Task Complexity and Time Pressure: Impacts on Activity-Travel Choices

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To Chunyan

Preface

Every PhD candidate has his or her own story to tell about the exciting, inspiring, but sometimes difficult journey to reach the finishing end. Mine is no special one in general, but surely significant to my life in all senses.

I was about to find my career in business after finishing my Master study. Bert, my then Master thesis supervisor, intrigued me with the possibility of being a PhD candidate. The research topic was ‘Behavioural Aspects of Supernetwork’, which sounded interesting already. After an inspiring and smooth talk with Bert and Caspar, I was convinced that being a PhD candidate was surely challenging but rewarding at the same time, and that I should take this opportunity to further explore the academic world and further explore myself. The later interview with Eric in Eindhoven only strengthened that impression. Luckily, Bert, Caspar, and Eric also saw the potential in me, and then I became a PhD candidate.

These five years as a PhD candidate really opened my eyes, enhanced my knowledge, and shaped my view on this world. Being a PhD candidate was not just about exploring the academic knowledge to address my own research topic, but more importantly trained me to have a perspective on this world with a rigorous scientific attitude. Such a rewarding experience, as I fathom, would be unique to me at least for a very long time if not for a life time.

It wasn’t always a smooth journey, along which there were many ups-and-downs. However, I was fortunate enough to have Caspar, Bert and Eric by my side to guide me through. Caspar, your sharp and meticulous thinking, your tender and persuading approach, and your unreserved help and support was essential to me, for which I owe you endless gratitude. As a supervisor and a role model, for me, you are second to none! Bert, your gush of new ideas and helpful suggestions, your refreshing management style, your all-time positive attitudes, and your generosity and kindness, always inspired me, for which many thanks are far from enough. Your ‘half-funny’ jokes and ‘bullet-speed’ talk are always missed. Eric, your

extensive knowledge, your thorough reasoning, and your down-to-earth personality, consistently impressed and helped me, which I deeply appreciate. I really miss the chat in which everything and anything could be discussed with you.

The group in which I carried out the PhD research consists of a bunch of nice colleagues, to whom I would love to sincerely express my gratitude. Zack, my dear friend, roommate, and colleague, without you my life in the Netherlands would have been deducted of enjoyment. Maarten and Jan-Anne, your help on my research is much appreciated, but more importantly it's our many casual and funny conversations that helped me feel at home and I really enjoyed them. Niek, the execution of my simulator experiment would never have gone that smooth if you had not assisted me. My office roommates, Nilesh and Ozgul, our talks and discussions on a broader range of topics always delighted me. Finally, I am pleased to say that it was truly a privilege to work in the Transport and Logistics Group. All the colleagues have helped to create such a friendly, cosy, and supportive environment that it has become a struggle for me to find another one similar.

Living abroad for many years alone inevitably begged for my parents' understanding, unconditional support and encouragement, for which I can never repay. I am blessed to be your son. Chunyan, my dear, it must be tough for you to endure the time when we were separated by two continents, but we came through it together and were bounded even more tightly than before. Your continuous love and encouragement were always an important driving force to keep me forging ahead. Thank you with all my heart!

Last but not least, I want to acknowledge NWO for funding this research and its support in other various ways. I would also like to extend my gratitude to the Faculty of Technology, Policy and Management, Delft University of Technology for facilitating this research.

Chao Chen

Shanghai, September 2014

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1. Introduction

1.1 Background of the research

1.1.1 Increasing accessibility

One of the central aims of transport policy-makers (e.g. European Commission 2011; Department of Transport 2012) and many transportation researchers (e.g. Murray 2003; Geurs and van Wee 2004; Lacono et al. 2010) is to improve accessibility in transportation. It is generally acknowledged (e.g. European Commission 2004) that there are essentially two ways to achieve improvements in that respect: a first approach is to expand physical infrastructure capacity, and a second approach is to increase the efficient use of existing infrastructures and transportation services. In many societies, especially highly developed and urbanised ones, it is increasingly felt that the former of these two approaches (i.e., expanding physical infrastructure) comes with a number of critical disadvantages, such as need for high amounts of capital investments, large areas of land use, lengthy period of construction time, and relatively large impacts on environment (Banister and Berechman 2000; Flyvbjerg et al. 2003).

As many of these disadvantages are moderated if not absent in the second approach (i.e., better use of infrastructure and transportation services), the interest in this approach is growing among policy-makers (e.g., Department of Transport 2004; European Commission 2011; Ministry of Infrastructure and the Environment 2011) and researchers (e.g., Meyer 1999; Gärling and Schuitema 2007). One prominent example of such an approach is road pricing (Lewis 1993). Nevertheless, its application is rather limited, despite its huge potential repeatedly shown in the academic literature (e.g., Jones 1995; Yang and Huang 2005). One critical reason contributing to this limited implementation from a driver's perspective is "perceived infringement on freedom and unfairness" (Jakobsson et al. 2000), while political motives driven by these public opinions may also further halt the applications (Chorus et al. 2011).

However, there is an alternative direction of the latter approach that is less controversial, which recently in particular has been gaining interest among a small but growing number of researchers. It aims at improving accessibility by increasing the level of *network synchronisation* through strategies related to improving the interconnectivity of different transportation networks, such as bus, train and car networks. Examples are synchronising the time tables of different public transportation services or realizing Park and Ride facilities near railways stations. In addition, as people travel because they want to conduct an activity at another location, the geographical location of these activity locations may also be synchronised with transportation networks. Hence, those who advocate this approach believe that sustainable accessibility can be enhanced by improving synchronisation, while increasing physical infrastructures to only a limited extent (e.g., enhancing interconnectivity between different public transport (PT) modes (e.g. train and bus), establishing park and ride facilities near train station, and adding or relocating supermarkets or day-care centres with more flexible opening hours near train stations, etc.). In practice, noticeable efforts following this direction have already been taken. For example, in the Netherlands, Dutch Railways is developing their railway stations from just a node in the network where travellers can embark trains towards activity centres with offices, shops, meeting places, food stores and stalls, and leisure facilities. Similarly, large shopping centres have been realised at the central stations of Utrecht and Hamburg. Recent findings have shown that synchronisation of networks along the temporal and/or spatial dimensions as exemplified above holds potential of achieving significant gains in accessibility. Geurs et al. (2006) showed that by relocating commercial and non-commercial services to the surrounding areas of the future high-speed railway stations in Randstad[1] region may lead to an average accessibility gain of 5 % relative to a reference scenario.

1.1.2 Traveller behaviour

In principle many distinctive synchronisation strategies of various directions can be developed, however, it is not yet clear how effective each strategy is. As methods to ex-ante evaluate synchronisation strategies were largely missing, a multi-stage Supernetwork model was developed (Liao et al. 2010; Liao et al. 2011; Liao et al. 2013a; Liao et al. 2013b) as a first innovative step to understand the synchronisation strategies. Very briefly stated, this model is able to predict for any individual within a certain urban system given his or her daily activity program, how this program is implemented. More specifically, the model predicts when people are traveling, where they are traveling to, which mode they are using, via which route they travel, where they park their car or bike (if using a private mode), and at which PT stop they access, egress and transfer (if using a public transport mode). This model allows comparing the travel impacts of different synchronisation strategies.

An important part of this Supernetwork model is concerned with traveller behaviour. The underlying assumption of the Supernetwork model is that travellers would be able to choose their favourite daily activity-related travel alternatives from their choice sets independent of choice situations they are faced with. In another word, no matter how complex the choice situations would become (e.g. a much larger choice set), traveller are always capable of selecting their favourite alternatives. However, introducing network synchronisation strategies to the society would most probably make travellers' choice situations more complex. It may be doubted whether such an assumption can still hold in the context of choosing between

[1] Randstad is an urbanized region in the western part of the Netherlands. It consists of the four largest Dutch cities Amsterdam, Rotterdam, The Hague, Utrecht, and the surrounding areas, with a population around seven million.

different travel implementations of complete activity programs. More specifically, if synchronisation strategies are implemented many more options for activity program implementation[2] will become available, and consequently travellers' choice sets[3] may inevitably become larger. These options are called activity-travel choices in this research. Furthermore, as these options themselves may become very complex (which may consist of several travel trips[4] in one single option), it takes much effort and time from the travellers to evaluate each of them. This thus raises the additional question whether individuals are able and willing to do this, given the limited time many individuals in highly developed countries have available because of busy schedules. Therefore, because of this task complexity as induced by synchronisation strategies and time pressure (the two aspects that constitute the content of a choice situation in this research) travellers may not be able to choose the more effective ways to conduct their activity program offered by increased network synchronisation. Consequently, not every individual will benefit even if synchronisation would allow them to complete their activity program in a more effective way. This would mean that potential gains in sustainable accessibility of synchronisation strategies as predicted by the Supernetwork model may not be reached. Therefore, in the context of modelling choice in highly synchronised networks it is important to study the impacts of task complexity and time pressure and take these impacts into account while making predictions. In the following task complexity and time pressure are discussed in more detail.

Task complexity

A stark contrast between the existing, yet less synchronised networks and the highly synchronised ones lies in travellers' opportunities of easily chaining their activities with related travel on a daily basis. More specifically, the highly synchronised networks offer a much richer set of feasible activity-travel alternatives. For example, the construction of new P&R-facilities may increase the availability of multimodal alternatives, synchronised timetables may increase the availability of more public transit options, more activity locations (e.g., shops, supermarkets, and day-care centres, etc.) situated near the multimodal transit points may provide travellers with more attractive travel alternatives that can reduce their overall travel time for a whole day. Notwithstanding the potential benefits brought up by these enhanced opportunities, travellers may have increasing numbers of travel alternatives to choose from. These upgraded choices themselves also pose more challenges to the travellers, with respect to the growing complexity of choice tasks. For the purpose of conciseness and consistency in the thesis, the "task" in this research refers to the task to choose an implementation of a daily activity program, more specifically, the choice when and where to conduct the activities, and how to travel to those activities (e.g. mode and route choice). Consequently, complexity of the task of making a choice is simplified as the phrase of "task complexity" in this thesis.

As found in various literatures in and outside the transportation field, task complexity does have non-negligible impacts on choice. Swait and Adamowicz (2001) examined several types of choice, including choosing yogurt, canoeing site, work mode, courier, apartment rental and

[2] For a normal workday, a traveller would usually execute several activities, e.g., working, grocery shopping, escorting children to or from school, etc. These activities in a day together form a so-called activity program.

[3] A choice set is a set of choice options from which a traveller can choose.

[4] Since each activity in the simulator usually has its own distinctive geographic location, some activities (e.g. grocery shopping) may have multiple locations of its own. In order to execute them all in a day, people may have to travel between the respective locations. If we define traveling between two activity locations as one trip, conducting an activity program usually consists of several trips.

camping site, concluding that task complexity does affect inferences about choice model parameters and that context effects, such as complexity, have a clear impact on choice. Arentze et al. (2003), using single trip-based mode choice data, found that task complexity also has an impact on choice. However, the empirical data used in these studies either belong to the categories of either non-travel-related consumer products or single-trip based mode choice. Though they indicate the existence of the impacts of task complexity on choice, it is still unclear at the moment whether the results concerning these impacts can be readily applied to the context of choosing between different activity-travel choices, i.e., a choice task that is typically more complex.

Time pressure

Intuitively speaking, if there is a limit on how much time a traveller has to make a choice, it can induce certain pressure on the traveller. This particular type of pressure as caused by a limited time for making a choice is called time pressure. As discussed before, this may be caused by the complexity of the choice task in combination with generally limited available time of individuals caused by busy schedules and the need to arrive on time at their activity locations. Furthermore, travellers may also feel time pressure when they have to change their activity agenda during a day due to a cancelled appointment on a short notice, and they subsequently have to choose a new travel option in a short time. Another example is that the train a traveller has planned to take has been cancelled, forcing the traveller to find another travel option to continue his or her travel. From the perspective of opportunity cost (e.g., Payne et al. 1996; Rieskamp and Hoffrage 2008), if a traveller does not do so in a timely fashion, the consequence may well be that some existing favourable options become foregone with every moment delayed in decision-making.

The impacts of time pressure on decision-making have been frequently investigated in psychology. Edland and Svenson (1993) overviewed the research efforts of 30 years, highlighting the importance of including the impact of time pressure in high-level decision-making processes. Hahn et al. (1992) reported that the decision quality is much influenced – with a possibility of inverse-U shape with information load – by the presence of time pressure. Similarly, Maule and Edland (1997) and Ahituv et al. (1998) suggested that time pressure usually impairs the performance of decision-making. There are also ample evidences in marketing literature. Nowlis (1995) found that consumers when choosing brands would be influenced by time pressure, though this may not necessarily lead to a switch of decision strategies. Suri and Monroe (2003) suggested that an increase in time pressure from low level to high level will be likely to result in a reduction in the extent of systematic information processing. Haynes (2009) also reported that with high time pressure and more choice alternatives, decision-makers are usually dissatisfied with their decisions and often feel frustrated.

However, in traveller behaviour research, the impact of time pressure on choice has not received much attention. The majority of the efforts that deal with “time” in transportation are actually focusing on time as something related to travel time itself, hence as one of the most important attributes of the travel alternatives. Time pressure of making a choice, which concerns with the time of decision-making process, is hardly touched upon in traveller behaviour research. Thus, there is a lack of understanding of the impacts of time pressure on choice in traveller behaviour research, particularly in the context of daily activity choice and related travel. Consequently, there is also a lack of understanding of possible interactions between choice task complexity and time pressure on choice in the same context.

Discrete choice theory

These daily activity-related travel choices are usually discrete in nature: destination, travel mode, and route choices all can be understood as being made from a finite set of mutually exclusive and discrete alternatives. Ever since the 1970s, Discrete Choice Theory (DCT) (McFadden 1973) has become the dominant theory to model discrete choice behaviour. Therefore, the efforts of understanding the impacts of task complexity and time pressure on activity-travel choices, which are so far incomplete in literature, can be made in the framework of discrete choice modelling. In another word, the discrete choice models that help understand the impacts of task complexity and time pressure should be further developed.

1.2 Research goals

Given the potential importance of task complexity and time pressure for the prediction of travellers' choices in the context of highly synchronised networks, it is important to study the impacts of these two aspects on travellers' choices in order to improve the evaluations of the synchronisation policies in terms of traveller behaviour. However, it is unclear at the moment how these two aspects together should be properly modelled and what the impacts of these two aspects are on travellers' choices. In light of these, the following research goals of this thesis are formulated. This research primarily aims:

Goal 1

To develop coherent discrete choice models that can accommodate the impacts of both task complexity and time pressure on travellers' choices simultaneously

This goal is essentially to further develop discrete choice models that can help understand the impacts of task complexity and time pressure on travellers' choices. Therefore, in these new models, task complexity and time pressure should be properly modelled so that their impacts on the choices can be investigated.

Goal 2

To collect relevant data concerning the impacts of task complexity and time pressure on travellers' daily activity-travel choices in the context of highly synchronised networks

Reaching this goal is an intermediate step to achieve the understanding of the impacts of task complexity and time pressure on travellers' daily activity-travel choices. Should the theoretical discrete choice models be developed by reaching the first goal, without the support of the data, the understanding can only remain at an early stage and no concrete findings can be made or confirmed. However, as the concepts of task complexity and time pressure are short of straightforwardness as compared with those of travel time and travel cost, the collection of these relevant data may require more innovative ways to achieve. Besides, the emphasis on travellers' daily activity-travel choices in the context of highly synchronised networks is particularly important to the research as the impacts of task complexity and time pressure may be arguably more relevant in this condition.

Goal 3

To gain insight in traveller behaviour in the context of highly synchronised networks, with an emphasis on capturing the possible impacts of task complexity and time pressure

By reaching Goal 1 and Goal 2, the research would have the necessary ingredients to capture the possible impacts of task complexity and time pressure on travellers' choices, which is the third goal of this research.

This research also aims: (the secondary goal)

To utilize the gained insights to provide the relevant societal implications, in particular with respect to policies involving highly synchronised networks

This goal is to derive more relevant societal insights based on yet not confined to the insights attained from the reach of the previous three goals. By doing this, the potential benefits of the research towards the society can be clearly demonstrated. However, compared with the other three goals, this goal stays in a less prominent position and only serves as a secondary research goal.

1.3 Methodology and the scope of the research

To reach the research goals of this thesis, several methods will be adopted, including literature review, model construction, Stated Preference data collection by using a travel simulator, estimating econometric models, and societal implication-related analyses.

1.3.1 Literature review

Each of the next three chapters starts with a respective literature review aimed at reviewing the relevant state-of-the-art knowledge including substantive findings as well as theoretical and methodological contributions to the particular topics, upon which further contributions will be made.

1.3.2 Construction of choice models

The first research goal of this thesis involves developing choice models that can accommodate the impacts of task complexity and time pressure. As the objective is to improve the models that predict the travel changes due to synchronisation policy strategies, hence the Supernetwork model, the same framework on which this model is based is adopted, that is the DCT framework. This framework has been developed and applied extensively and comprehensively in the last fifty years and has become the dominant method in the research of traveller behaviour (McFadden 1974; Ben-Akiva and Lerman 1985; Train 2003).

However, under the umbrella of DCT, not all modelling attempts in the existing literature share the same perspective on people's decision-making mechanism. The paradigm of random utility maximization (RUM) is the most widely applied one. Briefly stated the RUM assumes that decision-makers evaluate and compare all possible alternatives known to them and eventually choose the alternative that maximises their utility. RUM is widely adopted as it proves to be very proper and elegant for the quantitative analysis of traveller behaviour (McFadden 2001). Although the efforts of exploring and developing paradigms other than RUM are indeed worthwhile and deserve credits and attentions, there is no strong evidence yet in pragmatic applications to demonstrate that RUM has been systematically out-performed by others. Various and continuous efforts into extending RUM paradigm have further facilitated the use of RUM paradigm in traveller behavioural research. A branch of these efforts has been devoted to the so-called Heteroscedastic models (e.g., Bhat 1995; Hensher et al. 1998; Louviere et al. 2008), which allow more flexible error structures in the utility function. As will be argued in the next chapter, Heteroscedastic models are especially convenient to model the impacts of task complexity and time pressure on travellers' choices.

1.3.3 Stated preference data collection by using travel simulator

In order to estimate the developed travel behaviour models, choices travellers make among alternatives need to be observed. In travel behaviour research, typically two types of data are distinguished, namely Revealed Preference (RP) data and Stated Preference (SP) data. In RP data collections, data are gathered about real world alternatives including the alternative(s) the respondent actually has chosen. In SP data collections, hypothetical alternatives are presented to participants, of which they select the alternative that they would choose in real life situations.

The big advantage of RP data is that they actually represent choices people have made in real life (Samuelson 1948; Houthakker 1950). Hence, the external validity of the models estimated from these data is potentially high. On the other hand, RP data have a series of disadvantages of which those most relevant for this study will be briefly discussed now. A first disadvantage of RP data is that high correlations among explanatory variables are often spotted, for example, travel time and travel costs are often highly correlated (Wardman 1988). This severely decreases the efficiency of the data with the result that the coefficients of some explanatory variables only become statistically significant if substantial amounts of data are gathered and thus typically very large numbers of respondents are needed. Another disadvantage is that by its nature RP methods do not allow observing choices of alternatives that do not exist in real life. As discussed before, synchronisation policy strategies may introduce new alternatives for implementing activity programs. Although some elements of those alternatives may already exist in the real world, those alternatives for implementing activity programs cannot yet be observed in real life (Adamowicz et al. 1994). A final disadvantage of RP methods is that it is difficult if not impossible to systematically, reliably and accurately observe information about the decision-making process.(Hensher 1994). This is especially a disadvantage in this research, as information on the complexity of tasks and the amount of time pressures need to be observed, which is virtually impossible with RP approaches.

SP data collection methods provide solutions for these disadvantages of RP methods. First, SP methods allow researchers to efficiently and intricately control experimental conditions to such a level that choice outcomes can be traced back to each of the explanatory variables under investigation with a relatively small number of respondents and therefore relatively low costs. Next, as the choice alternatives are constructed and controlled by the researchers, SP methods allow observing choices for alternatives that do not yet exist. Finally, SP methods make it possible to create sufficient variations in choice task complexity and time pressure levels required to estimate the developed econometrics models. Given these advantages of SP over RP methods, SP methods are the proper choice for collecting the data in this research.

The use of SP data has been a major advance in traveller choice modelling. With the continuous development (e.g. Louviere and Hensher 1982; Hensher 1994; Louviere et al. 2000), SP methods have gained much attention in transportation. However, SP methods face the issue of external validity, which reflects to what extent the respondents participating in SP experiments would behave the same way in real life as they do in the experiment. It is often argued against SP methods that a respondent does not feel the consequences of his or her choices in a SP experiment, and that he or she probably to a much lesser extent takes into consideration the efforts of changing his or her choices during the process while they would do so in real life. Even though it is virtually impossible to assure that people would behave in SP experiments the same way as they do in in real life, it is widely acknowledged that external validity can be increased by constructing choice situations in such a way that they as much as possible realistically mirror real-life travel environments. Travel simulators (e.g., Chen and Mahmassani 1993; Mahmassani and Jou 2000; Bonsall and Palmer 2004; Chorus et al. 2007; Prendinger et al. 2011), a special type of SP methods, are probably best suited to increase the realism of the choice tasks and in addition allow observing information about the choice process or allow manipulating different choice contexts. Compared with the conventional SP methods (e.g., paper-pencil survey, web-based survey, etc.), travel simulators usually provide illustrative and interactive user interfaces, stimulating respondents to more actively involve themselves in the experiment and allowing for easy interactions between respondents and experimental conditions. Therefore, in this research a fairly sophisticated activity-travel simulator (ATS) concerning travellers' daily travel choices will be developed to collect the data.

1.3.4 Model estimation

As soon as the mathematical models and the required data are ready, the model is estimated from the data collected by the activity-travel simulator. Most of estimation procedures involve maximization of some function, such as the likelihood function, the simulated likelihood function, or squared moment conditions (Train 2003). Some existing and free estimation packages may help estimate those models with convenience and efficiency. The software applied in this research is Biogeme, developed by the group in EPFL led by Prof. Michel Bierlaire. It is an open source freeware designed for the estimation of discrete choice models. Among other models, it allows the estimation of Heteroscedastic models (Bierlaire 2008).

1.3.5 Societal implication-related analyses

In order to reach the third research goal, a series of societal implication-related analyses are implemented. First, the implications derived from this research concerning transport policies are analytically explained. Transport policies are herein narrowly defined as the public policies that can be implemented by governments, with the primary aim to improve productivity and quality in the transport sector. In particular, the important and yet relevant policy implications are identified. The implications for travel information service providers are next explicated. In particular, the focus rests on the implications for travel information content, travel information format, and travel information load.

1.4 Structure of the dissertation

In this section, it is described how this PhD thesis is structured and how the chapters relate to the research goals.

Chapter 2 first provides a literature review of the existing modelling efforts into the impacts of task complexity and time pressure on traveller's decision-making. It helps identify what sorts of impacts these two aspects exert and what modelling approaches may be most appropriate to incorporate them. Then a Heteroscedastic model is formulated, embedding the impacts of choice task complexity and time pressure on traveller's choices. This chapter is intended for reaching the first research goal.

Chapter 3 is devoted to developing the activity-travel simulator. First, an introduction to the design of the simulator is presented. This is followed by a description of the simulator in more detail. Next, the data collection procedure is described including the recruitment of the respondents and the actual application of the travel simulator. Finally, the respondent feedbacks concerning their experience of using the simulator are reported. It is oriented to the reach of the second research goal.

Chapter 4 first specifies the respective operational Heteroscedastic models proposed in Chapter 2. Then the specified models are estimated by using Biogeme based on the data collected in chapter 3. The results are subsequently analysed and discussed. It aims at reaching the third research goal.

Chapter 5 first presents the main conclusions from the previous three chapters. By combining relevant state-of-the-art knowledge and state-of-the-practice transportation policies with the knowledge attained from these chapters, this last chapter also draws the implications for policy and research . It intends to reach the secondary research goal.

2. Modelling the impacts of task complexity and time pressure on travellers' choices

2.1 Introduction

Both task complexity and time pressure, as argued in Chapter 1, may have impacts on travellers' choices, especially in highly synchronized mobility networks. In order to understand these impacts, a crucial step is to model these impacts in a rigorous manner. This chapter presents discrete choice models that are capable of simultaneously incorporating the impacts of task complexity and time pressure on travellers' choices.

The chapter is organized as follows: Section 2.2 introduces the discrete choice framework and the adopted Random Utility Maximization (RUM) paradigm. Section 2.3 presents a RUM-based Heteroscedastic model that can incorporate the impacts of task complexity and time pressure. It then discusses how task complexity and time pressure can be formulated in the proposed Heteroscedastic model. Section 2.4 finally concludes the chapter.

2.2 Discrete Choice Theory, the Random Utility Maximisation paradigm, and the (Mixed) Multinomial Logit model

Given that excellent textbooks are available on the topics mentioned in the title of this subsection (e.g., Ben-Akiva & Lerman, 1985; Train, 2009), only a brief and generic overview of relevant notions and concepts will be presented here.

Travellers' choices are usually discrete in nature: destination, travel mode, and route choices all can be understood as being made from a finite set of mutually exclusive and discrete alternatives. Ever since the 1970s, Discrete Choice Theory (DCT) (McFadden 1973) has become the dominant theory to model discrete choice behaviour. DCT postulates that, from the analyst's perspective, the probability that the decision-maker would choose an alternative from a given and finite choice set is conditional upon the decision-makers' tastes, attributes (features of the alternatives and/or the decision-maker) and the decision rule adopted.

The dominant operational paradigm within DCT is that of Random Utility Maximization or RUM (McFadden 1973). In RUM, each choice alternative in the given and definitive choice set is assumed to be associated with a corresponding utility perceived by the decision-maker; he or she is further assumed to choose the alternative that yields his or her maximum utility. The utility consists of a systematic or observed portion, and a random or unobserved error component:

$$U_i = V_i + \varepsilon_i \tag{2.1}$$

where
U_i, is the utility of alternative *i;*

ε_i, is the stochastic (random) component of the utility, reflecting the idiosyncrasies of the choice process and possibly unobserved attributes, and more generally the notion that the analyst cannot 'look in the head of the decision-maker'.

Louviere et al. (2002) investigated in detail the composition of the random component, which is defined as "unobservable (unexplainable) component of utility that represents researchers' inability to ever fully observe or understand all facets of behaviour germane to particular behavioural outcomes of interest". Note that this paper also argues that conditions, contexts, circumstances or situations that are relevant during the choice process may influence the variance of the random component.

V_i, is the systematic component of the utility, i.e. that part of the utility which can be linked to attributes and estimable tastes. Although there are various ways to specify this utility component, the dominant approach adopted by researchers and practitioners alike is the linear additive approach. Its popularity is primarily due to its intuitive and simplistic nature (e.g. Lancaster 1966). According to this approach, if there are *K* distinctive attributes, V_i has the following expression:

$$V_i = \sum_{k=1}^{K} \beta_k \cdot x_{ik} \tag{2.2}$$

where
β_k, is the taste regarding attribute *k*;
x_{ik}, is the value of attribute *k* of alternative *i.*

Given a decision-maker has a feasible and finite choice set C, the probability of choosing alternative *i* has the following expression:

$$P(i) = \Pr(U_i \geq U_j, \forall j \in C, j \neq i) \tag{2.3}$$

$$P(i) = \Pr(V_i + \varepsilon_i \geq \max(V_j + \varepsilon_j), j \in C \ , j \neq i) \tag{2.4}$$

where
$P(i)$ is the probability of choosing alternative *i;*
C is the choice set in consideration.

Depending on the assumptions regarding the distribution of the random component of the utility, different choice probability formulations arise. If it is assumed that the random component ε_i is independently and identically distributed (IID) Extreme Value type I with a normalized variance σ^2 equal to $\pi^2/6$ (this normalization is needed for identification purposes) equation (2.4) translates into (McFadden, 1973):

$$P(i) = \frac{e^{V_i}}{\sum_{j \in C} e^{V_j}} \tag{2.5}$$

This yields the so-called Multi-Nomial Logit Model (MNL), which is arguably the simplest, most elegant and most popular RUM model. The IID assumption implies that the random error for alternative j is independent from that of alternative i, and that the errors of all alternatives have the same variance. This latter assumption is called homoscedasticity, and will be relaxed in the next subsection.

Without the normalization of the variance of the error component (which is inversely related to the scale of the utility (μ) in the sense that $\mu = \frac{\pi}{\sqrt{6} \cdot \sigma}$), a more general form of MNL model can be obtained:

$$P(i) = \frac{e^{\mu \cdot V_i}}{\sum_{j \in C} e^{\mu \cdot V_j}} \tag{2.6}$$

Note that this non-normalized model is not identifiable and hence cannot be estimated, due to the confounding of scale and error term variance. However, in the next section it shows how the scale can be parameterized as a function of time pressure and task complexity, leading to an identifiable and estimable model formulation. If equation (2.2) is substituted into equation (2.6), this becomes:

$$P(i) = \frac{e^{\mu \cdot \sum_{k=1}^{K} \beta_k \cdot x_{ik}}}{\sum_{j \in C} e^{\mu \cdot \sum_{k=1}^{K} \beta_k \cdot x_{jk}}} \tag{2.7}$$

For the sake of elegance, it is assumed that β is a transposed vector of K attribute tastes and x_i is a vector of *K* attribute values of alternative *i,* then equation (7) can rewritten as:

$$P(i) = \frac{e^{\mu \cdot \beta \cdot x_i}}{\sum_{j \in C} e^{\mu \cdot \beta \cdot x_j}} \tag{2.8}$$

If it is assumed that tastes β are random across the sample population, then the Mixed Multi-Nomial Logit (ML) model (in its random parameter form) arises (e.g. McFadden and Train 2000; Train 2003).

$$P(i) = \int \frac{e^{\beta \cdot x_i}}{\sum_{j \in C} e^{\beta \cdot x_j}} \cdot f(\beta) \cdot d\beta \tag{2.9}$$

where $f(\beta)$ is the probability density function for β.

2.3 Modelling the impacts of task complexity and time pressure: the Heteroscedastic Logit model

It has been acknowledged by many researchers that the assumed underlying decision-making process of multi-attribute Utility Maximization requires intensive efforts from a decision-maker. When a choice task assigned to the decision-maker is quite complex (e.g., it contains a large choice set with many attributes per alternative) and when such a task has to be finished under time pressure, it is less likely that the decision-maker is always able to select the alternative of the highest utility from the set. In other words, it is likely that the amount of noise or random error associated with the decision increases.

One approach[5] to handle the impacts of task complexity on choice behaviour is to allow for the variance of the random component in the utility function to be a function of task complexity. Since the variance of the random component is confounded with the scale of the utility, this is equivalent to the notion that the scale of the utility is a function of task complexity. As each choice task may be associated with a different level of task complexity, the scale is no longer identical for all the choice tasks. This gives rise to a more flexible RUM-based model, called Heteroscedastic Logit.

The core feature of Heteroscedastic models is that the random component is no longer identically distributed across alternatives. Daganzo (1979) first developed a close-formed discrete choice model that has this feature, allowing for different variances for the random components with an independent negative exponential distribution. Bhat (1995) proposed a Heteroscedastic Logit (HL) model. Its successful construction and estimation has paved way for the further development of Heteroscedastic models. DeShazo and Fermo (2002) utilized a HL model to evaluate the impacts of the complexity of choice sets on choice consistency. Arentze et al. (2003) took a similar approach to demonstrate that the variance of the random component rises with the increase of task complexity. Caussade et al. (2005) further applied the HL model with the scale parameter specified as a function of task complexity. Finally, Scarpa et al. (2010) used the HL model to investigate variation in the scale parameter induced by both differences in types of decision-makers and in types of experimental design. Fiebig et al. (2010) developed a so-called generalized MNL model, not only accounting for (random) scale heterogeneity but (random) coefficient heterogeneity as well, i.e., a model that combines the Mixed Logit and HL models.

To my knowledge, there are no DCT-based modelling attempts to embed the impacts of time pressure on choice making, which is in stark contrast to the amount of efforts devoted to modelling the impacts of task complexity on choices. The majority of the research that is concerned with time pressure impacts on choices focuses on the impacts on choice processes

[5] Other approaches have also been adopted to tackle the impacts of task complexity in DCT. For example, one assumes that if choice task becomes more complex, decision-makers would ignore certain attributes (e.g., Swait and Adamowicz, 2001; Hensher et al., 2005). In essence, these approaches assume that if choice task becomes more complex, decision-makers would switch to decision rules other than Utility Maximization.

or/and judgments, and is qualitative in nature (e.g. Edland and Svenson 1993; Diederich 1997).

Time pressure can be properly considered as a constraint on the 'supply side' of cognitive computation capacity, and therefore the notion of time constraint is often used in this context as well (e.g. Suri and Monroe 2003). Nowlis (1995) postulated, drawing on empirical evidence, that consumers faced with time pressure may accelerate their choice process while still using the same decision rule. Intuitively speaking, given the same choice task and the same decision rule adopted, compared with a decision made under no time pressure, the decision-making process under time pressure would probably induce more mistakes/inconsistencies when evaluating choice alternatives and maximizing utility. The approach used in this thesis for modelling the impacts of time pressure on choices is based on this assumption. Similar to the approach of modelling the impacts of task complexity, the impacts of time pressure on a traveller's choice is incorporated in Heteroscedastic models[6] by assuming that the variance of the random component of the utility is a function of time pressure.

In equation (2.6), the scale μ is constant across choice sets (in other words, the model is homoscedastic, as contrary to heteroscedastic). However, in the HL model the scale is no longer constant but it is parameterized as a function of task complexity and time pressure. This function takes the following form to ensure non-negativity (see (e.g. DeShazo and Fermo 2002) for an early application of the exponential function in this context):

$$\mu_s = \exp(a(D_s, T_s, Int(D_s, T_s))) \tag{2.10}$$

where

$a(\,)$ is a linear function of its arguments and associated parameters;

D_s is the measurement of task complexity in choice situation *s;*

T_s is the measurement of time pressure in choice situation *s*;

$Int(D_s, T_s)$ is the measurement of the interactive effect of task complexity and time pressure. That is, apart from the separate impacts of task complexity and time pressure on choice, it is hypothesized that the impact of any of these two factors may be dependent on the level of the other factor.

Incorporating the parameterization of the scale factor in equation (2.6) leads to the following HL expression for the choice probability:

$$P_s(i) = \frac{e^{\mu_s \cdot V_i}}{\sum_{j \in C} e^{\mu_s \cdot V_j}} \tag{2.11}$$

6 Similar to that of choice task complexity, some literature also implies other DCT-based modelling approaches. Dhar and Nowlis (1999) found that under time pressure, consumers are more likely to consider unique attributes among alternatives and less likely to consider common attributes. In addition, their experiment participants recalled more attributes (unique and common) with no time limit than under time pressure. Kaplan et al. (1993) suggested that under time pressure people may use alternative decision rules to simplify the cognitive task.

Although the general form of the HL model is constructed in equation (2.11), the concrete measurements of task complexity, time pressure and the interactive effect of the two have not been specified yet. To enable this, a review of the relevant literature is presented below.

2.3.1 Measuring task complexity

Intuitively, a definition of task complexity could be quite straightforward in terms of the difficulty to evaluate and choose one's favourite alternative from a given choice set. However, to quantify this theoretical concept, a variety of approaches can be adopted. Of these approaches to measure task complexity in the literature, two have gained particularly high levels of popularity. The first one relies on 'dissecting' the components of a choice task, in the sense of counting the number of normatively required acts (e.g. evaluating the value of one attribute of one alternative means one act.) to finish the task (Wood 1986). The second approach is essentially to introduce a proxy indicator that reflects task complexity. For example, Diederich (2003) used decision time as a measure of conflict strength in decision-making. Conflict here relates to choice in that a conflict can be resolved by making a choice. Therefore, the stronger a conflict becomes, the more difficult to make a choice.

The first approach: dissecting the choice task

Within the fields of psychology, economics, consumer research and transportation, the overwhelming majority of the literature concerning task complexity has taken this approach.

Payne (1976) and subsequent work (e.g., Lussier and Olshavsky 1979; Timmermans 1993; Arentze et al. 2003) identified and used two important dimensions to describe the complexity level of a choice task: the number of alternatives and the numbers of attributes per alternative. The task complexity is assumed to increase as the number of alternatives increases, and as well as the number of attributes per alternative increases. Therefore, if it is assumed that task complexity is the product of the number of alternatives and the number of attributes, the task complexity of Task One and that of Task Two in Table 2.1 are equal, while that of Task Four is the highest among the four tasks. The rank of the task complexity levels between the first two tasks and Task Three cannot be determined, as none is dominant in both of the two dimensions of the task complexity. However, in the context of this research, it is plausible to assume that the number of attributes is unlikely to vary. Thus, it is reasonable to assume that only the number of alternatives is relevant in this context.

Payne (1982) later identified another important source of task complexity, i.e., similarities between alternatives. For example, a decision-maker is presented with the first two choice tasks in Table 2.1. In terms of the number of alternatives and the number of attributes, these two choice tasks are identical in task complexity. The only difference is that the alternatives in the second task are comparatively distinctive in terms of values of the attributes, while this is not the case in the first task. As such, the decision-maker would probably struggle to make a choice in the first task as it is more difficult to distinguish between the alternatives, compared with the second task.

Table 2.1: Four sample tasks

Attribute	Attr. A	Attr. B	Attr. C
Taste	0.2	0.1	0.1
Task One			
Alt. 1	5	10	15
Alt. 2	6	11	14
Task Two			
Alt. 1	5	10	15
Alt. 2	6	11	10
Task Three			
Alt. 1	5	20	n/a
Alt. 2	6	18	n/a
Alt. 3	4	22	n/a
Task Four			
Alt. 1	5	16	4
Alt. 2	6	12	6
Alt. 3	4	17	5

Swait and Adamowicz (2001) have innovatively translated the notion of entropy (Shannon 2001) to describe overall complexity of choice task. Its advantages lie in the fact that only one single aggregate indicator (the entropy) is used to express task complexity, which makes it quite simple and elegant, and that attributes are coupled with a priori attribute taste, which addresses similarities between alternatives in a more meaningful manner. The indicator is specified as follows:

$$H(\pi_x) = -\sum_{j=1}^{J} \pi(x_j) \log \pi(x_j) \geq 0$$

where $\pi(x_j)$ is an a priori probability of choosing alternative j from the given choice set.

The more complex a choice task is, the higher this indicator value becomes. If there is a dominant alternative that has a choice probability of one while those of the remaining alternatives equal zero, then this indicator has a minimum value of zero. If all the alternatives have the same a priori probability, ceteris paribus, then the indicator has a maximum value. However, this measure is quite different from the others. Firstly, the formulation of the entropy requires knowledge about the a priori probabilities of the alternatives, which is usually unknown and often one of the desired outcome of choice models. Therefore, the usual practice is to calculate it with a priori attribute taste by the means of estimating MNL models. Secondly, the role of the number of attributes as part of choice task complexity is diminished entirely in the formulation. Instead, the focus of entropy is primarily on behavioural complexity, based on preference similarity. For example Table 2.1, both the entropy indicators of Task Three and Task Four are equal to 1.098, assuming the tastes equal to 0.2, 0.1, and 0.1 respectively for the three attributes, thus accordingly suggesting equal choice task complexity for the two tasks. However, Task Four appears to be more complex than Task Three, since an additional attribute needs to be considered in Task Four.

The second approach: search for direct indicator

This approach essentially means searching an indicator that directly measures (perceived) task complexity. By searching the relevant literature only one such indicator can be found: the decision time a person has spent on a choice task when there is no time pressure. This is a quite intuitive operationalization of task complexity.

Its validity originates from the assumption that decision time highly correlates with the amount of cognitive efforts devoted to choice making, which as such reflects task complexity: i.e., the more decision time is consumed, the more cognitive efforts are made, and the more complex a given choice task is, given that the same decision rule is used (as is assumed in this thesis). Later work appears to suggest that decision time (under no time pressure) may indeed be considered as a useful indicator for task complexity (Diederich 2003).

Compared with the indirect measures as explained beforehand, this direct measure of task complexity is highly personalized. This is because even for a same choice task two distinctive decision-makers may assess its complexity differently, probably resulting in a difference in decision time. It may imply that this direct measure is more personal and hence induces more variation in the sample – so it is easier to do statistical analysis. Given this advantage of personalization, when possible, this direct measure of task complexity by using decision time should be preferred.

The relationship between μ_s and the task complexity measures

There are two hypotheses concerning the relationship between μ_s and the task complexity measures: 1) with the increase of task complexity measure, μ_s is expected to become smaller, suggesting a diminishing ability of the decision-maker to correctly compute the observed utilities of all the alternatives in the choice set, inducing more "randomness" in choice outcome; 2) rather than a monotonic relationship, with the increase of task complexity measure, μ_s may first become larger and then smaller, resulting in an inverted-U shape relationship between μ_s and the task complexity measures. Figure 2.1 graphically shows these two hypotheses, with the dotted line for the first and the solid line for the second hypothesis. Which hypothesis is the more reasonable one will be empirically answered in Chapter 4.

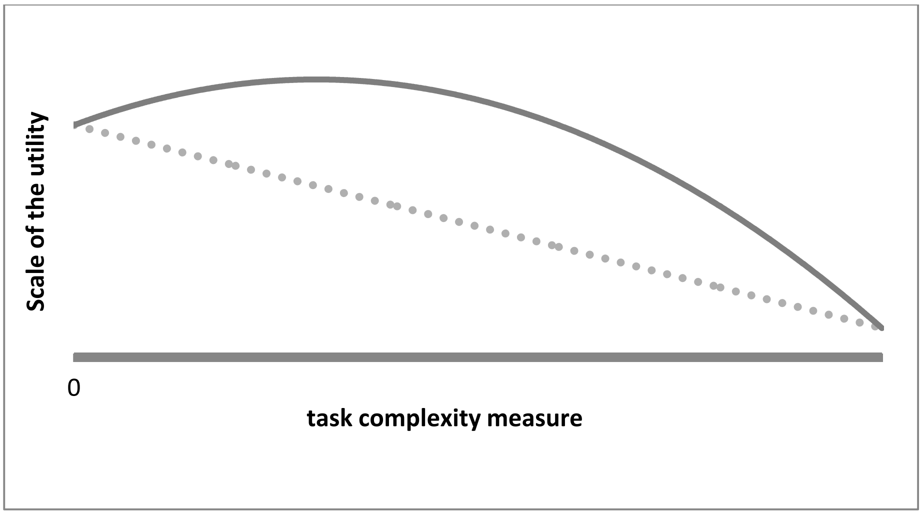


Figure 2.1: Visualization of the proposed relationship between the scale of the systematic part of the utility function μ_s and the value of the task complexity measure

Note: This figure is only for the purpose of demonstrating the shape of the qualitative relationship between the two variables.

2.3.2 Measuring time pressure

The approach that most of the relevant research has adopted to measure the time pressure level is based on how much time a decision-maker is allowed to make his decision (i.e., decision time budget). This time budget is a priori constrained and usually set-up by researchers (e.g. Nowlis 1995; Ordóñez and Benson Iii 1997; Dhar and Nowlis 1999). For a simple example, given a same task, many decision-makers are asked to make their choices within 10 seconds, 30 seconds, and 60 seconds respectively. By this approach, the time pressure induced by 10 seconds of decision time limit is assumed to be higher than that induced by 30 seconds, while 30 seconds is assumed to induce a higher level of time pressure than 60 seconds. That is: it is assumed that the less decision time budget a decision-maker has, the more time pressure he experiences, *ceteris paribus*. However, based on this method one of course cannot know with certainty to what extent a given budget would actually translate into time pressure, nor can it be inferred whether a decision time budget that "pressures" one decision-maker has a similar effect on another decision-maker. For the same example above, one decision-maker may use 30 seconds to make his or her decision given a budget of 60 seconds, while another decision-maker may use 59 seconds out of 60 seconds to complete the same task. Using the time-budget measure, the time pressure levels that both decision-makers have experienced would be measured as being the same. However, it is much more reasonable to postulate that the latter decision-maker has experienced a higher time pressure level than the first decision-maker, as the latter has almost used up all his or her decision time budget.

In light of these disadvantages, this research intends to construct another measure of time pressure, which combines the decision time budget and the actual decision time under pressure. It is formulated as follows:

$$DS_s = DT_s / DTB_s$$

, where
DS_s is the time pressure measure for choice situation s;

DT_s is the actual decision time for choice situation *s*;

DTB_s is the decision time budget for choice situation *s*.

For the same example above, the value of this new measure DS_s equals to 0.50 for the first decision-maker and 0.98 for the second decision-maker. Intuitively speaking, this difference of the DS_s values reflects the notion that the second decision-maker has experienced a higher time pressure level than the first decision-maker. Should DS_s approach 0, this implies the presence of an extremely large decision time budget or equivalently the absence of time pressure. Should DS_s approximate 1, it suggests a choice is made at a moment when almost no time is left for additional thinking, implying a high time pressure level.

Since an increase of time pressure is assumed to be associated with an increase in the randomness of choice, one may at first sight be compelled to expect that the scale of the systematic part of the utility function of choice alternatives would become smaller as DS_s increases. Therefore, it may be hypothesized that the scale of the systematic part of the utility function monotonically decreases as a function of DS_s. This hypothesis is roughly depicted as the dotted linear line in Figure 2.2.

However, this hypothesis may not necessarily reflect the true nature of this measure. If the value of DS_s is close to 1 (e.g. 0.98 in the example above), it is reasonable to think that it reflects a high time pressure level, leading to a smaller scale of the utility. If the value of DS_s is more remote from 1 but still not close to 0 (e.g. 0.50 in the example above), this can safely be interpreted as implying less time-pressure, causing an expected increase in the scale of the utility. However, when the value of DS_s is close to 0, a more subtle picture appears: obviously, the time pressure in this situation is less than it was when DS_s was either 0.5 or close to 1, but the relation with the scale of the utility is not straightforward: the fact that the individual only used a very small fraction of the available time budget may well signal absence of engagement with the choice task. In other words, the low value of DS_s may well be interpreted as a signal that the decision-maker spent only a very limited amount of time because he or she did not care about choosing the best alternative. This, of course, would suggest that values of DS_s close to 0 are expected to lead to relatively small scales of the utilities of alternatives. In combination, one may expect an inverted U-shape, rather than a monotonic relation, between DS_s and the scale of the utility. This hypothesis is roughly depicted as the solid curving line in Figure 2.2. Moreover, given the reasoning underlying the second hypothesis, it may be considered more suitable to term this DS_s as engagement/time pressure index rather than time pressure index alone.

Whether or not the scale for DS_s = 0, or for DS_s= 1, is higher, and where exactly is the location of the maximum scale, is of course an empirical question. More generally, it is unclear at the moment which of the two hypotheses can be supported empirically. Given the data collected in Chapter 3, Chapter 4 will give an empirical answer to this.

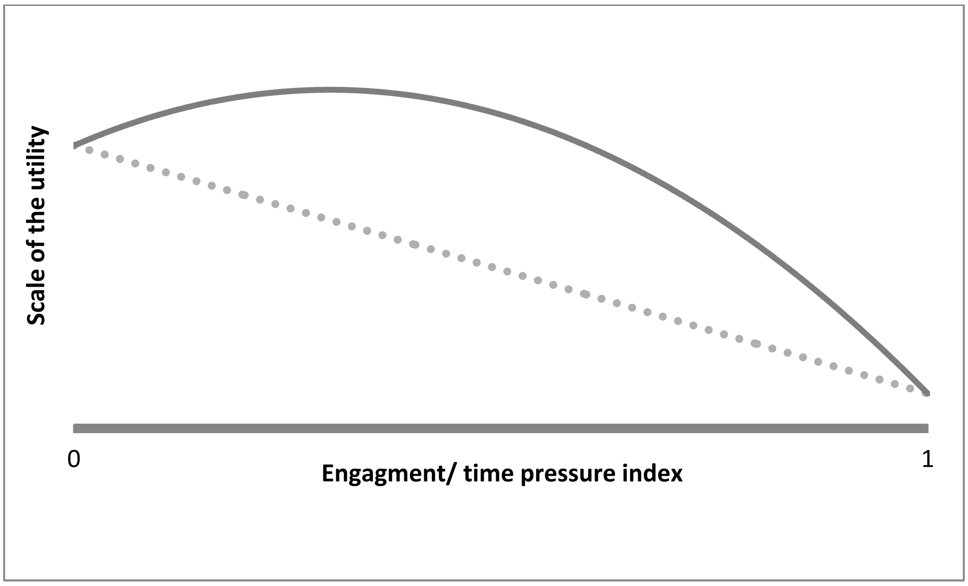


Figure 2.2: Visualization of the proposed relationship between the scale of the systematic part of the utility function and the value of engagement/ time pressure index

Note: This figure is only for the purpose of demonstrating the shape of the qualitative relationship between the two variables.

2.4 Conclusions

In RUM (Random Utility Maximisation), each choice alternative in the given and definitive choice set is assumed to be associated with a corresponding utility perceived by the decision-maker, and he or she would choose the alternative that yields the maximum utility. The utility consists of a systematic or observed portion, and a random or unobserved error component. The latter component reflects the idiosyncrasies of the choice process and possibly unobserved attributes, and more generally the notion that the analyst cannot 'look into the head of the decision-maker'. Conditions, contexts, circumstances or situations (e.g., task complexity and time pressure in this research) that are relevant during the choice process may influence the variance of the random component.

The approach taken in this research to model the impacts of task complexity and time pressure on choice is to allow for the variance of the random component in the utility function to be a function of task complexity and time pressure. Since the variance of the random component is confounded with the scale of the utility, this is equivalent to the notion that the scale of the utility is a function of task complexity and time pressure. As each choice task may be associated with a different level of task complexity and time pressure, the scale is no longer identical for all the choice tasks, which gives rise to a more flexible RUM-based model, called Heteroscedastic Logit Model.

Though various indirect measures of task complexity were introduced in literature (e.g. number of alternatives, entropy, etc.), decision time, which a person has spent on a choice task when there is no time pressure, is preferred as a suitable indicator that directly measures (perceived) task complexity. This is a quite intuitive operationalization of task complexity. Its validity originates from the assumption that decision time highly correlates with the amount of cognitive efforts devoted to choice making, which as such reflects task complexity. Two competing hypotheses on the relationship between the scale and the task complexity measure (i.e., decision time) are formulated. Given the data collected in Chapter 2, Chapter 4 will give an empirical answer to which of two hypotheses can be supported.

In light of the disadvantages of using the conventional fixed-time-budget as time pressure index, this research constructs another measure of time pressure, which combines the decision time budget and the actual decision time. It is formulated as the product of the actual decision time divided by the decision time budget received. Similarly, two competing hypotheses are formulated on the relationship between the scale and the time pressure index. Given the data collected in Chapter 2, Chapter 4 will give an empirical answer to the question which of two hypotheses can be supported.

However, it is worth mentioning that decision time as a direct measure of task complexity should be not confused with the engagement/time pressure index where decision time is also used. The former decision time can serve as a measure of task complexity only when it is recorded under the condition of **no** time constraint. The latter decision time is one of the components that together form the engagement/time pressure index and it is recorded only when there is time constraint on decision-making.

3. A computer-based activity-travel simulator

3.1 Introduction

Chapter 2 has presented the discrete choice-based Heteroscedastic models that embed the impacts of choice task complexity and time pressure on choice making in mobility networks. In order to estimate those models, data on travellers' choices need to be collected. Given the targeted context of daily activity travel, the data requirement of the models formulated in Chapter 2 has clearly indicated that besides the two conventional attributes of travel time and travel cost, three additional attributes, namely the amount of travel alternatives in a given choice set, the number of daily activities in an assigned activity program, and the engagement/time pressure level in a choice task, need to be properly varied in the data for model estimation. As argued in the Introduction chapter, a travel-simulator approach is the most suitable method for observing those choices.

Travel simulators have been gaining popularity with the aim of addressing the issue of validity in collecting SP data. Compared with the conventional SP methods (e.g., paper-pencil survey, web-based survey, etc.), travel simulators usually provide illustrative and interactive user interfaces, stimulating respondents to more actively involve themselves in the experiment and allowing for easy interactions between respondents and experimental conditions. Bonsall and Palmer (2004) developed a two-dimensional (2D) travel simulator to collect data on driver's car parking behaviour, in which an experiment participant takes a first-person view (the images shown on the screen simulate the eye-sight of a person) of driving a car when approaching parking lots. In order to collect data concerning the effects of travel information, Chorus et al. (2007) presented a more abstract 2D interface of a travel simulator to an experiment participant, the travel context of which is based on one single trip. Prendinger et al. (2011) created a 3D travel simulator to attain the data of drivers' acceptance of intelligent transport system. Sun et al. (2012) utilised a travel simulator equipped with a concise 2D map to collect data concerning traveller's activity rescheduling, route choice and information acquisition decisions under multiple uncertain events. Inspired by these efforts, a computer-based activity travel simulator (ATS) is developed and presented in this chapter.

While most of the previous mentioned travel simulators typically consider only single trips, ATS deals with complete daily activity programs, hence with all trips made for a whole day. Given this context, a 2D interface looks appropriate enough to illustrate the information of implementing a daily activity program, while 3D ones may appear excessive.

This chapter is organized as follows. Section 3.2 starts with describing the activities that will included in the simulator. Section 3.3 describes on the basic design of ATS with respect to the experiment. Section 3.4 focusses on the elaborate variations in task complexity and time pressure. Section 3.5 describes the execution of the experiment. Section 3.6 focuses on the validation of the simulator. Finally, Section 3.7 concludes the chapter with discussions.

3.2 A focus on activity-travel

The starting point for the development of ATS is the notion that a traveller needs to conduct some activities in a weekday. In order to carry out these activities that can be situated in different geographically dispersed locations away from his or her home, the traveller must make a choice for his or her travel to reach all these locations from home and then get back to home to finish the day. ATS assumes for the traveller which activities s/he is supposed to do for the day and which travel alternatives (i.e. the choice set) the traveller can take into consideration. That is to say, given the activities assigned by ATS, the traveller needs to choose his or her favourable travel alternatives from the choice set provided by ATS.

For a normal workday, a traveller would usually execute several activities, e.g., working, grocery shopping, escorting children to or from school, etc. These activities in a day together form a so-called activity program. While each activity in the simulator has at least one distinctive geographic location, some activities (e.g. grocery shopping) may have multiple locations of its own (alternative destinations). In order to execute them all in a day, people may have to travel between the respective locations. If traveling between two activity locations is defined as one trip, conducting an activity program usually consists of several trips. In addition, it is assumed that a traveller can choose between different main travel modes, i.e., bicycle, private car, public transport, and a combination of the previous three (walking is explicitly considered as a transferring mode either between two main travel modes for multi-modal travel or between adjacent activity locations and main travel models. Moreover, the timely order to execute activities (defined as activity sequence) may differ. For example, people can choose first to go to fitness training and then visit a supermarket, while the reverse order is also viable. In short, it appears that for a given activity program (even for one that consists of only one activity), there can be many travel possibilities to execute it. Any one of these possibilities for a given activity program is defined here as a choice alternative. To be more specific, an alternative in a choice set is considered the execution of a complete activity program, which contains the following basic elements:

- timely ordered sequence of the activities;
- geographic locations of the activities; and
- trip between the activity locations (including trip modes, their respective travel time and travel cost).

In order to provide a more realistic travel context, ATS additionally manifests the activity-associated travel burdens. For example, a choice for a trip by bicycle from a supermarket to home after grocery shopping, is not only affected by travel time and travel cost, but also by a grocery-associated travel burden like transporting the purchased groceries on the bicycle. Therefore, this kind of travel burdens needs to be shown in ATS.

Although the purpose of including activities in ATS is to help create a more realistic travel context, it is important to note here that this research does not extend its interest further on traveller's perception of intrinsic attractiveness of activity locations. For example, how much variety of goods one supermarket offers for grocery shopping is not concerned in this search as a criterion for choosing between two supermarkets. The determining factor is only their geographic locational attractiveness.

Since in real life there are so many daily activities that an individual person can possibly have, it is not only difficult but unnecessary as well to include all these activities in ATS, as only the ones commonly shared by most of the travellers may warrant attention from this research. Thus, a set of typical activities may suffice to serve the purpose[7]. As a result, ATS has selected a few typical activities from different activity categories. Though there are several ways to classify daily activities, the most popular one is to divide them into three categories, namely primary, maintenance and leisure activities (e.g., Dijst 1999; Wen and Koppelman 2000; Axhausen et al. 2002; Bhat and Koppelman 2003). Primary activities are those daily activities that are most important to travellers, e.g. work. Maintenance activities are those ones required to maintain one's living and normally sustained with a daily or weekly regular frequency, e.g. grocery shopping. Leisure activities are those recreational ones that are not necessary but with which people occasionally are entertained with. Excluding business-related activity and education-related activity, the following list contains the activities that have been included in ATS according to the three categories:

- *Primary*: work;
- *Maintenance*: grocery shopping, fitness and escorting children to school[8];
- *Leisure*: leisure shopping and meeting friends.

3.3 The design of ATS

ATS has created a hypothetical travel environment. Participants have to assume that they recently moved to this environment. Figure 3.1 shows an example of the interface of ATS. As illustrated in this figure, there are two cities ("Stad A" and "Stad B" in Dutch language). The supposed home is located in Stad A, while the work location in Stad B. City A and B are located farther from each other as can be seen in the figures. This geographical separation is symbolised with the black space between the two cities. The school is located near home. Work place, home and the school, have only one single location, while all other activities can be conducted at two alternative locations. One of those locations is in the neighbourhood of home, and another is clustered with others near the train station in Stad A, the aggregate of which is called integrated facility.

Although the activity of meeting friends can occur in multiple locations in real life, ATS assumes that a cafeteria would be the only place for it. This is due to the consideration of simplifying the setting of ATS without hampering the reach of its overall goal, as it is reasonable to think that other friend-meeting places (except at home) may not make a huge difference from a cafeteria as long as the theme of the activity is mainly about meeting friend (e.g., getting together and casual chats).

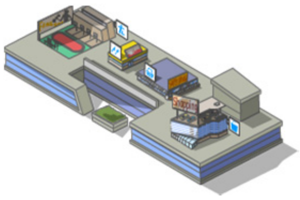
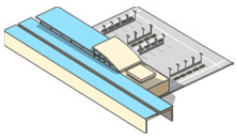
[7] A later feedback from the ATS participants may confirm this notion.
[8] In the category of maintenance activities, "escorting children to school" is only available to respondents who have this routine in their real life.

Table 3.1: Icons of the activity locations in the interface and their functionalities

In Stad A, *close* to home

Icon	Location	Activity
	*home*	
	*supermarket*	Grocery shopping
	*fitness/sport centre*	Fitness/sport
	*shopping centre*	Leisure shopping
	*cafeteria*	Meeting friends
	*school*	Escorting children to school

In Stad A, further *away* from the activity locations above

Icon	Location	Activity
	*integrated facility* (containing *supermarket, fitness/sport center, shopping center,* and *cafeteria*)	Grocery shopping, Fitness/sport, Leisure shopping, Meeting friends
	Train station City A	Where a train to City B can be taken

In Stad B

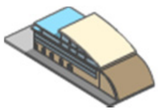
Icon	Location	Activity
	*Office*	Work
	Train station city B	Where a train to City A can be taken

Table 3.1 shows the icons of the activity locations in the interface, and their respective activity functionalities. Table 3.2 shows the icons of the travel modes in the interface. It is worth noticing that some icons shown in Table 3.2 not only indicate their travel modes but the additional travel burdens associated with their respective travel modes in particular trips. If the content of a trip is to take a child from school to home and the mode is riding a bicycle, the fifth icon in the table (with a child in the rear of the bicycle) would be shown rather than the third icon. If a trip is to travel from a supermarket to home after a grocery shopping by riding a bicycle, the fourth icon in the table (with a shopping bag in front of the bicycle) would be shown rather than the third icon. If a trip is to travel from a supermarket to home after a grocery shopping with a child by riding a bicycle, then the sixth icon would be shown rather than the third icon.

Table 3.2: Icons of the travel modes in the interface and their functionalities

Icon								
Mode	Private Car	Train	Bicycle	Bicycle carrying bags	Bicycle with child	Bicycle with child, carrying bags	Walk	On foot carrying bags

Figure 3.1: An example opening interface of ATS

As previously introduced, there is one activity, “escorting children to school”, which may only apply to those participants who escort children to school on a daily basis. Moreover, participants that are private car-users may have more car-oriented travel alternatives in their real life than public transport-users. Therefore, in order to induce more realistic behaviours from the experiment participants, the experiment is tailor-made for each of the four groups that can be formed along the dimensions of escorting or not escorting children to school and car or public transport user. The differences of the settings between these four groups exist in activity program (where there is the activity of "escorting children to school" or not) and in travel alternatives (more car-oriented or more public transport-oriented). However, ATS does not further distinguish between people who practise sports and those who don't, and between people who do grocery-shopping and those who don't, etc. It is reasonable in the sense that unlike "escorting children to school" the participants usually have the similar experiences of carrying out those activities. Therefore, even if the participants may no longer practise sports or do grocery shopping, they would not find these activities as completely unfamiliar.

The design of ATS was finished in the first half of Year 2011. From the second half of that year till early Year 2012, with the help of Hydom Co. Ltd., a software company, the Java-based ATS was fully programmed, deployed to the server of Delft University of Technology, and ready for use.

3.4 Task complexity and time pressure

This section describes how task complexity and time pressure is varied in the simulator. To reduce redundancy, the set-up of the experiment is illustrated for only one of the four distinguished groups, i.e. the group of "not escorting children to school" and "private car-user". The settings of the other three groups can be found in Appendix I.

3.4.1 Varying choice task complexity levels

As suggested in Chapter 2, two critical explanatory variables may control choice task complexity level in an activity travel context. The first is the number of activities in an activity program. The second is the number of travel alternatives in a choice set given the activity program, i.e. the number of ways in which an activity program can be executed. The approach taken in this research to vary choice task complexity levels is to ask each participant to make choices from several similar travel choice sets. Each set is varied with a unique combination of these two variables denoting complexity, since this approach can help generate a large amount of data for the model estimation. Table 3.3 shows the six travel choice sets assigned to the participants under the condition of no time pressure. Another series of six choice sets is presented to each participant under the condition of time pressure, though in terms of the number of travel alternatives and the number of activities in an activity program, they are identical to the previous choice sets. Therefore, in total a participant would have to make choices in twelve choice sets. Table 3.4 shows the contents of the activity programs of the respective choice sets listed in Table 3.3. It is probable that choice tasks that include more activities and more alternatives than the ones shown in Table 3.3 may become too complex for participants to handle, thus running the risk that the participants would detach themselves from the experiment. Task 6 in this example therefore may presumably be the most complex choice task assigned to a participant, as it consists of four travel alternatives in the choice set, and four activities included in the activity program. On the contrary, Task 1 in this example is assumed to be the least complex one assigned, since it only consists of two travel alternatives with only one activity in the program.

Table 3.3: An example of the travel choice sets assigned

		Nr. of activity-travel alternatives in choice set		
		2	**3**	**4**
Nr. of activities in an activity program	**1**	*Set 1*		
	2	*Set 2*	*Set 3*	
	3		*Set 4*	*Set 5*
	4			*Set 6*

Table 3.4: The activity programs assigned to their respective choice sets

Set	**Activity Program**
Set 1	Work
Set 2	Work, Grocery shopping
Set 3	Work, Fitness
Set 4	Work, Fitness, Grocery shopping
Set 5	Work, Meeting friends, Fitness
Set 6	Work, Leisure shopping, Fitness, Meeting friends

3.4.2 Varying travel alternatives

According to Table 3.3, in Set 2 (i.e. work and grocery shopping), there should be two travel alternatives to choose from. As explained earlier, even this comparatively simple activity program can be executed in several possible ways, depending on the activity sequence, the activity locations, and the respective travel modes. Therefore, it is important to select the most appropriate ones as the alternatives of the choice sets. Three principles, which are listed below, have been developed to help achieve this selection, the motivations of which are based upon reflecting some of the usual scheduling practices in people's daily life, as well as realizing some of the ideas of synchronizing activity locations with travel:

- For participants who are car-users, at least one full-car travel[9] alternative should be provided, while for those who are public transport-users (PT users), at least one full-PT travel[10] alternatives should be provided; For activities that have multiple optional

[9] A full-car travel alternative is defined in ATS as one in which all the travels between activity locations are carried out by in the mode of car.

[10] A full-PT travel alternative is defined in ATS as one in which the travels between activity locations are carried out in train and bicycle, while no car is involved.

locations, one travel alternative should be characterized as clustering the locations of these activities in an integrated facility.

- Except the activity of "escorting children to school", in terms of time order, all the other activities should come after the activity of "work";

Given these principles, the travel alternatives corresponding to Table 3.3 and 3.4 for the participants who do not escort children to school and who are car-users are shown in Table 3.5.

3.4.3 Specifying mode availability and varying travel time and travel cost

As shown in Table 3.5, there is at least one travel leg between each pair of two physical locations. A travel leg is any direct travel link between two locations, which differs from a travel trip that may include several travel legs (e.g. a multi-leg trip as opposed to a single-leg trip). However, for some travel legs, only a single travel mode is available: between Train Station A and Train Station B only the train is available; the direct travel link between Office and Home is only available for car; and the travel link between Office and Train Station B is only available for walk.

Table 3.5: Activity-travel alternatives for participants who do not escort children to school and who are car-users

Set Nr.	Activity-travel alternatives
1	Home (car)* Office (car) Home
	Home (PT)** Office (PT) Office
2	Home (car) Office (car) Supermarket (car) Home
	Home (PT) Office (PT) Integrated facility*** (PT) Home
3	Home (car) Office (car) Fitness centre (car) Home
	Home (car, PT)**** Office (PT) Integrated facility (car) Home
	Home (PT) Office (PT) Integrated facility (PT) Home
4	Home (car) Office (car) Fitness centre (car) Supermarket (car) Home
	Home (car, PT) Office (PT) Integrated facility (car) Home
	Home (PT) Office (PT) Integrated facility (PT) Home
5	Home (car) Office (car) Fitness centre (car) Cafeteria (car) Home
	Home (PT) Office (PT) Integrated facility (PT) Home
	Home (car, PT) Office (PT, car) Fitness centre (car) Cafeteria (car) Home
	Home (car, PT) Office (PT) Integrated facility (car) Home
6	Home (PT) Office (PT) Integrated facility (PT) Home
	Home (car, PT) Office (PT, car) Fitness centre (car) Shopping centre (car) Cafeteria (car) Home
	Home (car, PT) Office (PT) Integrated facility (car) Home
	Home (car) Office (car) Fitness centre (car) Shopping centre (car) Cafeteria (car) Home

Note:
* Items within the brackets indicate travel mode between two activity locations;
** PT can be a multi-modal travel (e.g. a combination of train and cycling);
*** Integrated facility is near train station where fitness centre, supermarket, shopping centre and meeting place are clustered together;
**** (car, PT) suggests the involvement of mode transfer.

In order to estimate the coefficients of the tastes for travel time and travel cost, as formulated in all the models shown in Chapter 2, travel time and travel cost need to be varied properly in the experiment. For any travel leg, the travel time and the travel cost corresponding to its travel mode are randomly drawn from a certain range of values for each choice task and for each participant. Table 3.6 demonstrates the ranges of the values for these travel legs. Before the experiment execution, 10 sets of simulated data that were randomly generated from these ranges of the values by using a simple MNL model (that only considers travel time and travel cost, and its tastes of the two attributes are assumed) were re-estimated with the same MNL model. The results suggested that all the 10 sets of data had such sufficient variations in travel time and travel cost that the MNL model was estimable. With this test, it is reasonable to suggest that the design of the attribute values is sufficient.

Table 3.6: the ranges of values for the travel legs

	Travel time(min)	Travel cost(€)
Within Neighbourhood*		
Cycling	6 – 10	0
Car	3 – 5	1 – 2
Between Neighbourhood and Train Station A		
Cycling	12 – 16	0
Car	6 – 10	2 – 3
Between Train Station A and Integrated facility		
Walking	1 – 3	0
Cycling	1 – 3	0
Between Train Station A and Train Station B		
Train	35 – 45	4 – 6
Between Train Station B and Office		
Walking	3 – 5	0
Between Neighbourhood and Office		
Car	46 – 56	7 – 10

Note: Neighbourhood represents all the activity locations within the home neighbourhood. The travel between any pair of activity locations within the neighbourhood is assigned with the same ranges of values, while the travel between any activity location within the neighbourhood and one activity location outside the neighbourhood also has the same ranges of values.

3.4.4 Varying decision time budget

As mentioned earlier, ATS would also assign choice tasks to a participant when there is a time limit for making a decision. Shown in Chapter 2, the specification of measuring time pressure as well as engagement (as termed engagement/time pressure index in Chapter 2) takes the following form:

$$DS_s = DT_s / DTB_s \tag{3.1}$$

where

DS_s is the calculated time pressure measure in choice situation s;

DT_s is the observed individual specific decision time in choice situation *s*;

DTB_s is the individual specific decision time budget in choice situation *s*.

With this specification, the value of the decision time budget, which indicates how much time a participant has to make his decision, is the only variable that can be controlled for by the researcher, while the decision time is observed from each individual decision-maker. It is arguably better not to fully randomize the decision time budget so that a participant would not be either fully stressed out in extreme cases when assigned with a very small decision time budget or fully relaxed when assigned with a very large decision time budget. In this experiment, the decision time budget is therefore derived with the following formula:

$$DTB_s = \textit{time factor} * \text{decision time under no time pressure} \tag{3.2}$$

The decision time with no time limit is the observed decision time of the same task taken by the same participant under the condition of no time pressure. In that case, the time factor would be 1. The *time factor* is set up based on each task assigned to the experiment participants, with the goal of neither stressing out nor relaxing them fully. To obtain its values for each choice set, a small-scale pilot experiment was carried out. 20 people were recruited for this pilot run, who were randomly divided into three groups. For the first group of 7 people, the time factors all take the value of one. A brief interview was conducted afterwards, asking their opinions about the extent they felt pressured to make their decisions for each of the tasks. Then based on the results from the first group, with the aim that a participant should be neither over-stressed nor over-relaxed during the choice tasks with time limit, the time factor values were adjusted. The second group of 6 people took on the adjusted values. With the same routine, the time factor values were marginally re-adjusted. The final group of 7 people tested the experiment with the latest adjusted coefficients, the results of which helped determine the final values of the time factor respective to each choice task as shown in Table 3.7. Although the values of the time factor were adjusted with the three rounds of pilot experiment, the result still looked arbitrary, which from hindsight can be further improved.

Table 3.7: Coefficients of decision time budget as to actual decision time with no time limits

Choice Task Nr.	1	2	3	4	5	6
Value of time factor	0.7	0.7	0.7	1.1	0.9	1.1

3.5 Execution of the SP experiment

3.5.1 A typical process of the experiment

In order to ensure satisfactory data to be collected during the experiment, each participant underwent the experiment in a controlled environment. First of all, a participant listened to a live presentation of around 10 minutes about the goal in Dutch language, the content, and the procedure of the experiment, and could ask any questions s/he has concerning the experiment. During the presentation, some important points were stressed. For example, the participant was explicitly informed that whichever activity location s/he prefers, as long as the activity is the same, the duration of the activity and the inherent attractiveness of the activity locations are the same across all the travel alternatives. A user manual[11] in Dutch language is placed on his or her computer table, which can be read before and consulted with during the experiment. S/he could also ask an experiment supervisor any relevant questions during the process.

Prior to entering ATS, the participant answers eleven basic questions concerning his or her socio-demographic characteristics. Depending on whether s/he has a private car at his or her disposal or not and whether s/he has to escort children to school on a daily basis or not (the

[11] A copy of the manual in English can be found in Appendix II.

two questions that are among the eleven), s/he would be put into one of the four designated groups introduced in Section 3.4.

When entering ATS, the participants one by one finish the choice tasks one to six under no time constraint, i.e., s/he could take as much time as s/he feels like when making a choice. More specifically, the moment the participant logs into ATS, an interface like the one shown in Figure 3.1 would be shown. On the right side of the top, under the label “Taak” the content of the assigned activity program is shown. In this case, only one activity “werken” (work in Dutch) is in the program. To the right of the middle, two travel alternatives are listed in the panel. By clicking the yellow button tagged “Toon op kaart” (show on map) by the right side of each alternative, its respective mobility information can be both animatedly visualized on the abstract map in the middle of the interface and concisely narrated in the bottom panel of the interface, as exampled in Figure 3.2.

It is important to note that at any moment in time, the specific information of *only a single* alternative can be shown on the interface, so that it is impossible to see all the alternatives listed in full detail in a single screen. As such, to see and compare the different alternatives, the participant has to look at the alternatives one by one. After evaluating each of the travel alternatives, the participant can choose his or her favourable alternative, by checking the respective circle right under the panel listing all the travel alternatives. The instant it is done, the button “Invoeren” to confirm his or her choice would be transformed from grey colour into bright colour. Once the participant clicks the highlighted button “Invoeren”, ATS then automatically moves on to the next task. The same process reiterates until all the six tasks are finished.

Figure 3.2: An example of showing the specific information of one alternative in ATS

Figure 3.3: An example interface of ATS when there is a decision time budget

Then the participant takes a break of any duration s/he feels like to prevent possible experiment fatigue. The participant subsequently finishes the other six choice tasks with the same choice task complexity levels as to those of the previous six tasks (though as explained earlier, the travel time and travel cost of each travel leg are randomised), however the participant is now given a restrictive decision time budget for each choice. Figure 3.3 shows an example of the interface of ATS when a participant would have to finish the choice task under time pressure, where in the upper-right corner a countdown clock showed how many seconds were left for choice making (i.e., decision time budget). If the participant fails to reach a decision within the given time budget, ATS would inform him or her that because of this, a choice is randomly and automatically made by ATS instead[12]. With these six tasks finished, the participant has completed all the tasks assigned to by ATS. Before stepping out, the participant would also complete a questionnaire survey about how s/he experienced the experiment, which finalizes the whole experiment.

3.5.2 Participant recruitment

Two criteria have been used to recruit the experiment participants. People, who work at least two days a week and who commute to towns or cities other than their own place of residence, form the population targeted for this experiment, as this group of people may easily identify themselves with the travel settings provided by ATS. With this requirement of sampling, Intomart was hired for the participant recruitment service, which is one of the biggest market research companies in the Netherlands. In May and June 2012, 200 participants were recruited by Intomart from its existing panel to join this experiment. € 20 of incentive and €10 of travel cost has been paid to each person who joined the experiment. The experiment was executed in a controlled computer room in Delft University of Technology. 200 participants joined the experiment in a sequence of eight sessions, in each of which no more than 40

[12] The results suggest that out of the total number of 194*6=1164, 15 records from by 13 people are registered as random choice made ATS, which only takes up 1.29 % of the whole data.

persons were allowed inside a computer room that had the capacity of 80 persons, to ensure that every participant could be closely monitored by an experiment supervisor and that the chances of the participants' interactions with each other could be kept at a minimum level.

Table 3.8: Characteristics of the experiment participants (n=194)

Characteristics	Value	Frequency (%)
Job	Paid Job	96.3
	Volunteer	2.6
	Others	1.1
Commuting to work (per week)	>=4 days	85
	4> and >=2 days	11
	<2 days	4
Age	20-30	12.3
	30-40	15.4
	40-50	31.4
	50-60	31.4
	60-70	9.3
Gender	Male	69
	Female	31
Education	Lower Education	10.3
	MAVO/VMBO	23.7
	HAVO	11.8
	VWO	5.2
	WO/HBO	49.5
Marriage	Single	36.1
	Married	44.8
	Partner/Living together	19.1
Group	Car and no escort*	58.3
	Car and escort	6.7
	No car and no escort	28.8
	No car and escort	6.2

Note: "Escort" here means dropping or picking-up children at school

Table 3.8 shows the main characteristics of the participants. In total, 194 valid entries of data from 194 participants were recorded in the database. Almost all participants have a paid job and a few were volunteers or had another job position. 85 % of those with paid jobs commute to work at least four days a week. For the rest of the background characteristics, except that nearly half of the participants belong to the category of WO/HBO[13] in education, the sample is fairly heterogeneous. Moreover, over 58% of the participants belong to the designated group of having private car and having no children to escort to school, while only a few participants need to escort children to school.

As presented above, the desired population is defined as people who own a car, work at least two days a week and commute to towns or cities other than their own place of residence. The representativeness of the sample data with respect to the desired population is discussed below. The respondents were taken and recruited from an existing panel. Although it is difficult to determine whether people in a panel were the same people as those who did not join a panel, the underlying and more 'answerable' question is whether these people in the

[13] WO/HBO stands for university education or university of Higher Professional education, MAVO/VMBO intermediate vocational education, HAVO senior general secondary education, and VWO pre-university education in Dutch education system.

panel would make different choices than people not in the panel. It is argued here that this may not be the case. Although as a commercial company Intomart would not share the insights of the recruitment mechanism as to how the people joined the panel, they ensured us that the sample was representative. Though it may be doubtful, the motive of pursuing financial reward may convince us that the conclusion is reasonable. The most important motive for a person to join the panel is probably earning financially-related benefits. In ATS, travel cost is an important variable for the participants to evaluate the activity-travel alternatives. These two elements share the same root of pursuing financial rewards, which may make the participants easily relate to the choices made in ATS. In this sense, the representativeness was enhanced. However, it is harder to tell whether this resulted in a systematic bias of value-of-time-alike parameters in a particular direction.

Nevertheless, even if the bias exists, this may not pose as a critical issue for this research. The main research goals are not concerned with estimating unbiased values-of-time-alike parameters, but examining whether task complexity and time pressure have impacts on activity-travel choices. It is hard to postulate that people who have a lower or higher value of time would be more or less affected by task complexity and time pressure, at least not with respect to the randomness of their choices.

3.6 Validation of the simulator experiment

As mentioned earlier, compared with RP methods, SP methods may suffer from the lack of external validation for data collection. Therefore, it is important to explore to what extent the SP-based Travel Simulator is a valid tool for data collection. The ultimately legitimate way to do so is to show that observed choices made within ATS "resemble those made in real life under comparable conditions" (Chorus et al. 2007). However, the important reason to develop ATS rather than using RP methods lies in the fact that "choices made in real life under comparable conditions" are foreseeably difficult to attain: such a dilemma makes this ultimate approach of validation rather impractical.

However, there are also indirect approaches to help validate ATS, which have been adopted in this research. First, as prerequisites to induce real behaviour from the experiment participants, they must adequately understand the function of ATS and the process of the experiment, and preferably enjoy the experiment. Once these are met, it is reasonable to think that the participants are more likely to be engaged in the experiment. The self-reported feedbacks from the participants after they have completed the experiment are useful to demonstrate whether these prerequisites are indeed met or not. Second, Chorus et al. (2007) suggest that using a less strict validation, a simulator may be regarded as a valid way to collect data when it is established that observed behaviour made within the simulator resemble intuitions concerning what kind of behaviour would be made in real life.

3.6.1 Self-reported feedbacks from the respondents

The experiment participants (of 194 valid entries) were asked to rate five statements, each on a five-point scale ranging from to "completely disagree" denoted as 1 to "completely agree" denoted as 5, regarding their evaluations of the experiment, as listed in Table 3.9. The table suggests that the overwhelming majority of the participants were able to remain focused during the experiment process, felt the information shown in ATS was illustrative, understood the experiment well, and enjoyed the experiment as a whole, while only a small proportion of the participants felt that activity programs presented to them were not sufficiently realistic to their real life situation. Overall, this feedback suggests rather positive evaluations from the participants.

Table 3.9 Self-reported feedbacks on the experiment

Variable	**Counts**	**Proportion**
It was easy to understand the travel simulator.		
1 very much disagree	1	1
2 disagree	2	1
3 neutral	15	8
4 agree	82	42
5 very much agree	94	48
Average (**4.37**)		
It was easy to remain focused during the experiment.		
1 very much disagree	1	1
2 disagree	7	3
3 neutral	6	3
4 agree	99	51
5 very much agree	81	42
Average (**4.30**)		
The information shown in the abstract map was illustrative.		
1 very much disagree	1	1
2 disagree	1	1
3 neutral	5	2
4 agree	68	35
5 very much agree	119	61
Average (**4.56**)		
The daily activity programs presented in the experiment look realistic for my situation.		
1 very much disagree	8	4
2 disagree	18	9
3 neutral	50	25
4 agree	89	45
5 very much agree	29	17
Average (**3.58**)		
It was enjoyable to participate in the experiment.		
1 very much disagree	1	1
2 disagree	4	2
3 neutral	7	4
4 agree	106	54
5 very much agree	76	39
Average (**4.30**)		

The average ratings obtained in this research are quite comparable to those attained in another travel simulator (Chorus et al. 2007). In Chorus et al's experiment, similar evaluations on the participants' feedback on their simulator are obtained, with the following four statements: 1) I found it difficult to remain concentrated during the experiment; 2) I found it difficult to identify with the different travel situations; 3) I found the travel simulator easy to understand; 4) I enjoyed participating in the experiment. They found that the average ratings of the four statements are 2.24, 1.94, 4.19 and 4.47 respectively (the small values of the first two are due to the negative formulations in the answers of the two statements). If the first two statements would be reformulated by replacing the word 'difficult' with 'easy', the ratings of the two might be transposed to 3.76 and 4.06 respectively. It may be argued that the choice task in the travel simulator in this study is a complex task, but a very concrete one, while the choice task applied in Chorus' at al.'s travel simulator was less complex, but more abstract. That comparable results are found for both simulators, indicates that indeed travel simulators succeed in engaging participants in complex choice tasks, which increases our trust that the observed choices reflect real life choice behaviour better than observed in standard SP choice tasks.

3.6.2 Consistency of ATS data

As mentioned in Section 3.1, ATS can be validated when it is established that observed behaviour made within ATS resemble intuitions concerning what kind of choices would be made in real life. Usually, these intuitions should be formulated at a very basic, general level (Chorus et al. 2007). The following are the intuitions formulated for ATS:

For **travel choices**

1a. The higher the overall travel time, the lower the choice probability;
1b. The higher the overall travel cost, the lower the choice probability;
1c. The larger the total number of travel interchanges, the lower the choice probability;

For **task complexity**

2a. The larger the number of travel alternatives in the choice set, the more decision time used;
2b. The larger the number of activities in the activity program, the more decision time used;

The first two propositions (1a and 1b) of intuition 1 are quite straightforward. One travel interchange (1c) here means a break of travel where a traveller has to either switch to another travel mode or enter an activity location in a travel alternative. A larger number of travel interchanges suggests that a traveller would have to make more transfers either between travel modes or between travel modes and activity locations, which travellers generally do not prefer (Krygsman et al. 2004). In terms of intuition 2, with the increase of the number of travel alternatives and the number of activities included in a choice set, the choice task complexity levels shall generally increase, inducing more decision time to make a choice.

Intuition 1)

With regard to intuition 1 a simple Multi-Nomial Logit model was applied to estimate the tastes for travel time, travel cost and the number of travel interchanges, based on the data collected. Each of the alternatives presented to participants, especially those alternatives that consist of one or more public transportation legs and/or multi-modal travel, contains multiple interchanges. Much research (e.g., Hine and Scott 2000; Wardman and Hine 2000) indicates that the number of travel interchanges in a travel alternative is also an important attribute that helps determine the attractiveness of a travel alternative. Therefore, it is reasonable to include this attribute as well in the systematic component of the utility function. It is expected that the values of all the three tastes should take a negative sign. The model is specified without the consideration of choice task complexity and time pressure. We've specified the systematic component of the utility function, V_i as:

$$V_i = \beta_{TT} \cdot TT_i + \beta_{TC} \cdot TC_i + \beta_{TI} \cdot TI_i \tag{3.3}$$

where

TT_i, total travel time (door-to-door) of alternative *i*;

TC_i, total travel cost of alternative *i*; and

TI_i, the number of travel interchanges in alternative *i*.

The main segment (e.g. the group of "car and no escort" as shown in Table 3.3) is selected to estimate this model by using Biogeme, yielding an adjusted rho square index of 0.152. As the aim of this model to test general internal validity of the SP data, this model performance is acceptable. As shown in Table 3.10, the values of β_{TT}, β_{TC} and β_{TI} all take negative signs and are statistically significant, which indicates that with the increase of travel time, travel cost and the number of travel interchanges, the utility of the travel alternative would become smaller, indicating a lower probability of choosing this alternative. Thus, intuition 1 can be confirmed. Moreover, by calculating the value of $\beta_{TT} * 60/\beta_{TC}$, the average value for travel time saving can be attained, which equals to 18.07 €/hour based on the sample data. This value seems to be in line with the estimates of value for travel time saving from other research (e.g., Hensher 2001; Hess et al. 2005; Shires and De Jong 2009; Hensher and Greene 2011). Moreover, by calculating the value of β_{TI} / β_{TT}, the value of average travel time per travel interchange saving can be attained, which equals to 29.84 minutes per interchange. This value is larger than that in Hensher et al. (2013), which is 18.25 based on the data collected from Sydney, Australia. There may be two reasons of distinctive nature that result in this difference. The first one is that the value attained here is derived from the estimates of a very basic MNL model: a more advanced discrete choice-based model may produce a different value that may be much closer to the one from Hensher et al. (2013). The second reason is that apart from the possible regional distinction, this difference may be also due to the fact that the data used in Hensher et al. (2013) is collected from PT users, while the segment of the data used in the model here belongs to car-users who may be much less tolerable towards travel interchanges. Therefore, the value of average travel time for per travel interchange saving attained from this data may be considered as reasonable.

Table 3.10: Consistency of travel choices

Coefficients	**Value**	**t-stat**
β_{TC}	-0.0415	2.74
β_{TT}	-0.0125	2.16
β_{TI}	-0.373	14.41

Intuition 2)

With respect to the first and the second proposition of intuition 2, the value of the decision time ranges from 1.61 seconds to 623 seconds per choice tasks in the dataset. Recall that the number of activities ranges from 2 to 4, and the number of travel alternatives ranges from 2 to 4. The correlation between the decision time and the number of activities equals to 0.10 (p-value < 0.01), which is statistically significant and has a positive sign. The correlation between the decision time and the number of travel alternatives equals to 0.147 (p-value <

0.01), which is also significant and has a positive sign. As may be expected, the correlation with the number of alternatives is stronger as it may take more time to consider an additional alternative, than just only considering an additional activity in an activity program. From these results, it is reasonable to suggest that intuition 2) can be supported.

3.7 Conclusions and discussions

This chapter has explained the development of an activity-travel simulator. This simulator allows collecting data about activity travel choices that allow modelling the possible impacts of task complexity and time pressure.

A computer-based travel simulator is a special type of SP experiment, which has gained growing popularity in academia which is considered as an appropriate and improved way to collect SP data. It intends to help mitigate the problem of external validity associated with SP methods. In the simulator, participants make choices among alternatives that describe the execution of complete activity programs. Task complexity is varied by varying across the choice sets both the number of activities included in the activity program and the number of activity program executions to choose from. In addition, choices are observed for a choice situation without time pressure and a situation with a travel time budget. In total, 194 persons participated in the travel simulator. The majority of the participants has a paid job and 85 % of those with paid jobs commute to work four days or more per week. The results of the various validation methods have increased our trust in the validity of the activity-travel simulator.

Notwithstanding the overall legitimacy of the travel simulator approach, there are some points in the detailed design of the experiment that can be further improved. In Sub-section 3.4.4, it is evident that the result of the time factors looks arbitrary. By design the possibility of observing the extreme cases of ultimate time pressure experience was excluded. For example, a choice situation is excluded where a choice that usually takes 60 seconds to think is only assigned with 5 seconds. Traveller behaviours under these circumstances cannot be observed by using this experimental setup, as decision time budget should be more or less proportional to its normal decision time. Moreover, the values of the time factor are correlated with the increased complexity of the choice task, which implies that the more complex a choice task is, the larger the time factor becomes. As such, the participants may not feel as much time pressure in a more complex choice situation as in a less complex one. However, such correlations between engagement/time pressure index and choice task numbers have not been strongly supported in the data collected (as the correlation equals to -0.165). Moreover, as can be seen in Table 3.7, the values of the time factor vary across choice tasks but are constant within a given choice task. Nonetheless, the fact that eq. (3.1) combined with eq. (3.2) includes individual's decision time under time pressure *and* under no time pressure, fortunately created enough variation in engagement/time pressure index to jointly estimate engagement/time pressure and task complexity effects in these models. With hindsight, the setup would have been better – for reasons for creating more random variations in experimental conditions – to randomly vary the values of the time factor across and *within* tasks, as this would have allowed for a more efficient simultaneous identification of engagement/time pressure effects and task complexity effects (since the latter also vary between tasks but not within tasks).

4. The impacts of task complexity and time pressure on travellers' choices: empirical findings

4.1 Introduction

Chapter 2 develops the theoretical discrete choice models that incorporate impacts of task complexity and time pressure on travellers' choice. Chapter 3 subsequently explains the data collection effort. With the data available, it is now possible to estimate the developed models. Furthermore, based on inspection of the estimation results, insights can be gained concerning the impacts of task complexity and time pressure on travel choice behaviour. This chapter serves the purpose of operationalizing the models developed in chapter 2, presenting the estimation results, and interpreting the results.

Section 4.2 of this chapter constructs four operational choice models ranging from a simple MNL model to a more advanced Heteroscedastic Mixed Logit model. Subsequently, Section 4.3 analyses and compares all the estimation results. Section 4.4 finishes the chapter with conclusions and discussions.

4.2 Specifying the discrete choice-based models

As explained earlier in Chapter 2, the critical difference between a Heteroscedastic Logit (HL) model and a Multi-Nomial Logit (MNL) model lies in the assumption regarding the random component of the utility function. The MNL model assumes that the random component of the utility function is independently and identically drawn from a Type I extreme value distribution (IID property) which has a constant variance for all alternatives and individuals. As the variance of the distribution of the random component of utility and the scale of the systematic component of utility are confounded, this assumption equivalently states that the scale of the systematic utility is the same across choice alternatives in the MNL model. The Heteroscedastic Logit (HL) model relaxes the assumption that the random component of the utility function is drawn from an identical distribution (i.e. a distribution with constant variance). In other words, the HL model allows the scale of the systematic component of the utility function to vary across choice alternatives and individuals. As explained in Chapter 2, this property of the Heteroscedastic Logit model can be exploited to model the impacts of task complexity and time pressure on the scale of the systematic component of the utility function.

However, irrespective of the assumptions regarding scale / error variance, the systematic components of the utility functions of both the models can share the same functional form. As such, a logical first step in specifying the discrete choice-based models is to specify the functional form of the systematic component of the utility function, which is the same for the MNL model and the HL model; and the second step is to specify the functional form of the model's scale, which differs between model types (MNL versus HL). Finally, choice probabilities for both model specifications are formulated.

4.2.1 The systematic component of the utility function

Recall that the data collected for the model estimation is within the context of an activity-travel program for a given workday. The choice alternatives presented in the experiment essentially refer to a sequence of trips between activity locations (including travel modes, and their respective travel time and travel cost). Given this context, the systematic component of the utility function should include three conventional attributes associated with travel, namely the (total) travel time, the (total) travel cost and the number of travel interchanges of a choice alternative. For the sake of easy readability of the mathematical equations in this chapter, the utility function of a choice alternative is formulated from a single representative person's perspective. Therefore, the subscript representing a particular person is in general suppressed from the equations in this chapter. As such, the systematic component of the utility function can be formulated as the following linear-in-parameter formulation:

$$V_i = \beta_{TT} \cdot TT_i + \beta_{TC} \cdot TC_i + \beta_{TI} \cdot TI_i \tag{4.1}$$

where

TT_i, total travel time of alternative *i*;

TC_i, total travel cost of alternative *i*; and

TI_i, the number of travel interchanges in alternative *i*.

A plausible improvement on eq. (4.1) would be the inclusion of an intrinsic preference for car over public transport in the systematic component of the utility function. This is done by creating a dummy-attribute which equals 1 one if a travel alternative features car as the main travel mode, and 0 otherwise. More specifically, as explained in Chapter 3, the travel context of the choice task includes travel between two cities. If the travel mode of these travels between cities is car in a particular travel alternative, then the car is considered as the main travel mode. As such, eq. (4.1) can be further extended to,

$$V_i = \beta_{TT} \cdot TT_i + \beta_{TC} \cdot TC_i + \beta_{TI} \cdot TI_i + \beta_{car} \cdot Car_i \tag{4.2}$$

where

Car_i equals 1 when alternative *i* employs car as the main travel mode, or 0 when it does not.

Eq. (4.2) completes the specification of the systematic component of the utility function[14].

4.2.2 The scale of the systematic component of the utility function

As explained in Chapter 2, to ensure its non-negativity, the scale is formulated in an exponential form with the following equation,

$$\mu_s = \exp(a(D_s, T_s, Int(D_s, T_s))) \tag{4.3}$$

where

$a(\ )$ is a linear function of its arguments and associated parameters;

D_s represents the impact of task complexity in choice situation *s*;

T_s represents the impact of engagement/time pressure in choice situation *s*;

$Int(D_s, T_s)$, relates to the interactive effect between task complexity and engagement/time pressure in choice situation *s*.

Specification of the impact of task complexity D_s

As explained in Chapter 2, there are two competing hypotheses concerning the relationship between μ_s and the task complexity measure. One linear and one quadratic parameter specification associated with the task complexity measures are sufficient enough to represent both of these two hypotheses.

Also introduced in Chapter 2, there are multiple approaches to measure task complexity. However, it is argued here that the decision time a person has spent on decision-making in the absence of a time constraint, which is an individualized and direct measure of task complexity for a given choice situation *s*, is the most suitable one to take. This is further supported by the fact that other indirect measures of task complexity are either empirically or theoretically inappropriate. More specifically, the linear parameter of *the number of the travel alternatives* not only produce the unexpected sign (which is positive in this case, suggesting more alternatives make choice task less complex) but is statistically insignificant (t-value of 1.57), while the quadratic form of the number of travel alternatives not only produce statistically insignificant linear and quadratic parameters (the t-values are -1.02 and 1.25) but produce insignificant estimates in travel time, travel cost, and the number of travel interchanges as well. On the other hand, the entropy measure of task complexity, whose focus is primarily on preference similarity, requires knowledge about the a priori probabilities of the alternatives. Ignoring many other important aspects of task complexity, this theoretical focus makes the use of entropy as a task complexity measure unsuitable. Therefore, decision time is used in subsequent model specifications for the measure of task complexity. More specifically, a linear and a quadratic parameter are used to represent the functional form of the relationship between the task complexity measure (i.e. decision time) and the impact of task complexity:

[14] It is worth mentioning here that the travel context of the SP experiment presented in Chapter 3 may induce the participants to consider some additional contextual attributes when evaluating their travel choices for a workday (e.g., carrying grocery bags while travelling, taking a child while cycling). In principle, these contextual attributes might also be included in the systematic component of the utility function. However, estimation results suggest that the impacts of these contextual attributes are statistically insignificant. As a consequence, these contextual attributes are not considered in the remainder of this chapter and thesis.

$$D_s = \lambda_{DT} \cdot DT_s' + \tau_{DT} \cdot DT_s'^{\,2} \tag{4.4}$$

Recall that there are two competing hypotheses concerning the relationship between μ_s and the task complexity measure: 1) with the increase of task complexity measure, μ_s is expected to become smaller, suggesting a diminishing ability of the decision-maker to correctly compute the observed utilities of all the alternatives in the choice set, inducing more “randomness” in choice outcome; 2) rather than a monotonic relationship, with the increase of task complexity measure, μ_s may first become larger and then smaller, resulting in an inverted-U shape relationship between μ_s and the task complexity measures. For the first hypothesis, Parameter λ_{DT} and τ_{DT} are expected to either have negative signs or equal 0 (in the latter case, there would be only one negative-sign parameter left), as higher levels of task complexity are expected to decrease the scale of the systematic part of the utility. For the second hypothesis, it is expected that Parameter λ_{DT} would take a positive sign while τ_{DT} would take a negative sign. One can test which of these two hypotheses holds (after inspecting the signs and significance levels of associated parameters).

Specification of the effect of time pressure T_s

Recall that in Chapter 2, two possible hypotheses were formulated concerning the impacts of time pressure on scale, as a result of different interpretations of the engagement/time pressure index. The first hypothesis is that scale would monotonically decrease as the index increases, suggesting that more time spent on decision-making, given a time constraint, always leads to more randomness in choice behaviour. The second hypothesis is that scale would first increase and then decrease as the index increases, implying that i) very short decision times are associated with high levels of randomness (due to limited engagement of the decision-maker); ii) medium decision times are associated with low levels of randomness (due to increased engagement of the decision-maker and still relatively low levels of time pressure); iii) high decision times are associated with high levels of randomness (due to high levels of time pressure).

By using the index in a linear as well as a quadratic[15] form simultaneously, one can test which of these two hypotheses holds (after inspecting the signs and significance levels of associated parameters).

$$T_s = \delta_T \cdot DS_s + \theta_T \cdot DS_s^2 \tag{4.5}$$

$$DS_s = DT_s \,/\, DTB_s \tag{4.6}$$

where

DS_s is the engagement/time pressure index;

DT_s is the decision time in choice situation s;

DTB_s is the decision time budget received for choice situation *s*

[15] Power functions whose numbers are more than 2 were tested. However, the parameters of the corresponding power numbers that are above 2 are statistically insignificant. Therefore, those parameters are set up as 0, resulting in the formulations in which there are only linear and quadratic figures left.

Given this equation, some expectations concerning the values of δ_T and θ_T with respect to each of the intuitions can be derived. In order that the model estimation result conforms to the first intuition that T_s would monotonically decrease as the engagement/time pressure index increases, the following condition that the first derivative of T_s on DS_s should be negative would be expected to meet:

$$T_s'(DS_s) = \delta_T + 2 \cdot \theta_T \cdot DS_s < 0, \quad DS_s \in [0,1]$$

In order to conform to the second intuition that T_s would first increase and then decrease as the engagement/time pressure index increases, it can be expected that the following conditions should hold, that there is a maximum value of T_s in between the DS_s value range between 0 and 1, and that T_s is a concave function within the DS_s value range between 0 and 1. To translate these three conditions with respect to the values of δ_T and θ_T, the following equations should hold:

a) $DS_s \in (0,1)$, $T_s'(DS_s) = \delta_T + 2 \cdot \theta_T \cdot DS_s = 0$, and thus $-\dfrac{\delta_T}{2 \cdot \theta_T} \in (0,1)$;

b) $T_s''(DS_s) = 2 \cdot \theta_T < 0$;

Specification of the interaction effect between task complexity and time pressure

In eq. (4.3), $Int(D_s, T_s)$ refers to the interaction effect between task complexity and time pressure in choice situation s. Given the specifications in eq. (4.4) and (4.5), this interaction effect can be formulated as the following:

$$Int(D_s, T_s) = \omega \cdot DT_s' \cdot DS_s \tag{4.7}$$

where ω is the parameter for this interaction effect. The sign of ω is expected to be negative, as the interaction effect between task complexity and time pressure may probably create more difficulty to choice making.

4.2.3 Choice probability

Now that the systematic component of the utility function and its scale have been specified, the choice probabilities with respect to the different model types can be derived.

MNL model

As discussed in Chapter 2, the probability of choosing alternative *i* from choice set C reads as follows in the MNL model:

$$P(i) = \frac{e^{V_i}}{\sum_{j \in C} e^{V_j}} \tag{4.8}$$

Mixed Logit (ML) model

The choice probability of the MNL model in eq. (4.8) assumes that there is no unobserved heterogeneity across individuals in terms of their tastes for alternatives and their attribute-levels. In other words, the estimated parameters represent the collective tastes of the sample population. However, it is quite reasonable to suspect such unobserved heterogeneity does exist. Therefore, a plausible improvement of the MNL model consists of assuming that the tastes of an individual are randomly drawn from a probability density function with pre-specified functional form. This gives rise to the so-called Mixed MNL model or simply Mixed Logit (ML) Model. Based on eq. (4.8), one can formulate the choice probability of an ML model (Train 2003) as

$$P(i) = \int_{\beta_{Car}} \int_{\beta_{TI}} \int_{\beta_{TC}} \int_{\beta_{TT}} \frac{e^{V_i(\beta_{TT},\beta_{TC},\beta_{TI},\beta_{Car})}}{\sum_{j\in C} e^{V_j(\beta_{TT},\beta_{TC},\beta_{TI},\beta_{Car})}} \cdot f(\beta_{TT},\beta_{TC},\beta_{TI},\beta_{Car}) \cdot d\beta_{TT} d\beta_{TC} d\beta_{TI} d\beta_{Car} \qquad (4.9)$$

where $f(\beta_{TT},\beta_{TC},\beta_{TI},\beta_{Car})$ is the joint probability density function for β_{TT}, β_{TI}, β_{TC} and β_{Car}.

As pointed by Hensher and Greene (2003), if there is more than one random taste in a mixed logit model, there may exist correlation of random parameters of attributes that are common across alternatives. However, in this research the correlations of the random parameters have not been tested and maintain a venue for further research. It is pragmatically assumed here that β_{TT}, β_{TI}, β_{TC} and β_{Car} are independent from each other, the practise of which is found not uncommon in empirical modelling in literature (e.g. Algers et al. 1998; Brownstone et al. 2000; Greene et al. 2006). Thus, eq. (4.8) can be further rewritten as

$$P(i) = \int_{\beta_{Car}} \int_{\beta_{TI}} \int_{\beta_{TC}} \int_{\beta_{TT}} \frac{e^{V_i(\beta_{TT},\beta_{TC},\beta_{TI},\beta_{Car})}}{\sum_{j\in C} e^{V_j(\beta_{TT},\beta_{TC},\beta_{TI},\beta_{Car})}} \cdot g(\beta_{TT}) \cdot q(\beta_{TC}) \cdot k(\beta_{TI}) \cdot h(\beta_{Car}) \cdot d\beta_{TT} d\beta_{TC} d\beta_{TI} d\beta_{Car} \qquad (4.10)$$

where *g, q, k* and *h* are the separate probability density functions for β_{TT}, β_{TI}, β_{TC} and β_{Car} respectively. To complete the specification of the ML model, *g, q, k* and *h* need to be further determined in terms of their functional form. This is done further below.

Heteroscedastic model

By combining eq. (4.3) and (4.8), the choice probability of a Heteroscedastic Logit (HL) model can be formulated as follows:

$$P(i) = \frac{e^{\mu_s \cdot V_i}}{\sum_{j\in C} e^{\mu_s \cdot V_j}} \qquad (4.11)$$

By combining eq. (4.3) and (4.10), the choice probability of a Heteroscedastic Mixed Logit (HML) model can be formulated as:

$$P(i) = \int_{\beta_{Car}} \int_{\beta_{TI}} \int_{\beta_{TC}} \int_{\beta_{TT}} \frac{e^{\mu_s \cdot V_i(\beta_{TT},\beta_{TC},\beta_{TI},\beta_{Car})}}{\sum_{j\in C} e^{\mu_s \cdot V_j(\beta_{TT},\beta_{TC},\beta_{TI},\beta_{Car})}} \cdot g(\beta_{TT}) \cdot q(\beta_{TC}) \cdot k(\beta_{TI}) \cdot h(\beta_{Car}) \cdot d\beta_{TT} d\beta_{TC} d\beta_{TI} d\beta_{Car} \qquad (4.12)$$

4.2.4 The models to be estimated

As stated in Section 4.1, this chapter mainly aims to help reach the third research goal, i.e. to gain insight in traveller behaviour in the context of highly synchronised networks, with an emphasis on capturing the possible impacts of task complexity and time pressure. To achieve this, four models with different levels of model sophistications are estimated.

Model 1: an MNL model, which only includes the total travel cost, the total travel time, the total number of interchanges, and the car preference as the attributes in the systematic component of the utility function:

$$P(i) = \frac{e^{V_i}}{\sum_{j \in C} e^{V_j}}$$

where $V_i = \beta_{TT} \cdot TT_i + \beta_{TC} \cdot TC_i + \beta_{TI} \cdot TI_i + \beta_{car} \cdot Car_i$

Model 2: a Heteroscedastic MNL model (HL), which is based on Model 1, with the additional specification on the scale of the systematic component of the utility function:

$$P(i) = \frac{e^{\mu_s \cdot V_i}}{\sum_{j \in C} e^{\mu_s \cdot V_j}}$$

where $\mu_s = e^{((\lambda_{DT} \cdot DT_s' + \tau_{DT} \cdot DT_s'^2) + (\delta_T \cdot DS_s + \theta_T \cdot DS_s^2) + \omega \cdot DT_s' \cdot DS_s)}$

Model 3: a ML model, which is based on Model 1, with the tastes of the four attributes randomly drawn from separate distributions:

$$P(i) = \int_{\beta_{Car}} \int_{\beta_{TI}} \int_{\beta_{TC}} \int_{\beta_{TT}} \frac{e^{V_i(\beta_{TT}, \beta_{TC}, \beta_{TI}, \beta_{Car})}}{\sum_{j \in C} e^{V_j(\beta_{TT}, \beta_{TC}, \beta_{TI}, \beta_{Car})}} \cdot g(\beta_{TT}) \cdot q(\beta_{TC}) \cdot k(\beta_{TI}) \cdot h(\beta_{Car}) \cdot d\beta_{TT} d\beta_{TC} d\beta_{TI} d\beta_{Car}$$

Model 4: a Heteroscedastic ML model (HML), which is based on Model 2, with the four attributes randomly drawn from separate distributions:

$$P(i) = \int_{\beta_{Car}} \int_{\beta_{TI}} \int_{\beta_{TC}} \int_{\beta_{TT}} \frac{e^{\mu_s \cdot V_i(\beta_{TT}, \beta_{TC}, \beta_{TI}, \beta_{Car})}}{\sum_{j \in C} e^{\mu_s \cdot V_j(\beta_{TT}, \beta_{TC}, \beta_{TI}, \beta_{Car})}} \cdot g(\beta_{TT}) \cdot q(\beta_{TC}) \cdot k(\beta_{TI}) \cdot h(\beta_{Car}) \cdot d\beta_{TT} d\beta_{TC} d\beta_{TI} d\beta_{Car}$$

Of these, model 4 is the most sophisticated one, as it allows one to capture the impacts of task complexity and time pressure while also accommodating for possible unobserved taste-heterogeneity.

4.3 Empirical results

The four models specified in the previous section are estimated using Pythonbiogeme, which is developed by Michel Bierlaire in Python language and running in a Linux environment (Bierlaire 2008). Halton draws were used to simulate the integrals for ML and HML models, and the number of the draws was gradually increased to 3000 where the stabilities of the estimated parameters of both the MNL and the HML models are achieved. Moreover, the dataset (as explained in Chapter 3) adopted for the estimation is from the group of the SP experiment participants which contains the largest sample size, for reasons explained below. The participants within this group are car-users with no duty of escorting children to school. In total, the dataset of this group contains 1356 choices made by 113 individual participants (with 12 choices made by each participant).

However, it is worth mentioning that the whole dataset of 194 participants have not been fully used for the model estimation. The key reason to this is that the estimation based on the whole data set by using the basic MNL model, though converged, produces a rather unsatisfactory result. The adjusted Rho square equals to 0.093, which indicates a fairly poor model fit. What is more critical is that the estimated taste of travel time is a statistically significant and positive-sign value of 0.0168 (t-test 5.33), which given the experiment setting is quite counter-intuitive. This implies that some unexpected variables that 'distort' part of the dataset may probably exist. So far, it cannot be achieved to exactly pinpoint these variables, thus leaving the search of them as a venue for further research. Notwithstanding, nearly 60% of the whole dataset has been utilized to estimate the models. The estimation results based on these 113 individual participants can provide meaningful insights, though more cautions to extrapolate the estimation results are warranted.

4.3.1 Functional form of the distributions of the Mixed Logit models

As explained earlier, the independent random distributions $g(\beta_{TT})$, $q(\beta_{TC})$, $k(\beta_{TI})$, and $h(\beta_{car})$ in the Mixed Logit model, as shown in eq. (4.10), still need to be determined. That is to say choices have to be made regarding which particular statistical distributions should be selected for $g(\beta_{TT})$, $q(\beta_{TC})$, $k(\beta_{TI})$, and $h(\beta_{car})$. As for $h(\beta_{car})$, since there is no a priori constraint towards the sign of the associated taste (i.e., the intrinsic preference for the car option), the default choice of a normal distribution looks like a reasonable one to choose.

Intuitively and theoretically speaking, β_{TT}, β_{TC} and β_{TI} should take negative signs, as individuals should prefer travel alternatives with less travel time, less travel cost and fewer travel interchanges. Although there are reports in the literature suggesting the possible existence of positive signs for β_{TT} (e.g.,Mokhtarian 1998; Mokhtarian and Salomon 2001), the occurrence of a positive sign given the experiment setting in this research can be considered implausible. This is due to the fact that many elements that may lead to such a positive sign (e.g., multi-tasking during travel or the pleasure of driving a car) are far from salient in the experiment conditions as participants were strongly reminded of the fact that the purpose of travelling in the experiment setting was for commuting to their respective activity locations. Therefore, it is strongly expected that β_{TT}, β_{TC}, and β_{TI} will all take negative signs.

Given this strong expectation, normal distributions – whose domain includes (large) positive values – look less suitable for $g(\beta_{TT})$, $q(\beta_{TC})$, and $k(\beta_{TI})$. Although lognormal distributions – which can ensure negativity in the signs - can serve as a candidate, their comparatively large skewness (implying the presence of a fairly large probability mass associated with (very) large and negative parameter values) may diminish their usefulness. The triangular distribution – which can ensure both negativity in the signs, symmetry and a bounded domain– looks like a more promising candidate for the distributions of the three tastes. To ensure negativity in the signs for triangular distributions, however, one additional constraint is needed: the sum of the mean and the spread of the triangular distribution should also take a non-positive sign, so that the whole distribution lies within either a positive-sign or a negative-sign range (Hensher and Greene 2003).

Notwithstanding the intuitive preference for the triangular distribution, both the ML and the HML model have been estimated with all three types of distributions (their respective model fit results are shown in Table 4.1). In terms of fit, models with lognormal distributions have an inferior performance relative to those with triangular and normal distributions. In combination with the theoretical considerations presented above, the lognormal distribution appears to be unsuitable. As shown in Table 4.1, the triangular distributions and the normal distributions are on a par with each other in terms of model fit, with the latter slightly outperforming the former. This slight difference in model fit is hardly a guarantee that the normal distributions should be preferred to the triangular distributions, as suggested by Hess et al. (2005). Moreover, the estimation results of the normal distribution imply that 36.7% of β_{TC}, 36.6% of β_{TT}, and 2.8% of β_{TI} would take a positive sign in the context of Model 4, while 36.9% of β_{TC}, 34.6% of β_{TT}, and 11.0% of β_{TI} would take a positive sign in the context of Model 3. Hence, large proportions of the estimates would take a positive sign when using normal distributions. In comparison, *all* the estimates generated by using triangular distributions by definition take a negative sign. Therefore, in light of theoretical superiority and empirical non-inferiority to the normal distributions, the triangular distributions is adopted for $g(\beta_{TT})$, $q(\beta_{TC})$, and $k(\beta_{TI})$. Thus, the estimation results for Models 3 and 4 that are presented subsequently are attained by using triangular distributions for $g(\beta_{TT})$, $q(\beta_{TC})$, and $k(\beta_{TI})$.

Table 4.1: Distribution comparisons with respect to the ML and the HML model

	ML		HML	
	Final Log-likelihood	Adjusted Rho-square	Final Log-likelihood	Adjusted Rho-square
Triangular	-1108.436	0.271	-1088.864	0.282
Normal	-1101.010	0.275	-1086.175	0.283
Lognormal	-1289.310	0.151	-1282.757	0.155

Note: 3000 Halton draws have been made for each distribution.

4.3.2 The impacts of task complexity and time pressure

As shown in Table 4.2, in terms of both adjusted rho and likelihood ratio test, all the models perform better than the ones to their left (the more constraint models) with regards to model fit. This suggests that the model fit is gradually and significantly enhanced by increased model sophistication in both the systematic component of the utility function and its scale. By comparing the HL with the MNL model, and the HML with the ML model, it can be seen that adding the impacts of task complexity and engagement/time pressure modestly increases model performance, irrespective of whether unobserved taste heterogeneity is accounted for or not. However, if the MNL is compared with the ML model, or the HL with the HML model, the results suggest that allowing for random taste heterogeneity has a much bigger effect on model fit. This strong performance of Mixed Logit models compared to models that do not allow for random taste heterogeneity should not come as a surprise in light of previous results obtained in other studies (e.g., Hensher and Greene 2001; Hensher and Greene 2003; Hess et al. 2005; Sillano and Ortúzar 2005). What is more important in the context of this study, is that the estimation results strongly suggest that the impacts of task complexity and engagement/time pressure on traveller's choice do exist, and that accounting for those impacts in choice models improves model fit.

Table 4.2: The results of the model estimation

	MNL		**HL**		**ML**		**HML**	
adjusted rho-square	0.150		0.171		0.271		0.282	
Initial log-likelihood	-1528.12		-1528.12		-1528.12		-1528.12	
Final log-likelihood	-1295.780		-1260.534		-1108.436		-1088.864	
Likelihood ratio test	464.68		535.172		839.368		878.512	
Nr. of draws					3000		3000[16]	
Nr. of parameters	3		6		5		8	
Parameters	**Value**	**t-stat.**	**Value**	**t-stat.**	**Value**	**t-stat.**	**Value**	**t-stat.**
Mean (β_{TC})	-0.0415	-2.74	-0.0738	-2.66	-0.115	-4.75	-0.159	-3.88
Spread (β_{TC})[17]					(0.115)		(0.159)	
Mean (β_{TT})	-0.0125	-2.16	-0.00669	-0.63	-0.0476	-5.10	-0.0636	-3.67
Spread(β_{TT})					(0.476)		(0.0636)	
Mean (β_{TI})	-0.373	-14.41	-0.690	-3.86	-0.590	-9.72	-0.938	-5.20
Spread(β_{TI})					0.406	4.21	0.590	2.63
Mean(β_{Car})[18]	0		0		0		0	
Stt.Dev.(β_{Car})					1.70	6.07	2.92	4.12
λ_{DT} [19]			-0.0101	-6.05			-0.00745	-3.16
δ_T			2.03	3.95			2.56	4.44
θ_T			-3.36	-4.58			-3.96	-5.01
Mean VTTS (€/h)	18.07				34.32		33.27	
Median VTTS					24.83		23.98	
Fixed VTTS[20]					24.83		24.00	
Mean VVATI (min/inter.)	29.84				17.17		20.49	
Median VVATI					12.40		14.77	
Fixed VVATI					12.39		14.75	
Mean VTIS (euro/inter.)	8.99				7.25		8.17	
Median VTIS					5.25		5.91	
Fixed VTIS					5.13		5.90	

[16] 3000 draws are empirically sufficient for a stable estimation results as Appendix III shows.

[17] To ensure non-positivity of β_{TC} and β_{TT}, the spreads of the triangular distributions are restricted to be less than or equal the absolute values of their respective means. In this case, the estimation results suggest that these spreads equal the absolute values of their respective means. Therefore, these triangular distributions do not produce separate t-statistics for their spreads.

[18] The estimates of Mean (β_{Car}) in all the four models are of very small values with opposite signs and highly insignificant (t-values are -0.54, -0.15, 0.81, and 0.34 respectively). Moreover, in terms of adjusted rho and likelihood ratio test, the four models that set the value of Mean (β_{Car}) as zero are all non-inferior to the corresponding ones that do not. Therefore, this value is fixed at zero in the subsequent models.

[19] The estimation cannot converge when τ_{DT} (i.e. the quadratic term) is included in the model. Thus, it is suppressed.

[20] Fixed VTTS equals Mean (β_{TT}) / Mean (β_{TC}) *60.

From here on, those estimation results that relate to the impacts of task complexity and time pressure shall be first discussed, before moving to a discussion of taste-parameters and their distributions.

The estimates of the HL model on the scale are quite stable and comparable to the ones produced by the HML model. Figure 4.1 shows the respective plots between the value of the engagement/time pressure index and the scale produced by the estimates of the HL and the HML model, given a constant level of task complexity. From the figure, it can be seen that the estimates of both the HL and the HML produce a similar relation between the engagement/time pressure index and the scale. This relation, and the stability of the relevant estimates of δ_T and θ_T, is not only found in these two models but in all the other specifications of the systematic component of the utility function that have been tested during the course of this research and are not reported in this thesis.

Intermezzo: a caution related to modelling the impacts of task complexity and time pressure when not accounting for random taste heterogeneity

The t-statistic of mean (β_{TT}) is -0.63 in the HL model, which indicates its statistical insignificance. Consequently, the estimates of the value of travel time savings produced by the HL model are drastically different from those produced by the MNL, ML, and HML model. Therefore, empirical analyses based on the estimates produced by the HL model can be considered highly unreliable, which implies that – on the data used – embedding the impacts of task complexity and time pressure into the conventional MNL model (i.e., without taking into account random taste heterogeneity) has led to a bias in the estimates of the taste for travel time. As a result, the estimates from the HL model are not used in the subsequent analyses.

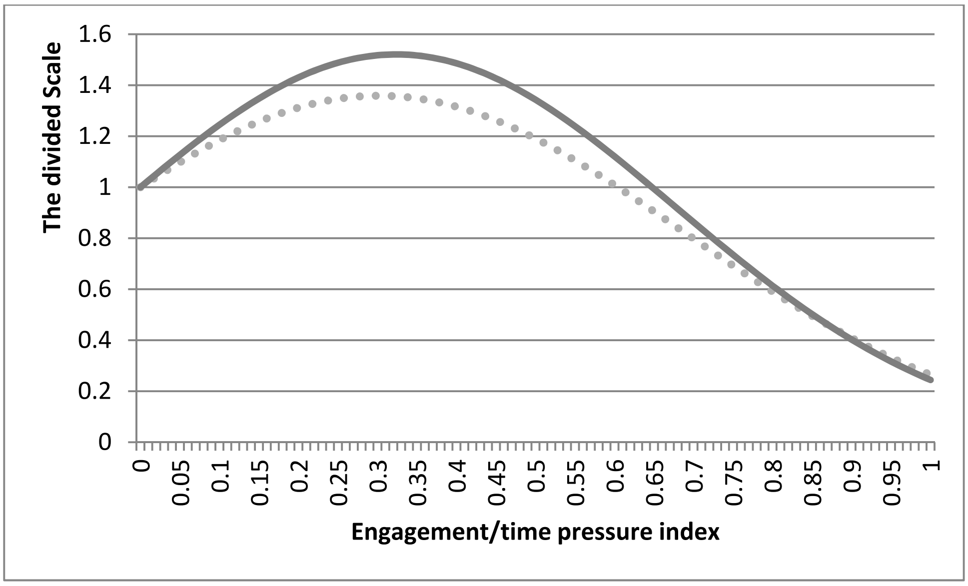


Figure 4.1: Plots of Engagement/time pressure index (DS_s) and the scale of the utility function divided by the task complexity-related specification ($\mu_s / e^{(D_s)}$) in Model 2 and 4

Notes:
The dotted line corresponds to Model 2, while the continued line corresponds to Model 4.

The impacts of task complexity

As shown in Table 4.2, the estimates of λ_{DT} in the HL and the HML model are all significant and all have taken negative signs. However, when τ_{DT} and its associated quadratic form of DT_s' are included in the model, the estimation cannot converge. Given this empirical result, it indicates that the first hypothesis concerning the relationship between μ_s and the task complexity measure is empirically the more plausible one to choose.

This suggests that the more complex the choice task is (as measured in terms of the decision time in the absence of time constraints), the smaller the scale of the systematic part of the utility function is, leading to more random choice.

The impact of time pressure

The values of δ_T and θ_T in the HML model support the hypothesis that the scale of the systematic component of the utility function first increases and then decreases as the engagement/time pressure index increases.

More specifically, δ_T and θ_T equal 2.56 and -3.96 respectively. Instead of a monotonic relationship, this suggests that given task complexity remains constant, the scale would first increase with the increase of the value of DS_s until it reaches its maximum value of 1.512 when DS_s approximates to 0.321 (when the first derivative function of DS_s equals to 0), and then the scale decreases until it reaches its minimum of 0.247 as the value of DS_s further increases towards 1. The minimum value of 0.247 suggests that when under high time pressure (as the engagement/time pressure index approximates 1) there is much more randomness in the choice outcome than is the case when little time pressure is felt. Importantly, however, it is easily seen that for values of DS_s close to 0, the scale of the utility is smaller than for intermediate values. This suggests that when very little time is used to reach a decision, this signals the absence of engagement with the choice task (more than that it signals the absence of time pressure). Therefore, it can be concluded that of the two hypotheses derived at the end of chapter 2, the second one is supported by our empirical outcomes:

- Travel choice outcomes tend to become more random when the choice is made at a moment when not much additional time is left for decision-making (suggesting the presence of time pressure);
- Very short decision times also lead to more random behaviour, although in that case there is no evidence of time pressure (interpreted in terms of a lack of engagement with the choice task among those who make a choice within a matter of a few seconds after being presented with the choice task).

The impact of the interaction effect

In eq. (4.7), apart from the separate impacts of task complexity and time pressure, there is a term describing the interaction effect between these two factors. However, in the course of the estimation efforts, the parameter ω for this interactive effect has been found statistically insignificant with p-values around 0.42. As a result, in the subsequent estimation efforts, ω was fixed at zero. In Chapter 2, it had been hypothesized that there may be an interaction effect between task complexity and engagement/time pressure. However, in the context of the data collected in this research and the models estimated, such an interactive effect has not been found. It may suggest that the impacts of task complexity and time pressure are independent effects. In other words, the impact of task complexity does not become greater when there is more time pressure, and vice versa.

4.3.3 The systematic component of the utility function

As indicated in Table 4.2, most of the estimates in the MNL, the ML, and the HML model for the total travel cost, the total travel time and the total number of interchanges are significant and all have taken a negative sign, as expected. The relatively large standard deviation of β_{Car} suggests that both strongly positive and strongly negative intrinsic preferences towards car travel exist in the data.

4.3.4 Value of travel time savings

For the last several decades, the notion of a value of travel time savings (VTTS) has been an important concept in transportation research. In the UK, for example, travel time savings have accounted for around 80% of the monetised benefits within cost-benefit analyses of major transport infrastructure projects (Mackie et al. 2001). Based on the results attained in this research, some implications can also be drawn towards the estimation of VTTS.

Mean, median, or fixed VTTS?

Given the fact that β_{TT} and β_{TC} are randomly distributed, the mean VTTS attained from either the ML or the HML model has to be an average ratio of simulated pairs of random draws from the triangular distributions of β_{TT} and that of β_{TC} respectively. As shown in the histograms of Figures 4.2 and 4.3[21], the distribution of the ratio of two triangularly distributed random numbers is by definition not a triangular one, and can be heavily skewed to one side. In this case, this distribution is positively skewed, suggesting that a large mass of simulated VTTSs is concentrated within a narrow range of values that are smaller than the mean VTTS. As shown in Table 4.2, the mean VTTSs of Model 3 and 4 are 34.32 and 33.27 €/h respectively, which are quite high values compared to the literature (Wardman 2012). This happens mainly because a random draw of β_{TC} close to the value of 0 can create outliers of extremely large VTTS, inflating the mean VTTS. Intuitively speaking, those outliers with large VTTS values are extremely unlikely to be found in real life. If this is the case, the question is if this mean VTTS is an appropriate VTTS to represent the sample population.

Perhaps the answer is negative. As Algers et al. (1998) suggest, there are two alternative VTTSs to replace the mean VTTS. The first one is to use the median VTTS rather than the average VTTS as a more representative VTTS of the sample population. The median is the numerical value separating the higher half of a probability distribution, from the lower half. (Brownstone and Small 2005) adopt medians to describe their travellers' VTTS and value of reliability. In Table 4.2, the median VTTSs of the ML and the HML model are 24.83 and 23.98 €/h, which are much smaller than their mean counterparts and more in line with VTTSs obtained in other studies. The second way is to simply treat mean (β_{TT}) and mean (β_{TC}) as

[21] One million random draws have been made for each distributions, the results of VTTS produced by which are stable.

the fixed estimates, by which the direct computation of Mean (β_{TT}) / Mean (β_{TC}) *60 as used in Model 1 would produce 24.83 and 24.00 €/h for Model 3 and 4 respectively. That is why in this research it is called the fixed VTTS. Interestingly, both the fixed VTTSs are almost equal to their median counterparts. The two ways proposed by Algers et al. (1998) empirically converge to produce the same results of VTTS. This may imply that using the median VTTS rather than the mean VTTS is more appropriate. Therefore, the median VTTSs are used for subsequent analysis instead of the mean VTTS.

VTTS comparisons

The (median) VTTSs derived from Model 1, 3, and 4 are 18.07, 24.83, and 23.98 €/h respectively. Results obtained in other studies (e.g., Hensher 2001; Hess et al. 2005; Shires and De Jong 2009; Hensher and Greene 2011) suggest that the VTTSs attained from the MNL, the ML, and the HML model remain in the comparable scale of a reasonable VTTS, though on the high side of the average VTTSs. There could be several factors contributing to these above-average VTTSs. First of all, as suggested by Wardman (2012), VTTS estimated from SP data is usually larger than that from RP data, which may be the case with this research. Secondly, the participants recruited in the experiment are mostly daily commuters who keep regular jobs and averagely have high education levels, who compared with the average in the population are more sensitive to travel time. As such, it is reasonable to attain the high VTTSs from these participants. Finally, the experiment setting is focused on daily commuting travels, which may also help produce the above-average VTTSs.

If the MNL and the ML model (or the HML) are compared, the difference in VTTS is quite noticeable, with 6.76 and 5.91 €/h respectively. This confirms the observation found in literature (e.g., Hensher 2001; Hess et al. 2005) that accounting for the taste heterogeneities in the systematic component of the utility function may heavily impact the estimates of VTTS.

If the ML and the HML model are compared with each other, the difference in VTTS is marginal, with 0.85 €/h. This shows that accounting for the impacts of task complexity and engagement/time pressure would have only modest impacts on the estimation of VTTS, especially in contrast to the impact of accounting for taste heterogeneity in the systematic component of the utility function.

4.3.5 Value of avoiding a travel interchange (in both time and cost)

The Value of avoiding a travel interchange (VATI) is particularly important for transport policies that involve public transportation and/or multimodal travel. It consists of two elements, namely VATI (min) for value of time and VATI (euro) for monetary value. Any transport policy that promotes multimodal travel has to deal with the fact that even if the overall travel time of a multimodal travel alternative is very short, travellers may still not choose the alternative because of its interchanges. In addition, the value of VATI (euro) can have a significant impact on the outcomes of Cost-Benefit Analyses of transport policies and projects.

Mean, median, or fixed VATI?

Similar to VTTS, given the fact that β_{TT} and β_{TI} are randomly distributed, the mean VATI attained from either the ML or the HML model has to be an average ratio of simulated pairs of two random draws from the two triangular distributions respectively. As shown in the histogram of Figure 4.4 and 4.5, and Figure 4.6 and 4.7, this distribution is positively skewed, suggesting a large mass of individually simulated VATIs concentrated within a narrow range of values that are smaller than the mean VATI. As shown in Table 4.2, the mean VATIs (min) of the ML and the HML model are 17.17 and 20.49 minutes respectively, which are much higher than their median counterparts of 12.40 and 14.77 respectively. Similarly, the mean VATIs (euro) of the ML and the HML model are 7.25 and 8.17 euros respectively, which are higher than their median counterparts of 5.25 and 5.19 euros respectively. Again, this happens mainly because a random draw of β_{IT} close to the value of 0 can create outlier of extremely large VATI, inflating the mean VATI. Intuitively speaking, those outliers with large VATI values are extremely unlikely to be found in real life. Comparable to the suggestion concerning VTTS, using the median VATI may also be more appropriate than using the mean VATI.

VATI comparisons

VATI generated by the MNL, the ML and the HML model are 29.84, 12.40, and 14.77 minutes per interchange respectively. In the meanwhile, VATI generated by the MNL, the ML and the HML model are 8.99, 5.25, and 5.91 euro per interchange respectively. The value produced by the MNL model is much larger than the other ones, and also larger than the value of 18.25 (min) found by Hensher et al. (2013). In contrast, the VATIs of the ML and the HML model come much closer to 18.25 (min). Therefore, it is reasonable to assume that the VATIs produced by the ML and the HML model are more credible than the one generated by Model 1. This suggests that accounting for unobserved taste heterogeneity may heavily influence the estimates of VATI.

If the ML and the HML model are compared with each other, there is a noticeable difference of 2.37 min/inter. and 0.66 euro/inter. of VATI. This indicates that accounting for the impacts of task complexity and engagement/time pressure modestly affects the estimate of VATI.

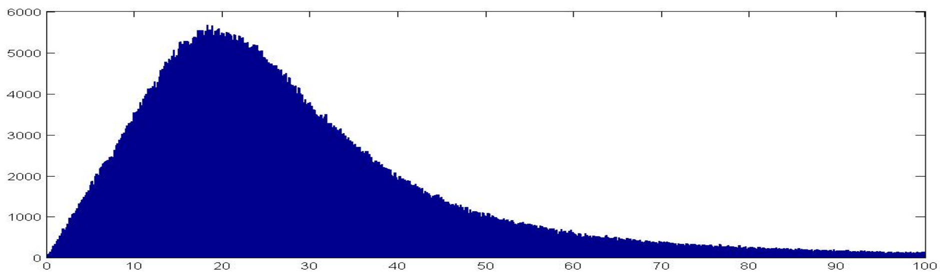


Figure 4.2: Simulated histogram of value of travel time savings in the ML model

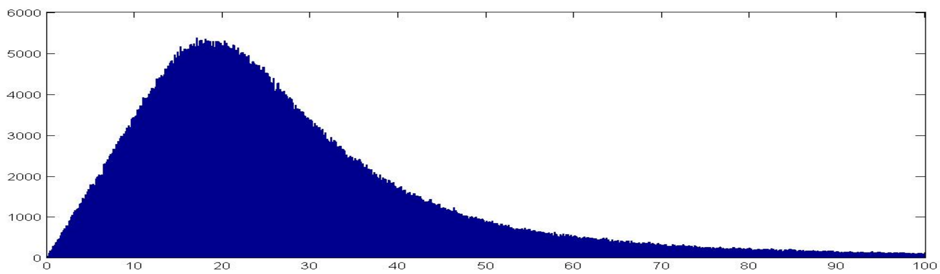


Figure 4.3: Simulated histogram of value of travel time savings in the HML model

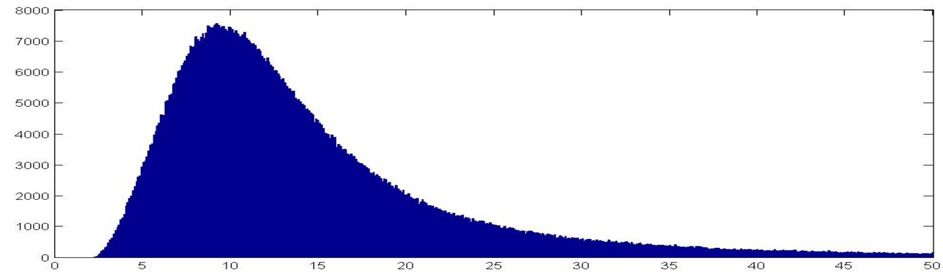


Figure 4.4: Simulated histogram of value of avoiding a travel interchange (min) in the ML model

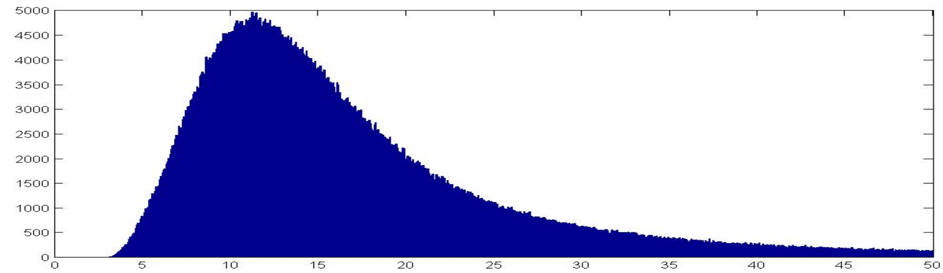


Figure 4.5: Simulated histogram of value of avoiding a travel interchange (min) in the HML model

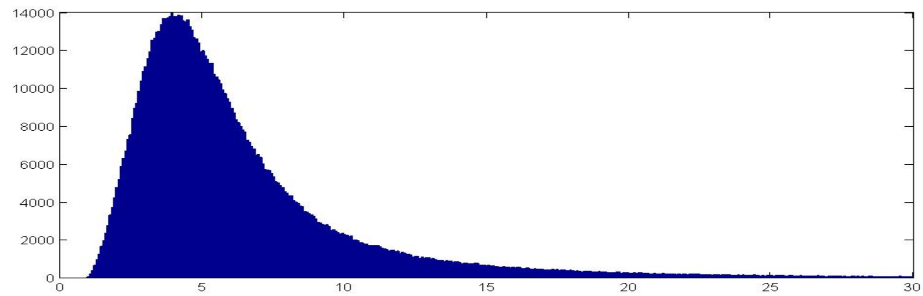


Figure 4.6: Simulated histogram of value of avoiding a travel interchange (euro) in the ML model

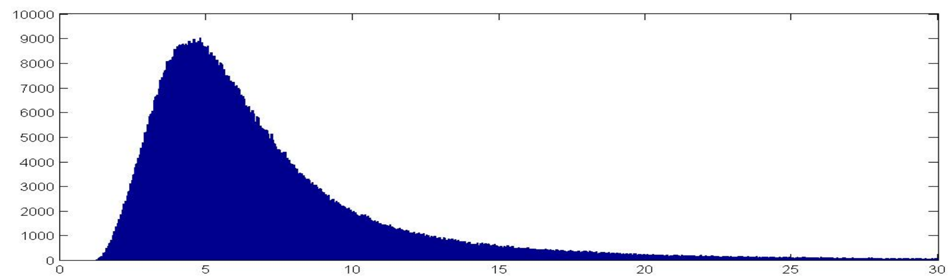


Figure 4.7: Simulated histogram of value of avoiding a travel interchange (euro) in the HML model

4.3.6 Choice probability predictions

Beyond the inspection of estimation results, an important question relates to the potential differences in choice probability predictions implied by the estimated Heteroscedastic models (which capture task complexity and time pressure) and their homoscedastic counterparts (which do not). As will be seen in the following illustration, this difference – and hence the bias resulting from not accommodating for task complexity and time pressure – can be substantial. For the sake of manifesting this difference, a choice task was selected that was considered as relatively complex by participants, in the sense that the average decision time (in the condition where no time constraints were present) was higher than those of other tasks. Recall that the task complexity indicator is individually specific, and hence even though the decision time of the selected choice task is relatively high, there is still much heterogeneity in perceived complexity among the participants. As shown in Table 4.3, the selected task involved a choice between four alternatives, each containing a relatively large number of travel interchanges.

Table 4.3: Choice task used for illustration

Alternative	**Travel cost (euro)**	**Travel time (min)**	**Nr. of travel interchanges**	**Car as the main travel mode**
1	10	118	7	No
2	15	117	9	No
3	12	110	8	No
4	19	121	5	Yes

For this choice task, choice probabilities for each of the four alternatives using the Heteroscedastic Mixed Logit[22] model were predicted and so were its homoscedastic counterpart. Four (two x two) conditions were distinguished: first, low task complexity for which the average decision time of 87 seconds was taken, and high task complexity for which the highest recorded decision time was taken for this task, being 227 seconds. Second, time pressure, which was varied in a low value, for which the value of the engagement/time pressure index that corresponds to the highest scale was taken – see Figure 4.5, and a relatively high value for which the value of 1 for the engagement/time pressure index was taken. Table 4.4 reports the simulation results. The table reports choice probabilities for the four alternatives as implied by the Homoscedastic Mixed Logit model, as well as by the Heteroscedastic Mixed Logit model (under the four different conditions); in addition, the choice probability difference between the most and least popular alternatives is reported. A first result is that for the condition of both low task complexity and low time pressure levels, the Heteroscedastic Mixed Logit model predicts more profound differences in choice probabilities than its homoscedastic counterpart, However, when time pressure increases to its maximum level (i.e., right before the time runs out), and keeping task complexity fixed, the Heteroscedastic Mixed Logit model predicts much less profound differences in choice probabilities than its homoscedastic counterpart. For respondents that consider the task to be highly complex (the two columns on the right hand side), the Heteroscedastic Mixed Logit model predicts less profound differences in choice probabilities than its homoscedastic

[22] Given the partly unreliable results obtained for the Heteroscedastic Logit model (see discussion further above) we choose to focus on the Mixed (Heteroscedastic) Logit models. Each choice probability was simulated using 1,000,000 multidimensional Halton draws.

counterpart, and especially so when much time pressure is present. In this latter situation, i.e., high levels of task complexity and time pressure, the difference between the Homo- and Heteroscedastic models is particularly striking: while the former model predicts that the most popular alternative is more than seven times as popular as the least popular alternative, the latter model predicts that the two are almost equally popular.

Table 4.4: Illustration of the modelled impact of task complexity and time pressure on choice probabilities

	Mixed Logit (Homoscedastic)	**Heteroscedastic Mixed Logit**			
		Low task complexity		*High task complexity*	
		Low time pressure	*High time pressure*	*Low time pressure*	*High time pressure*
P(alt1)	0.23	0.22	0.25	0.25	0.25
P(alt2)	0.06	0.05	0.19	0.14	0.23
P(alt3)	0.30	0.27	0.26	0.27	0.26
P(alt4)	0.41	0.47	0.30	0.35	0.27
P(alt4) – P(alt2)	0.35	0.42	0.11	0.21	0.04

These results are of course fully in line with expectations (and with theory) in the sense that higher levels of task complexity and time pressure were expected to lead to more random choice behaviour. This dependency of choice behaviour on task complexity and time pressure conditions is captured by the Heteroscedastic model, but ignored by its homoscedastic counterpart. To the extent that the Heteroscedastic model fits the data statistically better than its homoscedastic counterpart (as is the case on the data in this research), these results suggest that failing to incorporate task complexity and time pressure in activity-travel choice models may lead to non-trivial biases in forecasting.

4.4 Conclusions

This chapter serves the purpose of operationalizing the generic models proposed in chapter 2, and presenting and interpreting estimation results. To achieve this, four models with different levels of sophistications and their estimation results are presented.

The main results are as follows: firstly, high levels of time pressure and task complexity lead to a smaller scale of utility and hence to more random choice behaviour. Secondly, very short decision times also lead to more random behaviour, although in that case there is no evidence of time pressure. This phenomenon is interpreted in terms of a lack of engagement with the choice task among those who make a choice within a matter of a few seconds after being presented with the choice task. Thirdly, contrary to expectations, no empirical evidence is found for an interaction effect between task complexity and time pressure. In other words, the impact of task complexity on choice behaviour in the context of the collected data does not become more pronounced when there is a high level of time pressure (and neither vice versa). Fourthly, on the data, heteroscedastic models that incorporate the impacts of time pressure and task complexity achieve significantly higher levels of model fit than corresponding homoscedastic models that do not accommodate these effects. Fifthly, and more importantly than these differences in model fit, it is found that choice probability predictions differ substantially between estimated homo- and heteroscedastic models: the former predict much more pronounced differences in choice probabilities between alternatives than the latter, when there are relatively high levels of task complexity and time pressure. In other words, under these conditions, heteroscedastic models predict a much more even distribution of choice probabilities across choice alternatives, than their homoscedastic counterparts.

Finally, the results also show that accounting for the impacts of task complexity and engagement/time pressure may affect the estimation of the value of travel time savings and the value of avoiding interchanges, although not as much as the accommodation of random taste heterogeneity does.

5. Main conclusions and implications for policy and research

5.1 Introduction

This research aims to examine the impacts of task complexity and time pressure on travellers' activity-travel choices. These two aspects, as argued in Chapter 1, may have impacts on travellers' choices particularly when network synchronisation policies are implemented. To understand these impacts, three primary and one secondary research goals were conceived in Chapter 1. The following Chapter 2, 3, and 4 have respectively addressed the three primary goals in detail. This chapter first presents the main conclusions concerning the primary goals, and then draw implications for policy and research by utilizing the findings attained in the previous chapters. In doing so, the secondary goal of the research is addressed. Last but not least, the avenue for further research is also presented in the end.

5.2 Model developing (Goal 1)

To develop coherent discrete choice models that can accommodate the impacts of both task complexity and time pressure on travellers' choices simultaneously

A Heteroscedastic model that can simultaneously accommodate the impacts of both task complexity and time pressure on travellers' choices is developed in Chapter 2. As theoretically argued in Chapter 2 and empirically tested in Chapter 4 by using the Stated Preference choice data collected in Chapter 3, this Heteroscedastic model is tractable, coherent, structurally simple, and easily estimable.

It has been acknowledged by many researchers that the assumed underlying decision process of multi-attribute Utility Maximization would require intensive efforts from a decision-maker. When a choice task assigned to the decision maker is quite complex and when such a task has to be finished under time pressure, it can be argued that the decision-maker would become less able to select the highest utility alternative from the set.

The approach taken in this research to model the impacts of task complexity and time pressure on travellers' choices is to allow for the variance of the random component in the utility function to be a function of task complexity and time pressure. This is equivalent to the notion that the scale of the utility is a function of task complexity and time pressure, as the variance of the random component is confounded with the scale of the utility. In light of the fact that each choice task may be associated with a different level of task complexity and time pressure, the scale is no longer identical for all the choice tasks. This gives rise to a more flexible RUM-based model, called Heteroscedastic Logit model.

As far as measuring task complexity and time pressure are concerned, Chapter 2 reviews several approaches that can be implemented. For task complexity, there are two types of measurement, indirect assessment of choice task and a direct indicator. The former may include the number of alternatives, the number of attributes, the similarities between alternatives, and entropy measure, etc. This research suggests the direct indicator that uses decision time as a measure of task complexity is the better choice for the choice models. Compared with the indirect measures as introduced beforehand, this direct measure of task complexity is intuitive, direct and highly individualized. This is mainly because even for a same choice task two distinctive decision-makers may assess its complexity differently, probably resulting in a difference in decision time. It may imply that this direct measure may be a more accurate representation of task complexity.

As for time pressure, this research recommends using a so-called engagement/time pressure index, rather than adopting the conventional measure of varied fixed decision time budget, since the latter is in comparison to the former not only not individualized (i.e. the time pressure felt by one decision-maker may not be transferrable to another with a same fixed decision time budget), but too blunt as well since time pressure changes gradually.

5.3 Data collection (Goal 2)

To collect relevant data concerning the impacts of task complexity and time pressure on travellers' daily activity-travel choices in the context of highly synchronised networks

Given the targeted context of daily activity travel, the data requirement of the models formulated in Chapter 2 has clearly indicated that besides conventional attributes like travel time and travel cost, three additional attributes, namely the amount of travel alternatives in a given choice set, the number of daily activities in an assigned activity program, and the time pressure level in a choice task, need to be properly varied in the data for model estimation. As argued in Chapter 1, a travel-simulator approach is the most suitable method for observing those choices.

Compared with the conventional SP methods, travel simulators usually provide illustrative and interactive user interfaces, stimulating respondents to more actively involve themselves in the experiment and allowing for easy interactions between respondents and experimental conditions. They are invariably designed to help increase the validity of SP data. Inspired by these efforts, a 2D computer-based activity travel simulator (ATS) is developed in Chapter 2. While typically the previous mentioned travel simulators consider only single trips, ATS deals with complete daily activity programs, hence with all trips made for a whole day.

In the simulator, participants make choices with respect to the execution of complete activity programs. Task complexity is varied by varying across the choice sets both the number of activities included in the activity program and the number of activity program executions to choose from. In addition, choices are observed for a choice situation without time pressure and a situation with time pressure. In total, 194 persons participated in the travel simulator. The majority of the participants have a paid job and 85 % of those with paid jobs commute to work four days or more per week.

Two approaches have been taken to validate the ATS. Firstly, as prerequisites to induce real behaviours from the experiment participants, they must adequately understand the functionality of ATS and the process of the experiment, and preferably enjoy the experiment, which is an indication for their engagement in the experiment. The self-reported feedbacks from the participants after they complete the experiment are useful to demonstrate whether these prerequisites are indeed met or not. The results from the feedbacks have shown that the majority of the participants felt that it was easy to understand the travel simulator, easy to remain focused during the experiment, the information shown in the abstract map was illustrative, the daily activity programs presented in the experiment look realistic to them, and it was enjoyable to participate in the experiment. Secondly, Chorus et al. (2007) suggest that using a less strict validation a travel simulator may be regarded as a valid way to collect data when it is established that observed behaviours made within the simulator resemble intuitions concerning what kind of behaviours would be made in real life. The analyses of the data generated from the experiment show that the formulated intuitions have been confirmed. These intuitions include the ones concerning choice probability (a. the higher the overall travel time, the lower the choice probability; b. the higher the overall travel cost, the lower the choice probability; c. the larger the total number of travel interchanges, the lower the choice probability) and the ones concerning task complexity (a. the larger the number of travel alternatives in the choice set, the more decision time used; b. the larger the number of activities in the activity program, the more decision time used). Therefore, based on the validity tests conducted for the experiment, it is reasonable to think that ATS is a valid way to collect the required SP data.

5.4 Traveller behaviour in synchronized networks (Goal 3)

To gain insight in traveller behaviour in the context of highly synchronised networks, with an emphasis on capturing the possible impacts of task complexity and time pressure

To reach Goal 3 it is required that the theoretical models constructed in reaching Goal 1 should be estimated using the data collected when reaching Goal 2. Further analyses concerning the traveller behaviour in synchronized networks can then be made based on the estimation results.

Model estimation

Irrespective of the assumptions regarding scale / error variance, the systematic components of the utility functions of the RUM-based models can share the same functional form. As such, a logical first step in specifying the discrete choice-based models is to specify the functional form of the systematic component of the utility function, which is the same for the MNL model and the HL model; and the second step is to specify the functional form of the model's scale, which differs between model types (MNL versus HL). Finally, choice probabilities for both model specifications are formulated. By following these steps, four functional RUM-based models are specified for further analysis, including a MNL model that only includes the total travel cost, the total travel time, the total number of travel interchanges, and the car preference as the attributes in the systematic component of the utility function, a Heteroscedastic MNL model (HL), which is based on the MNL model with the additional specification on the scale of the systematic component of the utility function, a ML model, which is based on the MNL model with the tastes of the four attributes randomly drawn from separate distributions, and a Heteroscedastic ML model (HML), which is based on the HMNL model with the four attributes randomly drawn from separate distributions.

The estimation results suggest that all the four models can be estimated. In particular, the HML model, which can accommodate the impacts of both task complexity and time pressure on travellers' choices simultaneously, can not only be estimated but produce statistically significant and theoretically interpretable results as well.

The selection of the distributions

In addition to the analysis of the model estimates, it has been discussed in Chapter 4 that the applications of different random distributions in the Mixed Logit models. Although a normal distribution is the most popular one to choose for a random distribution, many literature advocates the idea that given particular circumstances surrounding the targeted estimates, other distributions may be given priority above the normal one. This is the similar case in my research. I suggest that it should be preferred to unbounded ones like normal distribution when the assumptions on the signs of the tastes are strongly held. This is well supported by the fact that the triangular distribution holds theoretical superiority and empirical non-inferiority above the normal one in the research.

However, the adoption of triangular distributions in ML or HML model, compared with normal distributions, has brought a particular issue concerning the derivations of the derived values, i.e., the value of travel time savings (VTTS) and the value of avoiding a travel interchange (VATI). Take VTTS for an example. Given the fact that β_{TT} and β_{TC} are randomly distributed, the mean VTTS attained from either the ML or the HML model has to be an average ratio of simulated pairs of random draws from the triangular distributions of β_{TT} and that of β_{TC} respectively. Interestingly, the distribution of the ratio of two triangularly distributed random numbers is by definition not a triangular one, and can be heavily skewed to one side. Then, a question arises concerning which of three derived values, namely the mean VTTS, the median VTTS, and the fixed VTTS should be chosen as the representative VTTS. Given the empirical evidence so far, I would argue that using the median or fixed values may be a better choice for representativeness than using the mean ones. However, I feel the evidence to support my argument may not be sufficient enough, thus making this topic an interesting avenue for further research.

The impacts of task complexity and time pressure

The insights this thesis provides into traveller behaviour in the context of highly synchronised networks mainly relate to the impacts of task complexity and time pressure on travellers' choices.

It is clearly demonstrated that the impacts of task complexity and time pressure on traveller's choice do exist. More specifically, the estimate associated with task complexity is statistically significant and takes a negative sign. This suggests that the more complex the choice task is (as measured in terms of the decision time with **no** time constraint), the smaller the scale of the systematic component of the utility function is, leading to more random choice. This result is in line with the relevant first hypothesis developed in Chapter 2.

The estimates associated with time pressure conform to the hypothesis that the scale of the systematic component of the utility function first increases and then decreases as the engagement/time pressure index increases, as depicted in Figure 6.1. More specifically, the two estimates, δ_T and θ_T equal to 2.56 and -3.96 respectively. Instead of a monotonic relationship, this suggests that given task complexity remains constant, the scale would first increase with the increase of the value of the engagement/time pressure index until it reaches its maximum value of 1.512 when the engagement/time pressure index approximates to 0.321 (32.1% of the decision time budget), and then the scale decreases until it reaches its minimum of 0.247 as the value of the engagement/time pressure index further increases towards 1. The minimum value suggests that when under extremely high time pressure (as the engagement/time pressure index approximates 1) there is much more randomness in the choice outcome than is the case when little time pressure is felt. In other words, the distribution of the choice outcome would tend to approximate towards a totally random choice when all the choice alternatives have the same choice probability.

Importantly, however, it is easily seen that for values of the engagement/time pressure index close to 0, the scale of the utility is smaller than that for intermediate values of the engagement/time pressure index. This suggests that when very little time is used to reach a decision, it may indicate the absence of engagement into the choice task.

To conclude, 1) travellers' choices tend to become more random when the choice is made at a moment when not much additional time is left for decision-making (suggesting the presence of time pressure); 2) Very short decision times also lead to more random behaviour, although in that case there is no evidence of time pressure (interpreted in terms of a lack of engagement with the choice task among those who make a choice within a matter of a few seconds after being presented with the choice task).

In Chapter 2, it had been hypothesized that there may be an interaction effect between task complexity and engagement/time pressure. However, in the context of the data collected in this research and the models estimated, such an interaction effect was not found to be significant (p-values around 0.42).

On the data, Heteroscedastic models that incorporate the impacts of time pressure and task complexity achieve higher levels of model fit than corresponding Homoscedastic models that do not accommodate these effects.

More importantly than these differences in model fit, it is found that choice probability predictions differ substantially between estimated Homo- and Heteroscedastic models: the former predict much more pronounced differences in choice probabilities between alternatives than the latter, when there are relatively high levels of task complexity and time pressure. In other words, under these conditions, Heteroscedastic models predict a much more even distribution of choice probabilities across choice alternatives, than their Homoscedastic counterparts.

5.5 Implications for policy and research (the secondary goal)

To utilize the gained insights to provide the relevant societal implications, in particular with respect to policies involving highly synchronised networks

5.5.1 Estimating VTTS and VATI

Incorporating task complexity and time pressure into the model have an impact on the value of travel time savings and the value of avoiding a travel interchange (VATI) implied by the model, though the specific pattern of the impact cannot be determined.

People generally prefer shorter travel times over longer. Many transport policies (such as new infrastructure or road pricing) aim to reduce travel times. Travel time savings therefore are a critical component of the evaluation of transport policy options. Synchronisation policies will probably first affect the value of travel time savings (VTTS) and secondly the value of avoiding a travel interchanges (VATI). This will be discussed in more detail.

First public transport policies will be discussed. In these policies the general transport costs of a trip depend on the value of the in vehicle time, walk time, waiting time and service headway, etc. (Wardman 2004). If policies aim to reduce the travel times, or more generally: the overall resistance of a transport trip (often referred to as the generalized transport costs, including time, costs, effort, perceived safety etc.) of public transport trips it is very important to have reliable estimates of all these components of the trip.

The VTTS is generally the single most important parameters for the estimation of generalized transport costs. The evaluation of policies to improve accessibility / reduce travel times are affected by the VTTS and VATI. Whereas the VTTS is relevant for any policy that has an impact on travel times, the VATI is particularly important for the evaluation of transport policies that involve transit, especially multimodal travel that is partly transit based. Any transport policy affecting multimodal travel would have to deal with the fact that in addition to the overall travel time of the trip, also the valuation of interchanges matter, and consequently the VATI is relevant.

Table 5.1: The results of the model estimation

	ML	**HML**
Mean VTTS (€/h)	34.32	33.27
Median VTTS	24.83	23.98
Fixed VTTS	24.83	24.00
Mean VATI (min/inter.)	17.17	20.49
Median VATI	12.40	14.77
Fixed VATI	12.39	14.75
Mean VATI (euro/inter.)	7.25	8.17
Median VATI	5.25	5.91
Fixed VATI	5.13	5.90

This research allows us to show that the derived value of these two parameters, namely the value of travel time savings (VTTS) and the value of avoiding a travel interchange (VATI) can be influenced by incorporating task complexity and time pressure into the model. Table 5.1 is an extraction from the results attained in Chapter 4. In comparison between the ML model that excludes the impacts of task complexity and engagement/time pressure and the HML model that includes, their respective VTTSs and VATIs appear to be different.

In the literature, there are many efforts to investigate and improve the reliable and accurate estimations of the VTTS and VATI (e.g. Mackie et al. 2001; Hess et al. 2005; Hensher et al. 2013). This research shows that incorporating two additional factors into the model may also impact the values of the two parameters implied. In Chapter 2, the Heteroscedastic models that embed the impacts of choice task complexity and time pressure on travel choice is presented and in Chapter 4, these models are estimated. In the analysis section of the latter chapter, the inclusion and the exclusion of choice task complexity and time pressure make noticeable differences in both parameters, as shown in Table 5.1. Although whether these differences are statistically significant or not is yet to be tested, it is plausible to say that they are at least significant in terms of policy sensitivity. Although a clear pattern has not been found in the impact of incorporating choice task complexity and time pressure into the model on VTTS and VATI implied, at least it is clear at the moment that this impact does exist.

5.5.2 Choice probability predictions

By ignoring in choice models the effects of task complexity and time pressure on activity-travel behaviour, policy makers are likely to overestimate traveller sensitivity to changes in the attributes of existing travel options or in the availability of travel options, when choices are made under conditions of high-level task complexity and time pressure.

The analysis in Sub-section 4.3.6 in Chapter 4 suggests that capturing the impacts of time pressure and task complexity in discrete choice models of activity-travel behaviour is also important from a practical or policy viewpoint; this holds even more in light of the fact that in real life, many activity-travel choices are made under conditions of considerable task complexity and time pressure. In other words, the Heteroscedastic models suggest that under these conditions, choice behaviour is governed to a large extent by randomness, implying a limited sensitivity to changes in the availability and characteristics of travel options. This should warrant attentions from policy makers that traveller sensitivity are likely to be overestimated in the attributes of existing travel options or in the availability of travel options, when these choices are made under conditions of high-level task complexity and time pressure.

5.5.3 Travel information service providers

Several travel information systems are available or in the design stage. Travellers can benefit from these systems. In addition they have the potential to change travel behaviour in such ways that they increase the efficiency of the transport system. Chorus et al. (2006) reviewed the literature concerning the usage of Travel Information Services, underpinning the importance to carry out relevant research aimed at designing travel information service as well as policy initiatives that aim at optimal use and effects of such services. Researchers have studied both the level of use of such travel information services as well as the impact of information provided on travel behaviour.

Though not directly related to the main findings of the research, some implications can be derived with respect to the second topic. It is advocated (1) that the current single-trip-based travel information service can be upgraded to at least multiple-trip-based travel information services, (2) that map-based information provision has an impact on travel, and (3) that the supply of travel information load to travellers should be properly limited.

Although the experiment explained in Chapter 3 is essentially concerned with traveller's activity-travel choices under the impacts of task complexity and time pressure, the setting of the experiment can actually be interpreted as a type of travel information services that provide travel information for a whole workday. The experiment has assumed a travel context in which a traveller, who has just moved to a new place, needs to finish some activities in a weekday. In order to carry out these activities at different locations, the traveller must schedule an activity program (including the locations of these activities and the order), starting and ending at home. The experiment provides the traveller with the travel alternatives (i.e. the choice set) that the traveller can choose from to finish the scheduled activity program. Therefore the experiment can be interpreted as a travel information service. The three implications of the findings as presented above will be discussed next.

Upgrading travel information service

Current state-of-the-practice travel information services provide trip-based travel information. This research advocates it is promising to develop a new type of upgraded travel information service that is multiple-trip-based and that arranges travel for a whole day.

Current travel information services only provide travellers information about options to travel between origin and destination. Travel services have different levels of sophistication in terms of the inclusion of personal preferences (e.g., a traveller's preferred travel mode, departure time, etc.). Two typical leading examples of such travel information service providers are Google Maps and (in the Netherlands) OV9292 (public transport information).

Notwithstanding the huge benefits provided by these travel information service providers, traveller's information demand may easily go beyond that. In many occasions, travellers may have to plan activities and related travel for the whole day. Chapter 3 shows that we included such choices in the experiment. In the real world, in such occasions, travellers have to derive travel options for each possible trip separately, and next schedule their activity-travel program. This is because there does not yet exist an upgraded travel information service that can assist them to schedule this program. In Chapter 3 the feedbacks attained from the experiment participants show that the majority of the participants can recognize the importance of scheduling activity-travel programs, and understand the travel simulator that provides them with the travel alternatives. Although these are no direct evidences indicating a large demand for such upgraded travel information services, it can be reasonably considered as an early sign of a potential demand for them. Thus, this research would advocate more attention to be paid to such services from both travel information service providers and academia.

Improving travel information format

Many efforts in the literature mainly focus on the contents of travel information service. More specifically, they intend to investigate the effects of the contents of travel information on travellers' choices. Nevertheless, there is an important element that has been generally ignored. There is virtually no research in transportation that looks into the effects of the format of the travel information on travellers' choices. This research however advocates that the format of the travel information may also be important and can influence choices.

This format essentially deals with how the travel information content is visually presented to travellers. As pointed out by Waygood et al. (2012), this format may have non-negligible effects on how effective a traveller would be able to process the travel information received. For example, a piece of a multimodal travel information can be either narrated in the form of abstract words / figures (as OV9292 does in Figure 5.1), visualized in a reality-augmented map, or a combination of the two (as Google Maps does in Figure 5.2). The intuition may be that the latter is preferred to the former for most travellers, which may be partially supported by many researches in fields like education and human learning (e.g. Najjar 1996; Mayer and Moreno 2002). In the experiment shown in Chapter 3 the travel information can be both animatedly visualized on the abstract map in the middle of the experiment simulator interface and concisely narrated in the bottom panel of the interface, as shown in Figure 5.3. With hindsight, it is regrettable that the experiment participants were not asked specifically of the questions concerning which way of the two information formats they preferred. However, since the majority of the participants report that they feel the information presented in the abstract map is very illustrative, it may imply that the majority of them think that the presented information format can be quite useful. Given this feedback, it may add supportive evidence to the abovementioned intuition. As such, it can be argued that the information format of Google Maps with the additional reality-augmented map can be effective in terms of conveying the travel information to travellers. Not only travel information service providers are recommended to explore this topic, but researchers are recommended to do more related research as well, because the findings are only preliminary, remaining largely as assumptions.

An important question is: do travellers adequately deal with all the information provided for a full travel-activity program? The experiment simulator of this research is based on the upgraded multiple-trip-based travel information service mentioned in the previous subsection. Therefore, in terms of the volume of travel information, it naturally exceeds that of trip-based travel information services like OV9292 and Google Maps. Comparatively, it is foreseeable that if OV9292 upgrades its travel information service to the multiple-trip level, the amount of narrative information presented to the traveller by using the same information format would be much more than that of the current OV9292 service, which would probably hinder travellers from effectively processing the received information. Although Google Maps has a reality-augmented map to facilitate travellers, the specific travel information (e.g., travel time and travel cost for each trip) are still presented in the narrative way. If Google Maps also upgrades its travel information service to the multiple-trip-based level, it is also foreseeable that travellers may find it difficult to effectively process the received information. However, the majority of the experiment participants report that they do not only find the travel information presented in the experiment illustrative but also that they understand the experiment simulator very well. This may imply the information format adopted in the experiment could be a feasible direction to present future multiple-trip-based travel information. Because the experiment simulator of this research is not designed as a full-fledged travel information system, it needs to be redesigned and tested before any real world services can be based on it.

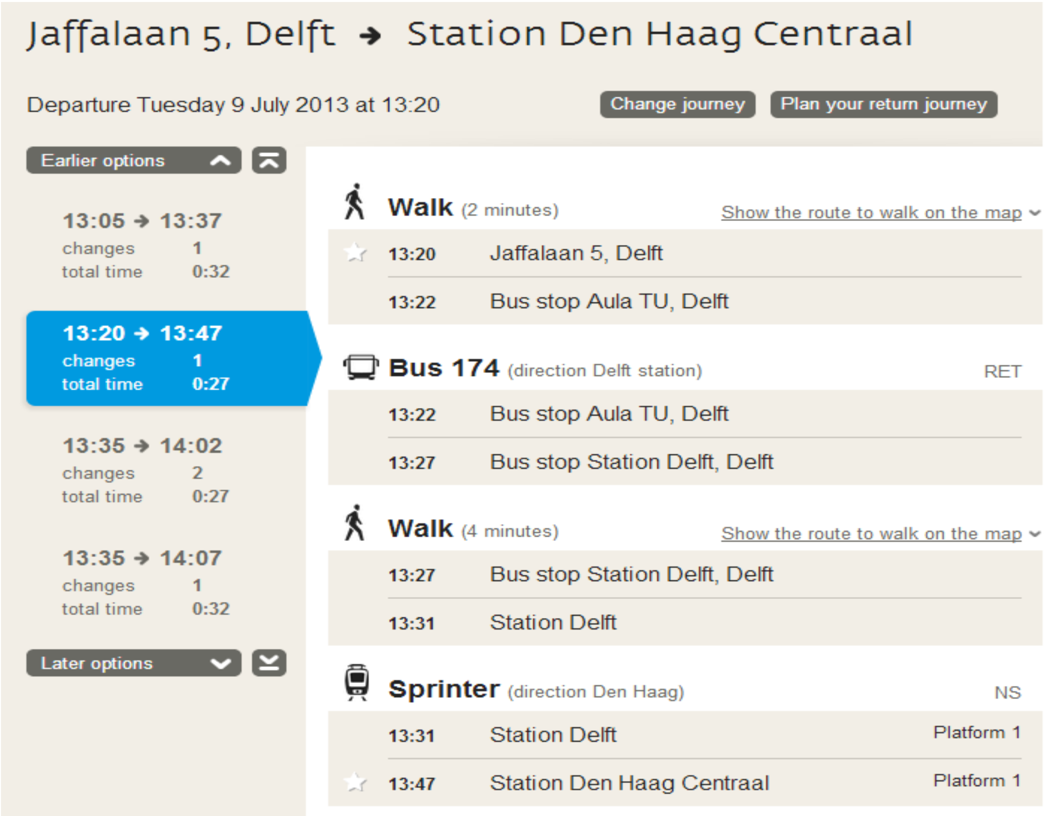


Figure 5.1: An example of the interface of OV9292 travel information service

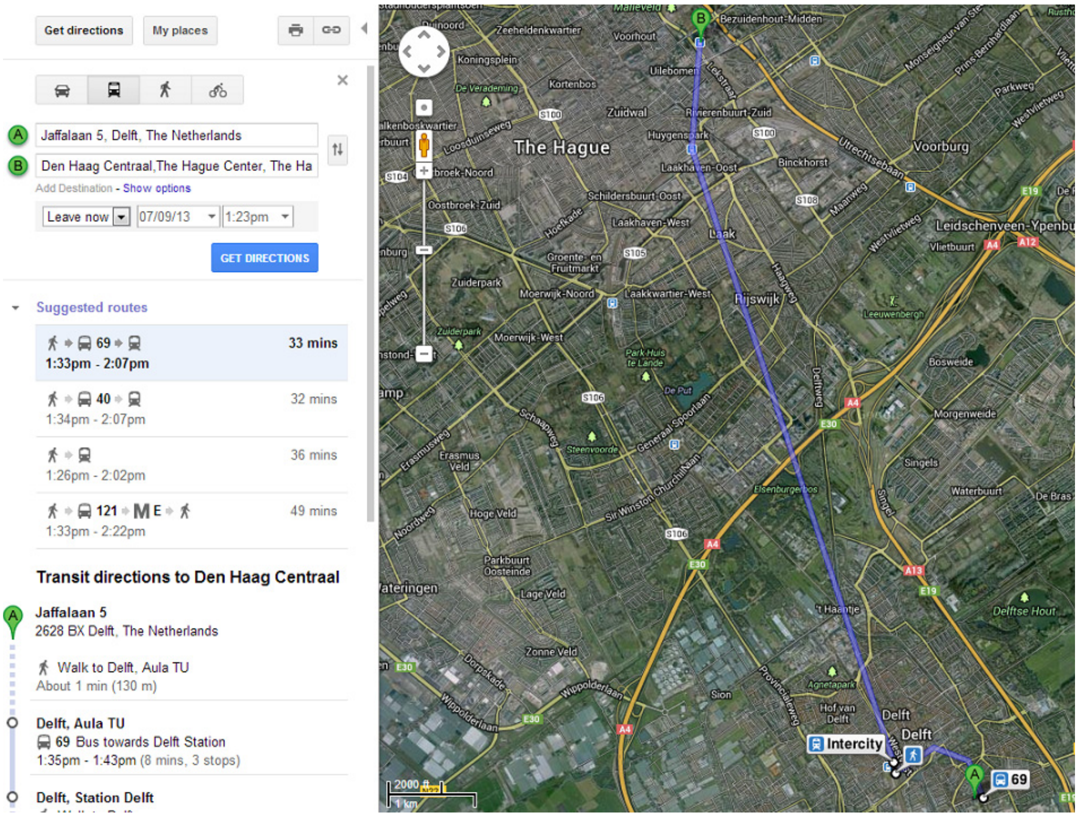


Figure 5.2: An example of the interface of Google Maps travel information service

Figure 5.3 An example of multiple-trip-based travel information from the experiment

More specifically, an effective format of multiple-trip-based travel information requires attaching the specific trip information directly to the reality-augmented maps. For Google maps, it is a relatively easy step to go ahead, as it not only possesses large amounts of activity-location information, which are the basis for the upgraded travel information service, but also can realize the unified format by simply adding another travel information layer atop the layer of the reality-augmented map. In comparison, a travel information service like OV929, which lacks data/resources needed for a reality-augmented map, may find it more difficult to improve the travel information format to the multiple-trip level.

Although this research found support for the usefulness of travel information services that allow for the planning of multiple trips and communicate results in a map-based format, it is not sure if map-based communication is the way to go for all potential users of such system. So, the map-based way of communication information could probably best be an option that users can choose, not the only way to communicate travel information.

Limiting the information load

The estimation results in Chapter 4 clearly show that the more complex a choice task is, the more randomly travellers choose. Such an increase of randomness in choice is undesirable not only for the traveller himself but also for the travel service providers. However, to reduce the complexity of choice tasks to the extreme of only one single alternative left in the choice set may also be undesirable, as traveller may still crave for the liberty to choose rather than being told what to do. Therefore, it is important to achieve a balance between the oversupply of travel information and the provision of traveller's liberty to choose. More research is needed to come to conclusions about this balance. For example, by collecting user data concerning the information provision, it would give the service providers more clues about this balance. For another example, it may work best if users of such systems can choose settings based on their preferences.

5.6 Avenue for further research

Firstly, as argued in Chapter 2, the Heteroscedastic models specified in this research can well accommodate the impacts of task complexity and time pressure on travellers' choices. The decision rule assumed by these models is linear additive utility maximisation-based, implying that even if task complexity and time pressure levels are high, travellers would always adopt this same decision rule to make their choices. There is some literature that suggests this may not necessarily be the case. Notwithstanding the fact that the Heteroscedastic Logit model performs adequately when accommodating the impacts of task complexity and time pressure, it would be interesting to construct models that adopt decision rules other than the linear additive utility maximisation-based one, which may provide additional insights into the impacts of task complexity and time pressure on travellers' choices.

Secondly, in Chapter 3, notwithstanding the overall legitimacy of the travel simulator approach, there are some points in the detailed design of the experiment that can be further improved. It is evident that the result of the time factors looks arbitrary. By design the possibility of observing the extreme cases of ultimate time pressure experience was excluded. For example, a choice situation is excluded where a choice that usually takes 60 seconds to think is only assigned with 5 seconds. Traveller behaviours under these circumstances cannot be observed by using this experimental setup, as decision time budget should be more or less proportional to its normal decision time. Moreover, the values of the time factor are correlated with the increased complexity of the choice task, which implies that the more complex a choice task is, the larger the time factor becomes. As such, the participants may not feel as much time pressure in a more complex choice situation as in a less complex one.

With hindsight, the setup should have been better – for reasons for creating more random variations in experimental conditions – to randomly vary the values of the time factor across and *within* tasks, as this would have allowed for a more efficient simultaneous identification of engagement/time pressure effects and task complexity effects (since the latter also vary between tasks but not within tasks).

With this improvement of design, some experiment participants would have experienced much more intense time pressure situations, and some would much less to the extent as if there were no time pressure at all. I would expect the curve depicted in Figure 4.5 would become even steeper where the minimum value of the scale would be smaller than that of now. In other words, the engagement/time pressure effect as found in this research may be underestimated. Thus, in light of these considerations, the experiment design needs further improvement.

In Chapter 4, the Mixed Logit model has four random tastes in the formulation. If there is more than one random taste in a Mixed Logit model, there may exist correlation of random parameters of attributes that are common across alternatives. However, it is pragmatically assumed in this research that the four random tastes are independent from each other, the practise of which is found not uncommon in empirical modelling in literature. Thus, the correlations of the random parameters have not been tested and maintain a venue for further research.

In this chapter, several directions are suggested for further research. Specifically, more research attention is advocated to be paid to the use of the activity-travel information services from both travel information service providers and academia, as this new type of travel information may benefit a lot to the users. This research also states the importance to achieve a balance between the oversupply of travel information and the provision of traveller's liberty to choose. To strike such a balance warrants further research to draw to a clear conclusion.

Appendices

Appendix I: The experiment settings for the other three groups of participants

The group of “escorting children to school” and “private car-user”

Table A.1: Travel choice sets assigned for the group of “escorting children to school” and “private car-user”

Nr. of activities in an activity program		Nr. of activity-travel alternatives in choice set: 2	3	4
	1	*Set 2*		
	2	*Set 1*	*Set 3*	
	3		*Set 4*	*Set 5*
	4			*Set 6*

Table A.2: The activity programs assigned for the group of "escorting children to school" and "private car-user"

Set	Activity Program
Set 1	Escorting children, Work
Set 2	Work
Set 3	Work, Grocery Shopping
Set 4	Work, Escorting Children, Grocery shopping
Set 5	Work, Grocery shopping, Fitness
Set 6	Work, Leisure shopping, Fitness, Meeting friends

The group of "not escorting children to school" and "none private car-user"

Table A.3: Travel choice sets assigned for the group of "not escorting children to school" and "none private car-user"

		Nr. of activity-travel alternatives in choice set		
		2	**3**	**4**
Nr. of activities in an activity program	**1**	*Set 1*		
	2	*Set 2*	*Set 3*	
	3		*Set 4*	*Set 5*
	4			*Set 6*

Table A.4: The activity programs assigned for the group of "not escorting children to school" and "none private car-user"

Set	Activity Program
Set 1	Work
Set 2	Work, Grocery shopping
Set 3	Work, Fitness
Set 4	Work, Fitness, Grocery shopping
Set 5	Work, Meeting friends, Fitness
Set 6	Work, Leisure shopping, Fitness, Meeting friends

The group of "escorting children to school" and "none private car-user"

Table A.5: Travel choice sets assigned for the group of "escorting children to school" and "none private car-user"

		Nr. of activity-travel alternatives in choice set		
		2	**3**	**4**
Nr. of activities in an activity program	**1**	*Set 2*		
	2	*Set 1*	*Set 3*	
	3		*Set 4*	*Set 5*
	4			*Set 6*

Table A.6: The activity programs assigned for the group of "escorting children to school" and "none private car-user"

Set	Activity Program
Set 1	Escorting children, Work
Set 2	Work
Set 3	Work, Grocery Shopping
Set 4	Work, Escorting Children, Grocery shopping
Set 5	Work, Grocery shopping, Fitness
Set 6	Work, Leisure shopping, Fitness, Meeting friends

Appendix II: Activity-travel simulator user manuel

General Introduction

This simulator creates a virtual situation, where you will be assigned with a pre-defined daily task, starting from your house. This task has the form of a sequence of activities. The simulator will always provide you with two or more options to fulfil your tasks. These options thus take the form of a so-called activity-travel schedule, which consists of a sequence of activities at various locations and associated travel arrangements. After reviewing the available options, you may decide which option is most favourable to you, and submit your answer to the simulator.

Once you submit your answer, the simulator will assign a new and different task to you, with a new and different set of options to choose from. Please be aware the travel time and the travel cost of each travel mode on each connection may also be different from those of the previous task.

You will be asked to complete several such tasks during the experiment. In the first half of the experiment, you can spend as much time as you want on each task. However, in the second half of the experiment, you will have to finish each task within a certain prefixed amount of time. There will be a countdown clock on the screen, indicating how much time there is left for you to choose your option. If you are not able to choose your option in time, the simulator will automatically and randomly select one for you.

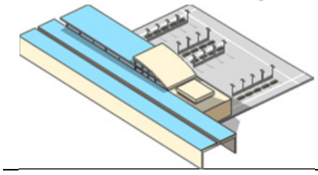
Introduction to the Setting

The geographical setting of your tasks involves two virtual cities: City A and City B. City A is where you live and perform the other activities. City B is where you work. As explained above, each task includes one or several activities. Each activity has its associated locations where the activity can be performed. Below is a list of these activities and the associated location icons that will appear on the simulator.

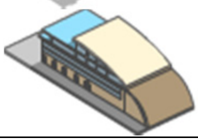
In City A, close to where you live

Icon	Location	Activity
	your house	
	supermarket	Grocery shopping
	fitness/sport center	Fitness/sport
	shopping center	leisure shopping
	cafeteria	Meet your friends
	school	Drop-off/pick-off your children

In City A, further away from where you live

Icon	Location	Activity
	integrated facility (containing supermarket, fitness/sport centre, shopping centre, and cafeteria)	Grocery shopping, Fitness/sport, Leisure shopping, Meet your friends
	Train station City A	Where you can take a train to City B

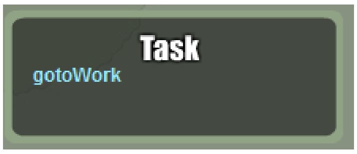
In City B

Icon	Location	Activity
	your office	Work
	Train station city B	Where you can take a train to City A

How to play the simulator

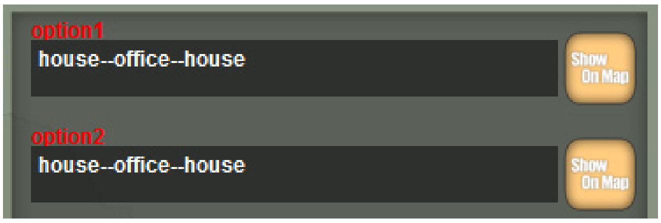
Step 1: Get familiar with the interface

When you enter the simulator interface for the first time, the computer screen will appear like this:

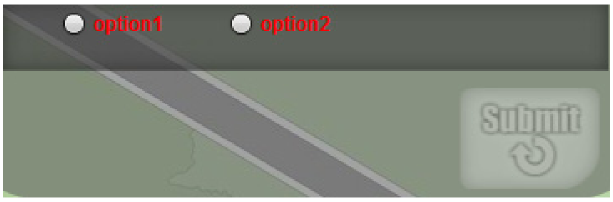


Task bar shows the activity (or activities) of your current task (in this case: “gotoWork”).

Countdown bar indicates how much time there is left for your to choose an option; if the bar does not show a decreasing number of seconds, it means that you can spend as much time as you want on your decision-making.



Two or more options are for you to choose from; here, only textual information regarding the sequences of the activity location is shown. Click on the button “show on map In order to receive more specific information about travel times, costs and modes of a particular option. This is placed at the right side of each option. (This step will be shown later.)



Here you can select your preferred option and submit your decision.

Step 2: Assess each option

In order to receive more specific information about the various options, you may click on the “show on map” buttons, which are placed at the right side of each option. By clicking the button, an animation will show specific information such as the location of the activities, and the travel modes that are used including their travel times and costs. An example is shown in the screenshot below. At the same time, clicking the “show on map” button allows you to see a summary of this information at the bottom of the interface. If you want to see the animation again, just click the “show on map” button again.

The information on the travel mode includes three parts: travel mode, travel time and travel cost. For example, , this icon, suggests that the travel mode is private car, the travel time is 35 minutes, and the travel cost is 8 euros.

An explanation on all the travel mode icons is listed below:

Icon								
Mode	Private Car	Train	Bicycle	Bicycle carrying bags	Bicycle with child	Bicycle with child, carrying bags	On foot	On foot carrying bags

After reviewing this information concerning the first option, if you want to assess the second option, just click the "show on map" button at the right side of Option 2 and you will see the following screenshot:

In this example, you can see that Option 1 and Option 2 are quite different from each other, although they are all “house—office—house”.

Step 3: Make your choice

Once you feel ready to make a choice between the various options, you may select an option and submit your answer to the simulator. For example, by selecting option1 and subsequently clicking the “submit” button, you choose option 1 and finish this task.

Step 4: Repeat the whole process and finish all the other tasks

After submitting your answer, the simulator will assign a new task to you again. Please be aware that in the next task, the activities, the options, and the travel (mode, time and cost) may be different from the ones in the previous task. For example, whereas the travel time and the travel cost of a particular travel connection in the previous task may have been 30 minutes and 5 euro respectively, in the current task these two numbers may become 15 minutes and 3 euro. Please repeat the process outlined above, finish your current task and be assigned another new task, until all the tasks are finished

Step 5: Make your choice under time pressure

In the second half of the experiment, the simulator will exert time pressure on you, in the sense that you will have to finish choosing a particular option within a certain pre-specified amount of time which may vary between tasks (in this example, the time available for you to make your choice is 50 seconds). If you are not able to submit your choice in time, then the simulator will automatically and randomly select an option for you.

Appendix III: The comparisons between different numbers of random draws

Table A.7: The estimation results of the Mixed Logit model with numbers of random draws equal to 1000, 2000, and 3000 respectively

Nr. of draws	**1000**		**2000**		**3000**	
adjusted rho-square	0.271		0.271		0.270	
Final log-likelihood	-1108.436		-1109.157		-1110.163	
Parameters	**Value**	**t-stat.**	**Value**	**t-stat.**	**Value**	**t-stat.**
Mean (β_{TC} **)**	-0.111	-4.47	-0.114	-4.93	-0.115	-4.75
Spread (β_{TC} **)**	(0.111)		(0.114)		(0.115)	
Mean (β_{TT}**)**	-0.0488	-5.27	-0.0479	-5.14	-0.0476	-5.10
Spread(β_{TT}**)**	(0.0488)		(0.0479)		(0.476	
Mean (β_{TI} **)**	-0.590	-9.70	-0.580	-10.19	-0.590	-9.72
Spread(β_{TI} **)**	0.363	3.41	0.404	-4.44	0.406	4.21
Mean(β_{Car} **)**	0		0		0	
Stt.Dev.(β_{Car} **)**	1.77	5.54	1.72	6.46	1.70	6.07

Table A.8: The estimation results of the Heteroscedastic Mixed Logit model with numbers of random draws equal to 1000, 2000, and 3000, respectively

Nr. of draws	**1000**		**2000**		**3000**	
adjusted rho-square	0.282		0.281		0.282	
Final log-likelihood	-1088.864		-1090.116		-1089.494	
Parameters	**Value**	**t-stat.**	**Value**	**t-stat.**	**Value**	**t-stat.**
Mean (β_{TC} **)**	-0.161	-3.88	-0.160	-3.81	-0.159	-3.88
Spread (β_{TC} **)**	(0.161)		(0.160)		(0.159)	
Mean (β_{TT}**)**	-0.0671	-3.85	-0.0631	-3.67	-0.0636	-3.67
Spread(β_{TT}**)**	(0.0671)		(0.0631)		(0.0636)	
Mean (β_{TI} **)**	-0.925	-5.35	-0.915	-5.30	-0.938	-5.20
Spread(β_{TI} **)**	0.558	3.06	0.582	3.06	0.590	2.63
Mean(β_{Car} **)**	0		0		0	
Stt.Dev.(β_{Car} **)**	3.07	4.48	2.88	4.24	2.92	4.12
λ_{DT}	-0.00754	-3.19	-0.00731	-3.11	-0.00745	-3.16
δ_T	2.58	4.45	2.56	4.44	2.56	4.44
θ_T	-4.00	-5.01	-3.96	-5.00	-3.96	-5.01

Summary

One of the central aims of transport policy-makers and many transportation researchers is to improve accessibility in transportation. It is generally acknowledged that there are essentially two ways to achieve improvements in that respect: a first approach is to expand physical infrastructure capacity, and a second approach is to increase the efficient use of existing infrastructures and transportation services. In many societies, especially highly developed and urbanised ones, it is increasingly felt that the former of these two approaches (i.e., expanding physical infrastructure) comes with a number of critical disadvantages, such as need for high amounts of capital investments, large areas of land use, lengthy period of construction time, and relatively large impacts on environment.

As many of these disadvantages are moderated if not absent in the second approach (better use of infrastructure and transportation services), the interest in this approach is growing among policy-makers and researchers. Increasing the level of network synchronisation through strategies related to improving the interconnectivity of different transportation and activity location networks belongs to this approach. Examples are synchronising the time tables of different public transportation services or realizing Park and Ride facilities near railways stations. In addition, as people travel because they want to conduct an activity at another location, also the geographical location of these activity locations may be synchronised with transportation networks. Hence, those who advocate this approach believe that sustainable accessibility can be enhanced by improving synchronisation, while increasing physical infrastructures to only a limited extent (e.g., enhancing interconnectivity between different public transport (PT) modes (e.g. train and bus), establishing park and ride facilities near train station, and adding or relocating supermarkets or day-care centres with more flexible opening hours near train stations, etc.).

In principle many different synchronisation strategies can be developed, however, it is not yet clear how effective each strategy is. As methods to ex-ante evaluate synchronisation strategies were largely missing, a Supernetwork model was developed as a first innovative step to

understand the synchronisation strategies. An important part of this Supernetwork model is concerned with traveller behaviour.

The underlying assumption of the Supernetwork model is that travellers would be able to choose their favourite alternatives from their choice sets independent of choice situations they are faced with. However, because of task complexity as induced by synchronisation strategies and time pressure travellers may not be able to choose the more effective ways to conduct their activity program offered by increased synchronisation. This would mean that potential gains in sustainable accessibility of synchronisation strategies as predicted by the Supernetwork model may not be reached. Therefore, in the context of modelling choice in highly synchronised networks it is important to study the impacts of task complexity and time pressure and take these impacts into account while making predictions.

Given the potential importance of task complexity and time pressure for the prediction of travellers' choices in the context of highly synchronised networks, it is important to study the impacts of these two aspects on travellers' choices in order to improve the evaluations of the synchronisation policies in terms of traveller behaviour. However, it is unclear at the moment how these two aspects together should be properly modelled in the discrete choice modelling framework and what the impacts of these two aspects are on traveller choice. In light of these, the following research goals of this thesis are formulated. This research primarily aims:

To develop coherent discrete choice models that can accommodate the impacts of both task complexity and time pressure on travellers' choices simultaneously;

To collect relevant data concerning the impacts of task complexity and time pressure on travellers' daily activity-related travel choices in the context of highly synchronised networks;

To gain insight in traveller behaviour in the context of highly synchronised networks, with an emphasis on capturing the possible impacts of task complexity and time pressure.

Besides these three primary goals, this research also aims as a secondary goal *to utilize the gained insights to provide the relevant societal implications, in particular with respect to policies involving highly synchronised networks.*

To reach the research goals of this thesis, several methods are adopted, including literature review, model construction, Stated Preference data collection by using a travel simulator, estimating econometric models, and societal implication-related analyses. In particular, the paradigm of random utility maximization (RUM) is applied for model construction. Briefly stated the RUM assumes that decision makers evaluate and compare all possible alternatives known to them and eventually choose the alternative that maximises their utility. In order to estimate the developed travel behaviour models, choices travellers make between among alternatives need to be observed by adopting Stated Preference (SP) data. More specifically, hypothetical alternatives are presented to participants, of which they select the alternative that they would choose in real life situations.

Goal 1

The Heteroscedastic model, which is tractable, coherent, structurally simple, and easily estimable, is constructed to model the impacts of task complexity and time pressure on travellers' choices. In specific, the variance of the random component in the utility function is formulated as a function of task complexity and time pressure. Since the variance of the random component is confounded with the scale of the utility, this is equivalent to the notion that the scale of the utility is a function of task complexity and time pressure. As each choice task may be associated with a different level of task complexity and time pressure, the scale is no longer identical for all the choice tasks, which gives rise to a new RUM-based model, called Heteroscedastic Logit model. Decision time as a measure of task complexity is an appropriate choice for the choice models, as it is intuitive, direct and individualized. As for time pressure, this research recommends using a so-called engagement/time pressure index, rather than adopting the conventional measure of varied fixed decision time budget, since the latter is in comparison to the former not only not individualized (i.e. the time pressure felt by one decision-maker may not be transferrable to another with a same fixed decision time budget), but too blunt as well since time pressure changes gradually.

Goal 2

Given the data requirement, an activity-travel-simulator (ATS) approach is the most suitable method for observing those activity-travel choices. Travel simulators have been gaining popularity since the mid-1990s with the aim of addressing the issue of validity in collecting SP data. Compared with the conventional SP methods, travel simulators usually provide illustrative and interactive user interfaces, stimulating respondents to more actively involve themselves in the experiment and allowing for easy interactions between respondents and experimental conditions. While typically the previously mentioned travel simulators consider only single trips, ATS deals with complete daily activity programs, hence with all trips made for a whole day.

In the simulator, participants make choices with respect to the execution of complete activity programs. Task complexity is varied by varying across the choice sets both the number of activities included in the activity program and the number of activity program executions to choose from. In addition, choices are observed for a choice situation without time pressure and a situation with time pressure. In total, 194 persons participated in the travel simulator. The majority of the participants have a paid job and 85 % of those with paid jobs commute to work four days or more per week.

Two approaches have been taken in this research to validate the ATS. Firstly, as prerequisites to induce real behaviours from the experiment participants, they must adequately understand the functionality of ATS and the process of the experiment, and preferably enjoy the experiment, which are the indications for their engagement in the experiment. The self-reported feedbacks from the participants after they complete the experiment are useful to demonstrate whether these prerequisites are indeed met or not. The results from the feedbacks have shown that the majority of the participants felt that it was easy to understand the travel simulator, easy to remain focused during the experiment, the information shown in the abstract map was illustrative, the daily activity programs presented in the experiment look realistic to them, and it was enjoyable to participate in the experiment. Secondly, using a less strict validation a travel simulator may be regarded as a valid way to collect data when it is established that observed behaviours made within the simulator resemble intuitions concerning what kind of behaviours would be made in real life. The analyses of the data generated from the experiment show that the formulated intuitions have been confirmed. These intuitions include the ones concerning choice probability (a. the higher the overall travel time, the lower the choice probability; b. the higher the overall travel cost, the lower the choice probability; c. the larger the total number of travel interchanges, the lower the choice probability) and the ones concerning task complexity (a. the larger the number of travel alternatives in the choice set, the more decision time used; b. the larger the number of activities in the activity program, the more decision time used). Therefore, based on the validity tests conducted for the experiment, it is reasonable to think that ATS is a valid way to collect the required SP data.

Goal 3

The analyses on the estimation results suggest that the impacts of task complexity and time pressure on traveller’s choice do exist. More specifically, the estimate associated with task complexity is significant and takes a negative sign. This suggests that the more complex the choice task is (as measured in terms of the decision time in the absence of time pressure), the smaller the scale of the systematic component of the utility function is, that is more random choice.

Additionally, the estimates associated with time pressure support the hypothesis that the scale of the systematic component of the utility function first increases and then decreases as the engagement/time pressure index increases. To conclude, 1) travellers’ choices tend to become more random when the choice is made at a moment when not much additional time is left for decision making (suggesting the presence of time pressure); 2) Very short decision times also lead to more random behaviour, although in that case there is no evidence of time pressure (interpreted in terms of a lack of engagement with the choice task among those who make a choice within a matter of a few seconds after being presented with the choice task).

It was hypothesized that there may be an interaction effect between task complexity and engagement/time pressure on travellers’ choices. However, in the context of the data collected in this research and the models estimated, such an interaction effect was found to be close to zero and statistically insignificant.

On the data, Heteroscedastic models that incorporate the impacts of time pressure and task complexity achieve higher levels of model fit than corresponding Homoscedastic models that do not accommodate these effects.

More importantly than these differences in model fit, it is found that choice probability predictions differ substantially between estimated Homo- and Heteroscedastic models: the former predict much more pronounced differences in choice probabilities between alternatives than the latter, when there are relatively high levels of task complexity and time pressure. In other words, under these conditions, Heteroscedastic models predict a much more even distribution of choice probabilities across choice alternatives, than their Homoscedastic counterparts.

The secondary goal

This research recommends to include task complexity and time pressure in choice models so that more reliable and accurate estimation of the Value of Travel Time Savings (VTTS) and the Value of Avoiding a Travel Interchange (VATI) can be achieved. However, it is important to realize that these recommendations are deduced from experiments.

As far as travel information service providers are concerned, it is recommended to upgrade their travel information services to a higher level that arranges travel for a whole day (i.e. multiple-trip-based travel information service) – the current generation only provides single-trip-based travel information. Secondly, it is recommended that travel information service providers should at least provide travellers with an option in which travel information, especially multiple-trip-based travel information, can be conveyed in a way similar to the augmented-map-based format as used in this research.

Thirdly, it is concluded that the supply of travel information to travellers should be limited, as too much of it may result in an increase of randomness in choice. However, to reduce the complexity of choice task to the extreme of only one single alternative left in the choice set may also be undesirable, as traveller may still crave for the liberty to choose rather than being told what to do. Therefore, it is important to achieve a balance between the oversupply of travel information and the provision of traveller's liberty to choose.

Avenue for further research

Firstly, the Heteroscedastic models specified in this research can well accommodate the impacts of task complexity and time pressure on travellers' choices. The decision rule assumed by these models is linear additive utility maximisation-based, implying that even if task complexity and time pressure levels are high, travellers would always adopt this same decision rule to make their choices. There is some literature that suggests that this may not necessarily be the case. Notwithstanding the fact that the Heteroscedastic Logit model performs adequately when accommodating the impacts of task complexity and time pressure, it would be interesting to construct models that adopt decision rules other than the linear additive utility maximisation-based one, which may provide additional insights into the impacts of task complexity and time pressure on travellers' choices.

Secondly, notwithstanding the overall legitimacy of the travel simulator approach, there are some points in the detailed design of the experiment that can be further improved. It is evident that the result of the time factors looks arbitrary. By design the possibility of observing the extreme cases of ultimate time pressure experience was excluded. With hindsight, the setup should have been better – for reasons for creating more random variations in experimental conditions – to randomly vary the values of the time factor across and *within* tasks, as this would have allowed for a more efficient simultaneous identification of engagement/time pressure effects and task complexity effects (since the latter also vary between tasks but not within tasks). With this improvement of design, some experiment participants would have experienced much more intense time pressure situations, and some would much less to the extent as if there were no time pressure at all. In other words, the engagement/time pressure effect as found in this research may be underestimated. Thus, in light of these considerations, the experiment design needs further improvement.

Thirdly, the Mixed Logit model has four random tastes in the formulation. If there is more than one random taste in a Mixed Logit model, there may exist correlation of random parameters of attributes that are common across alternatives. However, it is pragmatically assumed in this research that the four random tastes are independent from each other, the practise of which is found not uncommon in empirical modelling in literature. Thus, the correlations of the random parameters have not been tested and maintain a venue for further research.

Finally, several additional directions for future research are recommended. More research attention is recommended to be paid to the use of the activity-travel information services from both travel information service providers and academia. Moreover, to achieve a balance between the oversupply of travel information and the provision of traveller's liberty to choose warrants further research to draw to a clear relevant conclusion.

Samenvatting

Eén van de centrale doelen van beleidsmakers en transportwetenschappers is het vergroten van de bereikbaarheid. In principe zijn er twee manieren om dit te bereiken: door de capaciteit van de fysieke infrastructuur uit te breiden of door de bestaande infrastructuur en transportdiensten beter te benutten. In veel samenlevingen, en in ontwikkelde en verstedelijkte samenlevingen in het bijzonder, wordt de eerste manier meer en meer gezien als één die gepaard gaat met een aantal kritieke nadelen, zoals de noodzaak voor grote investeringen, het beslag op de bestaande ruimte, de lange constructieduur en de relatieve grote milieueffecten.

Sinds veel van deze nadelen gemitigeerd of afwezig zijn binnen de tweede benadering (het efficiëntere gebruik van bestaande infrastructuur en transportdiensten), krijgt deze in toenemende mate de aandacht van beleidsmakers en onderzoekers. Eén van de strategieën die hoort bij deze aanpak is het vergroten van de mate van netwerksynchronisatie, wat mogelijk is door de interconnectiviteit van verschillende transport en activiteitenlocatie netwerken te verbeteren. Voorbeelden zijn het synchroniseren van reisschema ' s van openbaar vervoersdiensten of het realiseren van Park & Ride voorzieningen naast een treinstation. Omdat mensen reizen om een bepaalde activiteit uit te voeren op een andere locatie, kan synchronisatie ook bereikt worden door de geografische locatie van activiteiten af te stemmen met transportnetwerken. Diegenen die deze aanpak voorstaan geloven dat duurzame bereikbaarheid bereikt kan worden door verbeterde synchronisatie, wat slechts minimale infrastructurele aanpassingen vereist (e.g. het verbeteren van de interconnectiviteit tussen verschillende openbaar vervoersdiensten (trein en bus), het implementeren van Park & Ride voorzieningen bij treinstations, en het toevoegen of verplaatsen van supermarkten of kinderopvangen met meer flexibele openingstijden nabij treinstations).

In principe kunnen veel verschillende synchronisatiestrategieën ontwikkeld worden. Het is echter niet duidelijk hoe effectief iedere strategie is. Omdat methoden om synchronisatiestrategieën ex ante te evalueren niet bestaan, is als eerste innovatieve stap een supernetwerk model ontwikkeld om synchronisatiestrategieën beter te begrijpen. Een belangrijk deel van dit supernetwerk model heeft betrekking op reisgedrag.

De onderliggende assumptie van het supernetwerk model is dat reizigers in staat zijn om hun favoriete alternatief te kiezen uit hun keuzesets onafhankelijk van de keuzesituaties waarmee ze geconfronteerd worden. Omdat synchronisatiestrategieën leiden tot een grotere taakcomplexiteit en tijdsdruk, is het echter mogelijk dat reizigers niet in staat zijn om de effectievere manieren om hun activiteitenprogramma uit te voeren te kiezen (die voorvloeien uit de toegenomen synchronisatie). Dit zou betekenen dat de potentiële winsten van synchronisatiestrategieën in termen van duurzame bereikbaarheid, zoals voorspeld door het supernetwerk model, niet gerealiseerd worden. In de context van het modelleren van keuzes in sterk gesynchroniseerde netwerken is het daarom belangrijk om de effecten van taakcomplexiteit en tijdsdruk te onderzoeken en hun effecten mee te nemen in het doen van voorspellingen.

Gegeven het potentiële belang van taakcomplexiteit en tijdsdruk voor de voorspelling van reizigerskeuzes in de context van sterk gesynchroniseerde netwerken, is het van belang om de effecten van deze twee aspecten op de reizigerskeuzes te onderzoeken om zo tot betere evaluaties te komen van synchronisatiemaatregelen in termen van reisgedrag. Op dit moment is het echter onduidelijk hoe deze twee aspecten op de juiste wijze gemodelleerd kunnen worden binnen het raamwerk van discrete keuzemodellen en wat de invloeden van deze twee aspecten op reizigerskeuzes zullen zijn. Tegen deze achtergrond zijn de volgende onderzoeksdoelen geformuleerd:

Het ontwikkelen van coherente keuzemodellen die de invloeden van zowel taakcomplexiteit als tijdsdruk op de reizigerskeuzes tegelijkertijd kunnen accommoderen.

Het verzamelen van relevante data aangaande de invloeden van taakcomplexiteit en tijdsdruk op de dagelijkse activiteit-gerelateerde reiskeuzes van reizigers in de context van sterk gesynchroniseerde netwerken.

Het krijgen van inzicht in reisgedrag in de context van sterk gesynchroniseerde netwerken, met een nadruk op het vaststellen van de mogelijke invloeden van taakcomplexiteit en tijdsdruk.

Naast deze drie primaire doelen, *heeft dit onderzoek als tweede en secundaire doel om de verkregen inzichten te vertalen naar maatschappelijk relevante implicaties, specifiek in relatie tot beleid op het gebied van sterk gesynchroniseerde netwerken.*

Om deze doelen te bereiken zijn de volgende methoden toegepast: een literatuurstudie, modelconstructie, verzameling van Stated Preference data middels een reissimulator, schatting van econometrische modellen, en maatschappelijke implicatie analyses. De modelconstructie is gebaseerd op het paradigma van random utility maximization (RUM). Kortgezegd veronderstelt RUM dat reizigers alle mogelijke alternatieven kennen, evalueren en vergelijken en uiteindelijk het alternatief kiezen dat hun nut maximaliseert. Om de ontwikkelde reisgedrag modellen te schatten, moeten de keuzes die reizigers maken geobserveerd worden door middel van een Stated Preference (SP) survey. Binnen een dergelijk survey worden hypothetische alternatieven aan reizigers voorgelegd en wordt hen gevraagd om het alternatief te kiezen dat zij in de werkelijkheid waarschijnlijk zouden kiezen.

Doel 1

Om de invloeden van taakcomplexiteit en tijdsdruk op de reizigerskeuzes te modelleren is een heteroscedastisch model geconstrueerd dat handelbaar, coherent, structureel simpel en makkelijk schatbaar is. Binnen dit model is de variantie van de error component in de nutsfunctie geformuleerd als een functie van de taakcomplexiteit en de tijdsdruk. Omdat de variantie van de error component gecorreleerd is met de schaal van het nut, is dit equivalent aan het idee dat de schaal van het nut een functie is van de taakcomplexiteit en de tijdsdruk. Gegeven dat elke keuzetaak gepaard kan gaan met een verschillende mate van taakcomplexiteit en tijdsdruk, is de schaal niet langer identiek voor alle keuzetaken. Dit levert een nieuw RUM-gebaseerd model op, namelijk het Heteroscedastic Logit model. De tijd die nodig is om een keuze te maken kan als een geschikte indicator worden beschouwd voor de mate van taakcomplexiteit in keuzemodellen, omdat deze intuïtief, direct en geïndividualiseerd is. Voor de tijdsdruk beveelt dit onderzoek aan om een zogenaamde betrokkenheid/tijdsdruk index te gebruiken, in plaats van een conventionele indicator van gevarieerde vaste keuzebudgettijd. De conventionele indicator is ten opzichte van deze index niet alleen niet-geïndividualiseerd (i.e. de tijdsdruk die iemand voelt is niet per se overdraagbaar naar iemand anders met dezelfde vaste keuzebudgettijd), maar ook te grof omdat de tijdsdruk gradueel verandert.

Doel 2

Gegeven de datavoorwaarden, is een activiteit-reis-simulator (ATS) aanpak de meest geschikte methode om de activiteit-mobiliteit keuzes te oberserven. Reissimulatoren die als doel hebben om de validiteit van SP-data te vergroten zijn sinds het midden van de jaren 90 steeds populairder worden. In vergelijking met conventionele SP methoden hanteren reissimulatoren illustratieve en interactieve gebruikersinterfaces waardoor respondenten gestimuleerd worden om meer betrokken te zijn bij het experiment en zorgen ze er ook voor dat respondenten makkelijk met de experimentele condities kunnen interacteren. Hoewel reissimulatoren in het verleden alleen enkele trips beschouwden, kan de ATS omgaan met volledige dagelijkse activiteitenprogramma’s, dus met alle trips voor een gehelde dag.

In de simulator maken participanten keuzes met betrekking tot de uitvoering van complete activiteitenprogramma’s. Taakcomplexiteit is gevarieerd door zowel het aantal meegenomen activiteiten in het activiteitenprogramma als het aantal activiteitenprogramma uitvoeringen waaruit gekozen kon worden te variëren tussen keuzesets. Keuzes worden daarnaast geobserveerd voor een keuzesituatie zonder tijdsdruk en een situatie met tijdsdruk. In totaal hebben 194 personen deelgenomen aan de reissimulator. De meerderheid van de participanten heeft een betaalde baan en 85% van diegene met een betaalde baan reizen vier of meer dagen per week naar het werk.

Er zijn twee aanpakken gehanteerd om de ATS te valideren. Als voorwaarden om reëel gedrag uit het experiment af te leiden, moesten participanten allereerst goed de functionaliteit van ATS en het proces van het experiment begrijpen. Daarnaast moesten ze het bij voorkeur ook leuk vinden om te doen. Dit zijn indicatoren voor hun betrokkenheid bij het experiment. De zelf-gerapporteerde terugkoppeling van de participanten, nadat zij het experiment hadden afgerond, zijn gebruikt om aan te tonen of aan deze voorwaarden inderdaad is voldaan. De resultaten van de reacties tonen aan dat de meerderheid van de participanten de reissimulator makkelijk vond om te begrijpen en ook dat het makkelijk was om gefocust te blijven tijdens het experiment. Ook vonden de participanten de getoonde informatie in de abstracte kaart illustratief en werden de dagelijkse activiteitenprogramma’s realistisch bevonden. De meerderheid vond het ook leuk om deel te nemen aan het experiment. Ten tweede, als een minder strikte vorm van validatie kan gesteld worden dat een reissimulator valide is als vastgesteld kan worden dat de geobserveerde gedragingen intuïtief overeenkomen met de gedragingen die men zou kunnen verwachten in de werkelijkheid. De analyse van de door het experiment gegenereerde data laat zien dat de geformuleerde intuïties bevestigd worden. Deze intuïties omvatten diegene die betrekking hebben op de keuzekansen (a. hoe hoger de algemene reistijd, hoe lager de keuzekans; b. hoe hoger de algemene kosten, hoe lager de keuzekans; c. hoe groter het totaal aantal knooppunten, hoe lager de keuzekans) en diegene die betrekking hebben op de taakcomplexiteit (a. hoe groter het aantal reisalternatieven in de keuzeset, hoe hoger de gebruikte beslissingstijd; b. hoe groter het aantal activiteiten in het activiteitenprogramma, hoe hoger de gebruikte beslissingstijd). Op basis van de uitgevoerde validiteitstesten is het daarom aannemelijk om te denken dat ATS een valide manier is om de benodigde SP data te verzamelen.

Doel 3

De analyses van de schattingsresultaten suggereren dat er inderdaad invloed uitgaat van taakcomplexiteit en tijdsdruk op de keuzen van reizigers. Specifieker gesteld: de schatting gerelateerd aan taakcomplexiteit is significant en heeft een negatief teken. Dit suggereert dat hoe ingewikkelder de taak is om te kiezen (gemeten in de tijd nodig om te besluiten terwijl er geen tijdsdruk is), des te kleiner de schaal van de systematische component in de utiliteitsfunctie is; het wordt meer een willekeurige keuze.

Daarnaast ondersteunen de schattingen gerelateerd aan tijdsdruk de hypothese dat de schaal van de systematische component van de utiliteitsfunctie eerst toeneemt en dan afneemt naarmate de betrokkenheid/tijdsdrukindex toeneemt. Concluderend: 1) reizigers maken willekeurigere keuzen op momenten dat er weinig extra tijd over is om een beslissing te nemen (wat de aanwezigheid van tijdsdruk suggereert); 2) zeer korte besluittijden leiden ook tot willekeuriger keuzen wanneer er geen bewijs van tijdsdruk is (geïnterpreteerd als een gebrek van betrokkenheid bij de keuzetaak bij diegenen die een keuze maken binnen enkele seconden nadat de keuzetaak aan ze is gepresenteerd).

De hypothese was dat er een interactie-effect op de keuzen van reizigers zou kunnen zijn tussen taakcomplexiteit en betrokkenheid/tijdsdruk. In de context van de dataverzameling in dit onderzoek en de daarop geschatte modellen werd echter een interactie-effect aangetoond dat dicht bij nul lag en statistisch insignificant was.

Gerelateerd aan de data bereiken heteroscedastische modellen die de effecten van taakcomplexiteit en betrokkenheid/tijdsdruk meenemen hogere niveaus van modelfit dan overeenkomende homoscedastische modellen die deze effecten geen plaats kunnen geven.

Belangrijker dan dit verschil in modelfit is dat de voorspellingen van keuzewaarschijnlijkheid substantieel verschillen tussen de homo- en heteroscedastische modellen: de eerstgenoemde modellen voorspellen geprononceerdere verschillen in keuzewaarschijnlijkheden tussen alternatieven dan de tweede-genoemde indien er relatief hoge niveaus van taakcomplexiteit en tijdsdruk zijn. Heteroscedastische modellen voorspellen onder deze condities met andere woorden een veel gelijkmatigere verdeling van keuzewaarschijnlijkheden over keuzealternatieven dan de homoscedastische tegenhangers.

Het secundaire doel

Dit onderzoek beveelt aan om taakcomplexiteit en tijdsdruk mee te nemen in keuzemodellen zodat betrouwbaardere en accuratere schattingen gemaakt kunnen worden van de 'waarde van reistijdbesparing' en de 'waarde van het vermijden van een overstap tijdens een reis'. Het is echter belangrijk te realiseren dat deze aanbevelingen zijn afgeleid uit experimenten.

Met betrekking tot aanbieders van reisinformatie wordt aanbevolen om de reisinformatie op te vijzelen naar een hoger niveau waarbij reizen gedurende een gehele dag gepland kunnen worden (met andere woorden reisinformatiediensten voor meervoudige verplaatsingen) – de huidige generatie levert uitsluitend informatie voor enkelvoudige verplaatsingen. Ten tweede wordt aanbevolen dat aanbieders van reisinformatie op zijn minst reizigers de optie aanbieden waarbij ze reisinformatie, vooral voor meervoudige verplaatsingen, kunnen ontsluiten op een manier zoals gebruikt in dit onderzoek waarbij aan kaarten informatie is toegevoegd ('augmented-map-based formats').

Ten derde wordt geconcludeerd dat het aanbod van reisinformatie beperkt zou moeten blijven omdat teveel informatie zou kunnen leiden tot een toename van willekeur in de keuzen. Aan de andere kant kan het reduceren van de keuzetaakcomplexiteit tot slechts één alternatief in de keuzeset ook ongewenst zijn omdat reizigers toch hechten aan de vrijheid om te kunnen kiezen in plaats van dat ze wordt verteld wat ze moeten doen.

Richtingen voor verder onderzoek

De heteroscedastische modellen zoals gespecifieerd in dit onderzoek kunnen op de eerste plaats goed de effecten van taakcomplexiteit en tijdsdruk op de keuzen van reizigers accommoderen. De veronderstelde beslisregel in deze modellen is gebaseerd op lineaire additieve nutsmaximalisatie, die inhoudt dat zelfs bij hoge niveaus van taakcomplexiteit en tijdsdruk reizigers altijd dezelfde beslisregel hanteren wanneer ze een keuze maken. Er is literatuur die suggereert dat dit niet noodzakelijkerwijs het geval is. Niettegenstaande het feit dat het heteroscedastische logit model adequaat presteert bij het accommoderen van de effecten van taakcomplexiteit en tijdsdruk zou het interessant kunnen zijn modellen te maken die andere beslisregels hanteren dan de lineaire additieve nutsmaximalisatie. Dit zou aanvullende inzichten kunnen opleveren in het effect van taakcomplexiteit en tijdsdruk op de keuzen van reizigers.

Niettegenstaande de in zijn algemeenheid geldende redelijkheid van de reissimulatoraanpak is er een aantal punten in het gedetailleerde ontwerp van het experiment dat kan worden verbeterd. Het is duidelijk dat de resultaten van de tijdsfactoren arbitrair lijken. In het ontwerp werd de mogelijkheid uitgesloten om extreme casussen van ultieme tijdsdruk te kunnen observeren. Met de wijsheid van nu zou de opzet van het experiment verbeterd kunnen worden – met als reden het creëren van meer random variatie in de experimentele condities - door het random variëren van de tijdsfactorwaarden tussen en binnen taken omdat deze opzet het mogelijk zou hebben gemaakt om betrokkenheid/tijdsdrukeffecten en taakcomplexiteitseffecten efficiënter tegelijkertijd te kunnen identificeren (omdat de laatstgenoemde soort van effect varieert tussen taken maar niet binnen taken). Met deze verbetering in het ontwerp zouden sommige deelnemers aan het experiment intensere tijdsdruksituaties hebben ondervonden, en sommigen veel minder tot de situatie alsof er totaal geen tijdsdruk was. Het betrokkenheid/tijdsdrukeffect zoals aangetoond in dit onderzoek is, met andere woorden, mogelijk onderschat. In het licht van deze overwegingen is het nodig, kortom, om het ontwerp van het experiment verder te verbeteren.

Ten derde, de mixed logit model heeft vier random smaken. Als er meer dan één random smaak aanwezig is in een mixed logit model zou er correlatie kunnen zijn tussen random parameters van attributen die gemeenschappelijk zijn bij alternatieven. Vanuit pragmatische overwegingen is verondersteld dat de vier random smaken onafhankelijk zijn van elkaar. Deze praktijk is niet ongewoon in de literatuur van empirische modelering. De correlatie van de random parameter is dus niet getest en vormt een terrein voor verder onderzoek.

Tenslotte worden verscheidene aanvullende richtingen voor verder onderzoek aanbevolen. Meer aandacht wordt aanbevolen naar onderzoek van het gebruik van activiteit-reisinformatiediensten zowel bij reisinformatiedienstverleners als in de academische wereld. Bovendien vergt het bereiken van een evenwicht tussen enerzijds een overaanbod van reisinformatie en anderzijds de voorziening dat reizigers vrijheid hebben om te kiezen nader onderzoek.

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