income	6	25.3494***	0.0003	16.4075**	0.0117	25.9120***	0.0002

Notes: Robust standard errors: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These findings suggest that the socio-demographic differences play a role in shaping rescheduling behaviour. However, to maintain a manageable model structure and ensure estimation stability, the choice models estimated in Section 8.3 were conducted at the population-level, focusing on the average choice behaviour of all respondents.

8.2.4 Reflection on the effect of perceived time pressure on choice selection

With respect to the perceived impact of time pressure, Figure 8-2 presents the distribution of responses to the question: "Do you feel that time pressure affected the way you made your choices?" Participants selected from five response options ranging from "Definitely" to "Definitely not".

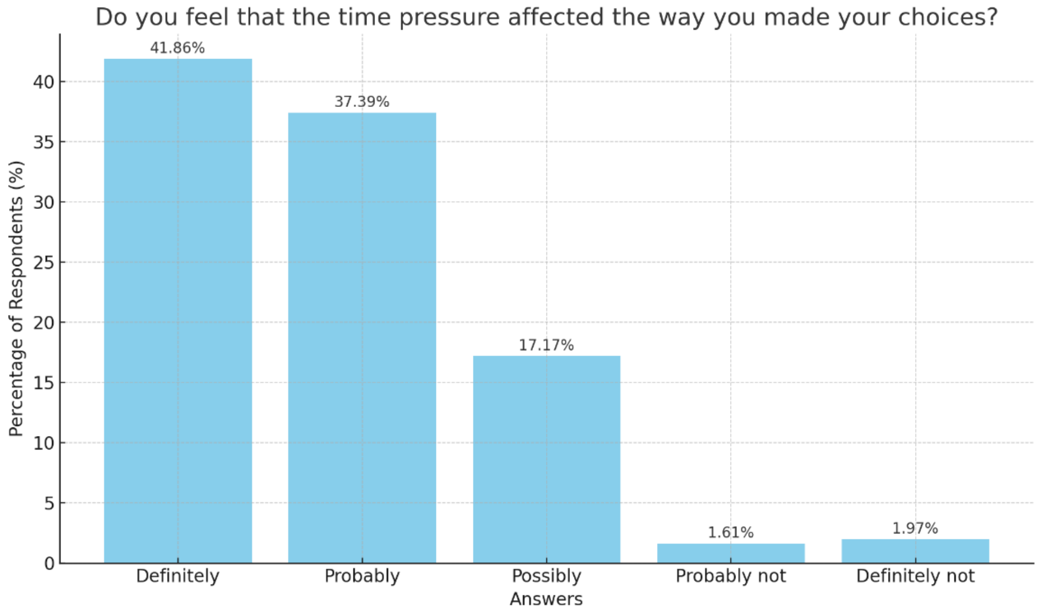


Figure 8- 2 Summary of reflection on question 'Do you feel that the time pressure affected the way you made your choices?'

Figure 8-2 shows that a majority of the respondents (79.25%, which is the sum of the "Definitely" and "Probably" categories) believed that time pressure had notable influences on their decision-making processes. Specifically, 41.86% of the respondents felt that time pressure definitely affected their decision-making and 37.39% believed it probably had an effect. Additionally, 17.17% of respondents indicated that time pressure may have influenced their choices, whereas only 3.58% reported that time pressure was unlikely or certainly did not affect their choice decisions. These findings illustrate that the design of the survey successfully elicited participants' sensitivity to time constraints, aligning with the intended focus of the survey.

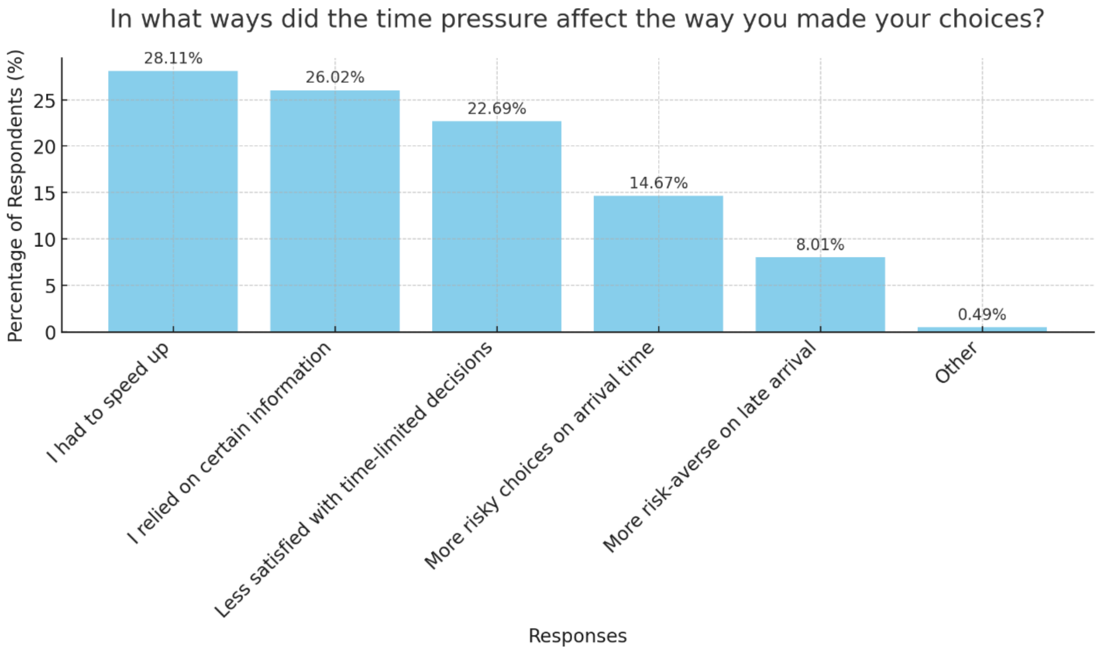


Figure 8- 3 Summary of reflection on question 'In what ways did the time pressure affect the way you made your choices?' (multiple-choice question)

Figure 8-3 presents the responses to the survey question "In what ways did time pressure affect the way you made your choices?", highlighting various behavioural impacts of the time pressure imposed by time budget constraints. The most frequently reported effect, noted by 28.11% of the respondents, was the need to make faster decisions. A further 26.02% indicated that they relied on specific pieces of information to guide their choices under time pressure. In addition, 22.69% reported feeling less satisfied with the decisions made under time constraints compared to those made without time limitations. Time pressure also appeared to influence risk preferences, such that 14.67% of the respondents tended to make riskier choices regarding arrival times, while 8.01% became more risk-averse, particularly to the possibility of being late.

8.2.5 Decision on working from Home

Whether the respondents' decisions on working from home (WFH) were influenced by their perceived time pressure during decision-making was also examined. Figure 8-4 compares the numbers of respondents choosing WFH w/ and w/o TP across different scenarios. The presence of time pressure was associated with a greater tendency among respondents to opt for working from home, suggesting a generally increased aversion to the risk of late arrival under constrained temporal conditions. This effect is particularly pronounced in Scenario 2, where participants were expected to provide a brief verbal update to their line manager during a meeting, an activity characterised by high importance and low flexibility. In Scenario 3, a substantial proportion of respondents also chose to participate remotely when the event involved breakfast networking and live-stream panel discussion. This pattern suggests a growing acceptance of virtual participation as a convenient and socially normative alternative, and a comparatively lower value placed on networking itself.

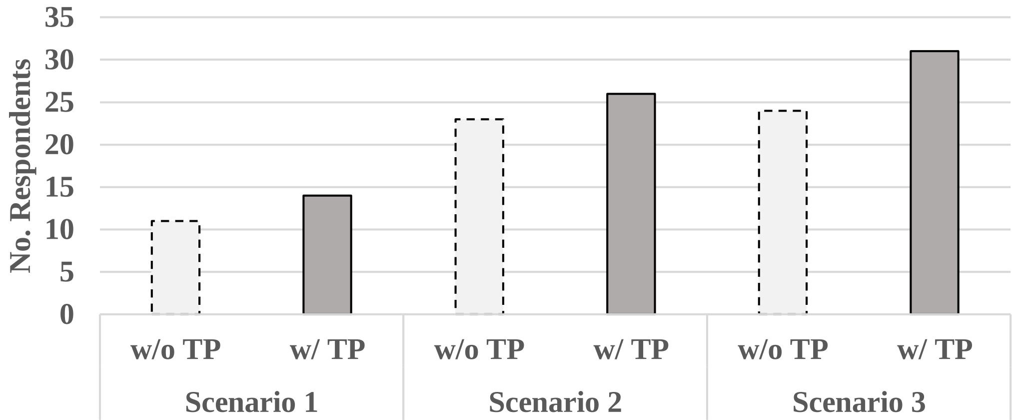


Figure 8- 4 The number of respondents that decided to WFH without or with TP in each scenario.

8.2.6 Perception of transport disruption

The influence of COVID pandemic on people's perception of transport disruptions was also investigated. Figure 8-5 shows that, regarding the statement 'Traffic disruptions don't affect my travel to work as badly as they did before the COVID-19 pandemic', 67% of the participants who commuted by private vehicles strongly agreed (32%) or somewhat agreed (35%) with the statement, which is much higher than the percentage of respondents who generally disagreed (4% of somewhat disagreed and 3% of strongly disagreed).

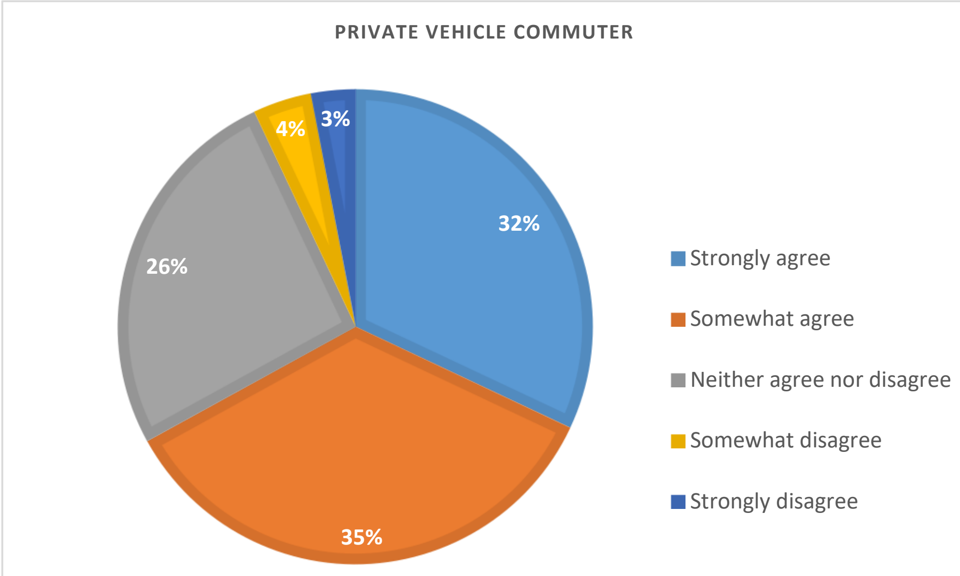


Figure 8- 5 Attitude composition of respondents towards the question 'Traffic disruptions don't affect my travel to work as badly as they did before the COVID-19 pandemic'.

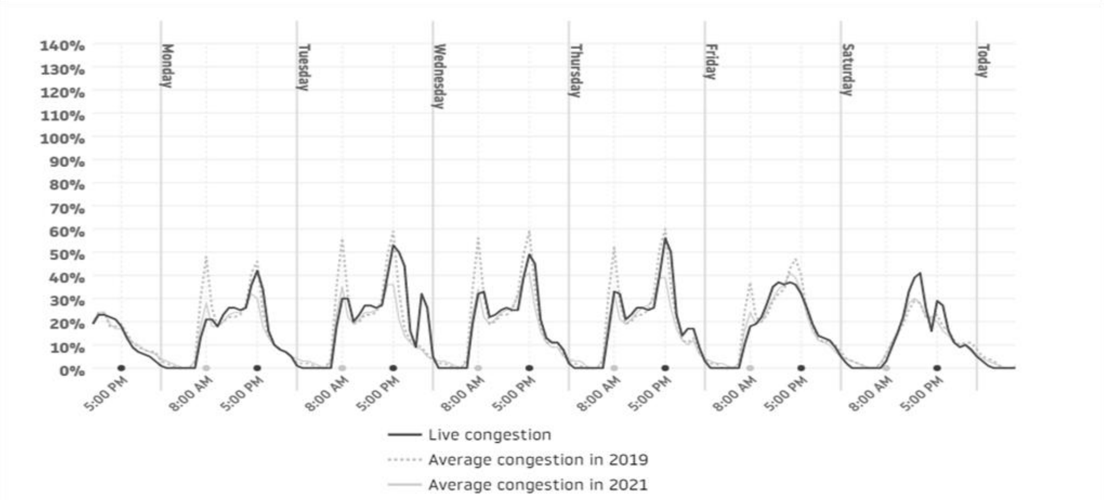


Figure 8- 6 Cross-sectional data on hourly congestion levels in seven days in Glasgow, UK. Source: TomTom https://www.tomtom.com/en_gb/traffic-index/glasgow-traffic/. Time accessed: 07/08, 2022.

The changes of the perception toward transport disruptions are explainable, as a new normal has potentially emerged and maintained as a result of the COVID-19 pandemic. As was noted earlier, the average number of days people travel to work has experienced a decline. The trend was more clearly observed in a preliminary pilot conducted in a high education institution, where the frequency decreased from 4.9 days (SD = 0.25 day) a week pre-COVID to an average of 3.3 days (SD = 1.1 day) a week after the pandemic. These behavioural changes have been reflected in traffic patterns, as illustrated in Figure 8-6, where weekday congestion levels in 2022 were apparently alleviated compared to those in 2019. One notable change is that the morning traffic (8 am) on Monday and Friday has particularly witnessed a significant reduction, plausibly because workers with hybrid arrangements tend to designate these days as home-based, effectively extending the weekend buffer. Furthermore, the congestion levels between 9 am and 12 pm in 2022 was consistently lower than in 2019 and 2021. This implies that people are more flexible with their working hours, a further indication of the new normal established by the pandemic.

8.3 Travel Choice Modelling Results

8.3.1 Base nested logit model

The determination of the base NL model involved a comparative analysis of various model options by specifying different sets of attributes and systematically introducing these attributes into the NL framework to assess their impact on model performance.

Unlike the approaches that assume a known statistical distribution of arrival time to represent travel time reliability, a bounded uncertainty approach was adopted in this work where the arrival time was provided to fall within a defined range bounded by the earliest and latest possible arrival time. This representation reflects the format commonly used by navigation applications. Accordingly, the earliest arrival time (AT_Min), expected arrival time (AT_Exp) and latest arrival time (AT_Max) were incorporated into the utility function through the formulation of schedule earliness (SE) and schedule lateness (SL), expressed respectively as SE_{min} and SL_{min} for AT_Min, SE_{exp} and SL_{exp} for AT_Exp, and SE_{max} and SL_{max} for AT_Max.

As defined in Equations 7-6a and 7-6b in Section 7.2, the values of schedule earliness (SE) and schedule lateness (SL) were determined using two piecewise functions based on the difference between the preferred arrival time (PAT) and each of the three presented arrival times (AT). If estimated arrival time was earlier than PAT (i.e., AT < PAT), SE was assigned a positive value equal to (PAT – AT), while SL was set to zero. Conversely, if the individual arrives later than PAT (i.e., AT > PAT), SL took the value (AT – PAT), and SE was set to zero. That is to say, only one of the two variables was active for any given observation. The sensitivities of both directions were captured through the estimated coefficients of SE and SL in the utility function, allowing the model to reflect asymmetrical preferences for early and late arrival.

Given that maintaining SE and SL for the three possible AT's in the utility function could cause the collinearity issue in the specification, the SE and SL related to each AT were tested in pairs separately alongside other key attributes such as travel time and travel cost. This enabled a systematic evaluation on how different model specifications captured the travel choice behaviour, assisting in the identification of the attributes that are likely to receive greater attention from individuals.

By comparing the models' goodness-of-fit measures, i.e., the log-likelihood and adjusted rho-square in this work, the combination of attributes which yielded the most robust and fittest model could be identified. The model, which consistently demonstrated good performance in terms of the statistical metrics and maintained theoretical soundness and interpretability, was subsequently selected as the base NL model.

Although multiple attributes including time and monetary cost of travel were presented to participants in the survey, SE and SL were found to dominate the performance of the basic NL model. According to the results, the model involving SE_{max} and SL_{max} associated with AT_Max and travel time provided good overall fit and reasonable interpretation of attributes from the behavioural perspective. Hence, from this point onward, the estimated value for β_{SE} and β_{SL} refers to SE_{max} and SL_{max} respectively.

Table 8-3 presents the estimation results of the basic NL model. The alternative-specific constants (ASCs) represent the baseline utilities of the choice alternatives relative to WFH, which was set as the reference alternative with its utility normalised to zero. ASCs capture the effect of unobserved factors not explicitly modelled. The estimated ASCs for all other choice alternatives are positive and statistically significant, implying that, without accounting for explanatory variables, all the other alternatives were more favoured to WFH. The magnitudes of the ASCs vary across alternatives, withβ_{ASC}^{RS} (3.1489) and β_{ASC}^{RR} (2.9096) being the largest, indicating a relatively strong inherent preference for these alternatives even after accounting for explanatory variables, which may reflect habitual choice tendencies, perceived reliability, or unobserved factors shaping preference. In contrast, the lower values forβ_{ASC}^{RRED}(0.6338),

β_{ASC}^{RSED} (0.775), and β_{ASC}^{MSED} (0.6861) though being still statistically significant, indicating weaker baseline utilities and therefore less attractiveness in the absence of other attributes.

The coefficient for travel time (TT) was estimated to be negative, meaning that the utility decreases with increasing TT. This is behaviourally consistent with expectations, reflecting individuals' general aversion to longer TT. However, the magnitude of the estimate is relatively small and statistically insignificant. This might be attributed to two factors: (1) limited variations in TT within the dataset, which weaken the model's ability to identify its effect; and (2) possible multicollinearity between TT and its related variables such as SE and SL, making it hard to isolate its effects on utility.

The coefficient for schedule earliness SE_{max} is positive, suggesting that greater earliness leads to an increased utility. This reflects a preference for arriving early over being late in the designated transport disruption circumstance. However, the SE-related coefficient is not statistically significant, indicating that this preference is weak or inconsistent across respondents and that the SE did not exert a strong or systematic influence on scheduling choices in the context of a disrupted network where the possibility of arriving early was small.

The estimated coefficient for schedule lateness SL_{max} is negative. This suggests that travellers in the sample strongly preferred to avoid being late, with lateness exerting a substantial negative influence on utility. Notably, the disutility associated with SL_{max} is greater than that of SE_{max}, highlighting an asymmetry in travellers' sensitivity to schedule deviations. The statistical significance of the coefficient further confirms the robustness of this effect, reinforcing the behavioural insight that punctuality, particularly avoiding lateness, is a key consideration in scheduling decisions.

The logsum parameter B_I is statistically significant, indicating that the choice alternatives within the lower nest (in this case, the grouped early departure alternatives) exhibit strong correlations in their unobserved utility components. This confirms that the nested structure was appropriate and improves upon a simple MNL. The base model thus provides a foundation for the extending the analysis to NL-dummy and HNL models. The nested logit (NL) model shows a substantial improvement in fit compared to the null model, with the log-likelihood increasing from 5055.5 (Null LL) to 3504.8. The corresponding ps.R^2 of 0.304 indicates a reasonably good explanatory power for a discrete choice model, suggesting that the specified variables capture a significant share of the variation in observed choices.

Table 8- 3 Optimisation results of the NL, NL-dummy, and HNL models.

	NL		NL-dummy		HNL	
Null LL	**-5055.5**		**-5055.5**		**-5055.5**	
Log-L	**-3504.832**		**-3497.407**		**-3473.283**	
ps. R^2	**0.30381**		**0.30681**		**0.31039**	
No. Param.	**10**		**14**		**26**	
Param.	Mean (Std. Err.)	t-stat (p-val.)	Mean (Std. Err.)	t-stat (p-val.)	Mean (Std. Err.)	t-stat (p-val.)
β_{ASC}^{RR}	2.9096 (0.3941)	7.38 (0.00)	2.8898 (0.3737)	7.73 (0.00)	2.2196 (0.3006)	7.38 (0.00)
β_{ASC}^{RS}	3.1489 (0.3218)	9.78 (0.00)	3.1456 (0.3022)	10.41 (0.00)	2.612 (0.2322)	11.25 (0.00)
β_{ASC}^{MS}	2.6231 (0.3333)	7.87 (0.00)	2.6184 (0.3141)	8.34 (0.00)	2.0729 (0.2297)	9.02 (0.00)
β_{ASC}^{RRED}	0.6338 (0.3251)	1.95 (0.05)	0.6346 (0.3179)	2 (0.05)	0.2702 (0.2142)	1.26 (0.21)
β_{ASC}^{RSED}	0.775 (0.2796)	2.77 (0.01)	0.7645 (0.2694)	2.84 (0.00)	0.3087 (0.1731)	1.78 (0.07)
β_{ASC}^{MSED}	0.6861 (0.2988)	2.3 (0.02)	0.6772 (0.2873)	2.36 (0.02)	0.2536 (0.1783)	1.42 (0.16)
TT	-0.0045 (0.0058)	-0.79 (0.43)	-0.0042 (0.0056)	-0.75 (0.45)	0.0009 (0.004)	0.21 (0.83)
β_{SE}	0.0179 (0.0115)	1.55 (0.12)	n/a	n/a	n/a	n/a
β_{SE}^{S1}	n/a	n/a	0.0016 (0.0185)	0.09 (0.93)	0.0031 (0.0096)	0.33 (0.74)
β_{SE}^{S2}	n/a	n/a	0.0139 (0.0173)	0.8 (0.42)	0.013 (0.011)	1.19 (0.23)
β_{SE}^{S3}	n/a	n/a	0.0292 (0.0162)	1.8 (0.07)	0.0254 (0.012)	2.11 (0.03)
β_{SL}	-0.0245 (0.0054)	-4.52 (0.00)	n/a	n/a	n/a	n/a
β_{SL}^{S1}	n/a	n/a	-0.0153 (0.0056)	-2.71 (0.01)	-0.0151 (0.0045)	-3.32 (0.00)
β_{SL}^{S2}	n/a	n/a	-0.0245 (0.0057)	-4.27 (0.00)	-0.0227 (0.0053)	-4.25 (0.00)

β_{SL}^{S3}	n/a	n/a	-0.0355 (0.0059)	-6.01 (0.00)	-0.031 (0.006)	-5.16 (0.00)
B_I	0.3208 (0.0852)	3.76 (0.00)	0.3044 (0.0744)	4.09 (0.00)	0.2108 (0.0489)	4.31 (0.00)
a^{S1}	n/a	n/a	n/a	n/a	-0.9701 (0.8928)	-1.09 (0.28)
a^{S2}	n/a	n/a	n/a	n/a	0.3828 (0.9682)	0.4 (0.69)
a^{S3}	n/a	n/a	n/a	n/a	0.9473 (1.1303)	0.84 (0.4)
b^{S1}	n/a	n/a	n/a	n/a	0.9436 (0.6236)	1.51 (0.13)
b^{S2}	n/a	n/a	n/a	n/a	-0.5956 (0.6651)	-0.9 (0.37)
b^{S3}	n/a	n/a	n/a	n/a	-0.6838 (0.7231)	-0.95 (0.34)
a_m^{S1}	n/a	n/a	n/a	n/a	-14.7354 (6.3931)	-2.3 (0.02)
a_m^{S2}	n/a	n/a	n/a	n/a	-14.5944 (4.4894)	-3.25 (0.00)
a_m^{S2}	n/a	n/a	n/a	n/a	-5.5566 (1.8188)	-3.06 (0.00)
b_m^{S1}	n/a	n/a	n/a	n/a	12.7931 (3.2868)	3.89 (0.00)
b_m^{S2}	n/a	n/a	n/a	n/a	10.9828 (2.5425)	4.32 (0.00)
b_m^{S3}	n/a	n/a	n/a	n/a	6.4201 (1.4299)	4.49 (0.00)

8.3.2 Effect of scheduled workplace activity

Regarding the specification of dummy variables in simulating the three different designated scenarios at work (as presented in Section 6.2.5.1), dummy-based attribute specific model was developed to depict potential different behaviour across subtypes. In this case, S_1, S_2, and S_3 are dummy variables representing the three possible scheduled workplace activities. The variable S_k equals 1 if the scenario corresponds to the activity k, and 0 otherwise. The three scenarios were differentiated by SE-related (i.e., β_{SE}^{S1}, β_{SE}^{S2} and β_{SE}^{S3}) and SL-related dummy variables (i.e., β_{SL}^{S1}, β_{SL}^{S2} and β_{SL}^{S3}) to allow the same attributes associated with TT to describe the commitment-dependent resistance of respondents to arriving early or late. This approach provided a more intuitive way in interpretating respondents' behaviour in real-life situations.

The NL-dummy model, which introduces dummy variables into the basic model, resulted in a minor improvement in overall model fit, as indicated by the log-likelihood and the pseudo-R^2 values. These results suggest that the updated model offers a better representation of the observed data. The coefficient β_{SL} remains consistently negative and statistically significant across all three scenarios, providing robust evidence that travellers have a strong aversion to lateness. The positive β_{SE} estimate across all the scenarios indicates that participants preferred early arrival across all work commitment types, aligning well with the assumptions. Although the coefficient is not statistically significant, its direction remains behaviourally plausible and contributes to the explanatory capability of the model. It suggests that a latent preference for earliness might not be consistently strong across all the individuals or scenarios but still carries interpretive values.

As results shown in Table 8.3, when the NL-dummy model accounts for potential differences in SE and SL across Scenarios #1, #2 and #3, the estimated coefficient β_{SE}^{S1} in Scenario #1 is smaller than β_{SE}^{S2} in Scenarios #2 and β_{SE}^{S3} in Scenarios #3. Also, β_{SL}^{S1} has the lowest lateness aversion of the three scenarios. These results suggest that the activity of meeting with team colleagues for new project planning is considered to have higher flexibility over the start time than meeting with senior manager (Scenario #2) or attending breakfast meeting for networking and panel discussion (Scenario #3).

Besides, the estimated values of β_{SE}^{S3} and β_{SL}^{S3} further suggest that in Scenario #3, respondents exhibited the strongest preference for earliness and the greatest aversion to lateness among all the scenarios. This pattern may be attributed to the nature of Scenario #3, which involved a group-based activity where lateness could result in a perceived loss of social capital, while early or punctual arrival signals commitment and professionalism. Although Scenario #2 entailed a group meeting with a manager and thus carries a certain degree of formality, it represented a more routine interaction. In contrast, Scenario #3 was less frequent and offered a valuable opportunity for social exposure, which might heighten respondents’ sensitivity to arrival timing.

The inclusion of commitment-dependent dummy variables highlights the inherently context-sensitive nature of scheduling behaviour. Early arrival tends to be more valued in hierarchical or formal settings where punctuality signals respect and professionalism, compared to peer-level or informal contexts that afford greater flexibility in terms of arrival time. The model also captures the heightened sensitivity to lateness in more structured, group-based commitments, suggesting that the perceived cost of late arrival increases with the formality and social visibility of the activity.

8.3.3 Effect of time pressure

Instead of adopting a constant scale parameter for all the participants, the HNL model specifies the scale parameter as a function of perceived time pressure. This is operationalised through the time pressure index (TPI), defined as the ratio of the time spent on decision making t_{use} relative to the allotted decision time budget t_{bud}. The HNL model shows clear improvements in both log-likelihood and pseudo-R^2 values. The log-likelihood value rose from –3497.407 to –3473.283, indicating a better alignment between the model predictions and observed choices. At the same time, the pseudo-R^2 value increased from 0.30681 to 0.31039, reflecting an enhanced explanatory capability. The consistent improvements in model performance suggest that the specification of scale parameter with TPI better captures the behavioural patterns underlying in the data.

The estimated parameters of the HNL model are reported in Table 8-3. The parameters a and b determine the scale parameters of the upper nest. In this notation, the superscript 1, 2 or 3 denote Scenario #1, #2 and #3, respectively (a^{S1}, a^{S2}, a^{S3}, b^{S1}, b^{S2} and b^{S3}). The subscript m indicates the parameters associated with the lower nest, corresponding to the alternatives grouped under early departure (i.e., a_m^{S1}, a_m^{S2}, a_m^{S3}, b_m^{S1}, b_m^{S2}, and b_m^{S3}). As noted in Chapter 6, the decision-making time (t_{use}) was recorded during the survey using a timer embedded in each choice set, while decision time budgets (t_{bud}) were varied to impose different levels of time pressure on respondents, thereby different values of TPI are generated.

According to the results, the estimated parameters for the upper nest (i.e., a^{S1}, a^{S2}, a^{S3}, b^{S1}, b^{S2} and b^{S3}) were found to be statistically insignificant across all the scenarios. A plausible explanation is that the alternatives presented in the upper-level nest (Choice Set 1) largely consisted of options that, under the transport disruption, would have resulted in considerable lateness if the respondent departed at their originally planned time. In such cases where all options are generally unfavourable, making a choice is relatively straightforward, and thus the role of perceived time pressure in shaping decisions was limited. In contrast, the parameters estimated for the lower nest (Choice Set 2) indicate greater statistical significance, suggesting that the influence of time pressure became more pronounced when more meaningful trade-offs exist among alternatives. This pattern highlights that time pressure exerts a stronger behavioural effect when the choice context involves competitive trade-offs, rather than uniformly undesirable options.

The relationship between TPI_m and the scale parameter $\mu_m^{'}$, as estimated from parameters a_m and b_m for the lower nest under each scenario is illustrated in Figure 8-7. The variation of $\mu_m^{'}$ with TPI_m exhibits a hump shape with its peak at the TPI_m of around 0.4-0.5. This implies that when respondents used roughly 40–50% of their available decision time, they appear to be most attentive to differences in utility across alternatives. At these moderate levels of TPI_m, the scale parameter is higher, meaning that choices were less random and more strongly guided by the relative utilities of the options. In contrast, relatively random choice behaviour was observed at low TPI_m levels, leading to less systematic choices. It is noted that a low TPI_m value approaching zero cannot be simply interpreted as an absence of time pressure but may instead reflect a lower level of engagement or interest. Similarly, as TPI_m approaches 1, indicating increased perceived time pressure, choices tend to become more erratic, likely reflecting rushed decision-making and reliance on superficial comparisons. These findings suggest that the influence of perceived time pressure on decision-making is both non-linear and non-monotonic: choice consistency peaks at moderate levels of perceived time pressure but declines at both low and high extremes.

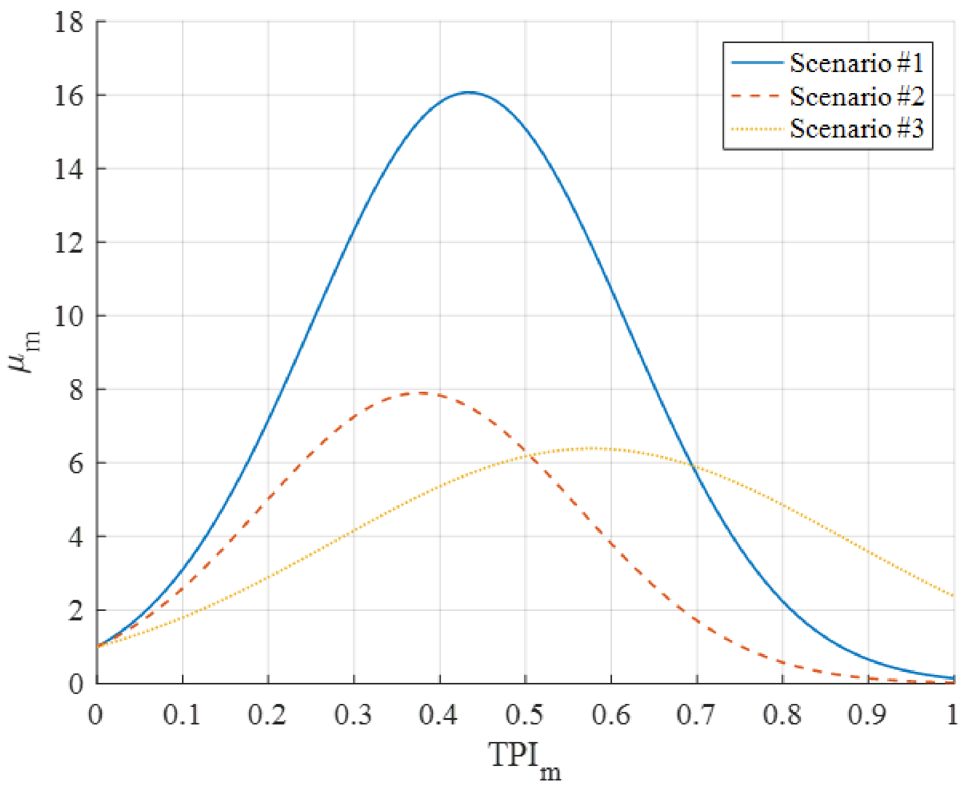


Figure 8- 7 Variations of scale parameters $\mu_m^{'}$ with TPI_m in lower nest (Choice Set 2) under the three scenarios.[Note: $\mu_m^{'} = exp(a_m \cdot TPI_m^2 + b_m \cdot TPI_m)$]

Compared to the NL-dummy model which neglects the effect of perceived time pressure and applies a constant scale parameter of about 3.3 (i.e., $1/B_I = 1/0.3044$) to represent decision-making in the lower nest, the HNL model allows μ_m to vary dynamically with TPI_m. The results demonstrate that this specification more effectively captures variations in participants' sensitivity to utility differences between alternatives across different levels of time pressure, thereby revealing hidden behavioural effects captured through heteroscedasticity.

8.3.4 Choice of working from home

To examine the conditions under which participants opt for WFH rather than the early departure alternatives, the choice probability of the alternatives within the choice set 2 or the lower nest was estimated based on the HNL model for comparative analysis. Within the set of early-departure options, $ALT_{m\_}$ SP_r|ED and $ALT_{r\_}$ SP_r|ED exhibited comparable frequencies of selection and were chosen in more cases than $ALT_{m\_}$

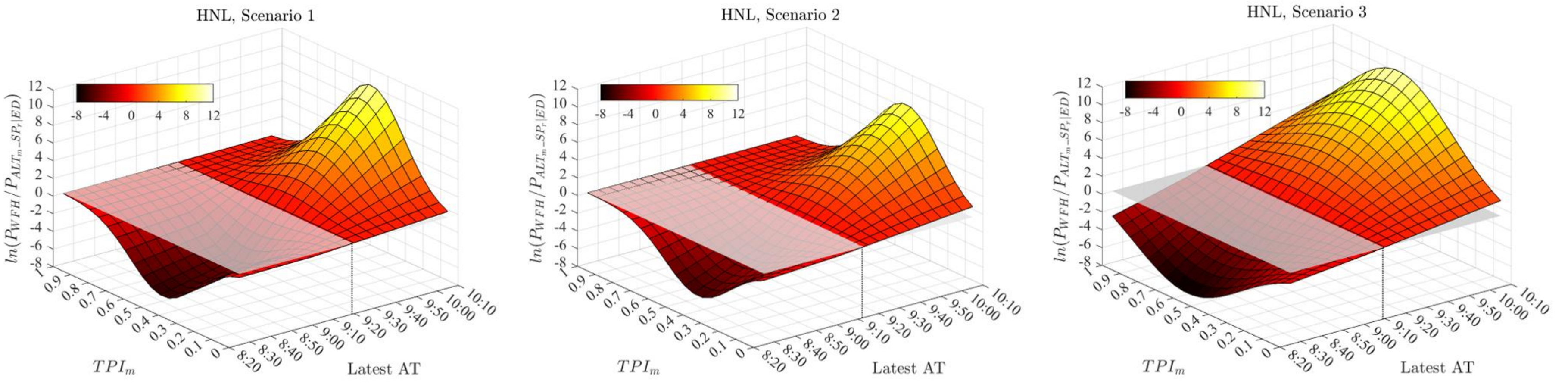
RR_r |ED, therefore, $ALT_m\_\ SP_r$ |ED was adopted as the reference alternative for comparison with WFH for analytical brevity.

Figure 8-8 shows choice probability ratios between WFH and $ALT_r\_\ SP_r$|ED that are estimated under different combinations of TPI_m and latest AT so as to identify of how TPI_m and latest AT affect the likelihood of WFH being chosen across different scenarios. The choice probability ratio was presented in the form of natural logarithm for an appropriate scale, thereby enhancing the visualisation. A positive natural logarithm indicates that WFH has a higher choice probability than $ALT_m\_\ SP_r$|ED, and vice versa. Across the three scenarios, the relative likelihood of WFH compared with the selected early-departure alternative $ALT_m\_SP_r$|ED demonstrates a clear dependence on both the TPI_m and the latest AT. A consistent pattern emerges in which TPI_m approaches to extremes (i.e., 0 or 1) reduce the relative attractiveness of WFH, while later AT values increase its likelihood of being chosen.

Despite the three scenarios showing similar patterns of choice probability ratios on average, they are differentiated by the tipping point or threshold of latest AT beyond which WFH becomes more likely to be chosen than the comparative alternative (i.e., log-ratio turning positive). The tipping points of latest AT occur at 09:19 in Scenario 1, 09:12 in Scenario 2, and 09:09 in Scenario 3, respectively. Relative to Scenario 1, the threshold shifts 7 minutes earlier in Scenario 2 and 10 minutes earlier in Scenario 3. The incremental change between Scenarios 2 and 3 is smaller (3 minutes). This shift indicates that under Scenarios 2 and 3, participants are inclined to favour WFH at earlier arrival times compared with Scenario 1, suggesting an increased sensitivity to schedule delay in those contexts.

In addition to the tipping point of latest AT, the gradient within the positive log-ratio region is differentiated across scenarios. Although the estimated magnitude of SL in Scenario 1 (β_{SL}^{S1} =-0.0151) is the smallest compared with Scenario 2 (-0.0227), and Scenario 3 (-0.031), the log-ratios in the range around 0.4-0.5, escalate sharply with latest AT once the tipping point is exceeded, indicating a strong and decisive shift in favour of WFH. This is because the high-level scale parameter estimated at of around 0.4~0.5 in Scenario 1 is greater than those that are estimated in Scenarios 2 and 3 (see Figure 8-7). The appropriate time pressure perceived by participants heightens their increasing favour of WFH when latest AT exceeds the tipping point. By contrast, Scenarios 2 and 3 exhibit smoother gradients of positive log-ratios, implying that the favour of WFH increases more evenly over a wider range of latest AT beyond tipping points.

These results demonstrate while the qualitative relationship among TPI_m, latest arrival time, and the choice probability ratio remains robust across scenarios, the quantitative threshold for choosing WFH advances by up to ten minutes depending on contextual conditions. This earlier tipping behaviour in Scenarios 2 and 3 highlights an increased sensitivity to schedule delay, suggesting that under these conditions, participants require less lateness to justify switching to WFH. While the potential influence of order cannot be entirely ruled out, the behaviourally consistent and theoretically aligned pattern of results suggests that the observed differences among scenarios are primarily attributable to the design characteristics rather than presentation sequence.



(a) (b) (c)

Figure 8- 8 Natural logarithms of choice probability ratios between WFH and $ALT_{m}\_\ SP_{r}|ED$ depicted by the HNL models for Scenarios (a) #1, (b) #2, and (c) #3.

8.4 Conclusions and Discussions

Utilising the data collected from the designed online survey, three discrete choice models were developed and compared to investigate individuals' rescheduling behaviour in the context of a transport disruption. The basic Nested Logit (NL) model serves as a benchmark, capturing general preferences without contextual differentiation. The commitment-sensitive NL model (NL-dummy) extended the basic model by introducing work commitment-related dummy variables to reflect the influence of commitments with different levels of formality and social expectations on travel rescheduling decisions. The heteroscedastic NL (HNL) model further advanced the model by allowing the scale parameters of utility functions to vary with perceived time pressure, thereby capturing changes in decision consistency under different levels of time pressure. The development of the three models forms a structured and behaviourally grounded approach to understanding how travellers adjust their rescheduling preferences in response to both contextual demands and psychological states. The comparative analysis demonstrates that the incorporation of contextual and psychological factors significantly enhances the explanatory capability of rescheduling models, providing valuable insights into adaptive travel decision-making under uncertain circumstances.

The empirical findings validate the expectations that, **firstly**, participants exhibited strong emphasis on arrival time when evaluating rescheduling alternatives, with a particular focus on achieving an earlier arrival time and minimising the potential for lateness in the context of unexpected transport disruptions. **Secondly**, the inclusion of work commitment-related dummy variables highlights the inherently context-sensitive nature of rescheduling behaviour. Early arrival is typically seen as a sign of professionalism and respect in more hierarchical or formal situations, whereas informal or peer-level contexts allow for more leniency in timing. In addition, greater aversion to lateness in structured, group-oriented activities is observed, indicating that the perceived penalty for being late intensifies with the level of formality and social accountability of the work commitment. **Thirdly,** the heteroscedasticity introduced by varying scale parameters with time pressure reveals hidden behavioural dynamics. Time pressure exerts a pronounced influence on decision-making primarily when individuals face complex or competitive trade-offs, rather than when choice alternatives are uniformly unattractive. The analysis indicates that the effect of time pressure is non-linear: decision consistency, reflected in the degree of determinism, is higher at moderate levels of time pressure, but diminishes at both low and high extremes, suggesting that both disengagement and rushed deliberation can lead to more stochastic choice behaviour. Such evidence points to the potential value of incorporating heuristic or bounded rationality models as complements to traditional choice frameworks. **Lastly,** with flexible working arrangements which are now widely accepted across many industries, rescheduling to work from home on the day of an unexpected disruption has become a viable option. The results show that the quantitative threshold for choosing working from home advances by up to ten minutes depending on contextual conditions. In scenarios that demand greater punctuality, formal engagement, or group-based commitments, participants require less lateness to justify switching to work from home.

Despite the robustness of the model and the validity of the conclusions drawn from the collected data, certain limitations remain. In terms of the experimental design, the variation between attribute levels on travel time and its variability could be more finely tuned to detect participants' sensitivity to these attributes as well as increase the trade-off between alternatives. Additionally, the presence of the continuous countdown timer displayed alongside the choice set may have subtly encouraged respondents to make quicker decisions in the first choice set, to prevent time overruns and ensure task completion. The reset of the timer only became apparent to participants when they selected the "depart earlier" option and progressed to the second choice set. Future designs should include clearer communication about the timer and introduce more diverse experimental conditions.

While the analysis revealed that socio-demographic characteristics such as age, education, and income are significantly associated with choice behaviour, this study adopted a population-level approach to preserve model parsimony and estimation stability. As a result, socio-demographic heterogeneity was not explicitly incorporated into the modelling framework. Future research could build on this work by developing extended models that account for differences across socio-demographic groups, thereby offering a more comprehensive understanding of variability in rescheduling behaviour.

It is also important to acknowledge the limitations of stated preference surveys, such as the potential for bias induced by repeated experiments and the limited degree of contextual realism (Louviere *et al.*, 2000). Although the experimental design was carefully constructed to mitigate these issues, the collected data nonetheless exhibited certain biases, which were subsequently addressed through a data screening process to minimise their potential impact on the model. Furthermore, while the experiment was grounded in realistic scenarios, it ultimately relied on hypothetical settings that may not fully capture actual behaviour to the same extent as revealed preference data. Consequently, integrating stated and revealed preference data in future research could strengthen the robustness and enhance the external validity of travel behaviour models (Train, 2009b).

Chapter 9 Synthesis of Findings and Implications for Future Research and Practice

The complexity of individual travel behaviour becomes particularly evident under dynamic and uncertain conditions (Li, Hensher and Zeng, 2022). This is especially true in cases where unforeseen transport disruptions occur, creating time pressures for travellers and leading to deviations in rescheduling choices. The legacy of the COVID-19 pandemic, most notably the widespread adoption of flexible hours, hybrid arrangements, and remote working, further complicates the analysis of emerging travel patterns (Balbontin *et al.*, 2021). Within this evolving context, the interplay between the dynamic traffic conditions and the individual-level decision-making highlights the growing need to understand how travellers adapt their behaviour in real time to enhance the behavioural realism of transport simulation frameworks. This research contributes to the academic literature by addressing the research gaps and to inform current practices in traffic operations, disruption management, and strategic transportation planning.

9.1 Summary of Research and Key Findings

This research is structured into two main parts, as outlined in Chapter 1. Prior to addressing the core research objectives, a comprehensive review of the relevant literature was conducted in order to establish a theoretical foundation, identify research gaps, and inform the development of the proposed model. This review covers the evolution of choice modelling, with particular attention to the influence of time pressure, commuting and telecommuting behaviour in the context of the COVID-19 pandemic, as well as the agent-based simulation models and frameworks applied to dynamic activity-travel rescheduling.

The first part of the research was guided by the research objective of developing an enhanced simulation model and implementing the extended MATSim functionality in the Cottbus network to evaluate the effects of real-time information provision on travel behaviour within a multi-modal transport network. The model was designed to accommodate travellers' multi-dimensional activity-travel rescheduling behaviours and to effectively analyse the impacts of unplanned transport disruptions on network performance. To this end, the study first identified the key functional requirements necessary for effective simulation. The agent-based transport simulation platform MATSim, introduced in Chapter 3, served as the foundation for model development. Substantial enhancements to the existing module were made in Chapter 4, including the integration of real-time traffic data and the implementation of a full range of dynamic multi-dimensional rescheduling strategies to better reflect the complexity of real-world travel behaviour. These enhancements were rigorously tested and evaluated to ensure improvements in both accuracy and reliability. To demonstrate the applicability and effectiveness of the enhanced model, a case study was conducted in Chapter 5 based on the Cottbus scenario.

The case study results confirmed the enhanced Within-Day Replanning Module as a valuable framework for disruption analysis. By capturing transport users' multi-dimensional adaptive responses in a multimodal environment, the model illustrated how travellers adjust dynamically under severe events such as bridge closures. Incorporating decision-making constraints, particularly the time budget allocated for replanning, revealed its notable influence on rescheduling outcomes. These findings highlight the module's potential to improve the realism of agent-based simulations while also providing insights for the assessment and refinement of transport management policies and operational strategies. On this basis, the research supports the identification of opportunities to strengthen network resilience and optimise performance under disrupted conditions. Furthermore, the enhanced simulation models proposed in this research demonstrate strong potential for transferability and application to other cities and regions, thereby serving as a practical tool for transport planners and policymakers seeking to improve system robustness and efficiency.

The second part of the research sets out to understand how commuters reschedule their daily travel to work in response to unexpected transport disruptions, within the evolving context of post-pandemic hybrid and remote working practices. To achieve this, a survey was designed to collect stated preference data that could be used to investigate the decision-making of commuters on rescheduling travel-activities. The survey was designed to capture information about respondents' trade-offs between alternative travel options, their responses to different work-related scenarios and the time spend on making a specific decision under different varying time budgets. The data collected from the survey allowed the researcher to obtain reliable information for choice analysis and model the potential impacts of time pressure.

Drawing on data from a purpose-designed online survey, this study developed and compared three discrete choice models to examine individual rescheduling behaviour in response to transport disruptions. The basic Nested Logit (NL) model provided a benchmark for capturing general preferences. Building on this, the commitment-sensitive NL model, incorporated work commitment-related variables, to account for the influence of contextual formality and social expectations on rescheduling decisions. The heteroscedastic NL (HNL) model introduced variation in scale parameters to reflect changes in decision consistency under different levels of perceived time pressure. This structured modelling approach enabled a deeper understanding of how travellers adjust their decisions in response to both situational conditions and underlying psychological factors. The comparative analysis confirmed that integrating contextual and behavioural heterogeneity significantly improves the explanatory power of rescheduling models, offering deeper insights into adaptive travel behaviour under uncertainty.

The empirical findings of this study offer valuable insights into travellers' behavioural responses to unexpected transport disruptions. Participants demonstrated a strong sensitivity to arrival time, prioritising minimising lateness when evaluating rescheduling alternatives. The utilisation of work commitment-related variables revealed that rescheduling behaviour is highly context-dependent, with stricter punctuality preferences observed in formal or group-based work settings. The analysis of heteroscedastic choice behaviour further uncovered that time pressure affects decision-making in a non-linear manner - decision consistency peaked at moderate levels of time pressure but declined under both low and high extremes, suggesting that cognitive disengagement or rushed judgement leads to more stochastic choices. Finally, the study highlighted the role of remote working as a viable rescheduling option: when online participation was permitted, individuals who were averse to lateness often opted to work from home in response to anticipated travel delays, underscoring the strategic use of flexible work arrangements to preserve punctuality.

This section of research makes several key contributions to the field of travel behaviour modelling. Firstly, it advances the understanding of individual activity-travel rescheduling decisions under conditions of unexpected transport disruption, with particular attention to the influence of post-pandemic hybrid working arrangements. Secondly, by incorporating contextual variables related to work commitment and modelling behavioural heterogeneity under varying levels of perceived time pressure, the study enriched specification moves beyond conventional discrete choice models and offers a more behaviourally realistic representation of commuter decision-making. These methodological advancements not only enhance the explanatory power of discrete choice models but also provide actionable insights for transport operators and policymakers seeking to develop more adaptive, user-centred disruption management strategies.

9.2 Contributions

This research makes four principal contributions towards advancing the understanding and modelling of commuter responses to transport disruptions, with primarily emphasis on *methodological contributions*:

Firstly, the study extended the capabilities of the MATSim Within-day Replanning module to incorporate multi-dimensional activity-travel reschedules with the aid of real-time information provision within a multi-modal network affected by unexpected transport network disruption. The enhanced module, fully integrated within the agent-based simulator, formed a comprehensive modelling framework that captures disruption dynamics, traffic information dissemination, and rescheduling decisions in both space and time dimensions.

In addition, drawing on the data collected through a purpose-designed online survey, the research contributes to a deeper understanding of how transport users reschedule their intended travel when confronted with unexpected disruption. It reveals how commuters trade off among multi-dimensional alternatives, including the option of working from home, thereby enriching the empirical knowledge of behavioural adaptation under disruption scenarios.

Furthermore, this research contributes to the understanding of how the evolving post-pandemic work environment, characterised by hybrid and flexible arrangements, shaped rescheduling decisions. By incorporating variables that captured the nature and formality of workplace commitments, the research advanced activity–travel rescheduling models to account for context-specific decision dynamics. This offered a more comprehensive understanding of commuter behaviour in contemporary labour markets.

Lastly, this research examined the role of perceived time pressure as a psychological factor influencing rescheduling choices, recognising its effect to the underlying decision-making mechanisms in situations where unforeseen increases in travel time could lead to significant delays in arriving at work. By incorporating perceived time pressure in relation to the model, this research provides valuable insights into how urgency and cognitive load influence the interpretation of information and subsequent rescheduling behavioural responses to unplanned disruptions.

This thesis is expected to provide *practical contributions* in the following perspectives:

This study has enhanced an agent-based transport modelling to produce a more accurate representation of transport disruption through the incorporation of dynamic interactions between travellers' behaviour and the evolving traffic conditions. The enhanced Within-day Replanning module within MATSim has proven to be a valuable tool for analysing the impacts of disruptions on traveller's adaptive behaviours and the overall efficiency of transport systems. Beyond reproducing individual responses, it enables the application of different failure scenarios to stress test networks and identify critical nodes and links where failures would have the most severe consequences. Building on this, the framework supports the evaluation of alternative investment and adaptation strategies, allowing policymakers and transport planners to compare business-as-usual with intervention options, each assessed in terms of their associated costs and benefits. In this way, this study contributes to the development of more responsive and robust transport systems for future transportation networks.

Furthermore, this research has examined the multifaceted changes in commute travel patterns that emerged as a consequence of pandemic, particularly in the context of widespread adoption of flexible and hybrid working arrangements. By analysing the impacts of these new work practices on commuting behaviour across different scenarios, the study suggests that strategies to improve network resilience should not be limited to traditional transport interventions. In some cases, an effective option may be to support or facilitate work-from-home arrangements, thereby reducing pressure on the network altogether. These insights provide practical guidance for policymakers and transport planners in developing more resilient, efficient, and adaptable systems that align with the realities of a dynamic, post-pandemic workforce.

9.3 Discussions and Outlook

While this research offers valuable insights into travel behaviour under disruption, certain limitations should be acknowledged. These limitations provide a foundation for future work to further refine the modelling framework, extend its applicability, and enhance its behavioural realism in more diverse contexts.

One key direction for future work is to further calibrate and validate the enhanced MATSim within-day replanning model using empirical data. Behavioural parameters related to rerouting, departure-time change, mode switching, and working from home could be estimated using observed data, such as GPS trajectories, smart-card records, or traffic counts. In addition, the two parts of the thesis could be more closely integrated by using the stated preference data to validate and refine the behavioural parameters in the enhanced MATSim model. The SP results could provide empirical evidence on commuters' rescheduling preferences under different disruption, work-arrangement, and perceived time-pressure conditions. This would allow the MATSim behavioural parameters to be calibrated so that simulated agent responses better reflect observed decision-making patterns, thereby strengthening the link between individual behavioural evidence and system-level simulation outcomes under transport disruptions.

Another key direction for future research is to improve the representation of behavioural heterogeneity in decision-making. While random utility maximisation

(RUM) offers a rigorous framework for capturing rational utility-driven choices, it may not fully account for the simpler heuristic strategies that travellers often rely on when operating under time pressure or uncertainty. Conversely, heuristic models can represent bounded rationality, but lack the systematic structure of RUM. A latent modelling framework provides a promising pathway to integrate these perspectives, allowing utility-maximising behaviour and heuristic approaches to coexist within a single structure. Such an approach would enable models to better capture the diversity of traveller responses and yield a more nuanced understanding of how individuals perceive, evaluate, and adapt to disruption across varying levels of urgency and complexity.

Building upon the above limitation, future work should further incorporate socio-demographic heterogeneity through advanced modelling approaches such as latent class models. The latent class models enable segmentation of the population into distinct behavioural groups, with class membership explained by factors such as age, income, education, employment status. This makes it possible to identify systematic differences in how subpopulations evaluate and respond to disruptions, including the extent to which the perceived time pressure influences their reliance on utility-maximising or heuristic strategies. Incorporating such heterogeneity would not only strengthen the explanatory power of rescheduling models but also provide a firmer basis for designing targeted and equitable transport policies that reflect the diverse needs and pressures faced by commuters.

An additional limitation of this study relates to the treatment of work from home arrangements within the research design. At the time the research was conceived, the prevalence of remote and hybrid working was emerging, but since then, flexible and remote working has become far more widely adopted and are now a settled feature of the modern labour market, meaning that commuters may more readily opt to work from home in response to disruption. Future research should therefore examine how the availability of this option interacts dynamically with perceived time pressure, travel delays, and individual attitudes toward punctuality. Incorporating such adaptive behaviour would provide a more comprehensive understanding of the interplay between transport disruptions and contemporary work practices, and offer deeper insights into how flexible working policies can contribute to network resilience and traveller wellbeing.

Furthermore, future research could extend the modelling framework to a whole-day activity perspective. The current study focuses primarily on the morning commute, whereas real-world rescheduling decisions are embedded within a broader daily activity chain. Extending the model to capture full-day activity scheduling would allow for the analysis of interdependencies between work, household, and discretionary activities, as well as secondary trips, thereby providing a more comprehensive understanding of system-wide responses to disruption.

Finally, although this research primarily focused on the analysis of car commuters, the stated preference survey also collected responses from public transport users, which has not been fully utilised in the current analysis. Future work could extend the modelling framework to explicitly incorporate public transport user behaviour, including mode-specific constraints and adaptation strategies, thereby broadening the applicability of the framework to multimodal transport systems.

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Appendices

Appendix A: Supplementary Description to Rescheduling Behavioural Assumptions Input

Pre-trip Rescheduling

Route Switch

- **Search rule**: if the additional travel time along the original route r_o results in a late arrival at the next planned activity $epi_{n+1,act}$ that exceeds a predefined threshold θ_1:
$$t_{r_o} - t_o \geq \theta_1$$
then a search for a better alternative route is triggered.
- **Stop rule**: The shortest path $r_{sp}$is found, with $t_{r_{sp}}$as cost of time.
- **Decision rule**: if the excess travel time of the original route r_o compared to the shortest available path r_{sp} is greater than or equal to a predefined threshold γ_1.
$$t_{r_o} - t_{r_{sp}} \geq \gamma_1$$
then select r_{sp} and consider an early departure; otherwise, stick to the original route r_o and consider an early departure.

The indifference band γ represents the acceptable divergence between the estimated cost of the original route r_o and the shortest path route r_{sp}. When the difference exceeds this threshold, r_{sp} is selected. This implies that individuals remain indifferent to switching routes if the potential time saving falls below the tolerable margin.

In this context, route choice and departure time are regarded as joint decisions, as travellers often adjust both simultaneously to ensure arrival by their preferred arrival time (PAT). For instance, a change in route alone or an earlier departure alone may not guarantee an on-time arrivalr_{sp}combination might achieve this objective. Therefore, the flexibility to modify departure time is retained irrespective of whether a route switch occurs, reflecting the interdependence between these two dimensions of travel behaviour.

Early Departure

- **Search rule**: if the estimated arrival time, based on the preferred departure time d_o and the updated travel time t^*(subject to the outcome of route decision), exceeds the latest acceptable arrival time $(PAT + \theta_1)$ at $epi_{n+1,act}$:

$$d_o + t^* \geq PAT + \theta_1$$

  then consider departure earlier.

- **Stop rule**: find the earliest feasible departure time d^* that enables an agent to offset the time cost and still arrive at the destination by $(PAT + \theta_1)$, subject to the constraint of a limited decision-making window available before the scheduled departure $(d_o - t_{bud}{}^*)$:

$$d^* = min\ (PAT + \theta_1 - t^*, d_o - t_{bud}{}^*)$$

- **Decision rule**: if the new departure time d^* allows the agent to arrive by $(PAT + \theta_1)$:

$$d^* + t^* \leq PAT + \theta_1$$

  then choose early departure time d^*; otherwise considering other mode of transport.

Mode Switch

- **Search rule**: if the new departure time d^* cannot allow the agent to arrive by $(PAT + \theta_1)$:

$$d^* + t^* > PAT + \theta_1$$

  then consider mode switch.

- **Stop rule**: find least cost bus route $r_{sp,bus}$, the corresponding travel time $t_{r_{sp,bus}}$ and departure time d_{bus}, subject to the limited decision-making window available before the scheduled departure $(d_o - t_{bud}{}^*)$, i.e., $d_{bus} \geq (d_o - t_{bud}{}^*)$.
- **Decision rule**: if taking bus with an achievable departure time d_{bus} can allow arrive within $(PAT + \theta_1)$:

$$d_{bus} + t_{r_{sp,bus}} \leq PAT + \theta_1$$

  then switch to bus; otherwise considering trip cancellation.

Trip & Activity Cancellation

- **Search rule**: if switching to $r_{sp,bus}$ cannot allow the agent to arrive by $(PAT + \theta_1)$:

$$d_{bus} + t_{r_{sp,bus}} > PAT + \theta_1$$

  then consider trip cancellation.

- **Stop rule**: stop after attempt without satisfactory plan.
- **Decision rule**: if both options lead to a late arrival beyond the acceptable threshold of opting to WfH.

$$d_{bus} + t_{r_{sp,bus}} > PAT + \theta_{WfH} \text{ and } d^* + t^* > PAT + \theta_{WfH}$$

then cancel the trip and the next activity associated to it, otherwise chooses the option with the earlier time to arrival:

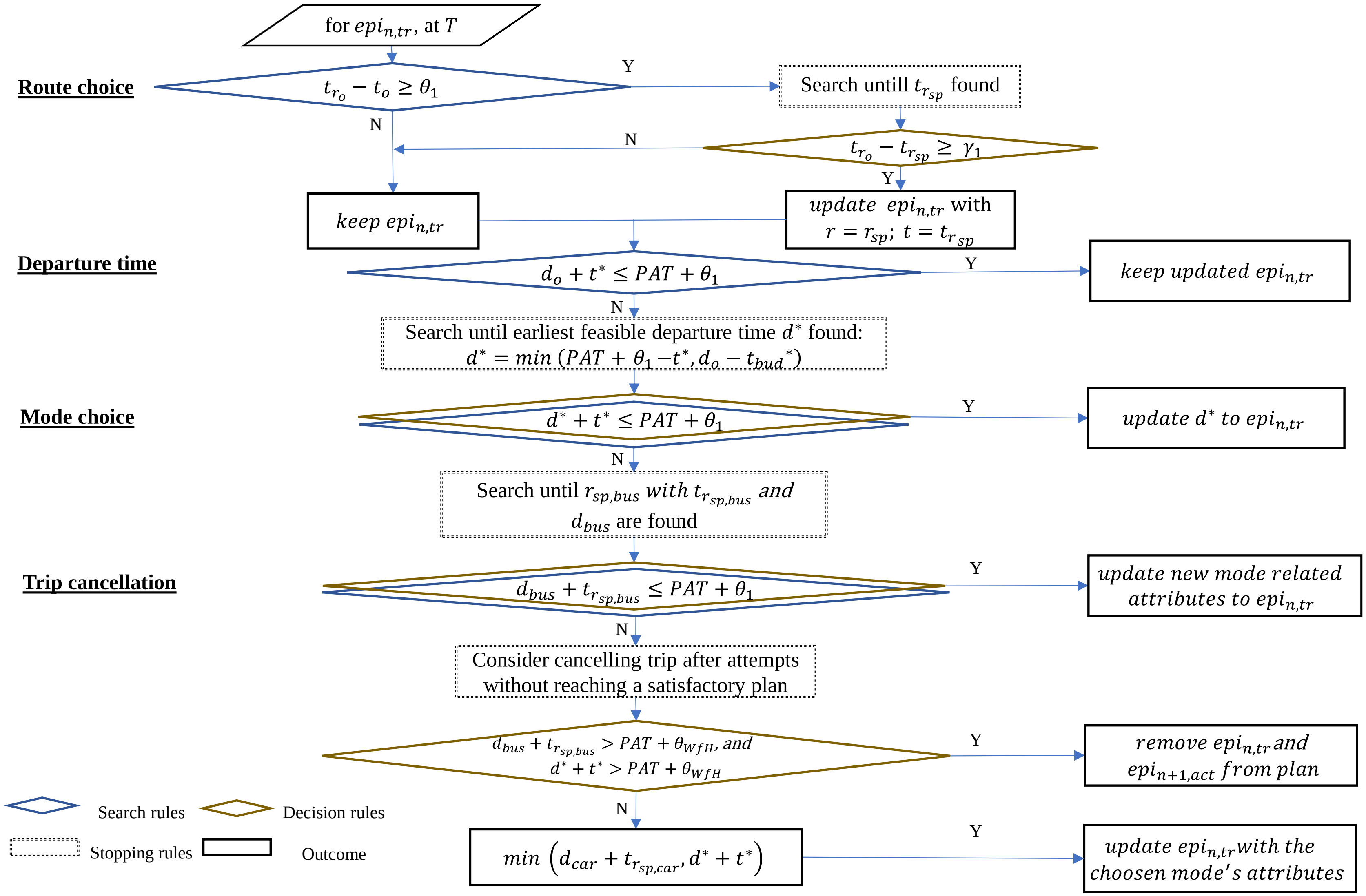
$$min\ \left(d_{car} + t_{r_{sp,car}}, d^{*} + t^{*}\right)$$

Each decision-making process takes time, the remaining decision time budget ${t_{bud}}^{*}$ is therefore updated accordingly.

$${t_{bud}}^{*} = t_{bud} - \sum \Delta T_i$$

$$\sum \Delta T_i \in \{\Delta T_{RS}, \Delta T_{ED}, \Delta T_{MS}, \Delta T_{WFH}\}$$

The actual set of ΔT_i subtracted depends on the depth of the rescheduling logic executed by the agent.



Appendix A-1 Decision-making flow chart for pre-trip rescheduling

En route Rescheduling

Route Switch

- Search rule: for an agent who does not realise the disruption until en route, if the additional travel time along the original route r_o results in a late arrival at the next planned activity $epi_{n+1,act}$ that exceeds a predefined threshold θ_2:
$$t_{r_o} - t_o \geq \theta_2$$
then search for navigating a better route.
- Stop rule: The shortest path r_{sp} is found, with $t_{r_{sp}}$ as cost of time.
- Decision rule: if the excess travel time of the original route r_o compared to the shortest available path r_{sp} is greater or equal to a predefined threshold γ_2.
$$t_{r_o} - t_{r_{sp}} \geq \gamma_2$$
then select r_{sp}; otherwise keep original planned route r_o.

Literature-Based Parameter Value Assignment for Sensitivity Analysis

For this study, parameter values were determined based on evidence from the literature. Specifically, the values employed for indifference bands were guided by empirical data from various case studies reported in previous research.

The formulations of early-side and late-side indifference bands relative to the PAT have been examined by many previous researchers. For pre-trip rescheduling, commuters are more likely to reschedule when they foresee a late arrival than an early arrival (Mahmassani and Liu, 1999). This study placed greater emphasis on the late side, as the primary focus was on mitigating the adverse effects of transport network disruptions. Field study approaches make such data available which permits the observation and understanding of the dynamic decisions of travellers in real traffic networks. Since the tolerance of the lateness was reported to be 9.18 mins for workplace (Mahmassani and Jou, 2000), terms θ_1 and θ_2 are assumed to be uniformly distributed between 0 and 9.18 mins. In addition, γ_1 and γ_2 are assumed to be normally distributed within their respective relative indifference bands which have an average of 19% with a standard deviation of 4.8% for the pre-trip decision and an average of 18% with a standard deviation of 3.5% for the en route decision (Mahmassani and Liu, 1999). In this case, the value of θ_{WfH} was set to 30 minutes for the purpose of running the simulation. However, the simulation results indicated that no agents chose to cancel their work activity, as most were able to compensate for potential lateness by adjusting their departure time or switching routes, without the need to drop their work activity.

Appendix B: Survey

Example Questionnaire [habitual private vehicle user]

Start of Block: Introduction and consent

Severe Weather Disruption and Travel Behaviour

Department of Civil and Environmental Engineering, University of Strathclyde

Participants:
Participants who are at least 18 years of age, currently drive private vehicles or take public transport to work on a regular basis or have done so in the past years.

Research Purpose:
The data collected in this survey will contribute to an understanding of:
1. How travellers reschedule their daily plans in response to disruptions in different scenarios.
2. How the covid pandemic has changed travellers' ability and attitude towards commuting.

Procedure:
You are invited to take part in an online survey. It should take you *around 10 minutes* to complete the survey.
A prize draw is being held, with the chance to win *one of eight £20 Amazon vouche*rs. To enter the draw, you will be asked to provide your email address at the end of the survey.

Confidentiality:
Taking part in this survey is entirely voluntary and your responses will be anonymous. You have the right to withdraw from the survey at any time, without having to provide a reason and without any detriment. This research was granted ethical approval by the University of Strathclyde Ethics Committee.

Thank you for reading this information - if you have any questions/concerns during or after the research, please contact the researcher: Jingsi.li@strath.ac.uk or the chief investigator: n.s.ferguson@strath.ac.uk.

If you would like to participate, you will be asked to indicate that you have read and understand the information by checking the acknowledgment accompanying the consent form. You will be asked some questions to determine your eligibility and, if selected, you can then take part in the online survey.

Page Break

X→

Q - I consent to participate in this research project and agree that:

- I confirm that I have read and understood the information sheet for the above project and the researcher has answered any queries to my satisfaction.
- I understand that my participation is voluntary and that I am free to withdraw from the project at any time up to the completion and submission of my questionnaire responses.
- I understand that I cannot withdraw my data from the study after the submission of my questionnaire responses because my responses will be anonymised at that point.
- I understand that the online questionnaire response will be held by the researcher until 31 July 2023.

Please select the appropriate option below and then click on the arrow. Thank-you.

○ Yes, I consent

○ No, I do Not consent

Skip To: End of Survey If I consent to participate in this research project and agree that:I confirm that I have read and understood and u... = No, I do Not consent

End of Block: Introduction and consent

Start of Block: Pre-choice

JS X→

Q - Which of the following options best describes your current job status? *(Tick all that apply)*

▢ Working full-time

▢ Working part-time

▢ On maternity or paternity leave

▢ Unemployed and looking for work

▢ Not currently working, and not looking for work

▢ Student

▢ Retired

▢ None of the above (please specify) ____

Page Break

Q - How do you normally travel to your current job?

- Answer for your usual travel to the place where you spend the most time
- Select the option for the longest part of your journey by distance
- Select one option only

○ Driving a car or van

○ Passenger in car or van

○ Public transport - bus, minibus, or coach

○ Public transport - train

○ Public transport - underground, subway, or tram

○ On foot

○ Bicycle

○ Taxi or private hire

○ Motorcycle, scooter or moped

○ I don’t normally travel to my current job as I work from home

○ Other (please specify)

____

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Driving a car or van

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Passenger in car or van

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = On foot

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Bicycle

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Taxi or private hire

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Motorcycle, scooter or moped

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Other (please specify)

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = I don’t normally travel to my current job as I work from home

Page Break

Display This Question:

If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - bus, minibus, or coach

Or Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - train

Or Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - underground, subway, or tram

JS

Q - If you commute by using public transport in most cases, please enter the survey by clicking on this link.

Skip To: End of Survey If If you commute by using public transport in most cases, please enter the survey by clicking on th... Is Displayed

End of Block: Pre-choice

Start of Block: Context description - car

Display This Question:

If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Driving a car or van

JS

Imagine you are in the following situation:

You wake up in the morning and discover that there has been bad weather overnight which has disrupted your normal route to work due to flooding.

The time is currently 8:00 am.
You have a busy day at work. Your planned schedule is as follows:

- 8:30 am Leave home to travel to work
- 9:00 am Start the day with a planned diary engagement
- 5:00 pm Leave work

Before leaving for work, you had planned to prepare your diary for the day ahead and respond to emails. If you choose to leave for work earlier than planned you will lose the opportunity to do this, although you could deal with some straightforward tasks if you choose to travel by public transport.

(Car parking is available around the workplace, and the cost of parking is included in the overall monetary cost.)

End of Block: Context description - car

Start of Block: Participant task

JS

You will be asked to decide how you would adjust your travel plans under flooding induced transport disruption.

Here is an example question:

14

A time limit (in seconds) will be placed on your selection for some of the questions.

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Private car	Private car	Public transport	
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	48 + 2 mins	31 + 2 mins	41 + 7 mins	Leave earlier before 8:30
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:03 [8:58, 9:18]	9:18 [9:13, 9:23]	
Monetary Cost	£5.6	£4.4	£4.9	

Option 1 Option 2 Option 3 Option 4

Click on your preferred option

→

You will be presented with **three hypothetical scenarios in six choice tasks.**
One choice task of a certain scenario will have no time limit placed on your selection. While the other task will have a time limit of variable length placed on your decision to simulate the effect of decision-making under time pressure (as shown in the example).

End of Block: Participant task

Start of Block: Car_S1_No_TP

JS

Scenario 1/6: You have a work meeting as described below:

Team meeting to plan a new project

Schedule: 9:00 – 10:00, with some flexibility over the start and end times
Attendees: Five colleagues who you work with on a daily basis

Involvement: The meeting will involve referring to multiple documents and figures, and using a flip chart or whiteboard to work together on the plan.
Flexibility: You can join the meeting remotely if absolutely necessary

----

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Private car	Private car	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	48 + 2 mins	36 + 2 mins	41 + 7 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:08 [9:03, 9:23]	9:18 [9:13, 9:23]	
Monetary Cost	£5.6	£4.4	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Private car	Private car	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	48 + 2 mins	36 + 2 mins	41 + 7 mins	
Departure time	8:00	8:00	8:10	
Expected Arrival Time [Earliest, Latest]	8:50 [8:45, 9:05]	8:38 [8:33, 8:53]	8:58 [8:53, 9:03]	
Monetary cost	£5.6	£4.4	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

End of Block: Car_S1_No_TP

Start of Block: Car_S1_TP

JS

Scenario 2/6:
You have a work meeting as described below:

Team meeting to plan a new project

Schedule: 9:00 – 10:00, with some flexibility over the start and end times
Attendees: Five colleagues who you work with on a daily basis
Involvement: The meeting will involve referring to multiple documents and figures, and using a flip chart or whiteboard to work together on the plan.
Flexibility: You can join the meeting remotely if absolutely necessary
----

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **12 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Private car	Private car	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	68 + 2 mins	44 + 2 mins	41 + 7 mins	
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:16 [9:11, 9:31]	9:18 [9:13, 9:23]	
Monetary Cost	£6.8	£5.6	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Private car	Private car	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	68 + 2 mins	44 + 2 mins	41 + 7 mins	
Departure time	8:00	8:10	8:10	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	8:56 [8:51, 9:11]	8:58 [8:53, 9:03]	
Monetary cost	£6.8	£5.6	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 1

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 2

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 3

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 4

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 4

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: Car_S1_TP

Start of Block: Car_S2_No_TP

JS

Scenario 3/6:
You have a work meeting as described below:

Meeting with senior management

Schedule: 9:00 – 10:00 with no flexibility over the start and end times
Attendees: Your manager and other senior colleagues
Involvement: Formal meeting with fixed agenda. You will be asked to give a brief verbal update on a current project
Flexibility: You can join the meeting remotely

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Private car	Private car	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	68 + 2 mins	40 + 2 mins	41 + 7 mins	
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:12 [9:07, 9:17]	9:18 [9:13, 9:23]	
Monetary Cost	£6.8	£5.6	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Private car	Private car	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	68 + 2 mins	40 + 2 mins	41 + 7 mins	
Departure time	8:00	8:00	8:00	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	8:42 [8:37, 8:47]	8:48 [8:43, 8:53]	
Monetary cost	£6.8	£5.6	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

End of Block: Car_S2_No_TP

Start of Block: Car_S2_TP

JS

Scenario 4/6:
You have a work meeting as described below:

Meeting with senior management

Schedule: 9:00 – 10:00 with no flexibility over the start and end times
Attendees: Your manager and other senior colleagues
Involvement: Formal meeting with fixed agenda. You will be asked to give a brief verbal update on a current project
Flexibility: You can join the meeting remotely

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **20 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Private car	Private car	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	68 + 2 mins	47 + 2 mins	41 + 7 mins	
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:19 [9:14, 9:24]	9:18 [9:13, 9:23]	
Monetary Cost	£6.8	£5.6	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Private car	Private car	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	68 + 2 mins	47 + 2 mins	41 + 7 mins	
Departure time	8:00	8:10	8:20	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	8:59 [8:54, 9:04]	9:08 [9:03, 9:13]	
Monetary cost	£6.8	£5.6	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... != Option 1

And Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... != Option 2

And Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... != Option 3

And Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... != Option 4

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 4

And Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... = Option 4

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: Car_S2_TP

Start of Block: Car_S3_No_TP

JS

Scenario 5/6:
You have a work meeting as detailed below:

Breakfast meeting hosted by your employer

Schedule:
9:00 to 9:30 am networking over tea/coffee
9:30 to 10:00 am panel discussion on a topic of high interest to you.
No flexibility over start and end times
Attendees: Individuals from within and outside your organization.
Involvement: Opportunity to chat informally with attendees before the panel discussion
Flexibility: The panel discussion will be live-streamed for those unable to attend the event
----
Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Private car	Private car	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	48 + 2 mins	33 + 2 mins	41 + 7 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:05 [9:00, 9:20]	9:18 [9:13, 9:23]	
Monetary Cost	£5.6	£4.4	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Private car	Private car	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	48 + 2 mins	33 + 2 mins	41 + 7 mins	
Departure time	8:00	8:10	8:20	
Expected Arrival Time [Earliest, Latest]	8:50 [8:45, 9:05]	8:45 [8:40, 9:00]	9:08 [9:03, 9:13]	
Monetary cost	£5.6	£4.4	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

End of Block: Car_S3_No_TP

Start of Block: Car_S3_TP

JS

Scenario 6/6:
You have a work meeting as detailed below:

Breakfast meeting hosted by your employer

Schedule:
9:00 to 9:30 am networking over tea/coffee
9:30 to 10:00 am panel discussion on a topic of high interest to you.
No flexibility over start and end times
Attendees: Individuals from within and outside your organization.
Involvement: Opportunity to chat informally with attendees before the panel discussion
Flexibility: The panel discussion will be live-streamed for those unable to attend the event
----
Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **12 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Private car	Private car	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	68 + 2 mins	51 + 2 mins	41 + 7 mins	
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:23 [9:18, 9:38]	9:18 [9:13, 9:23]	
Monetary Cost	£6.8	£6.8	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Private car	Private car	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	68 + 2 mins	51 + 2 mins	41 + 7 mins	
Departure time	8:00	8:00	8:00	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	8:53 [8:48, 9:08]	8:48 [8:43, 8:53]	
Monetary cost	£6.8	£6.8	£4.9	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... != Option 1

And Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... != Option 2

And Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... != Option 3

And Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... != Option 4

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 4

And Q - Your intention is to depart at 8:30 as planned Given the following options, which option of t... = Option 4

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: Car_S3_TP

Start of Block: Post-choice reflection

JS X→

Q - Thinking about the scenarios in which a time limit was imposed, do you feel that the time pressure affected the way you made your choices?

- ○ Definitely
- ○ Probably
- ○ Possibly
- ○ Probably not
- ○ Definitely not

Page Break

Display This Question:

If Q - Thinking about the scenarios in which a time limit was imposed, do you feel that the time pre... = Definitely

Or Q - Thinking about the scenarios in which a time limit was imposed, do you feel that the time pre... = Probably

Or Q - Thinking about the scenarios in which a time limit was imposed, do you feel that the time pre... = Possibly

JS X→

Q- In what way(s) did the time pressure affect the way you made your choices?
(Multiple choices are allowed)

- ☐ I had to speed up
- ☐ I relied on certain information
- ☐ I felt less satisfied with decisions made under time limits than decisions made with no time limits
- ☐ I tended to make more risky choices on arrival time.
- ☐ I tended to be more risk-averse on late arrival.
- ☐ Other (please specify) ________________________________

Page Break

JS X→

Q - Thinking about your normal journey to work, what is the minimum length of any unexpected delay before you would search for alternative travel options?

- ◯ 0 minutes – I always check to find out the best route/option
- ◯ 1-5 minutes
- ◯ 5-10 minutes
- ◯ 10-15 minutes
- ◯ Longer than 15 minutes
- ◯ I never check for alternative routes/options

End of Block: Post-choice reflection

Start of Block: Remote work

In this section, we would like to know how Covid pandemic affects your attitude towards commuting.

JS

Q - How many days per week did you normally travel to work before the covid pandemic?

	Days						
	1	2	3	4	5	6	7

Page Break

JS

Q - Typically, how many days per week do you currently travel to work?
(Please give your best estimate)

	Days						
	1	2	3	4	5	6	7

Page Break

JS X→

Q - You find out about serious transport disruption **less than one hour** before you plan to travel to work. How easy would it be for you to work from home?

- ◯ Very easy – I could do nearly all of my work from home if necessary.
- ◯ Generally easy – although there are some days when I would need to go to work.
- ◯ It depends what I have on – it would be easy some days but difficult on others.
- ◯ Generally difficult – although there are some days when I could work from home.
- ◯ Very difficult – nearly all of my work requires me to go to work.

Page Break

JS X→

Q - You find out about serious transport disruption **on the day before** you plan to travel to work. How easy would it be for you to work from home?

- ◯ Very easy – I could do nearly all of my work from home if necessary.
- ◯ Generally easy – although there are some days when I would need to go to work.
- ◯ It depends what I have on – it would be easy some days but difficult on others.
- ◯ Generally difficult – although there are some days when I could work from home.
- ◯ Very difficult – nearly all of my work requires me to go to work.

Page Break

JS X→

Q - How easily could you work from home on **three consecutive days** in the event of serious disruption affecting your journey to work?

- ◯ It would be very easy for me to work from home on three consecutive days.
- ◯ Most of the time it would be easy for me to work from home on three consecutive days.
- ◯ It depends what I have on – sometimes it would be easy, other times it would be difficult.
- ◯ Most of the time it would be difficult for me to work from home on three consecutive days.
- ◯ It would be very difficult for me to work from home on three consecutive days.

Page Break

JS X→

Q- Traffic disruptions don't affect my travel to work as badly as they did before the Covid pandemic.

- Strongly agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Strongly disagree

End of Block: Remote work

Start of Block: Demographic

In the last section of the survey, we want to learn a little bit more about you.

JS X→

Q - To which gender identity do you most identify?

- Male
- Female
- Non-binary
- Prefer not to say

Page Break

JS X→

Q - What is your age?

- ◯ Under 18
- ◯ 18 - 24
- ◯ 25 - 34
- ◯ 35 - 44
- ◯ 45 - 54
- ◯ 55 - 64
- ◯ 65 or older

Page Break

JS X→

Q - Do you have any caring responsibilities?

- ☐ Yes - children
- ☐ Yes - elderly people
- ☐ Yes - pet(s)
- ☐ No - I don't have any caring responsibilities

Page Break

JS X→

Q - What is the highest level of education you have completed? If currently enrolled in education, please give the highest award received to date.

- Secondary school
- Vocational or similar
- Some University but no degree
- University - Bachelor's degree
- University - Master's degree
- University - Doctorate
- Prefer not to say

Page Break

JS

Q - Which of the following best describes your personal income range last year?

- Less than £10,000
- £10,000 - £29,999
- £30,000 - £49,999
- above £50,000
- Prefer not to say

Page Break

JS

Q - How long does it normally take you to travel to work?

	minutes
	0 10 20 30 40 50 60 70 80 90 100 110 120
One way	

Page Break

JS X→

Q - In which country do you currently reside?

▼ Afghanistan (1) ... Zimbabwe (193)

End of Block: Demographic

Start of Block: Thanks & Further Feedback

JS

Thank you for spending time taking part in this survey.
Please kindly leave your comments on the following questions.

JS X→

Q - How do you satisfied with the experience of completing this survey?

- ◯ Very satisfied
- ◯ Somewhat satisfied
- ◯ Neither satisfied nor dissatisfied
- ◯ Somewhat dissatisfied
- ◯ Very dissatisfied

JS

Q - Have you experienced any confusion or unclear expression during completing the survey? If any, please specify.

____

____

____

____

JS *

Thank you again for your participation.
If you would like to participate in the prize draw to win one of eight £20 Amazon vouchers as a thank-you gift, please feel free to leave your email below.

____

End of Block: Thanks & Further Feedback

Example Questionnaire [habitual public transport user]

Start of Block: Introduction and consent

Severe Weather Disruption and Travel Behaviour

Department of Civil and Environmental Engineering, University of Strathclyde

Participants:
Participants who are at least 18 years of age, currently drive private vehicles or take public transport to work on a regular basis or have done so in the past years.

Research Purpose:
The data collected in this survey will contribute to an understanding of:
1. How travellers reschedule their daily plans in response to disruptions in different scenarios.
2. How the covid pandemic has changed travellers' ability and attitude towards commuting.

Procedure:
You are invited to take part in an online survey. It should take you *around 10 minutes* to complete the survey.
A prize draw is being held, with the chance to win *one of eight £20 Amazon vouche*rs. To enter the draw, you will be asked to provide your email address at the end of the survey.

Confidentiality:
Taking part in this survey is entirely voluntary and your responses will be anonymous. You have the right to withdraw from the survey at any time, without having to provide a reason and without any detriment. This research was granted ethical approval by the University of Strathclyde Ethics Committee.

Thank you for reading this information - if you have any questions/concerns during or after the research, please contact the researcher: Jingsi.li@strath.ac.uk or the chief investigator: n.s.ferguson@strath.ac.uk.

If you would like to participate, you will be asked to indicate that you have read and understand the information by checking the acknowledgment accompanying the consent form. You will be asked some questions to determine your eligibility and, if selected, you can then take part in the online survey.

Page Break

Q - I consent to participate in this research project and agree that:

- I confirm that I have read and understood the information sheet for the above project and the researcher has answered any queries to my satisfaction.
- I understand that my participation is voluntary and that I am free to withdraw from the project at any time up to the completion and submission of my questionnaire responses.
- I understand that I cannot withdraw my data from the study after the submission of my questionnaire responses because my responses will be anonymised at that point.
- I understand that the online questionnaire response will be held by the researcher until 31 July 2023.

Please select the appropriate option below and then click on the arrow. Thank-you.

○ Yes, I consent

○ No, I do Not consent

Skip To: End of Survey If I consent to participate in this research project and agree that:I confirm that I have read and u... = No, I do Not consent

End of Block: Introduction and consent

Start of Block: Pre-choice

JS X→

Q - Which of the following options best describes your current job status? *(Tick all that apply)*

☐ Working full-time

☐ Working part-time

☐ On maternity or paternity leave

☐ Unemployed and looking for work

☐ Not currently working, and not looking for work

☐ Student

☐ Retired

☐ None of the above (please specify) ____

Page Break

JS X→

Q - How do you normally travel to your current job?

- Answer for your usual travel to the place where you spend the most time
- Select the option for the <u>longest</u> part of your journey <u>by distance</u>
- Select <u>one</u> option only

◯ Public transport - bus, minibus, or coach

◯ Public transport - train

◯ Public transport - underground, subway, or tram

◯ Driving a car or van

◯ Passenger in car or van

◯ On foot

◯ Bicycle

◯ Taxi or private hire

◯ Motorcycle, scooter or moped

◯ I don’t normally travel to my current job as I work from home

◯ Other (please specify) ________________________________

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Passenger in car or van

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = On foot

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Bicycle

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Taxi or private hire

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Motorcycle, scooter or moped

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Other (please specify)

Skip To: End of Block If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = I don’t normally travel to my current job as I work from home

Page Break

Display This Question:

If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - bus, minibus, or coach

Or Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - train

Or Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - underground, subway, or tram

JS X→

Q - Do you have access to a private car on working days if you want to use it?

- ◯ Yes
- ◯ No

Page Break

Display This Question:

If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - bus, minibus, or coach

Or Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - train

Or Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Public transport - underground, subway, or tram

JS X→

Q - Do you work on job-related tasks (such as responding to emails) when you are on public transport?

- ◯ Never
- ◯ Sometimes
- ◯ About half the time
- ◯ Most of the time
- ◯ Always

Display This Question:

If Q - How do you normally travel to your current job?Answer for your usual travel to the place wher... = Driving a car or van

JS

Q- If you commute by driving a private vehicle in most cases, please enter the survey by clicking on this link.

Skip To: End of Survey If If you commute by driving a private vehicle in most cases, please enter the survey by clicking on... Is Displayed

End of Block: Pre-choice

Start of Block: Context description - pt w/o car

Display This Question:

If Q - Do you have access to a private car on working days if you want to use it? = No

JS

Imagine you are in the following situation:

You wake up in the morning and discover that there has been bad weather overnight which has disrupted your normal route to work due to flooding.

The time is currently 8:00 am.
You have a busy day at work. Your planned schedule is as follows:
8:30 am Leave home to travel to work
9:00 am Start the day with a planned diary engagement
5:00 pm Leave work

Before leaving for work, you had planned to prepare your diary for the day ahead and respond to emails. If you choose to leave for work earlier than planned you will lose the opportunity to do this, although you could deal with some straightforward tasks if you choose to travel by public transport.

End of Block: Context description - pt w/o car

Start of Block: Participant task - pt w/o car

Display This Question:

If Imagine you are in the following situation:You wake up in the morning and discover that there has... Is Displayed

JS

You will be asked to decide how you would adjust your travel plans under flooding induced transport disruption.

Here is an example question:

14 **A time limit (in seconds) will be placed on your selection for some of the questions.**

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3
Travel Mode	Public transport	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	34 + 12 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:16 [9:11, 9:21]	
Monetary Cost	£4.9	£5.6	

Option 1 Option 2 Option 3

Click on your preferred option

You will be presented with **three hypothetical scenarios in six choice tasks.**
One choice task of a certain scenario will have no time limit placed on your selection. While the other task will have a time limit of variable length placed on your decision to simulate the effect of decision-making under time pressure (as shown in the example).

End of Block: Participant task - pt w/o car

Start of Block: PT w/o Car_S1_No_TP

JS

Scenario 1/6: You have a work meeting as described below:

Team meeting to plan a new project

Schedule: 9:00 – 10:00, with some flexibility over the start and end times

Attendees: Five colleagues who you work with on a daily basis
Involvement: The meeting will involve referring to multiple documents and figures, and using a flip chart or whiteboard to work together on the plan.
Flexibility: You can join the meeting remotely if absolutely necessary
 ----
Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3
Travel Mode	Public transport	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	38 + 12 mins	
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:20 [9:15, 9:25]	
Monetary Cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3
Travel mode	Public transport	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	38 + 12 mins	
Departure time	8:00	8:10	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	9:00 [8:55, 9:05]	
Monetary cost	£4.9	£5.6	

Option 1 ○ Option 2 ○ Option 3 ○

Page Break

End of Block: PT w/o Car_S1_No_TP

Start of Block: PT w/o Car_S1_TP

JS

Scenario 2/6:
You have a work meeting as described below:

Team meeting to plan a new project

Schedule: 9:00 – 10:00, with some flexibility over the start and end times
Attendees: Five colleagues who you work with on a daily basis
Involvement: The meeting will involve referring to multiple documents and figures, and using a flip chart or whiteboard to work together on the plan.
Flexibility: You can join the meeting remotely if absolutely necessary

----

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **12 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3
Travel Mode	Public transport	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	34 + 12 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:16 [9:11, 9:21]	
Monetary Cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3
Travel mode	Public transport	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	34 + 12 mins	
Departure time	8:00	8:00	
Expected Arrival Time [Earliest, Latest]	8:50 [8:45, 9:05]	8:46 [8:41, 8:51]	
Monetary cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 1

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 2

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 3

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: PT w/o Car_S1_TP

Start of Block: PT w/o Car_S2_No_TP

JS

Scenario 3/6:
You have a work meeting as described below:

Meeting with senior management

Schedule: 9:00 – 10:00 with no flexibility over the start and end times
Attendees: Your manager and other senior colleagues
Involvement: Formal meeting with fixed agenda. You will be asked to give a brief verbal update on a current project
Flexibility: You can join the meeting remotely

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3
Travel Mode	Public transport	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	30 + 12 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:12 [9:07, 9:17]	
Monetary Cost	£4.9	£4.4	

Option 1 Option 2 Option 3

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3
Travel mode	Public transport	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	30 + 12 mins	
Departure time	8:00	8:00	
Expected Arrival Time [Earliest, Latest]	8:50 [8:45, 9:05]	8:42 [8:37, 8:47]	
Monetary cost	£4.9	£4.4	

O Option 1 O Option 2 O Option 3

Page Break

End of Block: PT w/o Car_S2_No_TP

Start of Block: PT w/o Car_S2_TP

JS

Scenario 4/6:
You have a work meeting as described below:

Meeting with senior management

Schedule: 9:00 – 10:00 with no flexibility over the start and end times
Attendees: Your manager and other senior colleagues
Involvement: Formal meeting with fixed agenda. You will be asked to give a brief verbal update on a current project
Flexibility: You can join the meeting remotely

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **12 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3
Travel Mode	Public transport	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	34 + 12 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:16 [9:11, 9:21]	
Monetary Cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3
Travel mode	Public transport	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	34 + 12 mins	
Departure time	8:00	8:20	
Expected Arrival Time [Earliest, Latest]	8:50 [8:45, 9:05]	9:06 [9:01, 9:11]	
Monetary cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 1

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 2

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 3

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: PT w/o Car_S2_TP

Start of Block: PT w/o Car_S3_No_TP

JS

Scenario 5/6:
You have a work meeting as detailed below:

Breakfast meeting hosted by your employer

Schedule:
9:00 to 9:30 am networking over tea/coffee
9:30 to 10:00 am panel discussion on a topic of high interest to you.
No flexibility over start and end times
Attendees: Individuals from within and outside your organization.
Involvement: Opportunity to chat informally with attendees before the panel discussion
Flexibility: The panel discussion will be live-streamed for those unable to attend the event
----
Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3
Travel Mode	Public transport	Public transport	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	44 + 12 mins	
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:26 [9:21, 9:31]	
Monetary Cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3
Travel mode	Public transport	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	44 + 12 mins	
Departure time	8:00	8:20	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	9:16 [9:11, 9:21]	
Monetary cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

End of Block: PT w/o Car_S3_No_TP

Start of Block: PT w/o Car_S3_TP

JS

Scenario 6/6:
You have a work meeting as detailed below:

Breakfast meeting hosted by your employer

Schedule:
9:00 to 9:30 am networking over tea/coffee
9:30 to 10:00 am panel discussion on a topic of high interest to you.
No flexibility over start and end times
Attendees: Individuals from within and outside your organization.

Involvement: Opportunity to chat informally with attendees before the panel discussion
Flexibility: The panel discussion will be live-streamed for those unable to attend the event

----

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **20 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3
Travel Mode	Public transport	Public transport	
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	50 + 12 mins	Leave earlier before 8:30
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:32 [9:27, 9:37]	
Monetary Cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3
Travel mode	Public transport	Public transport	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	50 + 12 mins	
Departure time	8:00	8:20	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	9:22 [9:17, 9:27]	
Monetary cost	£4.9	£5.6	

O Option 1 O Option 2 O Option 3

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 1

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 2

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 3

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 3

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: PT w/o Car_S3_TP

Start of Block: Context description - pt w/ car

Display This Question:

If Q - Do you have access to a private car on working days if you want to use it? = Yes

JS

Imagine you are in the following situation:

You wake up in the morning and discover that there has been bad weather overnight which has disrupted your normal route to work due to flooding.

The time is currently 8:00 am.
You have a busy day at work. Your planned schedule is as follows:
8:30 am Leave home to travel to work
9:00 am Start the day with a planned diary engagement
5:00 pm Leave work

Before leaving for work, you had planned to prepare your diary for the day ahead and respond to emails. If you choose to leave for work earlier than planned you will lose the opportunity to do this, although you could deal with some straightforward tasks if you choose to travel by public transport.

(Car parking is available around the workplace, and the cost of parking is included in the overall monetary cost.)

End of Block: Context description - pt w/ car

Start of Block: Participant task - pt w/ car

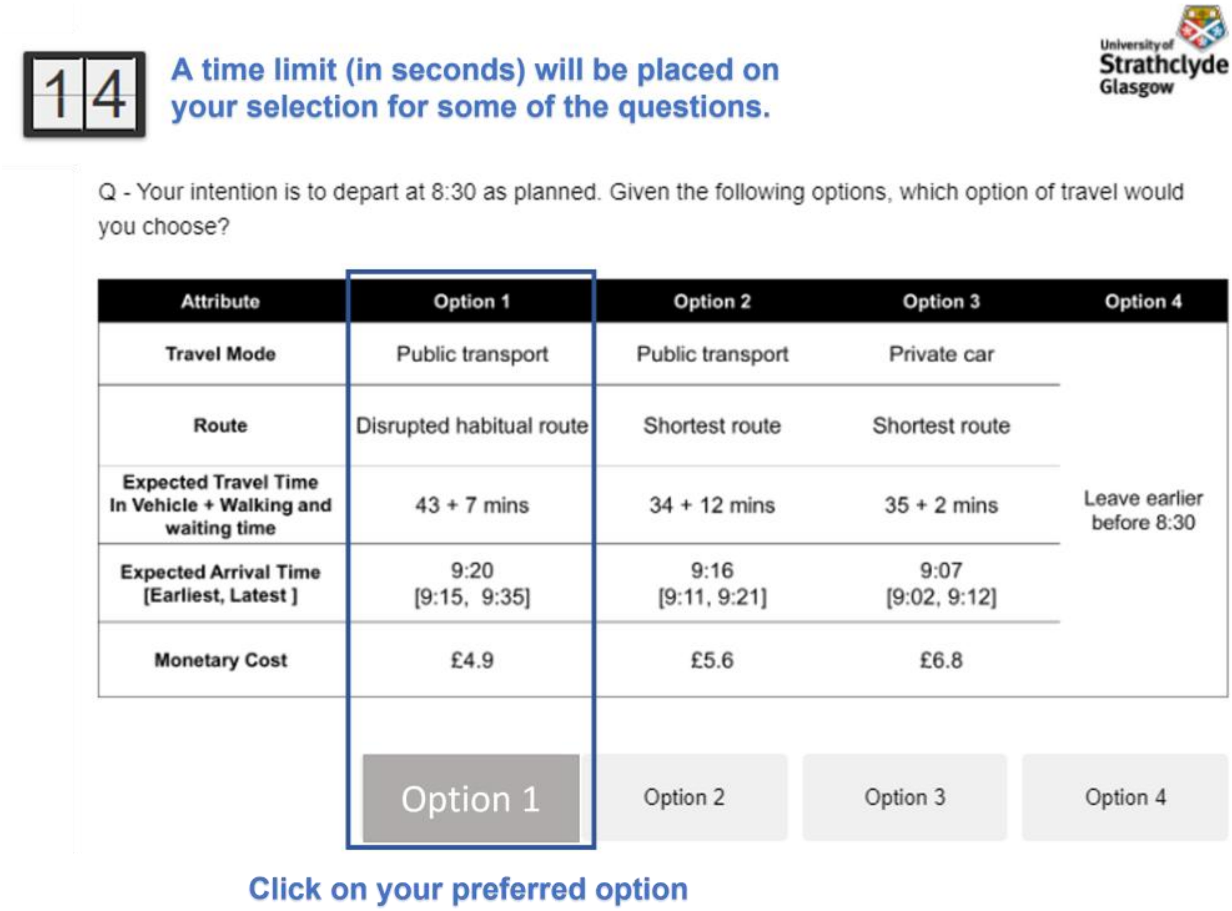
Display This Question:

If Imagine you are in the following situation:You wake up in the morning and discover that there has... Is Displayed

JS

You will be asked to decide how you would adjust your travel plans under flooding induced transport disruption.

<u>Here is an example question:</u>



14

A time limit (in seconds) will be placed on your selection for some of the questions.

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Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Public transport	Public transport	Private car	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	34 + 12 mins	35 + 2 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:16 [9:11, 9:21]	9:07 [9:02, 9:12]	
Monetary Cost	£4.9	£5.6	£6.8	

Option 1 Option 2 Option 3 Option 4

Click on your preferred option

You will be presented with **three hypothetical scenarios in six choice tasks.** One choice task of a certain scenario will have no time limit placed on your selection. While the other task will have a time limit of variable length placed on your decision to simulate the effect of decision-making under time pressure (as shown in the example).

End of Block: Participant task - pt w/ car

Start of Block: PT w/Car_S1_No_TP

JS

Scenario 1/6: You have a work meeting as described below:

Team meeting to plan a new project

\---

Schedule: 9:00 – 10:00, with some flexibility over the start and end times
Attendees: Five colleagues who you work with on a daily basis
Involvement: The meeting will involve referring to multiple documents and figures, and using a flip chart or whiteboard to work together on the plan.

Flexibility: You can join the meeting remotely if absolutely necessary

----

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Public transport	Public transport	Private car	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	38 + 12 mins	35 + 2 mins	
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:20 [9:15, 9:25]	9:07 [9:02, 9:12]	
Monetary Cost	£4.9	£5.6	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Public transport	Public transport	Private car	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	38 + 12 mins	35 + 2 mins	
Departure time	8:00	8:00	8:00	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	8:50 [8:45, 8:55]	8:37 [8:32, 8:42]	
Monetary cost	£4.9	£5.6	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

End of Block: PT w/Car_S1_No_TP

Start of Block: PT w/car_S1_TP

JS

Scenario 2/6:
You have a work meeting as described below:

Team meeting to plan a new project

Schedule: 9:00 – 10:00, with some flexibility over the start and end times
Attendees: Five colleagues who you work with on a daily basis
Involvement: The meeting will involve referring to multiple documents and figures, and using a flip chart or whiteboard to work together on the plan.
Flexibility: You can join the meeting remotely if absolutely necessary

----

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **16 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Public transport	Public transport	Private car	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	26 + 12 mins	35 + 2 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:08 [9:03, 9:13]	9:07 [9:02, 9:12]	
Monetary Cost	£4.9	£4.4	£6.8	

○ Option 1 ○ Option 2 ○ Option 3 ○ Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Public transport	Public transport	Private car	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	26 + 12 mins	35 + 2 mins	
Departure time	8:00	8:20	8:00	
Expected Arrival Time [Earliest, Latest]	8:50 [8:45, 9:05]	8:58 [8:53, 9:03]	8:37 [8:32, 8:42]	
Monetary cost	£4.9	£4.4	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 1

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 2

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 3

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 4

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 4

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: PT w/car_S1_TP

Start of Block: PT w/Car_S2_No_TP

JS

Scenario 3/6:
You have a work meeting as described below:

Meeting with senior management

Schedule: 9:00 – 10:00 with no flexibility over the start and end times
Attendees: Your manager and other senior colleagues
Involvement: Formal meeting with fixed agenda. You will be asked to give a brief verbal update on a current project
Flexibility: You can join the meeting remotely

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Public transport	Public transport	Private car	
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	50 + 12 mins	35 + 2 mins	Leave earlier before 8:30
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:32 [9:27, 9:37]	9:07 [9:02, 9:22]	
Monetary Cost	£4.9	£5.6	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Public transport	Public transport	Private car	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	50 + 12 mins	35 + 2 mins	
Departure time	8:00	8:10	8:20	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	9:12 [9:07, 9:17]	8:57 [8:52, 9:12]	
Monetary cost	£4.9	£5.6	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

End of Block: PT w/Car_S2_No_TP

Start of Block: PT w/car_S2_TP

JS

Scenario 4/6:
You have a work meeting as described below:

Meeting with senior management

Schedule: 9:00 – 10:00 with no flexibility over the start and end times
Attendees: Your manager and other senior colleagues
Involvement: Formal meeting with fixed agenda. You will be asked to give a brief verbal update on a current project
Flexibility: You can join the meeting remotely

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **20 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Public transport	Public transport	Private car	
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	30 + 12 mins	35 + 2 mins	Leave earlier before 8:30
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:12 [9:07, 9:17]	9:07 [9:02, 9:22]	
Monetary Cost	£4.9	£4.4	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Public transport	Public transport	Private car	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	30 + 12 mins	35 + 2 mins	
Departure time	8:00	8:20	8:10	
Expected Arrival Time [Earliest, Latest]	8:50 [8:45, 9:05]	9:02 [8:57, 9:07]	8:47 [8:42, 9:02]	
Monetary cost	£4.9	£4.4	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 1

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 2

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 3

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 4

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 4

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: PT w/car_S2_TP

Start of Block: PT w/Car_S3_No_TP

JS

Scenario 5/6:
You have a work meeting as detailed below:

Breakfast meeting hosted by your employer

Schedule:
9:00 to 9:30 am networking over tea/coffee
9:30 to 10:00 am panel discussion on a topic of high interest to you.
No flexibility over start and end times
Attendees: Individuals from within and outside your organization.
Involvement: Opportunity to chat informally with attendees before the panel discussion
Flexibility: The panel discussion will be live-streamed for those unable to attend the event
----

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

There is **no time limit** *placed on choices in this scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Public transport	Public transport	Private car	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	44 + 12 mins	35 + 2 mins	
Expected Arrival Time [Earliest, Latest]	9:40 [9:35, 9:55]	9:26 [9:21, 9:31]	9:07 [9:02, 9:12]	
Monetary Cost	£4.9	£5.6	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Public transport	Public transport	Private car	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	63 + 7 mins	44 + 12 mins	35 + 2 mins	
Departure time	8:00	8:20	8:10	
Expected Arrival Time [Earliest, Latest]	9:10 [9:05, 9:25]	9:16 [9:11, 9:21]	8:47 [8:42, 8:52]	
Monetary cost	£4.9	£5.6	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

End of Block: PT w/Car_S3_No_TP

Start of Block: PT w/car_S3_TP

JS

Scenario 6/6:
You have a work meeting as detailed below:

Breakfast meeting hosted by your employer

Schedule:
9:00 to 9:30 am networking over tea/coffee
9:30 to 10:00 am panel discussion on a topic of high interest to you.
No flexibility over start and end times
Attendees: Individuals from within and outside your organization.
Involvement: Opportunity to chat informally with attendees before the panel discussion

Flexibility: The panel discussion will be live-streamed for those unable to attend the event

----

Next, you will be asked to select how you would join this meeting given the ongoing transport disruption.

*You will have a maximum time of **16 seconds** to select your preferred option. If you don't select your preference within this time limit, the survey will move on to the next scenario.*

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

JS X→

Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of travel would you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel Mode	Public transport	Public transport	Private car	Leave earlier before 8:30
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	26 + 12 mins	35 + 2 mins	
Expected Arrival Time [Earliest, Latest]	9:20 [9:15, 9:35]	9:08 [9:03, 9:13]	9:07 [9:02, 9:22]	
Monetary Cost	£4.9	£4.4	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

[Timing on question: First Click, Last Click, Page Submit, Click Count]

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS X→

Q - You are seeking to depart earlier. Given the following options, which one will you choose?

Attribute	Option 1	Option 2	Option 3	Option 4
Travel mode	Public transport	Public transport	Private car	Work from home and join the meeting online
Route	Disrupted habitual route	Shortest route	Shortest route	
Expected Travel Time In Vehicle + Walking and waiting time	43 + 7 mins	26 + 12 mins	35 + 2 mins	
Departure time	8:00	8:20	8:00	
Expected Arrival Time [Earliest, Latest]	8:50 [8:45, 9:05]	8:58 [8:53, 9:03]	8:37 [8:32, 8:52]	
Monetary cost	£4.9	£4.4	£6.8	

O Option 1 O Option 2 O Option 3 O Option 4

Page Break

Display This Question:

If Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 1

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 2

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 3

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... != Option 4

Or If

Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 1

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 2

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 3

And Q - You are seeking to depart earlier. Given the following options, which one will you choose? != Option 4

And Q - Your intention is to depart at 8:30 as planned. Given the following options, which option of... = Option 4

JS

Q- You have run out of time for this question.
Don't worry. Please just click the arrow to move on.

End of Block: PT w/car_S3_TP

Start of Block: Post-choice reflection

JS X→

Q - Thinking about the scenarios in which a time limit was imposed, do you feel that the time pressure affected the way you made your choices?

- Definitely
- Probably
- Possibly
- Probably not
- Definitely not

Page Break

Display This Question:

If Q - Thinking about the scenarios in which a time limit was imposed, do you feel that the time pre... = Definitely

Or Q - Thinking about the scenarios in which a time limit was imposed, do you feel that the time pre... = Probably

Or Q - Thinking about the scenarios in which a time limit was imposed, do you feel that the time pre... = Possibly

JS X→

Q- In what way(s) did the time pressure affect the way you made your choices?
(Multiple choices are allowed)

- I had to speed up
- I relied on certain information
- I felt less satisfied with decisions made under time limits than decisions made with no time limits
- I tended to make more risky choices on arrival time.
- I tended to be more risk-averse on late arrival.
- Other (please specify) ________________________________

Page Break

JS X→

Q - Thinking about your normal journey to work, what is the minimum length of any unexpected delay before you would search for alternative travel options?

- ○ 0 minutes – I always check to find out the best route/option
- ○ 1-5 minutes
- ○ 5-10 minutes
- ○ 10-15 minutes
- ○ Longer than 15 minutes
- ○ I never check for alternative routes/options

End of Block: Post-choice reflection

Start of Block: Remote work

In this section, we would like to know how Covid pandemic affects your attitude towards commuting.

JS

Q - How many days per week did you normally travel to work before the covid pandemic?

	Days						
	1	2	3	4	5	6	7

Page Break

JS

Q - Typically, how many days per week do you currently travel to work?
(Please give your best estimate)

Days						
1	2	3	4	5	6	7

Page Break

JS X→

Q - You find out about serious transport disruption **less than one hour** before you plan to travel to work. How easy would it be for you to work from home?

- ◯ Very easy – I could do nearly all of my work from home if necessary.
- ◯ Generally easy – although there are some days when I would need to go to work.
- ◯ It depends what I have on – it would be easy some days but difficult on others.
- ◯ Generally difficult – although there are some days when I could work from home.
- ◯ Very difficult – nearly all of my work requires me to go to work.

Page Break

JS X→

Q - You find out about serious transport disruption **on the day before** you plan to travel to work. How easy would it be for you to work from home?

- ◯ Very easy – I could do nearly all of my work from home if necessary.
- ◯ Generally easy – although there are some days when I would need to go to work.
- ◯ It depends what I have on – it would be easy some days but difficult on others.
- ◯ Generally difficult – although there are some days when I could work from home.
- ◯ Very difficult – nearly all of my work requires me to go to work.

Page Break

JS X→

Q - How easily could you work from home on **three consecutive days** in the event of serious disruption affecting your journey to work?

- ◯ It would be very easy for me to work from home on three consecutive days.
- ◯ Most of the time it would be easy for me to work from home on three consecutive days.
- ◯ It depends what I have on – sometimes it would be easy, other times it would be difficult.
- ◯ Most of the time it would be difficult for me to work from home on three consecutive days.
- ◯ It would be very difficult for me to work from home on three consecutive days.

Page Break

JS X→

Q- Traffic disruptions don't affect my travel to work as badly as they did before the Covid pandemic.

- ◯ Strongly agree
- ◯ Somewhat agree
- ◯ Neither agree nor disagree
- ◯ Somewhat disagree
- ◯ Strongly disagree

End of Block: Remote work

Start of Block: Demographic

In the last section of the survey, we want to learn a little bit more about you.

JS X→

Q - To which gender identity do you most identify?

- ◯ Male
- ◯ Female
- ◯ Non-binary
- ◯ Prefer not to say

Page Break

JS X→

Q - What is your age?

- ◯ Under 18
- ◯ 18 - 24
- ◯ 25 - 34
- ◯ 35 - 44
- ◯ 45 - 54
- ◯ 55 - 64
- ◯ 65 or older

Page Break

JS X→

Q - Do you have any caring responsibilities?

- ☐ Yes - children
- ☐ Yes - elderly people
- ☐ Yes - pet(s)
- ☐ No - I don't have any caring responsibilities

Page Break

JS X→

Q - What is the highest level of education you have completed? If currently enrolled in education, please give the highest award received to date.

- Secondary school
- Apprenticeship
- College of further education
- University - Bachelor's degree
- University - Master's degree
- University - Doctorate

Page Break

JS X→

Q - Which of the following best describes your personal income range last year?

- Less than £10,000
- £10,000 - £29,999
- £30,000 - £49,999
- above £50,000
- Prefer not to say

Page Break

JS

Q - How long does it normally take you to travel to work?

	minutes
	0 10 20 30 40 50 60 70 80 90 100 110 120
One way	

Page Break

JS X→

Q - In which country do you currently reside?

▼ Afghanistan (1) ... Zimbabwe (193)

End of Block: Demographic

Start of Block: Further Feedback & Thanks

JS

Thank you for spending time taking part in this survey.
Please kindly leave your comments on the following questions.

JS X→

Q - How do you satisfied with the experience of completing this survey?

- ◯ Very satisfied
- ◯ Somewhat satisfied
- ◯ Neither satisfied nor dissatisfied
- ◯ Somewhat dissatisfied
- ◯ Very dissatisfied

JS

Q - Have you experienced any confusion or unclear expression during completing the survey? If any, please specify.

____

____

____

____

JS ✱

Thank you again for your participation.
If you would like to participate in the prize draw to win one of eight £20 Amazon vouchers as a thank-you gift, please feel free to leave your email below.

____

End of Block: Further Feedback & Thanks

Participant Information Sheet

[FOR USE WITH STANDARD PRIVACY NOTICE FOR RESEARCH PARTICIPANTS]

Name of department: Civil and Environmental Engineering
Title of the study: Investigating the effect of transport network disruption on travel behaviour

Introduction
This research is part of the Ph.D. project undertaken by Ms. Jingsi Li (Ph.D. student) who is studying within the Department of Civil and Environmental Engineering, University of Strathclyde, Glasgow G1 1XQ, Scotland.

Thanks for considering taking your time to complete the survey. Any further information can be contacted via the email: Jingsi.li@strath.ac.uk

What is the purpose of this research?

When making a travel decision, time pressure exists when an individual is required to make a quick decision to avoid or reduce the risk of disrupting their planned arrangements for the rest of the day. Time pressure increases if the available options are different from those which would normally be expected based on previous experience and knowledge. These situations often arise when there is an unforeseen incident on the transport network which causes a substantial increase in journey times, and which may even make some travel options impossible to carry out.

This investigation aims to understand how travellers reschedule their daily plans in response to travel disruption, as well as the effect of time pressure on travel behaviour. The investigation also aims to evaluate the likelihood of travellers' substituting working from home for travelling to their workplaces.

Do you have to take part?
Taking part in this survey is voluntary and you have the right to withdraw from the survey at any time, without having to give a reason and without any consequences.

To express our thanks for your participation, at the end of the survey you will have the opportunity to enter a prize draw to win one of eight £20 Amazon vouchers.

What will you do in the project?
You are invited to take part in an online survey. In the survey, you will be presented with a series of scenarios in which you will be asked to imagine that your journey to work has been disrupted by an event affect the road network. In each scenario we will present you with several options and ask you to choose your preferred option. Then, we will also ask you some questions about yourself and your attitude towards remote work.

You can start the survey anytime at your convenience. It should take no more than 15 minutes to complete.

Why have you been invited to take part?
Any individual who aged between 18 and 65 years old and currently drives/takes public transport to work, or has driven/took public transport to work in the recent past, is eligible to take part in this survey.

What are the potential risks to you in taking part?
There are no identified risks if you take part in this survey.

What information is being collected in the project?
We will record your choice over the alternatives to each question in the survey.

Who will have access to the information?
Only the Chief Investigator and named researcher will have access to the information collected in this survey. Data will only be accessed using the named researcher's and Chief Investigator's computers which are encrypted and password protected.

Where will the information be stored and how long will it be kept for?
The information will be stored on University of Strathclyde's Microsoft OneDrive account for as long as is required for analysis purposes and then will be deleted.

What happens next?
If you wish to participate you will be asked to sign a consent form before taking part in the survey. If you do not wish to continue, we thank you for your time.

Researcher contact details:
Jingsi Li, Department of Civil and Environmental Engineering, University of Strathclyde.
James Weir Building Level 5, University of Strathclyde, 75 Montrose Street Glasgow, G1 1XJ.
Contact email: Jingsi.li@strath.ac.uk

Chief Investigator details:
Dr. Neil Ferguson, Department of Civil and Environmental Engineering, University of Strathclyde. James Weir Building Level 5, University of Strathclyde, 75 Montrose Street Glasgow, G1 1XJ. Contact email: n.s.ferguson@strath.ac.uk

This research was granted ethical approval by the University of Strathclyde Ethics Committee. If you have any questions/concerns, during or after the research, or wish to contact an independent person to whom any questions may be directed or further information may be sought from, please contact:

Secretary to the University Ethics Committee
Research & Knowledge Exchange Services
University of Strathclyde
Graham Hills Building
50 George Street
Glasgow
G1 1QE

Telephone: 0141 548 3707
Email: ethics@strath.ac.uk

Consent Form

Name of department: Civil and Environmental Engineering
Title of the study: Investigating the effect of transport network disruption on travel behaviour

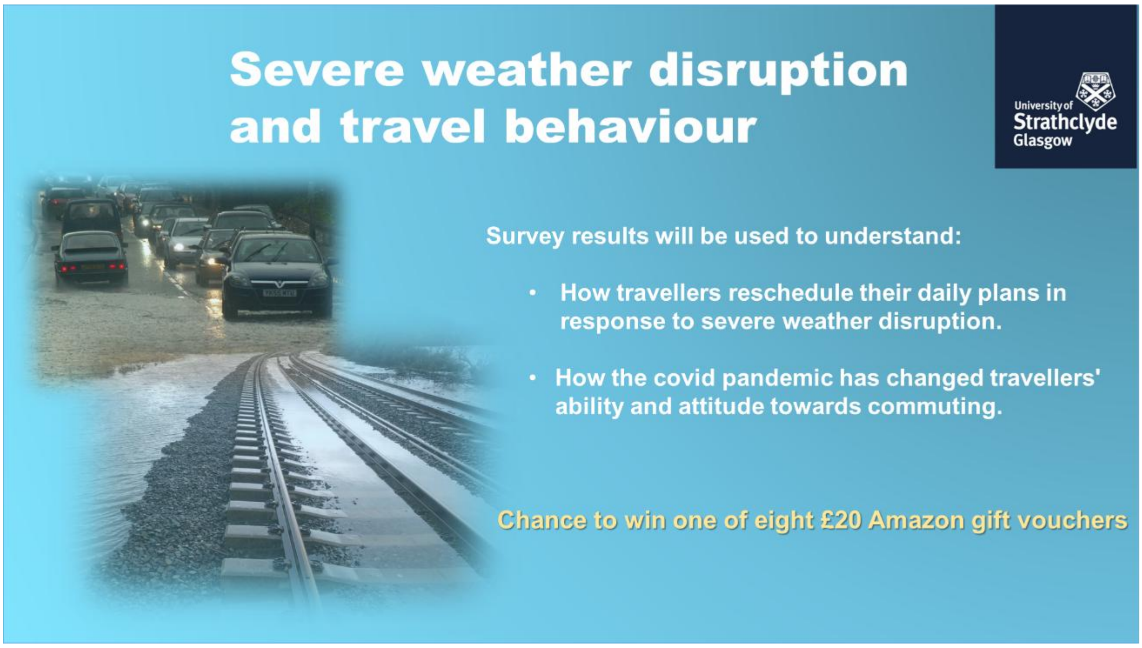
- I confirm that I have read and understood the Participant Information Sheet for the above project and the researcher has answered any queries to my satisfaction.
- I understand that my participation is voluntary and that I am free to withdraw from the project at any time, up to the point of completion, without having to give a reason and without any consequences.
- I understand that any information recorded in the research will remain confidential and no information that identifies me will be made publicly available.
- I understand that anonymised data (i.e., data that do not identify me personally) cannot be withdrawn once they have been included in the study.
- I consent to being a participant in the project.

☐ I confirm I have read and understand the above.

(PRINT NAME)	
Signature of Participant:	Date:

Survey Participant Recruitment Message

- **Image:**



- **Updated text for social media recruitment:**

Do you regularly travel to work by car or public transport? You are invited to participate in a short online research survey about the impact on *#travel behaviour* caused by *#severe weather #transport disruption*, conducted by *#StrathCivEng*. Chance to win £20 *#Amazon* vouchers!

Car user survey:

https://stratheng.eu.qualtrics.com/jfe/form/SV_bPLeBnU0WOIyMLA

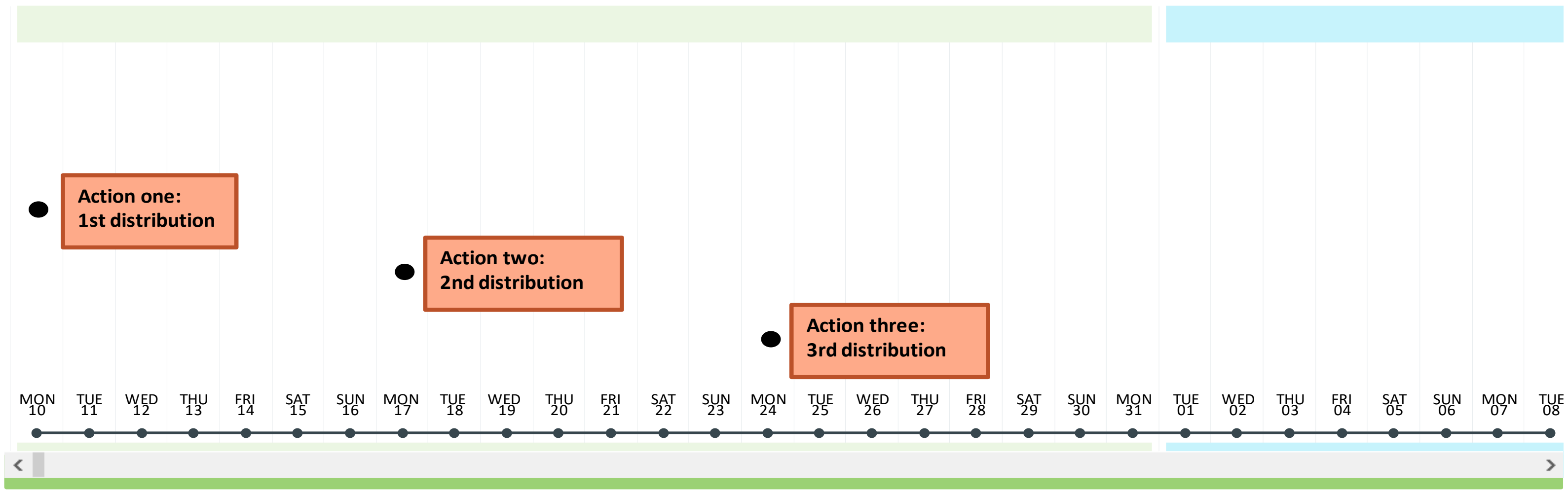
Public transport user survey:

https://stratheng.eu.qualtrics.com/jfe/form/SV_a4wiDMdsRbPDtRk

Thank you! Please feel free to share widely!

Survey Distribution Schedule

Timeline on Distributing the Survey on Social Media Channels



ENTER START DATE: **10/10/2022**

ACTIVITY	START	END	NOTES
Project Duration	10/10/2022	30/10/2022	The survey is planned to be distributed via departmental social media channels. The links are going to be open for **3 weeks**.
Action one: 1st distribution	10/10/2022	16/10/2022	Call for participants in the opening survey
Action two: 2nd distribution	17/10/2022	23/10/2022	Reminder notice at the beginning of the second week for the open survey
Action three: 3rd distribution	24/10/2022	30/10/2022	Reminder notice at the beginning of the last week for the open survey

Appendix C: Supplementary Description to Association of Participants' Choice Outcomes with Socio-demographics

Cross-tabulation and Chi-square Analysis

Gender Effects

Appendix C - 1 Cross-tabulation on gender

	Cases	$H_m\_H_r$ | PD	$H_m\_SP_r$ | PD	$ALT_m\_SP_r$ | PD	$H_m\_H_r$ | ED	$H_m\_SP_r$ |ED	$ALT_m\_SP_r$ |ED	WFH
Male w/ TP	689	0.2017	0.4107	0.2816	0.0145	0.0247	0.0479	0.0189
Male w/o TP	790	0.1886	0.4304	0.2785	0.0152	0.0443	0.0304	0.0127
Female w/ TP	462	0.1926	0.4762	0.2597	0.0087	0.0325	0.0195	0.0108
Female w/o TP	505	0.1921	0.4218	0.3030	0.0059	0.0297	0.0376	0.0099
Non-binary w/TP	15	0	0.5333	0.4000	0	0	0	0.0667
Non-b w/o TP	21	0.1429	0.6190	0.1905	0	0	0	0.0476
PNTS w/TP	3	1	0	0	0	0	0	0
PNTS w/o TP	3	0.3333	0	0.6667	0	0	0	0

(PNTS: prefer not to say)

Appendix C - 2 Chi-square analysis of gender categories and choice outcomes

CS and Categories	Degree of Freedom	All Scenarios		Without TP		With TP	
		χ^2	p	χ^2	p	χ^2	p
All + All	18	Exp. freq. in some cells of Non-b and PNTS < 5					
All + M&F	6	8.4614	0.2062	7.1277	0.3092	12.5170	0.0514
CS1 + All	9	Exp. freq. in some cells of Non-b and PNTS < 5					
CS1 + M&F	3	6.7756	0.0794	3.4421	0.3283	7.1080	0.0685

(CS: in which choice set; M&F: Female and male; CS1: choice set 1, includes alternatives $H_{m\_}\ H_r|\ PD$, $H_{m\_}\ SP_r|PD$, and $ALT_{m\_}\ SP_r|PD$)

Age Effects

Appendix C - 3 Cross-tabulation on age

	Cases	$\mathbf{H_{m}\_H_{r}}$ **| PD**	$\mathbf{H_{m}\_SP_{r}}$ **| PD**	$\mathbf{ALT_{m}\_SP_{r}}$ **| PD**	$\mathbf{H_{m}\_H_{r}}$ **| ED**	$\mathbf{H_{m}\_SP_{r}}$ **|ED**	$\mathbf{ALT_{m}\_SP_{r}}$ **|ED**	**WFH**
18-24yr w/ TP	146	0.2123	0.4589	0.2329	0.0068	0.0411	0.0411	0.0068
18-24yr w/o TP	164	0.1585	0.4878	0.2805	0.0122	0.0244	0.0183	0.0183
25-34yr w/ TP	659	0.1806	0.4401	0.2625	0.0167	0.0364	0.0395	0.0243
25-34yr w/o TP	732	0.1926	0.4331	0.2664	0.0137	0.0437	0.0383	0.0123
35-44yr w/ TP	328	0.2226	0.4299	0.3018	0.0061	0.0061	0.0274	0.0061
35-44yr w/o TP	390	0.1949	0.4077	0.3179	0.0077	0.0333	0.0282	0.0103
45-54yr w/ TP	35	0.2286	0.3429	0.4000	0	0	0.0286	0
45-54yr w/o TP	35	0.2286	0.3429	0.3714	0	0.0286	0.0286	0

Appendix C - 4 Chi-square analysis of age categories and choice outcomes

CS and Categories	Degree of Freedom	All Scenarios χ^2	All Scenarios p	Without TP χ^2	Without TP p	With TP χ^2	With TP p
All + All	18	Exp. freq. in some cells of CS2 < 5					
All + 18-44	12	Exp. freq. in some cells of CS2 < 5					
CS1 + All	9	26.9759	0.0014	Exp. freq. in some cells of 45-54yr < 5			
CS1 + 18-44	6	19.9574	0.0028	8.9481	0.1765	16.9304	0.0095

(CS: in which choice set; CS1: choice set 1, includes alternatives $H_{m\_}\,H_r|\,PD$, $H_{m\_}\,SP_r|PD$, and $ALT_{m\_}\,SP_r|PD$)

Education Effects

Appendix C - 5 Cross-tabulation on education

	Cases	**$H_m\_H_r$ | PD**	**$H_m\_SP_r$ | PD**	**$ALT_m\_SP_r$ | PD**	**$H_m\_H_r$ | ED**	**$H_m\_SP_r$ |ED**	**$ALT_m\_SP_r$ |ED**	**WFH**
Second. w/ TP	12	0.1667	0.3333	0.5000	0	0	0	0
Second. w/o TP	13	0.1538	0.3846	0.3846	0	0	0.0769	0
Voc. w/ TP	77	0.1948	0.3776	0.2857	0.0130	0.0260	0.0519	0.0519
Voc. w/o TP	86	0.1279	0.4767	0.2209	0.0233	0.0814	0.0349	0.0349
Uni. ND w/ TP	252	0.1508	0.4325	0.2778	0.0119	0.0595	0.0556	0.0119
Uni. ND w/o TP	279	0.1075	0.4409	0.3118	0.0108	0.0538	0.0609	0.0143
Bach. w/ TP	505	0.2198	0.4198	0.2832	0.0139	0.0198	0.0317	0.0119
Bach. w/o TP	570	0.1772	0.4158	0.3158	0.0105	0.0333	0.0368	0.0105
Master w/ TP	297	0.1953	0.4882	0.2424	0.0101	0.0168	0.0269	0.0202
Master w/o TP	345	0.2754	0.4319	0.2435	0.0116	0.0261	0.0029	0.0087
PhD w/ TP	26	0.3077	0.4231	0.2692	0	0	0	0
PhD w/o TP	23	0.5217	0.3913	0.0870	0	0	0	0
PNTS w/ TP	2	0	1	0	0	0	0	0
PNTS w/o TP	6	0	0.6667	0.3333	0	0	0	0

(Second.: Secondary; Voc.: Vocational; Uni.: University; Bach.: Bachelor; PNTS: prefer not to say)

Appendix C - 6 Chi-square analysis of education categories and choice outcomes

CS and Categories	Degree of Freedom	All Scenarios χ^2	All Scenarios p	Without TP χ^2	Without TP p	With TP χ^2	With TP p
All + All	36	Exp. freq. in some cells of rare categories < 5					
All + Uni-Ma	12	56.6443	0	Exp. freq. in some cells < 5			
CS1 + All	18	Exp. freq. in some cells of rare categories < 5					
CS1* + Uni-Ma	6	47.0288	0	44.7493	0	15.7440	0.0152

(CS: in which choice set; Uni-Ma: University to Master; CS1: choice set 1, includes alternatives $H_{m\_}H_r|\,PD$, $H_{m\_}SP_r|PD$, and $ALT_{m\_}SP_r|PD$)

Income Effects

Appendix C - 7 Cross-tabulation on income

	Cases	$H_m\_H_r$ | PD	$H_m\_SP_r$ | PD	$ALT_m\_SP_r$ | PD	$H_m\_H_r$ | ED	$H_m\_SP_r$ |ED	$ALT_m\_SP_r$ |ED	WFH
<10k w/ TP	41	0.2195	0.5366	0.1463	0.0244	0.0488	0.0244	0
<10k w/o TP	46	0.1522	0.4130	0.3478	0	0.0217	0.0435	0.0217
10k-30k w/ TP	332	0.2500	0.4187	0.2349	0.0120	0.0301	0.0422	0.0120
10k-30k w/o TP	359	0.1950	0.4457	0.2618	0.0111	0.0362	0.0418	0.0084
30k-50k w/ TP	402	0.1915	0.4055	0.2935	0.0199	0.0323	0.0498	0.0075
30k-50k w/o TP	454	0.1498	0.4626	0.2643	0.0154	0.0529	0.0419	0.0132
>50k w/ TP	387	0.1628	0.4703	0.2972	0.0026	0.0181	0.0181	0.0310
>50k w/o TP	445	0.2315	0.3888	0.3213	0.0090	0.0247	0.0157	0.0090
PNTS w/ TP	9	0	0.6667	0.3333	0	0	0	0
PNTS w/o TP	18	0.1667	0.3333	0.3333	0	0.0556	0	0.1111

(PNTS: prefer not to say)

Appendix C - 8 Chi-square analysis of income categories and choice outcomes

CS and Categories	Degree of Freedom	All Scenarios χ^2	All Scenarios p	Without TP χ^2	Without TP p	With TP χ^2	With TP p
All + All	24	Exp. freq. in some cells of rare categories < 5					
All + >10	12	38.3584	0.0001	Exp. freq. in some cells < 5			
CS1 + All	12	Exp. freq. in some cells of rare categories < 5					
CS1 + >10	6	25.3494	0.0003	25.9120	0.0002	16.4075	0.0117

(CS: in which choice set; CS1: choice set 1, includes alternatives $H_{m\_}\,H_r|\,PD$, $H_{m\_}\,SP_r|PD$, and $ALT_{m\_}\,SP_r|PD$)