Travel information impact on activity-travel patterns

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Travel Information Impact on Activity-Travel Patterns

PROEFSCHRIFT

der verkrijging van de graad van doctor aan de
Technische Universiteit Eindhoven, op gezag van de
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prof.dr. H.J.P. Timmermans

Copromotor:
dr. T.A. Arentze
Preface

This thesis is the result of my Ph.D study that I have conducted as a member of the Urban Planning Group, Eindhoven University of Technology (TU/e). It serves to document my study, which has been funded by NWO as the second part of PITA (Personal Intelligent Travel Assistant), a collaborative research program between TU/e and Delft University of Technology.

In this thesis, a general framework is introduced to describe activity-travel behavior under uncertainty and information provision. Based on this general framework, two latent class models are developed to capture heterogeneous risk attitudes in activity-travel behavior. These models are empirically tested against field data. A hypothetical activity-travel simulator is developed to collect empirical data on activity-travel rescheduling behavior using a web-based experiment.

Many people have supported me upon completing this study. I would like to take this opportunity to thank everyone who has supported and helped me during this research project. Among them, I wish to specially thank some of them for their contribution to this work.

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with Harry and Theo have proved to be one of my best learning experiences at the
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1. Introduction

1.1. Background

Over the past decades, the transportation research community has witnessed a shift from aggregated models to disaggregated models in the field of transportation planning and management. Researchers try to better understand individual traveler behavior in an attempt to improve predictions of the impact of planning and management decisions on activity-travel patterns. It should lead to better plans and better managerial strategies that make transportation in general more efficient and more sustainable both economically and environmentally.

Aside from single-facet travel behavior models that study a particular aspect of travel behavior, such as for instance departure time, mode choice, or route choice, more comprehensive activity-based models have been developed that simulate multi-faceted urban daily activity-travel patterns. The activity-based approach views daily activity-travel patterns as the result of a sequence of interdependent decisions that are made by households and individuals, constrained by time and space. The core concept is that travel demand manifests a derived demand from participation in out-of-home activities.

The paradigm shift to activity-based modeling can be partly attributed to the availability of suitable data and model estimation tools, and partly to dissatisfaction with traditional trip-based travel forecasting approaches in policy assessments and transportation management. Since the 1990s, a large body of activity-based studies has examined many aspects of individual activity-travel patterns, including scheduling decisions, time allocation and to some extent household interactions.

Most of this research has been concerned with the prediction and analysis of observed (facets of) daily activity-travel patterns. This line of work is especially
relevant for transportation planning applications in the sense that policy assessments traditionally depend on typical, observed patterns. In contrast, transportation management is more concerned with short term aspects of activity-travel patterns, such as traveler response to information provision. To some extent, this requires a shift in modeling approach. For example, in the context of the scheduling and rescheduling of activity-travel behavior, the concept of uncertainty becomes very important. In the short run, travel times and other elements of the transportation system and urban environment are uncertain, partly because they are inherently uncertain, partly because uncertainty arises due to the accumulated decisions of many individuals. Modelers therefore need to address the research question how individual travelers deal with uncertainty. In the short run, travelers may choose less uncertain alternatives to avoid risk, or may exhibit risk-taking behavior. This may lead to a re-scheduling of activities and travel, which in turn may trigger the search and evaluation of alternatives for other choice-facets using the same heuristic and utility model components recursively. Such decisions under uncertainty have not been explicitly addressed in the context of activity-based modeling, the currently dominant approach in travel forecasting.

To reduce such uncertainty, using developments in communication technology, transportation control agencies and commercial parties offer various types of passive and active travel information, either individually or collectively to travelers. Travel information is penetrating several sectors of the transportation system, both on the traveler’s side and management side. In this respect, static/dynamic traffic signs on the highway, GPS navigation systems, FM traffic broadcastings and other technology serve the sole purpose to move efficiently. Travel information is assumed to be able to help transportation system operations and help individuals to move along the transportation network more efficiently. Interestingly in this context, although the information is provided to better inform the travelers to reduce uncertainty, the provided travel information itself is uncertain as
information providers may not know or be able to perfectly predict the state of the travel system in some future point in time.

A special type of information device that is assumed to enter the market in the near future is a Personal Information Travel Assistant (PITA) that can provide highly customized information to individual travelers. It raises the question how this new information technology will affect the current transportation system. How will information provision affect individual travel behavior? And will individual travelers use and evaluate these information services? Answering these questions helps to improve the performance of the transportation system, suppliers (governments, state owned transportation companies) and consumers (individual travelers, transportation companies). A third potential beneficiary will be the information providers who design and provide information on the market as investments have to be justified.

Thus, the introduction of PITA technology brings new challenges to activity-based modeling. Using PITA, travelers may respond differently to the information provided. PITA may reveal new routes to an activity location, increasing the awareness and choice set of individual travelers. PITA may also provide more realistic information, for example correcting previous mis-conceived travel times for particular route/mode combinations. En-route dynamic travel information may warn a traveler about congestion ahead so that the traveler can plan a detour to avoid the jam. The information provider may even recommend a particular alternative route. Under such circumstances, activity-travel decisions become more complex. By acquiring information, travelers may reduce the uncertainty involved in short-term travel decisions. However, the responses to travel information in turn will lead to a changing travel situation elsewhere and later in the system. Moreover, the control strategies underlying travel advice may not necessarily be in the interest of the individual traveler. To further complicate the decision process, the travel
information itself may not be fully reliable, implying that the travelers need to assess the credibility of the information, not only in the context of rescheduling decisions, but also in the context of deciding whether or not to acquire travel information.

Thus, the challenge in activity-based modeling is to represent and model individual information search and activity (re)scheduling decisions under multiple sources of uncertainty and different degrees of travel information credibility. Uncertainty means that these decisions are based on subjective, context-specific, beliefs about the (future) state of particular facets of the transportation system and the urban environment. These beliefs can be implicitly or explicitly compared with experiences, actual state of the system, leading to a process of context-specific belief updating.

1.2. Research objectives

Given the inadequacy and paucity of current activity-travel research to address this research challenge, the goal of this PhD project is to contribute to our knowledge and understanding of activity-travel decisions under provision of (travel) information. More specifically, the main objective of the research project is to develop a model for studying the dynamic impact of PITA systems on daily activity-travel scheduling and rescheduling decisions.

To achieve this goal, several issues will be addressed. First, based on the available literature, and adding to it, we will develop a framework for short-run dynamic activity-travel decision processes, learning, inference and information acquisition. Secondly, assuming that different travelers may respond differently to information provided and will exhibit different risk taking/avoiding behavior, we need to find a way of incorporating the heterogeneity revealed in activity-travel decisions in the models. Finally, we need to estimate the model parameters and given the fact that
conventionally used travel surveys and activity-travel diaries do not collect data on
decisions under uncertainty nor on information acquisition decisions, this study
will develop and explore an alternative data collection approach, based on the
principle of interactive computer experiments.

1.3. Organization

This thesis reports the development of the activity-travel framework under
information provision and of models that capture individual heterogeneity in risk
attitude when considering the use of information and making activity-travel
decisions. The thesis is organized into eight chapters, starting with an introductory
chapter 1 which gives the background and motivation for this project and re-
articulates our research goals and methodological considerations. The social
relevance of the project is also discussed in this chapter.

Chapter 2 reviews the mainstream studies in the area of activity-based modeling
and travel information research. The review is not meant to be exhaustive; rather
some key aspects, concepts and modeling approaches are discussed in some detail
to provide a context and general orientation for this research project. The need of
incorporating an activity-travel decision model and information acquisition
decision model is pointed out in this discussion.

Chapter 3 introduces the development of the conceptual framework for activity-
travel decisions under uncertainty and information provision. The scheduling and
rescheduling process are represented as a decision tree that can explicitly take
uncertainty into account. Information acquisition in this framework is not different
from other travel decisions. Learning effects are represented by a Bayesian
updating procedure. The chapter also contains a discussion of a numerical
simulation, which was conducted to assess the face validity of the framework.
Chapter 4 discusses the models that handle heterogeneity in risk attitudes among individual travelers. Two types of modeling approaches are described in this chapter: a heuristic latent class model and a willingness-to-pay latent class model. In addition, this chapter discusses a general estimation method for these types of models. Numerical simulations serve to provide further evidence of face validity of the model configuration and to assess the estimation approach.

Having provided evidence of face validity, chapter 5 describes the development of an interactive web-based interactive computer experiment. This experiment was designed to collect data on information acquisition, rescheduling decisions and learning under uncertainty. It was developed because the dynamics of decisions under uncertainty are very difficult to observe and record in real world settings, leaving only the option of conducting experiments in hypothetical situations. The experimental design, hypothetical settings and internal control flow are explained. Sample characteristics are also reported.

Chapter 6 reports the model estimation results of the two models, heuristic latent class model and willingness to pay model, using the data from the web-based interactive experiments. The decision structures of both models are illustrated. Empirical estimation results indicate that both models are capable of representing heterogeneity in activity-travel decisions, in terms of heterogeneous risk attitude styles in the heuristic latent class model and heterogeneous information preferences in the willingness to pay model respectively.

In chapter 7, a psychometric scale to measure travel risk attitude is developed. The purpose is to develop an easy to use measurement scale on travel risk attitude. The validity of the travel risk scale is examined against two general risk scales: the recreational risk attitude scale and the future oriented time perspective scale.
Furthermore, the relationship between stated travel risk attitudes and this psychometric travel risk scale is explored.

Chapter 8 concludes the thesis. Major conclusions are drawn, limitations are discussed and possible avenues for future research are identified.
2. Travel patterns and travel information: A literature review

As can be deduced from the introductory chapter, this study builds heavily on the literature on activity-based modeling, models of travel information, decisions under uncertainty, the concept of heterogeneity in travel behavior, and models of learning processes. In this chapter, therefore, these key concepts and lines of previous research are reviewed. This review is by no means meant to be exhaustive in any of the above mentioned fields; rather, it serves as an introduction to these topic areas, allowing the reader to understand how the present study builds on previous research and where relative innovative contributions are made.

This chapter is organized as follows: Section 2.2 reviews the activity-based modeling approach and its applications. Section 2.3 reviews approaches that address decision making under uncertainty and travel information. Section 2.4 reviews studies about learning process in travel contexts, while Section 2.5 discusses the concept of heterogeneity in decision making. Section 2.6 provides a discussion and draws conclusions, which serve as a starting point for this research project. Based on these reviews, we will argue that there is a need to develop an integrated and coherent framework that incorporates uncertainty, travel information, learning and heterogeneity into an overall activity-based modeling approach.

2.1. Introduction

In modern cities, traffic situations deteriorate rapidly with an increasing population and an increasing number of vehicles. Congestion has become more of a common phenomenon than a rare occurrence. Consequently, travelers increasingly face a more uncertain traffic environment. The consequence of this increasing uncertainty on activity-travel scheduling processes is that people have to organize their schedule carefully so that they are sufficiently agile to adapt to unforeseen traffic
jams, especially when travel involves important activities. As information
technology penetrates all segments of society, it introduces changes in the
transportation system via new products and new services that may lead to drastic
changes in travel behavior patterns.

Travel information is widely available nowadays to the public in various forms at
different prices, and it is evolving quickly together with information technology,
especially with modern mobile communication technology. The provision of travel
information, both pre-trip and en-route, implies a potential reduction of uncertainty
about the state of the travel environment to the travelers. Perfectly credible
information would imply that travelers face no uncertainty about the present and
future state of the network and hence travelers in principle can maximize the
expected utility resulting from particular activity-travel decisions. However,
information sources are various as they differ in content and quality; information
may incorrectly describe the travel situation due to out-of-date information, lack of
information collection capability, etc. Moreover, the inherently uncertain nature of
some elements of the travel system and the urban environment does not allow an
exact prediction of delay time or waiting time. For instance, it is not possible to
predict exactly how long a traffic jam will last; travel information is only based on
a rough guess, experience or some model. It implies that even after acquiring
information, some degree of uncertainty will remain, and the traveler will need to
consider this remaining uncertainty.

A highly customized device, a personal intelligent travel assistant (PITA)\(^1\), has
drawn the attention of researchers in recent years. This information service is
assumed to be highly customized concerning individual’s characteristics and

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\(^1\) This advanced travel information service is also called ATIS (advanced travel information
system) or next generation travel information system in other researches; we will use PITA
and ATIS interchangeably throughout this research.
requirements, providing personalized travel advice dynamically besides normal guiding and navigating functionalities. Research findings pertaining to the use of travel information services suggest it does not yet play a pivotal role in organizing daily travel. For example, Kenyon and Lyons (2003) found that that current generation of travel information plays a trivial role in traveler’s mode choice. Other studies (e.g., Aarts et al., 1997; Verplanken et al., 1997; Kenyon and Lyons, 2003) also provided evidence that information effects on travel choice were largely countervailed by habitual travel decisions. Travelers are either unaware of the possible information source or they are unwilling to search for information and change their habitual behavior. Furthermore, if there are costs related to the acquisition of such information, a traveler has to trade-off these costs against the magnitude of uncertainty it can reduce, and in general willingness to pay for travel information is not high.

On the other hand, this situation may change. Navigation systems also have become quite popular and people’s general attitude with regard to such new technology may change, especially if the travel information becomes more personalized, up-to-date and if the need to consult travel information will increase. There is also evidence of plans of government agencies and information providers to use modern information and communication technology to persuade travelers to behave in a certain way to achieve some system-wide objectives.

In any case, the success of PITA systems in part depends on our ability to model information acquisition and use, and their impact on short-run activity-travel decisions in an activity-based modeling context. The latter is important in that an activity-based approach offers an integrated, comprehensive approach to travel behavior and has become dominant in academic research. Introduced originally in urban planning and time geography in the 1970s, but rapidly expanding since the mid 1990s, the fundamental principle of the activity-based approach stems from the
belief that travel demand is derived from individuals participating in out-of-home activities (Jones et al., 1983; Jones et al., 1990; Ettema, 1996; Arentze and Timmermans, 2000; Bhat and Koppelman, 2000). This principle characterizes what is generally considered a paradigm shift from discrete trip making to sequential travel behaviors that is driven by interdependent decisions made within households, constrained by time and space (Pas and Sundar, 1995; Buliung, 2005).

Traditionally, the activity-based approach has been used to assess long term planning proposals. Short-term dynamics and responses to travel information was not part of the dominant models. Thus, the information era brings new challenges to activity-based modeling as most current activity-based models do not take information acquisition behavior into account, while to the best of our knowledge dynamic behavior in reaction to information provision has been modeled for a limited number for specific facets only (e.g. departure time, route choice). There have not been any previous attempts to model complex, multi-faceted, rescheduling behavior under uncertainty, in reaction to travel information.

To position this research project, and provide the necessary background and motivation, the following sections briefly review the history and state-of-the-art in activity-based modeling, in travel decisions under uncertainty and information provision.

### 2.2. Activity-based modeling

In travel demand analysis, the term activity-based modeling covers a wide range of research in different, but related fields. It aims at predicting which activities are conducted where, when, with whom and for how long, using what transport mode and which route. Before the activity-based modeling era, transportation planning and travel forecasting were mainly based on so-called four step models that predicted sequentially and independently trip generation, trip distribution, modal
split and trip assignment. Extensive reviews are given in for example Mitchell (1954) and McNally (2000).

It is hard to give a simple definition of the activity-based modeling approach, because specific approaches differ in terms of scope, central concepts and modeling techniques. However, as argued by Arentze and Timmermans (2000), activity-based approaches have in common the notion that “… traffic patterns are the result and manifestation of the implementation of activity programs over time and space using the available transportation network. In turn, activity patterns emerge as the result of a complex interplay between the urban/physical environment, the institutional context, the transportation system, and individuals’ and households’ needs to realize particular goals in life and to pursue activities to survive, all of these within a particular economic, political, social and culture context”. They provide a definition that captures the essence of activity-based modeling, “…activity-based approaches in transportation research… aim at predicting which activities are conducted where, when, for how long, with whom, the transport modes involved and ideally also the implied routes decisions”. A more general and non-specific definition was adopted by Kitamura (1988) and Wang (1998) who indicated that activity-based modeling means “…the consideration of revealed travel patterns in the context of a structure of activities, of the individual or household, with a framework emphasizing the importance of time and space constraints ”.

The core concept underlining activity-based modeling approaches is the notion that demand for travel is derived from the desire of households and individuals to participate in activities whose locations are spatially distributed. Five fundamental features define the basis of activity-based modeling: (i) Travel is a demand, derived from activity participation; (ii) the sequence of the activities is the focal point; (iii) account is given of inter-personal interactions in the planning and execution phase
(household task assignment, company, etc.); (iv) a continuous time span (whole day) is being considered rather than discrete time slices (e.g. time of day approach), and (v) activities are constrained by time and space, institutional constraints and personal constraints. These features turn activity-based modeling into a rich, precise and comprehensive framework for travel demand analysis to the extent that models successfully capture the features individually and interdependently. It takes into account activity patterns, lifestyles and interactions between individuals. Thus, activity-based models can be used to assess policy (road pricing, inner city tariffs, etc.) and potentially the impacts of new information technologies (telecommuting, ATIS), and it may be the only adequate approach when dealing with these problems and policies.

Activity-based modeling has been extensively studied since the 1970’s, with two influential, seminal publications: Chapin’s book “Human activity patterns in the city” (Chapin, 1974) and Hägerstrand’s paper on What about people in regional science (Hägerstrand, 1970). Chapin advocated a new concept in urban planning theory at that time: planning should be based on an understanding of activity patterns. Hägerstrand and his co-workers’ work, which later became known as “time geography” has in common the focus on people, activities and activity patterns, but the key argument in their work was that we should analyze constraints that limit people to realize their preferences and maximize their utilities, and assess the impact of spatial and non-spatial policies. It should be realized that regional science and related disciplines such as geography focused on spatial entities, spatial structure and spatial dynamics, i.e. on the outcomes of behavioral decisions as opposed to these decisions themselves.

There are different ways to categorize activity-based models. For example, Buliung (2005) distinguished two genres, econometric and statistical approaches and mixed model systems based on the modeling approach used. Another categorization
was proposed by Arentze and Timmermans (2000) who classified activity-based models into four categories. This classification follows the separation of Hägerstrand and Chapin’s concepts in how activities are organized, namely, a constraints approach and a choice approach. They identify 4 categories: constraints-based models, utility-maximizing models, rule-based models (also known as computational process models) and simulation based models. The last category is somehow weakly defined, as the authors acknowledged, due to the fact that nearly all models have some kind of simulation features. In addition to these modeling approaches that incorporate multiple facets of activity-travel behavior, there is a rich literature on the analysis and modeling of single or dual aspects of activity-travel behavior. Among these, route choice decisions and departure time decisions are the mostly studied topics along with other aspects such as activity frequency analysis and activity participation, time allocation, and trip chaining.

2.2.1 Constraints-based models

Constraints-based models represent the first generation of activity-based models. They are directly based on Hägerstrand’s time geography. According to this theory, the planning, organization, and execution of activities are constrained by various spatial-temporal constraints. Three types of constraints were identified in this context: capacity, coupling and authority constraints.

Capacity constraints stand for physical limitations posed on a traveler by his/her biological need for sleeping and eating, travel speed limit of a certain transport mode, etc. Hägerstrand introduced the space-time prism concept to illustrate capacity constraints. The volume between the two cones in Figure 2.1 of space-time prisms defines an individual’s potential space path (Figure 2.2) between two activities.
Coupling constraints refer to the individual’s need to make social contacts with other individuals, for example, to meet friends for recreational purposes, to attend meetings with clients, etc. For the existence of coupling constraints, the space-time path of one individual should bundle with other individuals’ space-time paths. This bundle may happen at home, work, shops, cinemas, or even on the telephone or online. The bundles may happen as a fixed time table, for instance, regular meetings at work, or occasionally, such as recreational activities conducted with friends.

Authority constraints define the accessible resources to conduct an activity at a certain place at a certain time. For example, opening hours of shops, availability of seats in restaurants, are typical authority constraints. The vertical thick lines define authority constraints.
These three types of constraints define possible times and spaces for an individual to perform activities. Hägerstrand uses the concept of a space-time path (Figure 2.2) to represent an individual’s activity-travel pattern. The space-time path consists of stations and chains where stations represent activity locations and chains represent travel between activities. Hence, a natural question that can be asked is what the possible paths are that can be used to realize a given activity pattern.

Constraints-based models therefore examine the feasibility of a particular activity pattern in a specific time space environment. Usually, a set of activity patterns will be given beforehand, derived from observations of real activity patterns. Then, the time-space constraints that define locations of activities and their attributes, available transport modes and travel times between locations are introduced as input. Institutional constraints such as opening hours of a particular service at a particular location are added. The purpose of the model then is to test the feasibility of the observed schedules, given these various constraints reflecting particular policies, or to derive the possible paths that can be used to realize a given activity pattern. The latter is then often used as a measure of accessibility.
Two components comprise the core of constraints-based models: activity pattern generation and feasibility checking. To generate a set of activity patterns, a combinatorial algorithm, either exhaustive or non-exhaustive, is applied to generate all possible activity patterns. Then, feasibility checking eliminates activity patterns that do not satisfy given constraints. One of the earliest constraints-based models in this vein is PESASP model (Lenntorp, 1978). The model has been primarily used to check the feasibility of activity patterns under given home and work activity settings, and the modeling result gives an indication of the accessibility for each location in the study area. Hence, this model can be used to assess impacts of various changes such as improved public transportation services (travel times), land use (activity destinations), opening hours of shops and working hours. The model uses *a priori* defined activity list that an individual has to conduct as its input and exhaustively generates all possible activity patterns using a combinatorial algorithm. The activities in the activity program can be fixed or flexible in time and space. Fixed activities can only be conducted at a specific place and at a certain time, whilst flexible activities can be conducted at alternative locations or at another time of the day. A home activity is always included in the activity pattern as the start and end point of each activity pattern. PESASP then checks these generated activity patterns against given environmental constraints and removes infeasible patterns. The environmental constraints are defined by locations of activity destinations, opening hours of services and travel times between activity locations. PESASP takes into account four types of transport modes: walk, bike, car and public transport. It also takes into account walking and parking time in case the individual uses a car.

A similar constraints-based model is CARLA (Jones *et al.*, 1983), which shares the same objective with PESASP: finding feasible activity patterns under space time constraints. Two features distinguish this model from PESASP. First, activity patterns are generated in a tree structure that can avoid obvious infeasible patterns.
Terminal nodes represent complete activity patterns and intermediate nodes represent incomplete schedules. During the tree construction, if an intermediate node is found to violate any given constraint, the nodes afterwards are dropped from consideration to save computation time. Secondly, CARLA uses heuristic rules to check the feasibility of generated schedules, thereby further reducing the possibly large number of feasible schedules. These rules include logical rules that are incorporated into the design of the algorithm, environmental rules that represent temporal constraints and scheduling rules that reflect individual’s habitual behavior.

In the Netherlands, Huigen’s (1986) BSP model has very similar functionality to CARLA. This also applies to the MASTIC model (Dijst, 1995; Dijst and Vidakovic, 1997). Similar to CARLA, the BSP model evaluates the options to maintain the current activity pattern in a changed spatial-temporal setting. It exhaustively evaluates all possible sequences of activity-destination combinations. However, the way constraints are incorporated differs from CARLA. BSP allows that different trips in a chain are made by different modes. It defines available time windows specifically for destinations, not for activities. MASTIC uses the notion of action space, which is defined as the area within which persons can undertake activities, subject to a set of temporal and spatial constraints. The primary goal of this model is to identify the action space of individuals in terms of space-time prisms.

Later efforts of using constraints-based models re-emerged in GIS (geographical information system) research. Miller (1991, 1998, 1999) and Kwan (1997, 1998) showed how this kind of model can be included in GIS systems to produce useful accessibility indices. Despite the fact that these constraints-based models are valuable in policy analysis, their relevance for prediction is highly limited because these models assume fixed activity patterns and hence do not allow for rescheduling and do not predict individual’s responses to changing space time environments. Constraints-based models focus only on possible activity patterns.
which may differ from actual alternative activity patterns considered by individuals. As such these models focus on constraints in the environment and not on individual decision processes.

2.2.2 Utility-based models

Utility-based models, especial discrete choice models, have been dominant in urban planning and transportation research since the mid 1970s. These models are founded on micro-economic theory about consumer choice in market demand analysis. This theory states that individuals choose to consume commodities and services that yield the greatest amount of satisfaction or utility. Thus, choice represents an optimization process. Under these assumptions, individuals make perfectly rational decisions. Two types of utility maximization models can be identified depending on the nature of choice alternatives: micro-economic consumer theory and discrete choice theory (Ben-Akiva and Lerman, 1985). The choice alternatives in micro-economic consumer theory are generally assumed to be continuous and non-negative. Discrete choice theory, on the other hand, assumes that individuals choose the most awarding alternative among a finite set of alternatives which are mutually exclusive.

Utility-based models extend constraints-based models by adding a choice component to predict actual choices. Utility-based models use disaggregate modeling procedures, originally developed in the context of trip and tour-based models, to predict activity schedules. In particular, multinomial logit models have been used to predict an individual’s choice from a set of possible complete daily activity schedules, or alternatively, nested logit models have been used to predict choices at various stages in an activity scheduling process. In both cases, the choice of an activity schedule is predicted as the choice of the option that yields maximum utility.
Consumer theory models

In consumer theory, individuals will choose a bundle of consumption of commodities or services under a certain budget so that the derived utility from purchasing this bundle of commodities or services reaches the maximum. In mathematical notation, assume an individual has to choose from a bundle of two commodities with quantity \( q_1 \) and \( q_2 \), given his/her total budget \( I \). The utility derived from consuming these two commodities can be expressed as:

\[
U = \beta_0 q_1^{\beta_1} q_2^{\beta_2} \tag{2.1}
\]

where \( \beta_0 \), \( \beta_1 \) and \( \beta_2 \) are parameters for individual tastes difference. The choice problem can thus be expressed as:

\[
\underset{q_1, q_2}{\text{Max}} U = \beta_0 q_1^{\beta_1} q_2^{\beta_2} \tag{2.2}
\]

subject to

\[
p_1 q_1 + p_2 q_2 = I
\]

where \( p_1 \), \( p_2 \) are the prices for commodities \( q_1 \) and \( q_2 \) respectively.

This micro-economic consumer theory is especially useful in market research to calculate market demand and equilibrium prices. Attempts to use this type of model in transportation research can be found in time allocation and money allocation studies. Becker (1965) suggested a framework to explore how time and money are allocated among different activities. The core idea of Becker’s model is that time can be transferred into money. By extending work time, an individual can
earn more money. By performing non-work activities, individuals consume not only money, but also time, Becker’s model integrated the time component into the traditional utility function. The idea that people can freely trade-off between work time and money is a rather unrealistic assumption. To overcome this drawback, De Serpa (1971) included both time and money constraints in his model that aims at interpreting the value of time. Further, he added a technical constraint for the minimum time required to consume different market goods. Evens (1972) used only time as the source of direct utility in conducting activities, market goods are considered as activity costs that can be either positive or negative. Compared to Becker and De Serpa’s model, this model provides a more general framework to model the relationship between time and goods as it separates goods from utility functions.

A missing component in above models is the spatial factor. None of these models takes into account travel time/distance effects. Train and McFadden (1978) extended Becker’s model to investigate the wage usage rate regarding mode choices of work trips. In their model, travel cost and travel time are explicitly represented.

Despite the fact this type of consumer theory models provide valuable tools for investigating time and money allocation behavior, the bundle consumption behavior does not naturally reflect the travel decision alternatives an individual faces.

*Discrete choice models*

In discrete choice models, individuals are assumed to evaluate a finite set of discrete and mutually exclusive alternative and choose the one that gives the highest utility. Although the models can be derived from different theories, often reference is made to random utility theory. It assumes that individuals have a
perfect discrimination capability. That is, individuals are assumed to always choose the same alternative with the highest rewards in identical situations. That is to say, it assumes a deterministic, utility-maximizing decision rule. Utility however is stochastic. More specifically, the utility of alternative $i$ is defined as:

$$U_i = V_i + \varepsilon_i \quad (2.3)$$

$V_i$ is the deterministic part of the utility, $\varepsilon_i$ is the error term that captures unobserved attributes, unobserved taste variation among individuals, measurement errors and instrumental variables. Traditionally, the deterministic part of utility is assumed to be linear additive. Then, equation (2.3) becomes

$$U_i = \sum_{k} \beta_k X_{ik} + \varepsilon_i \quad (2.4)$$

where $X_{ik}$ is the $k-th$ attribute of alternative $i$, $\beta_k$ is the parameter of the $k-th$ attribute of alternative $i$. The deterministic term of the utility is therefore fully specified by parameter vector $\beta$. Various types of discrete choice models can be derived depending on the underlying assumptions of the distribution of the error terms $\varepsilon_i$.

Logit model and nested logit model
If the error terms are assumed to be independently and identically Gumbel distributed, the choice probability is then represented by the Multinomial logit model. The density distribution equals

$$f(\varepsilon_i) = e^{-\varepsilon_i}e^{-\varepsilon_i} \quad (2.5)$$
and the choice probability of alternative $i$ is given by

$$P_i = \frac{e^{\gamma_i}}{\sum_j e^{\gamma_j}} \tag{2.6}$$

The Multinomial logit model is the most widely used discrete choice model due to its simplicity and convenience in construction and estimation. It has been successfully applied in mode choice and destination choice in transportation research. An important property of the Multinomial logit model that results from its error term distributional assumptions is the Independence of Irrelevant alternatives (IIA) property. It says that the ratio of the probabilities of any two alternatives being chosen is independent of any other alternative. This property is considered unrealistic and a limitation in some applications since one would expect that similar alternatives have correlated error terms and this violates the assumption of independence.

To avoid the restrictive IIA assumption of the multinomial logit model, other models were developed. A family of models called Generalized Extreme Value (GEV) models uses a generalization of the extreme value distribution as the error term. The generalization can take many forms and allows correlations among alternatives. The correlation in alternatives can be more or less flexible depending on how the form distribution is specified. If no correlation among alternatives exists, the GEV model collapses into the multinomial logit model.

The Nested logit model is a direct extension of the multinomial logit model. It was proposed by Ben-Akiva (1973, 1974) to relax the independence assumption and allow correlations among alternatives. Nested logit models partition the choice set
into nests so that the subsets (nests) of the choices are mutually exclusive. Two properties hold when partitioning choice set into nests. First, IIA holds within nests, which means that the ratio of any two alternatives in same nest is independent of other alternatives in this nest. Secondly, the ratio of two alternatives in two different nests may depend on the attributes of other alternatives in the nests: IIA does not hold between different nests.

Probit model
The Probit model avoids the independence assumption by assuming the error terms can be presented in term of a normal distribution, \((\epsilon_1, \epsilon_2, ..., \epsilon_n) \sim N(0, \Omega)\). With full covariance matrix, \(\Omega\), the Probit model explicitly captures any pattern of correlations among all alternatives. This makes the Probit model very flexible in handling correlations. However, the main drawback of the model is the difficulty in estimation as the calculation of choice probabilities involves \(J-1\) dimensional numerical integrals which have no close form expression and must be approximated numerically by simulation. Moreover, the unobserved factors of alternatives in some situations are obviously not normally distributed. For example, the consumer’s willingness to pay for some attributes of alternatives is necessary positive.

Mixed logit model
Mixed logit models represent a highly flexible specification that can approximate any random utility model (McFadden and Train, 2000). The main idea of the mixed logit model is to consider more than one random component and keep the basic model in logit form. The multi-random components structure allows the mixed logit model to accommodate correlations and heteroscedasticity.

There are two ways to handle the correlations across alternatives and across choice situations. One way is to partition the error term which is assumed to be
independently and identically distributed into two additive parts and assume parameters as fixed. One part is correlated across alternatives and the other part is i.i.d. distributed. Thus, the utility function becomes

\[ U_i = V_i + [\eta_i + \varepsilon_i] \]  

(2.7)

where \( \eta_i \) denotes a random term whose distribution over individuals and alternatives depends on underlying parameters and observed data relating to alternative \( i \) and this individual. It can be defined as \( \eta_i = uz \) where \( u \) denotes a vector of random terms with zero means, \( z \) denotes vector of observed variables. \( \varepsilon_i \) is a random term with an i.i.d. distribution across alternatives and individuals and does not depend on any parameters or observed data. Both random terms have zero means. Random term \( \eta_i \) can take on normal, lognormal, triangle, etc. distributions depending on how the researcher specifies the models. If the \( \eta_i \) value is given, since the rest error term \( \varepsilon_i \) is assumed i.i.d., the conditional choice probability is equal to

\[ L_i = \frac{e^{\beta x_i + \eta_i}}{\sum_j e^{\beta x_j + \eta_j}} \]  

(2.8)

However, \( \eta_i \) value is unknown to the researcher. To calculate the unconditional choice probability, one has to integral \( \eta \) across all possible values,

\[ P_i = \int L_i(\eta)f(\eta|\Omega)d(\eta) \]  

(2.9)
where $L_i(\eta)$ is the logit form of the conditional choice probability given known $\eta$, $f(\eta|\Omega)$ is the density function of $\eta$ and $\Omega$ are the fixed parameters of the distribution.

This way of handling unobserved information by separating error terms is called the error components approach. The other way known as random parameter specification or the random coefficients approach treats the underlying parameters $\beta$ as random variables with own distributions $f(\beta)$ across individuals. The procedure of specifying the model is the same as for the logit model except that parameters $\beta$ can vary across the population with density $f(\beta)$. The utility function of alternative $i$ is

$$U_i = \beta x_i + \epsilon_i \quad (2.10)$$

The error term $\epsilon_i$ is i.i.d.. Thus, given $\beta$, the conditional probability equals

$$L_i(\beta) = \frac{e^{\beta x_i}}{\sum_j e^{\beta x_j}} \quad (2.11)$$

and the unconditional probability becomes

$$P_i = \int L_i(\beta) f(\beta|\Omega) d(\beta) \quad (2.12)$$

where $\Omega$ denotes the fixed parameters for distribution $f(\beta)$.

The error components approach and the random coefficient approach are formally equivalent. Since the deviation of a random term is essentially additive, the
estimation results are identical. Under random coefficient specification, equation (2.10), one can decompose $\beta$ in the random coefficient approach into mean $\alpha$ and deviation parts $u$ so that $U = \alpha x + ux + \epsilon$. Let $x = z$ where $z$ denotes a vector of observed variables as in error component specification, the equation turns into the error component specification with the mean part equals the fixed parameter part and deviation part equals $\eta$ in the error component specification. Vice versa, the error components specification can be seen as a random coefficient model with fixed parameters with zero deviation, plus a random parameter component with zero means ($\eta$) and the same i.i.d. error term $\epsilon$ (Train, 2003).

The existence of variable parameters enables the mixed logit model to capture heterogeneity of individual preferences in the sampled population. This model is widely used in recent transportation research. However, with this great flexibility, the simplicity of the logit model is lost and numerical simulation is required for parameter estimation.

Latent class models

Latent class models, also known as finite mixture models, take a similar concept to allow heterogeneity across individuals. However, rather than using a distribution of parameters, latent class models segment the population into latent classes. The basic idea is that the study population is comprised of a mixture of subpopulations (latent classes) each manifesting homogeneous choice behavior. Thus, within latent class, parameters are fixed, and across subpopulations, individuals show heterogeneous choice behavior.

The utility function is not different from the random coefficient model:

$$U_i = \beta x_i + \epsilon_i$$  \hspace{1cm} (2.13)
The conditional probability is equal to

\[ L_c(\beta_c) = \frac{e^{\beta_c z_i}}{\sum_j e^{\beta_j z_j}} \]  

(2.14)

\( \beta_c \) is the vector of parameters for class \( c \). The unconditional probability becomes

\[ P_i = \sum_c \alpha_c \cdot L_c(\beta_c) \]  

(2.15)

where \( \alpha_c \) denotes the probability of this individual belonging to class \( c \). It can take multinomial logit form:

\[ \alpha_{sc} = \frac{e^{z_i \theta_j}}{\sum_j e^{z_i \theta_j}}, \text{ where } j = 1 \ldots C, \theta_c = 0 \]  

(2.16)

\( z_i \) denotes a set of observable attributes that may be psychological constructs or socio-economic characteristics. \( z_i \) in this format is known as “concomitant variable” or “covariate variable”. \( \theta_c \) denotes the unknown class parameters. \( \alpha_{sz} \) can simply be a constant if there are no concomitant variables specified in the model. In that case, adopting a single attribute in \( z_s \) and setting this attribute to a constant “1”, the latent class probabilities would sum up to 1 by construction.

Bayesian estimation of discrete choice models
Bayesian methods for estimation have only been recently explored in transportation research. They have a stronger track record in other disciplines due to their flexibility in bringing non-sample prior information into the model framework and
their ability to avoid asymptotic approximation during model estimation. The slow adaptation of the Bayesian approach in transportation research may be largely attributed to the computational difficulty in Bayesian estimation. However, due to increased computation power and numerical algorithms, Bayesian methods can now handle very complex models.

The key difference between Bayesian models and classical inference approaches is that Bayesian models treat parameters as random variables which have a-priori distributions (e.g., Brownstone, 2001; Train, 2001). The Bayesian approach has the theoretical advantage that it provides exact information on the posterior distribution while classical inference approximates the posterior. Another merit of the Bayesian approach is its ability to make statements from small samples as well as large samples. Consider a model with parameter $\theta$. The researchers’ priori knowledge on parameters is specified as prior distribution $\pi(\theta)$, observed choices as $X$, given sampled data $Y$. Applying Bayes rule generates updated posterior distribution:

$$P(\theta | X) = \frac{L(X | \theta)\pi(\theta)}{L(X)}$$ (2.17)

where $L(X | \theta)$ is the likelihood of observing $X$ with parameter $\theta$. $L(X | \theta)$ is defined as $L(X | \theta) = \prod_{i=1}^{n} P(X_i | \theta)$ where $X_i$ denotes the $i-th$ observation. The marginal probability $L(X)$ of observation $X$, marginalized over $\theta$ is

$$L(X) = \int \pi(\theta)d(\theta)$$ (2.18)

All inferences then are based on the posterior distribution $P(\theta | X)$. However, one thing noteworthy, as Train (2003) pointed out, is that the Bayesian approach is
considered essentially an estimation procedure rather than a behavioral model, since taking a Bayesian approach does not necessarily mean that one should take a Bayesian perspective. When taking a Bayesian perspective, researchers may still take this approach as a parallel method to other discrete choice models mentioned above, it is often referred as the Hierarchical model in econometrics.

The computational performance of the Bayesian approach is better for normal distributions with a full covariance matrix and lognormal distributions compared to classical inference methods (Train, 2001). With fixed parameters, the Bayesian approach becomes slower than classical inference and the computation time gets worse in situations when parameters are bounded, such as triangle distributions. Due to its theoretical simplicity and with the computational burden removed, at least partly, by modern computer technology, the Bayesian approach is anticipated to be more widely applied in transportation research in the near future.

Progress in the development and application of utility-based activity-travel models has followed closely these developments in econometrics. After successful applications of single-facet models such as mode choice, route choice and departure time choice, studies using discrete choice models to look at full day activity patterns emerged subsequently. To deal with the complexity of many intra-related choices in activity modeling, early studies often made restrictive assumptions to simplify their models, especially in the early stage of applying the discrete choice approach in activity-based models. Adler and Ben-Akiva (1979) developed their seminal work with the simplified assumption that individuals decide at once about their full activity schedule. With this assumption, the complexity of activity patterns is reduced to a simple choice problem. Thus, a single error term logit model was used in their study. The model assumes that individuals evaluate a set of complete full day activity patterns based on a number of attributes and choose the one giving the highest utility. The decision procedure
is then captured by a multinomial logit model. This rigorous assumption poses several limitations on this model. Firstly, the model cannot address the interdependencies among activities, and is counterintuitive in that people make detailed plans for full daily activity schedules. Secondly, the model implies a perfect match between the chosen activity pattern and the executed schedule and does not take into account any re-scheduling decisions.

STARCHILD (Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decision), developed by Recker and his co-workers (Recker et al., 1986a,b) advanced this work one step further. This model has been applied to investigate, amongst other things, the impacts of variable work hours, and changes in network travel speed. It predicts the choice of a household activity schedule, while accommodating the inter-related time-space paths of household members with given activity schedules. The model assumes that the household is in charge of activity program generation, prioritization and allocation to each household member and individuals are conceptualized as execution units. Individual member of the household then take the assigned activity programs and translate these into activity patterns, that is, make scheduling decisions, during the execution phase. The individual activity program includes two types of activities, planned activities for which the scheduling process occurred prior to the action period and unplanned activities that occur during the action period. All feasible activity patterns comprise an “opportunity set” and are further filtered into an “option set” which is smaller and only includes distinct activity patterns. The utility of an activity pattern is derived from three time-components: travel time, waiting time and actual participation time. The choice of activity pattern is specified as a multinomial logit model. The specification of choice alternatives in STARCHILD is not much different from the model proposed by Alder and Ben-Akiva (1979) in the sense that both models assume individuals evaluate the full activity pattern at one point in time, although in STARCHILD, revisions of activity patterns, at least in theory,
can be done during the action period by means of allocating unplanned activities into available schedule slots.

An important step forward was made in the context of Bowman’s PhD study, who developed a daily activity model, which in the meantime has been further developed and has found application in several US cities (Bowman and Ben-Akiva, 1996, 1998, 2001). It can be viewed as the most comprehensive utility maximization based model framework. This model was first prototyped and applied in Boston and later extended and implemented in Portland. The model explicitly represents the choice of a daily activity pattern and incorporates the time of day decision. The model uses a tour-based approach in which “tours” are defined as a sequence of home-based trips that start and end at home. Tour characteristics consist of destination, travel mode and time of the day. Two types of tours are distinguished in this model, primary tours that involve primary activities (home, work, school, other) and secondary tours that involve additional home-based trips made for activities with lower priorities. An activity schedule is characterized as a multidimensional choice of primary activity, primary tour type, and the number and purpose of secondary tours. For each tour, the destinations, times of day and travel modes are modeled. The model is implemented as a nested logit model, with tour decisions conditioned by the choice of daily activity pattern (Figure 2.3). Hence, the choice made at one level is influenced by the expected maximum utility derived from alternatives at lower levels. This is captured by the logsum of the utilities at lower levels. In their prototype, the daily activity pattern model is a choice among 55 patterns. The model system design requires the explicit modeling of secondary destinations on tours, conditional on the choices for the primary destination.
As the authors acknowledged, the key feature of this model, the integrated daily schedule, is also the source of one of its two main weaknesses. Chaining tours to daily activity pattern results in a very large choice set which is behaviorally unrealistic and computationally difficult. Another weakness concerns how time is incorporated in the model. The time of day is aggregated into only 4 time periods, thus the temporal component of activity patterns can only be handled in a very limited way. Other problems include the omission of secondary stops on tours, incompleteness of the time of day linkages, and lack of household linkages. Nonetheless, the model provides a comprehensive way to break down complex activity-travel pattern choices into a number of partial choices.

Ettema et al. (1993, 1996, 2000) developed a utility-based stepwise adaptive scheduling algorithm to model the addition, deletion, substitution, and termination of activity chain. Conceptually, the model shows more similarity to computational process models in the sense that the focus is on the process of generating schedules and not on the final outcome of the schedules process, but operationally, discrete choice models are applied.
Their SMASH (Simulation Model of Activity Scheduling Heuristics) framework (Ettema et al., 1996) conceptualizes scheduling as a sequential adaptive process, partially based on satisficing rather than optimizing behaviors. That is, the assumption is made that scheduling is not solely determined by economically rational behavior characterized by time or distance minimization. Operationally, SMASH builds individual schedules in steps with each step governed by utility maximization theory. In the original paper, schedules were initialized without activities. Add, delete, and substitute functions complete individual schedules with the stop function ending the scheduling process. The final schedule stores activity locations and activity sequence. Operational evolution of the model led to the exclusion of the activity deletion and substitution functions. SMASH differs from STARCHILD in two major ways: the conceptualization of individual choice and the evolution of activity patterns during execution. Within STARCHILD, individuals select entire activity patterns from a potentially large choice set. SMASH builds schedules incrementally with the potential inclusion of sub-optimal activities. Choice set definition presented a challenge in both cases with SMASH also including all possible activity alternatives in the stepwise activity evaluation process. With respect to the second difference, Ettema et al. (1993) include the possibility to adjust schedules during travel, while STARCHILD activity patterns remain fixed during execution. Both the STARCHILD and SMASH experiments were conducted using small datasets for calibration, simulation, and validation. Compared to STARCHILD, SMASH provides results indicating that simulated schedules closely match observed schedules of respondents. In addition, realistic schedules emerged from a case study designed to examine scheduling response of a single working person and working parent to adjustments in the scheduling environment.
2.2.3 Computational process models

Computational process models (CPM) are essentially rule-based models. This mode arises from the criticisms on the utility-maximizing models. Cognitive psychologists argued that human beings are limited in computational power thus will not make decisions based on exhaustive comparisons of alternatives, rather, individuals make decisions using heuristics or rules (Simon, 1990), implying the decision process of individual is satisficing rather than optimizing. Individuals are assumed to yield a satisfactory solution using heuristics rules so that the efforts on data manipulation can be limited. Usually, computational process models focus more on how individuals build their schedules. That is, they focus on the process, include an explicit process model, rather than on activity-travel patterns as outcomes. One test of validity is whether observed schedules can be successfully generated by the model; these schedules do not serve as input. The assumption is that individuals learn from past experiences and through positive/negative feedbacks gradually build up heuristics. In doing so, individuals do not need to re-examine all choice alternative when facing a similar or new travel environment, rather, they consider only a small set of alternatives based on heuristics. Another characteristic of computational models is the explicit incorporation of Hägerstrand’s time-space constraints into the model structure.

The heuristics can be formalized as a production system which uses a set of IF…THEN… rules, or production rules. Production systems are generally used to conceptualize cognitive and mental aspects in decision making. The decision making process can be expressed as sequences of state-action pairs, within which, state represents the state of individual and the decision making process itself and action represents the decision taken in this state. Under this specification, the choice problem becomes a function of a set of conditions and facilitates production systems to constitute a flexible representation of human decision making processes.
Gärling et al. (1989, 1994) described a conceptual framework of activity scheduling operationalized in the form of production system approach: SCHEDULER. Household members’ interactions are explicitly defined in this model. Scheduling is defined as the process of deciding how to implement a set of activity choices within a given time span. The model starts with the decision which activity first to conduct, then the decision what activity next to conduct, and so on. Heuristic search is used in making consecutive activity choices, which assumes an individual chooses a set of activities instead of choosing from full length activity patterns. Based on prioritization of activities and crude judgment of the number of possible activities that can be conducted in a given time slot, the model retrieves a subset of activities for scheduling. Spatial and time constraints are applied during the scheduling process. In the “mental execution” stage, conflicts, such as overlapping end and start time that may lead to an infeasible schedule are resolved by changing the order of activities in conflicts or by replacing a chosen activity with a lower priority activity. A fully operational model has never been developed. SMASH (Ettema et al., 2001) can be viewed as a partial operationalization of the model, but differs in other respects. Components of the framework have been applied to analyze activity patterns of commuters after the introduction of tele-commuting (Golledge et al., 1994). This model was further refined by Kwan (1997) in its spatial search capabilities with enhanced procedures to generate feasible activity sets and routes. The resulting model, GISICAS aims at modeling pre-trip planning process regarding the use of ATIS (Advanced Travel information system) and is capable of generating schedules at the individual’s “current” location instead of only making schedules starting from home and work location. Much of this work however was based on rather simplifying assumptions underlying constraints-based modeling. Gärling et al. (1998) revised SCHEDULER into SCHEDULER2 with their focus mainly on understanding the planning process of non-routine activities. The scheduling process is conceptualized as the insertion of non-routine activities around routine activities. The Linkage to GIS was dropped in
SCHEDULER2. Although several authors such as Auld et al. (2009) have announced initiatives to operationalize this general framework, to date this did not truly happen. However, there is a rich literature on empirical analysis of scheduling and rescheduling processes (e.g., Chen and Kitamura, 2000; Joh et al., 2002; Roorda and Ruiz, 2008; Ruiz and Timmermans, 2008).

As indicated Ettema et al. (1993, 1996, 2000) developed SMASH, which was heavily inspired by SCHEDULER, but also contains principles of utility-maximizing behavior. SMASH conceptualized activity scheduling as a sequential adaptive process that is based on partially satisficing rather than maximizing behavior. In each step, individual can adapt the existing schedule by adding, deleting, or re-scheduling an activity. When an individual is satisfied with the found schedule, the decision process is completed. In each step, decisions are governed by utility maximizing theory using a nested logit model structure. The authors acknowledged that the use of nested logit model in step decisions is a step away from the deterministic heuristic model approach that usually applied. However, by building up schedules incrementally, the model is able to model adaptation in scheduling processes.

AMOS (RDC, 1995), which stands for Activity-Mobility Simulator, is another model that has been positioned as a computational process model, but at the same time is also based on utility-maximization. The model has five main components. The baseline activity-travel analyzer generates individual activity patterns using survey data, compares them with the network data to check logical consistency, and then generates a coherent baseline activity-travel pattern for each individual. The response option generator creates basic responses of individuals to the operation strategies using a combined neural network and multinomial logit approach. It uses the baseline activity-travel analyzer as output and social-demographical data as input. The activity–travel pattern modifier basically
modifies the results from the response option generator by iteratively checking and executing activity patterns feasibilities. Feasibility checking is based on time-space constraints by a set of logical condition rules. The evaluation module and acceptance routines evaluate alternative activity patterns based on utility functions. A statistic accumulator provides descriptive statistics of final feasible accepted activity patterns. Together with the baseline activity-travel pattern, this module can provide information on the changes induced by changes in policies or management strategies. This summary indicates that especially the modeling of traveler response to policies makes this model unique for its generation. It is the main reason why it has been positioned as a computational process model. Technically, however, the specification of the model is more in line with utility-based models.

To date, the only fully operational rule-based model is ALBATROSS, developed for the Dutch Ministry of Transport, Public Works and Water Management. The first version was published in 2000 (Arentze and Timmermans, 2000), but the model has been expanded and re-estimated on increasingly larger data sets. It is in its 4th version currently and work is still going on. The model was successfully applied in the Netherlands at both regional and national levels. The core part of ALBATROSS is its scheduling engine utilizing a set of IF…THEN… rules which make it a rule-based CPM model. One feature which makes the model distinct from other computational models is the derivation of rules. Rather than using pre-defined ad-hoc rules or relying on econometric decision models for decision making, ALABTROSS develops decision rules directly from activity-travel diary data using a data mining method. Activity Scheduling rules are represented by decision trees in version 1 and version 2 and are replaced by an enhanced form of decision trees in version 3 and version 4, incorporating parametric elements (PADT, parametric action decision trees, Arentze and Timmermans 2007). The parametric features PADT aims at overcoming the inadequacy of conventional rule-based models when dealing with continuous variables (travel cost, travel time, etc.).
Compared to decision tree approaches used in conventional rule-based models in which choice probabilities in leaf nodes are static, the PADT approach no longer considers travel time and travel cost consequences in the tree, but instead, PADT use this information in the action assignment phase. The probabilities associated with leaf nodes then are generated by a discrete choice model. Introducing PADT into ALBATROSS enables the model to calculate time and price elasticities and utility-based welfare measures for continuous variables and makes the model a competitive alternative to utility-based models in this respect.

ALBATROSS uses a sequential decision process to generate daily activity schedules of individuals in the context of a household. The scheduling engine handles the scheduling process, identifies relevant condition information for the decision unit, activates appropriate analytical and rule-based models in an inference unit to obtain this condition information and translates decisions made by the decision unit into appropriate operations on the evolving schedule. Furthermore, an important feature of the model is that generated schedules fully meet time and space-time constraints.

Another noteworthy rule-based activity-travel model is TASHA, developed by Miller and Roorda (2002, 2003). This modeling system aims at constructing the sequence of decisions that are made in the formation of a travel/activity schedule. The model resembles four step travel demand models in the sense that TASHA is conceptually divided into five steps: Activity generation, activity location choice, activity scheduling, household level tour mode choice and trip assignment. The activity scheduling step makes use of rule-based method. It builds a traveler’s activity schedule from bottom-up, beginning with the generation of individual and multi-person activity episodes, and inserting those activities into a feasible activity schedule. The conflicts in the activity schedule are resolved by shifting and changing activities’ duration as necessary where activities overlap in time. Activity
schedules (tours) emerge from this process. Furthermore, TASHA includes a tour-based mode choice model that explicitly evaluates ridesharing, vehicle allocation and joint travel to joint activities (Roorda and Miller, 2005; Roorda et al., 2006). The model was validated against empirical data (1996 and 2001 travel survey data for the Great Toronto Area), and the overall validation results “are strong enough to warrant the consideration of TASHA as an alternative to conventional modeling systems currently in use in the Greater Toronto Area”, as the authors stated (Roorda et al., 2008).

2.2.4 Micro-Simulation models

Miller (1997) defined micro-simulation models as an approach to model a dynamic system. The argument of using micro simulation model is that a closed form analytical representation of such system is generally not possible. This type of models involves disaggregate or micro level decision-making units such as individual persons, households and vehicles. At the core are the characteristics and behaviors of above mentioned decision units. Closely linked to complexity theory and agent-based modeling approach, some micro-simulation models are also considered agent-based models. Typically, a population synthesis procedure is the start of this kind of model.

Many of the current activity-based models focus on individual daily activity-travel patterns and can be viewed as micro simulation models given the inherently disaggregate nature of activity-based models, and the fact that these models typically incorporate some dynamics. In that sense PCATS, AMOS, ALBATROSS and the utility-based models are examples of micro simulation models. However, the micro-simulation models that we have in mind here do not attempt to represent observed distributions in terms of theoretical concepts, but rather are more data-driven and rely on sampling and enumeration procedures. An example is Axhausen (1990), representative of a strong tradition of applying micro simulation models in
Germany. Axhausen's contribution was to combine an activity chain simulation model with a mesoscopic traffic flow simulator. Axhausen’s work represents an early attempt to link an activity-based model directly to a network assignment model eventually leading to the MATSIM model (see below). Another noteworthy early example is MIDAS (Kitamura and Goulias, 1991, 1992, 1996) which was developed for the Dutch government. It is an operational micro-simulation forecasting tool for the national level. The model has socio-economic and demographic components and simulates household transitions, including births, deaths, household type changes and individual’s employment status change, personal income, driver's license possession and education status, car ownership, trip generation and modal split. Thus, the model has included most of the characteristics of activity-based micro-simulation modeling for travel forecasting.

RAMBLAS (Veldhuisen et al., 2000) predicts both activity patterns and traffic flows. This model segments a synthetic population based on social-demographic characteristics and assigns activity agendas to individuals using a national activity pattern data base. These agendas are then executed in a given area and adjusted to meet space-time constraints, taking into consideration speed on the transportation network that result from the accumulated results of individual decisions. The flexibility that is required to find consistent activity-travel patterns is found in allowing earlier departure times than observed in the sampled diaries. To assess the validity of the model, it was applied to approximately 640,000 individuals in the Eindhoven region, the Netherlands, and resulted in predicted traffic flows that were consistent with observed flows. The model manages and visualized the traffic flows for network links using GIS.

TRANSIMS (Barrett et al., 1995) represents the most ambitious attempt to date to develop a comprehensive micro-simulation travel demand forecasting model. The purpose of this model system is to provide transport planners with detailed
information on how changes in transport policy or infrastructure may affect travel behavior, congestion and pollution. TRANSIMS has a much stronger emphasis on simulating traffic and can also be useful for analysis of traffic safety. It combines activity-based travel demand generation with models of mode and route choice. The simulation makes use of cellular automata models (Simon and Nagel, 1998). As other simulation models, the system creates a synthetic population for a region from available data sets. Activity patterns are generated for the individuals in the population and transformed into individual trip plans. These plans act as inputs to the travel micro-simulation model. While the model involves a detailed microscopic simulation of traffic flows, the activity generation and scheduling parts are quite simple, compared to dedicated activity-based models. TRANSIMS formed the basis for the newly developed MATSIM platform (Balmer et al., 2005).

Another model suite difficult to classify is CEMDAP, developed by Bhat and his co-workers (Bhat et al., 2004). Unlike the utility-based and computational process models, the theoretical underpinnings of this model system are relatively weakly developed. In some sense, the model is close to the original four-step approach, adding the layer of activity participation and differentiating between patterns of workers and non-workers. Each facet of the activity-travel patterns is thus modeled separately and this results in 20+ submodels that are linked in a micro-simulation system. In that sense, CEMDEP has a lot in common with the simulation models described in this section. However, whereas these models are strongly data-driven, CEMDAP is based on highly advanced econometric model specifications.

Currently operational activity-based models mostly function in a static way in the sense that travelers do not learn and adapt their activity-travel schedules. Timmermans et al. (2001) and Joh (2004) suggested and implemented a utility-based model of activity-travel rescheduling behavior, AURORAa. The model accommodates (re)scheduling heuristics and learning process to model the
(re)scheduling process of routinized activities. This model aims to predict activity schedule adaptation in response to changes in the transportation environment. Travel decision facets such as mode, destination, sequence, duration, timing, etc., were taken into consideration. The underlying utility function is an S shape logistic equation that is able to capture different decision strategies. The behavior is not necessarily optimal (maximizing). Although the model was developed as a rescheduling model, the underlying principles can also be used as a model of activity scheduling behavior. The utilities of activities are assumed to be time, past experience and context-dependent. Individuals are assumed to reschedule their activities such that it will increase total utility, consistent with the overall decision strategy and subject to a set of (process) conditions.

Two components comprise the core of AURORA: (i) the utility of the adapted schedule which is a result of rescheduling depending on duration, travel mode, location, sequence and time-of-day of scheduled activities and (dis)utility of excluded activities; (ii) partial search heuristics that adjust schedule. Despite the authors call it a micro simulation model and the fact it is to some extent an agent-based micro-simulation model, the underlying decisions in the model are evaluated based on the overall utility of schedules. Thus, AURORA can also be viewed as a utility-based, albeit not a utility-maximizing model. AURORA explicitly models the adaptation process in travel behavior. This feature makes this model distinct from other models in the way it handles the utility of activities. It assumes the utility of an activity is a “S” shape curve that represents the idea that conducting a activity requires a certain amount of minimum time to fulfill its purpose and exceeding a certain period, spending extra time on this activity does not generate more satisfaction.

AURORA is estimated using a tailored genetic algorithm due to the lack of analytical solutions. In their study, the maximum utility was related to history only,
other aspects of activity schedules were not addressed. Data requirements were another issue. In their estimation, the data were normal travel diary data that were not collected for the purpose of the AURORA model. This plus the fact that the model was only partially implemented meant that the test range and implications of model estimation were rather limited. Furthermore, the model was based on the assumption that the marginal utility of each activity reflects equilibrium in the activity program. This assumption can sometimes be violated in real life observations. Though flexible and extendable and allowing learning/adaptation effects in activity based modeling, the original AURORA model did not specifically take into account decision under uncertainty and learning effects in repetitive scheduling executions.

This discussion shows that although substantial improvement has been made in different approaches to activity-based modeling, these models have only examined typical patterns. Dynamic adjustment, especially due to travel information provision has not received any attention in this literature. Research on the use and impact of travel information has largely remained an independent stream of research in transportation and urban planning. This body of research will be summarized in the next section.

2.3. Travel decisions under uncertainty and travel information

A key underlying assumption in research on travel information is that information is provided to reduce uncertainty faced by the travelers. Travelers are not always clear about existing alternatives, nor are they sure about the outcomes of some uncertain events in the transportation environment, mainly unforeseeable incidents, queues and congestion. Thus, uncertainty may arise from two aspects in travel choices, unfamiliarity of choice alternatives and uncertain events that are probabilistic in nature. This key assumption implies that the conceptual
frameworks and theories that underlie activity-based models of travel demand are ill-suited to address this problem of short-term adjustment of planned activity-travel schedules because these models do not explicitly consider uncertainty. A completely different set of theories for decision making under uncertainty has been developed and these theories have also found their way into travel behavior research. We will summarize the dominant theories in the next sections.

2.3.1 Dominant theories to model decisions under uncertainty

The dominant assumption is that travelers base their decisions on their perceptions of attributes and beliefs or subjective probabilities, rather than on the real situation and objective probabilities. In choice under risk, uncertainty is often represented by some unknown probability distribution of potential outcomes of choice alternatives. There is a subtle difference between risk and uncertainty which has undergone a long-running debate and is far from resolved. In early distinctions between these two concepts, “risk” refers to randomness with knowable probabilities and “uncertainty” refers to randomness with unknowable probabilities (Knight, 1921). Some economists (Shackle, 1949, 1961, 1979; Davidson, 1982, 1991) believe Knight’s distinction is crucial. They argue that Knight’s "uncertainty" may be the only relevant form of randomness for economics—especially when that is related to the issue of time and information. Knight’s "risk" situations are only possible in some controlled scenarios/experiments when the alternatives are clear and experiments can conceivably be repeated, e.g., established gambling games. Nonetheless, this distinction has been disputed by many researchers as well by arguing that Knight’s risk and uncertainty are one and the same thing. For instance, they argue that in Knight’s uncertainty, the problem is that the individual does not assign probabilities. Thus, it is a problem of "knowledge" of the relevant probabilities, not of their "existence". There are actually no probabilities out there to be "known", because probabilities are really only "beliefs". In other words, probabilities are merely subjectively-assigned
expressions of beliefs and have no necessary connection to the true randomness of the world. In this thesis, we will not distinguish between these two terms. Rather, we use both terms referring to situations where the decision-maker can assign mathematical probabilities to the randomness he is faced with.

Travel decisions under uncertainty were traditionally modeled in the context of expected utility theory (Von Neumann and Morgenstern, 1944) which is based on the assumption of rational behavior. Despite the intuitive appeal of the axioms, many choice patterns that violate the theory have been pointed out. Expected utility (EU) theory has been criticized for its lack of behavioral realism (e.g., Allais, 1953; Ellsberg, 1961; Avineri and Prashker, 2004). Researchers argued that expected utility theory does not give a valid representation of the way in which individuals deal with risky decisions under uncertainty, and thus expected utility theory stays as a normative behavioral model, not a descriptive behavioral model. Real life observations and psychological research revealed violations of expected utility theory in individuals’ decisions under small or large probability outcomes and in long run anticipation experiments. The Allais paradox (Allais, 1953) and the Ellsberg paradox (Ellsberg, 1961) are the best known violations of EU theory.

Allais presented situations that violate the independence axiom of expected utility theory, also known as the sure thing principle (Allais, 1953). This independence axiom basically articulates that if an agent always prefer prospect A to prospect B whether a possible future event X happens or not, then she should prefer prospect A despite having no knowledge of whether or not event X will happen. Or, in other words, if an agent is indifferent between simple lotteries L1 and L2, the agent is also indifferent between L1 mixed with an arbitrary simple lottery L3 with probability p and L2 mixed with L3 with the same probability p. Violating this axiom is known as “common consequence” problem. It is best illustrated with an example. Assume two experiments each consists two alternatives.
Experiment I:

1A. $1 million, with certainty
1B. ($1 million, 89%; nothing, 1%; $5 million, 10%)

Experiment II:

2A. (nothing, 89%; $1 million, 11%)
2B. (nothing, 90%; $5 million, 10%)

Allais asserted that most people prefer 1A > 1B, and most people prefer 2B > 2A. However, this is contradicted by the independence axiom in expected utility theory. In both experiments, A and B have a common outcome which will happen 89% of the time ($1 million for prospect 1, and zero for prospect 2). Thus, in expected utility, these equal outcomes should have no effect on the preference of the prospect. If the 89% ‘common consequence’ is disregarded, both gambles offer the same choice; a 10% chance of getting $5 million and 1% chance of getting nothing as against an 11% chance of getting $1 million. This has also been confirmed in several experiments.

Ellsberg paradox illustrates people’s aversion of ambiguity when they make choices under uncertainty. The paradox is presented as a game, in which participants were presented with 90 marbles in a bag including 30 red marbles and 60 unspecified mixture of blue and yellow marbles. Two choices between lotteries are specified as:

Experiment I:

1A win $100 if they pick a red marble
1B win $100 if they pick a blue marble

Experiment II:

2A win $100 if they pick a red or blue marble
2B win $100 if they pick a blue or yellow marble

Under expected utility theory, an agent will prefer prospect 1A to prospect 1B when she believes that drawing a red ball is more likely than drawing a blue ball.
Similarly she will prefer prospect 2A to prospect 2B when she believes that drawing a red or blue ball is more likely than drawing a blue or yellow ball. If drawing a red ball is more likely than drawing a yellow ball, then drawing a red or blue ball is also more likely than drawing a blue or yellow ball. So, if an agent prefers prospect 1A to prospect 1B, it follows that she will also prefer prospect 2A to prospect 2B. Or, instead if she prefers prospect 2B to prospect 2A, it follows that she will also prefer prospect 1B to prospect 1A. However, in surveys, most participants strictly prefer 1A > 1B and 2B > 2A, which shows an *aversion of ambiguity*. They go with a known quantity and thus also violate the sure thing principle. Ellsberg concluded that the degree of uncertainty must be taken into account in decision analysis.

A general tendency of risk taking in gain situations and risk avoiding in loss situations has been established and investigated by many researchers. As their work has shown, expected utility theory (EUT) can only explain a very small fraction of observed individual behaviors that are classified as rational behavior. A major proportion of people evaluate risky prospects inconsistently with expected utility theory. Experimental research in this area, in particular, Tversky and Kahneman (1992) has shown that large and small probabilities as well as gains and losses are valued differently, which is neglected by expected utility theory. Besides the work of Tversky and Kahneman, it has been shown in many experiments conducted in psychological and social studies that people have different perceptions towards gain and loss, and that perception of uncertainty or probability varies systematically according to this difference between loss and gains (Wu and Gonzalez, 1996; Wu, 1999).

Alternative theories to expected utility theory have been developed to alleviate the above mentioned inadequacies. Regret theory, simultaneously proposed by Bell, Loomes and Sugden (Bell, 1982; Loomes and Sugden, 1982), that uses pairwise
comparison of utilities, and Prospect Theory and cumulative prospect theory that use weighted probabilities and distinguishes between gains and losses are the best known non-expected utility theories to model uncertain decisions that have found interest in travel behavior research. There have also been attempts, mainly outside of transportation research, to extend EUT with additional components (e.g., Hey and Orme, 1994; Blavatskyy, 2005; Dagsvik, 2005). Their results show that with a stochastic error term, EUT is able to cope with risk-averse and risk taking effects, thereby at least partially matching prospect theory. In the following sections, we will briefly introduce expected utility theory, regret theory and prospect theory and discuss their application in transportation research.

**Expected utility theory and its variants**

Let \( X = (E_1 : x_1, E_2 : x_2, ..., E_n : x_n) \) denote a prospect, where \( E_i \) denotes the uncertain event and \( x_i \) denotes the outcome utility of this event. When the probabilities of uncertain event outcomes are known, the prospect then generates a probability distribution \( (p_1 : x_1, p_2 : x_2, ..., p_n : x_n) \). The expected utility of this prospect is defined as \( EU = \sum_{i=1}^{n} p_i \cdot x_i \). A rational individual will choose the prospect that yields the maximum utility. In this form, the decision-maker is assumed to form probabilistic beliefs or expectations about the state of nature and the future effects of his/her actions and process available information accordingly.

To account for risk and uncertainty, expected utility theory was extended with an error term to account for the randomness in discrete choice (Hey and Orme, 1994; McFadden, 2001). Hey and Orme (1994) found that EUT with some additional structure of error terms provides satisfactory predictions of individual choice and the same approach of adding an error structure can also be applied to non-expected utility models. Hey and Orme (1994) and their successors such as Blavatskyy (2005) used an extended EU model with random error terms to remedy the
persistent violation of the EU model. Configured in such way, EU model improves its descriptive power while remaining its tractability. Blavatskyy’s study shows that with the random error structure, the EU model has at least the same descriptive power as the Cumulative Prospect Theory model.

Moreover, expected utility theory can be modified in other ways to meet some of the criticisms. With respect to risk sensitivity, Polak (1987) indicated that modified utility functions can be used to represent concepts of risk aversion and risk seeking in expected utility theory. Senbil and Kitamura (2004) for example integrated the valuation of choice outcomes in terms of gains and losses into utility theory. Palma (2004) applied expected utility theory with non-linear utility functions for risk-averse travelers.

**Regret theory**
Regret theory (Bell, 1982; Loomes and Sugden, 1982) makes use of a two-attribute utility function that incorporates two measures of satisfaction, utility of outcomes which is identical to classical EU, and quantity of regret. In the simplest form of regret theory, regret is measured as the difference in value between utility actually received and the highest level of utility produced by other alternatives (Bell, 1982).

Let $A_i$ and $A_k$ be two potential actions that result in outcomes $x_i$ and $x_k$, respectively. The utility of consequence $x_i$ is given by a modified utility function $m_{ik} = M(x_i, x_k)$. This function allows the utility from having $x_i$ to be suppressed by “regret” when $x_i < x_k$, or enhanced by “rejoicing” when $x_i > x_k$.

The individual then seeks to maximize the expected modified utility of action $E^+_i = \sum_x p_x \cdot M_i(x_i, x_k)$ where $p_x$ is the probability of state $S$ across all possible actions. Regret theory will reduce to EUT in the special case where $M(x_i, x_k) = u(x_i)$.
Starmer (2000) argued that although “as a theory of pairwise choice, regret theory has limited applicability”, there are ways of generalizing the theory (Sugden, 1993; Quiggin, 1994) to suite general choice situations. To extend the theory to be applicable in choice between uncorrelated prospects, let $X$ and $Y$ be two prospects. The probability of choosing prospect $X$ with outcome $x_i$ and missing outcome $x_k$ of prospect $Y$ is $p_i^x p_j^y$, where $p_i^x$ is the probability of outcome $x_i$ in prospect $X$ and $p_j^y$ is the probability of outcome $x_j$ in prospect $Y$. Preferences between $X$ and $Y$ are then determined by the expression:

$$X \succ Y \iff \sum_i \sum_k p_i^x p_j^y \psi(x_i, x_k) > 0$$

(2.19)

where $\psi(x_i, x_k) \equiv M(x_i, x_k) - M(x_i, x_i)$. Under this configuration, regret theory can handle general uncertain decisions using prospects. This approach was adapted in recent travel behavior research (Chorus et al., 2006a). Chorus et al. (2008b) further generalized regret theory and formulated a Random Regret-Minimization model (RRM). Similar to Regret Theory, RRM asserts that individuals base their choices between alternatives on the wish to avoid the situation where a non-chosen alternative turns out to be more attractive than the chosen one, which would cause regret. Therefore, it assumes the individuals minimize anticipated regret rather than maximize utility when choosing between alternatives. RRM assumes that regret is partly unobservable by the analyst, leading to the addition of random error components. The authors showed that RRM-models are easily extended towards the case of risky travel choice, using the notion of Expected Regret. In addition, this approach can easily model the situation that travelers who feel uncomfortable with their current choice situation may postpone a travel choice and search for additional information first.
Prospect theory and cumulative prospect theory

To address irrationality in human decision making processes, prospect theory and cumulative prospect theory developed by Kahneman and Tversky have drawn most of the attention amongst non-EU models. In prospect theory, choice is based on transformed objective probabilities and outcomes as gains and loss.

Let $X$ and $Y$ be two prospects. The utility of a prospect is defined as:

$$V = \sum \pi(p_i)\nu(\Delta w_i)$$

(2.20)

where $\pi$ is a probability weighting function and $\nu$ is a value function, $\Delta w$ is the difference in outcome compared to a reference point. Prospect $X$ is preferred to $Y$ iff $V_x > V_y$.

Compared to expected utility theory, prospect theory assumes that the decision process is divided into two stages: “editing” phase and “evaluation” phase. In the editing stage, gains and losses in the different options are identified, and they are defined, ”coded”, relative to some neutral reference point, so as to establish an appropriate reference point for the decision at hand. Gain refers to the outcome when it exceeds this reference point and loss refers to when the outcome falls short of it. In the second stage, the evaluation phase, the decision maker evaluates the outcomes of each alternative by a value function and transforms objective probabilities into subjective probabilities by a probability weighting function.

The value function is S-shaped and it is concave for gains and convex for losses. Thus, this function allows diminishing sensitivity to change in both directions. The curves at zero, being steeper for small losses than for small gains implies loss
aversion when outcomes are considered a loss and risk seeking when outcomes are considered a gain.

In this way, this value function allows individuals to be risk-averse over gains but risk seeking over losses, with magnitude of losses higher than of gains. The decision-weight function $\pi$ is monotonically increasing, with discontinuities at 0 and 1, such that it systematically overweighs small probabilities and underweighs large probabilities. This allows the model to accommodate violations of expected utility such as the Allais paradox and Ellsberg’s paradox. As the authors stated, "the simplification of prospects in the editing phase can lead the individual to discard events of extremely low probability and to treat events of extremely high probability as if they were certain. Because people are limited in their ability to comprehend and evaluate extreme probabilities, highly unlikely events are either ignored or overweighted and the difference between high probability and certainty is either neglected or exaggerated." (Kahneman and Tversky, 1979) Cumulative prospect theory (Tversky and Kahneman, 1992) extended prospect theory by including rank-dependent probabilities. It further allows for different probability weighting for gains than for losses (Palma et al., 2008).

![Value function and weight function](image)

**Figure 2.4** Value function and weight function (Kahneman and Tversky, 1979)
Despite their theoretical appeal, prospect theory and cumulative prospect theory are difficult to test and apply in practice because they have many more degrees of freedom, especially in the editing stage than other theories (Camerer, 1989). The estimation difficulty in prospect theory has limited its application. Until very recently not much work has employed prospect theory due to this practical difficulty. Avineri (2004) has explored the application of prospect theory in travel behavior research with satisfactory results.

Mean variance approach
In most cases, uncertainty is represented by discrete probability distributions. When uncertainty is associated with continuous variables, one can, instead of using prospects to represent risky alternatives, use mean-variance as a representation of risk. This approach takes two parameters to represent uncertainty, the mean utility of possible outcomes and their variance (or standard deviation). The basic assumption is that risk is measured by variance, and that the decision criterion should be to minimize variance given expected return, or to maximize expected return for a given variance. Compared with the expected utility model, the mean variance model has an intuitively and parsimoniously representation of risk, or uncertainty. It says that individuals usually choose alternatives with higher mean preference and lower variance, which is the amount of uncertainty. It was considered a simpler yet adequate representation of uncertainty compared with the expected utility model.

The mean variance approach was employed mainly in financial economics for optimal portfolio choices (Levy and Markowitz, 1979; Kroll et al., 1984), and represents the basis of modern portfolio selection theory. It was developed in the 1950’s and 1960’s by Markowitz, Tobin, Sharpe and Lintner among others (Markowitz, 1952; Tobin, 1958; Sharpe, 1964; Lintner, 1965), and has been applied mainly in finance and investment studies. Tobin (1958) showed that the
mean-variance model is consistent with Von Neumann-Morgenstern postulates of rational behavior if the utility of wealth is quadratic. The mean variance approach has recently also been used in travel behavior research (Sen et al., 2001; Bogers and Zuyle., 2004; Chorus et al., 2006b; Li, 2009).

2.3.2 Travel decisions under uncertainty and travel information

Travel decisions without information services
Often, travelers are assumed to base their decisions on their perception of or their beliefs of reality rather than on any objective measure of reality (e.g., Koppelman and Pas, 1980; Bonsall, 2001; Golledge, 2002). Taking into account the stochastic and non-stationary nature of transportation systems, the management of the resulting uncertainties is central to a traveler’s decision problem. Without information, travelers exhibit some degree of inertia in their route choice, especially for home-to-work trips (Khattak et al., 1996; Polydoropoulou et al., 1996). Only after accumulated sufficient negative experience or after receiving information before the trip, travelers are more likely to divert to another options. For example, Khattak et al. (1996) found that travelers who are unfamiliar with alternative routes or modes are particularly unwilling to divert. This finding is consistent with the study of Kim and Vandebona (2002), who also found that drivers who are familiar with alternative routes have a high propensity to divert from their normal routes. Similarly, Bogers (2009) found travelers are very much driven by habit in their route choice. Reactions also differ. For example, Mahmassani and Herman (1989) and Mahmassani et al. (1991) found that commuters tend to adjust departure time more readily than to change routes. Route switching tends to occur only when the travelers continuously get frustrated from the outcomes of departure time adjustments. Mannering and Hamed (1990) and Abdel-Aty et al. (1994) found that commuters with a long travel distance switch departure time more often than commuters with short travel times. Furthermore,
travelers’ expected travel time on a particular route are based on their most recent experiences if they do not receive en-route travel information (Bogers, 2009).

Travel decisions under information provision
It is believed that travel information has effects on how the transport system will be used by travelers, both directly, through new products and services, and, indirectly, through reorganization of geographical locations and many types of activities that are supposed to affect travel demand, e.g. teleconferencing, e-commerce, self-employment. From a behavioral point of view, it is commonly believed that the use of travel information will reduce uncertainty (e.g., Bieger and Laesser, 2004), allowing travelers to make more efficient and precise travel decisions, which in turn improve the efficiency of transportation network facilities. Thus, rapid technology development allows new emerging transportation information services, with high expectations among managers, policy-makers and market players.

ATIS can promote greater use of inter-modal travel, e.g. by encouraging drivers to leave their cars at a Park and Ride and continue by public transport, by warning drivers and public transportation users to change their planned route/mode to avoid incidents, congestion or severe weather conditions. Parking information systems also contribute significantly to reducing city-centre congestion and pollution by alerting approaching drivers to available spaces. Research in the area of ATIS has received a great deal of attention in the recent past and it is believed by both the research and commercial communities that traveler information is central in dealing with transport challenges in congested towns and cities (e.g., Adler and McNally, 1994; Adler and Blue, 1998). Current applications for instance include dynamic road map displays in the vehicle and large electronic graphics signs mounted above the road which keep the traveler aware of the current traffic situation. These displays give information about the length of traffic jams, about capacity reduction due to road works or lane closures and provide actual travel
times over a given stretch of road. Research in this area is now focusing more on providing alternative route choices based on multi-modal travel and real-time information. The traveler will not only receive information from in-vehicle devices, but also from dynamic roadside display boards.

Given this high expectation, especially in recent years, many researchers (e.g., Targa et al., 2003) argued that a comprehensive behavioral framework must consider traveler decisions under normal and uncertain conditions and information acquisition decisions, and a large number of transportation researchers has focused their attention on travel information (e.g., Koppelman and Pas, 1980; Khattak et al., 1993; Polak and Jones, 1993; Emmerink et al., 1996; Verplanken et al., 1997; Polydoropoulou and Ben-Akiva, 1998; Hato et al., 1999; Abdel-Aty and Abdalla, 2004; Chorus et al., 2006c). Three specific topics have received relatively much attention: acquisition of travel information, the effects of travel information on specific facets of activity-travel patterns and the concept of risk and risk attitude. Some researchers especially focused on travel information acquisition behavior, such as for example Polak and Jones (1993), Schofer et al. (1993), Mannering et al., (1995), and Srinivasan et al., (1999). They suggested that people’s decisions to access/own information technology and acquire/use travel information are themselves decisions that must be measured and understood. This issue has been addressed in several studies in recent years (see e.g., Chorus et al., 2005; 2006a; 2007).

Researchers found that ATIS has a great potential in influencing commuters’ route choice even when advising a route different from the normal one (Abdel-Aty et al., 1994; Abdel-Aty et al., 1995; Abdel-Aty and Abdalla, 2004). Generally, commuters are willing to comply with advice from a prescriptive ATIS (Khattak et al. 1996; Lotan 1997). Abdel-Aty and Abdalla (2004) showed that providing traffic information increases the probability of drivers’ diversion from their normal routes.
Providing en-route and pre-trip information increases the diversion probability in general. Also, drivers’ familiarity with the device that provides the information and high number of traffic signals on the normal route will increase the diversion probability. Previous studies revealed that people demonstrate a risk seeking behavior when real time information is available (Ben-Elia et al., 2008). This is especially true when people lack long-term experience with respect to the travel time of given routes choices.

Khattak et al. (1994) found under incident conditions that ATIS quantitative delay information may induce about 40% of the commuters to change their route to work, mostly the people with greater diversion opportunities, knowledge of more alternate routes, and lower congestion levels on their best alternate route. In their study, the travel time savings achieved by ATIS usage (with quantitative information) were calculated. The potential annual benefits from ATIS route diversion, applicable to about 40% of commuters in the Golden Gate Bridge corridor, range from $124 to $324 per person. Further, Khattak et al. (1996) found that drivers are more likely to divert to another route when they learn about a delay before the trip.

Many aspects impact travel information acquisition behavior. First, socio-demographic characteristics of travelers affect their ownership and accessibility to travel information and therefore influence their use of travel information. The ownership or accessibility to ATIS was found to be strongly correlated with socio-demographic variables (e.g., Targa et al., 2003). They found that richer, highly educated, young travelers have more access to travel information than other groups. Similarly, male, high income, highly educated travelers and professionals tend to acquire travel information more often (e.g., Emmerink et al., 1996; Petrella and Lappin, 2004). However, highly educated drivers are less likely to divert, even when provided with information (Abdel-Aty and Abdalla, 2004). Second, in
general, travelers’ knowledge about their travel environment affects their information acquisition and compliance behavior. The more certain the traveler is about the travel environment, the less likely he/she will initiate an information search decision (Bieger and Laesser, 2004). People with greater exposure to travel time uncertainty are more likely to acquire travel information (Targa et al., 2003). Bonsall (1991, 1992) found that user compliance to information advices declined with decreasing quality of advice in an unfamiliar network. As familiarity with the network increased, drivers were less likely to accept advice from the information sources. Third, context variables were also found to play a role. Especially, trip purpose appears to influence travel information acquisition. Trips with a high time sensitivity are more likely to induce information search and usage. Commercial trips and business trips appear to lead to more information use than other trip purposes (e.g., Emmerink et al., 1996; Hato et al., 1999; Targa et al., 2003; Petrella and Lappin, 2004). Another interesting finding is that the transit commuters are more likely to acquire travel information and subsequently change their travel routine (Targa et al., 2003). Fourth, the extent to which travel behavior is habitual affects travel information acquisition as well. Verplanken et al. (1997) found that, compared to weak habit travelers, those who had a strong habit towards choosing a particular travel mode acquired less information and applied less elaborate choice strategies. Enhanced attention to the choice process initially did suppress habit effects in their series of choice trials. However, chronic habit effects emerged during later trials in spite of the manipulation. They argued that the reason why strong habit travelers acquire less information than weak habit travelers was because they were more certain about the attributes of the travel environment that they did not inspect.

One aspect that was not fully addressed in these studies is the reliability of the information source which may cause different reaction from travelers. Travel information from various sources varies in quality. An unreliable information
source that may misguide travelers may be dropped after a few try-outs. Even a relatively accurate information source, if it gives negative results at the first few rounds of use may probably be rejected by travelers for further use. Most current studies did not explicitly take this into account and most of them assume that a perfect information source was used.

2.4. Learning effects

It is assumed that travelers will gradually build up their beliefs and experience about the external travel environment. People learn and learning behavior involves the acquisition of information, accumulating experiences, and relating them to current conditions and perceptions to make decisions. People also forget past experiences as time elapses. Human learning has been extensively explored by psychologists (e.g., Einhorn and Hogarth, 1981; Eckstein et al., 2004; Wallsten et al., 2006) and economists (e.g., Roth and Erev, 1995; Breen, 1999; Camerer et al., 2002). Although it is widely acknowledged that learning is an important component of long term travel behavior, research on learning effects has not drawn much attention in transportation research until recently (e.g., Jha et al., 1998; Adler, 2001; Avineri and Prashker, 2005).

Studies provide empirical evidence on memory decay effects in learning. Chang and Mahmassani (1988) found in their simulation experiments that individuals adjust their departure time choice in response to previous experience, and that the most recent information, essentially the previous trip’s travel time, is the most important factor in current decisions. In the laboratory experiment study of Iida et al. (1992), which focused on route-choice behavior and dynamic adjustment over time, the estimates also suggests that recent travel experiences are more important than travel experiences long-time ago. Other studies (e.g., Bogers et al., 2007) reached similar conclusions. Findings also indicate that the adoption of ATIS information is linked to both the traveler’s past experience and the credibility of the
information source. Polak and Oladeinde (2000) conducted lab experiments, in which separate groups of subjects were provided with different level of information accuracy. They found that even bad information accelerates the speed of travelers' learning.

It should be noted that two types of learning behavior are generally considered. One concerns individuals’ perception of the real environment. Through repeated experiences, individuals will update their perception of attributes of the real world, which in turn decrease the variance for a specific attribute and serves as a base for their choices. A second type concerns the conditions of the travel environment which will affect the strategies that individuals apply in their choice behavior to find the best available action in a specific context (Timmermans et al., 2003b).

A key concept in learning behavior adopted by most studies of travel choice dynamics (e.g., Horowitz, 1984; Van Der Mede and Van Berkum, 1993) is **perception updating** process, implemented by re-calculating some weighted mean of previous experiences. Perception updating can be represented in two different ways, which are mathematically equivalent, but represent different concepts of individuals’ storage and classification of information (Timmermans et al., 2003b). One concept, **memory decay**, assumes that individuals remember all information about all previous experience including actions and outcomes. The perception updating process is then represented as a weighted average in which the influence of events is decreasing over time. The other concept, **expectation updating**, assumes that individuals do not remember all single experiences, but rather keep track of a single running mean, that is updated every time they experience new events. The new expectation is a weighted sum of the old expectation and the new experience.
Reinforcement learning

Horowitz (1984) suggested an equilibrium model in which travel choices on a particular day are based on weighted averages of measured travel times on previous days. The perceived travel cost of route \( i \) at travel time \( t \) is defined as

\[
\tilde{C}_i = \sum_{k=1}^{t-1} w_k (t-1) C_{ik} + \epsilon + \sum_{k=1}^{t-1} w_k (t-1) = 1, \quad \text{where} \quad \tilde{C}_i \text{ is the measured travel cost on route } i \text{ in time period } k, \quad w_k \text{ is the weight of experience at time } k. \text{The weight is associated with time (days) and various functions can be used to calculate it. The most weight function that draws most attention is}
\]

\[
\tilde{C}_i = a_i C_i + (1 - a_i) \tilde{C}_i, \quad \text{where } a_i, k = 2, 3, ..., \text{ is a sequence of constants satisfying } 0 \leq a_i \leq 1 \text{ (e.g., Nakayama et al., 1999; Timmermans et al., 2003a). This model thus accounts for a memory decay effect, which assumes that recent experiences have higher impact than older experiences: higher weights can be assigned to recent experiences. Other formulations of weighting average can be found. Oh et al. (2003) used a successive average model to represent the learning process. The updating of travel time is calculated by}
\]

\[
T(\alpha + 1) = (\alpha \times T(\alpha) + T_\epsilon(\alpha))/(1 + \alpha), \quad \text{where } T(\alpha + 1) \text{ denotes the updated perceived travel time after trip on day } \alpha, \quad T(\alpha) \text{ is the perceived travel time before trip on day } \alpha \text{ and } T_\epsilon(\alpha) \text{ is the experienced travel time during the trip on day } \alpha. \text{ Their updating mechanism suffers the shortcoming that when the time span of the modeling period becomes large, the newly gained experience has very low weight in updating travel time. Mahmassani and Chang (1986) utilized a radical weight scheme under Horowitz’s weighted average approach. They set up a myopic adjustment and experience-based model of perceived travel time for departure time choice which models the perceived travel time as a function of the latest day’s outcome exclusively, namely, they assign a weight 1 to the most recent experience and weight 0 for all other experiences. Despite possible computational advantages and some empirical evidence (e.g. Bogers (2009) found that traveler are myopic in}
perceiving travel time when en-route travel information was not available), this approach become less attractive when travel information is available. For example, in the same study, Bogers (2009) found that travelers take previously experienced travel time into consideration when en-route travel information is available. Ben-Akiva et al. (1991) proposed a model where the updated perceived travel time is a weighted average of the historically perceived travel time and the time provided by ATIS, where the weight indicates the relative importance of experience and information provided travel times. Some recent learning models (e.g., Avineri and Prashker, 2006; Bogers et al., 2007) employed Horowitz’s approach as well.

Timmermans et al. (2003a) generalized these learning models in the notion of reinforcement learning. Central to this conceptualization is that the outcomes of an action from choice made, positive or negative, will be incorporated into future choices. The expected outcome of action is thus based on previous experience. The general forms of expectation updating assume that individuals keep some summarized measure of past experiences which is incrementally updated (Sutton and Barto, 1998):

\[ Q_t(a) = Q_{t-1}(a) + \lambda [r_t - Q_{t-1}(a)] \] (2.21)

or

\[ Q_t(a) = \lambda r_t + (1 - \lambda)Q_{t-1}(a) \] (2.22)

where \( Q_t(a) \) denote the expected outcome of action \( a \) at time \( t \), \( \lambda \) denotes a habit strength, \( r_t \) denotes the outcome at time \( t \). If \( \lambda \) equals to zero, these equations assume there is no updating. If \( \lambda = \frac{1}{t} \), which means it varies along time, the
equations then imply that all past experiences are equally relevant. If \( \lambda \) is a constant, the equations become a weighted average of the initial estimated outcome and the past outcomes by extending \( Q_{i-1}(a) \) till the initial outcome:

\[
Q_i(a) = (1-\lambda)Q_{i-1}(a) + \sum_{i=1}^{t} \lambda(1-\lambda)^{i-1}r_i
\]  

(2.23)

The weight of past experience depends on how far away it is from the current time \( t \) and is decreasing exponentially. This generalization is consistent to nearly all theoretical concepts of learning models described above. The authors further suggested adding a weight parameter accounting for individuals’ judgment of each experience. The weight is defined as a deceasing function of the deviation between a predicted and the actual outcome (Arentze and Timmermans, 2003):

\[
w = g(\Delta), \; \Delta = |f'_i(x) - (f_i'(x^*) + \varepsilon_i)|
\]  

(2.24)

where \( f'_i(x) \) denotes the individual’s mental model for predicting outcomes based on perceived relevant attributes \( x \), \( f_i \) and \( x^* \) representing the “true” function and true attributes, \( \varepsilon_i \) is a stochastic component. The updating is thus

\[
Q_i(a) = Q_{i-1}(a) + w_{i-1}\lambda[r_i - Q_{i-1}(a)].
\]

How individuals make choices based on the expected outcomes forms his/her decision rule. When it is assumed that individuals choose the alternative that provides the maximum expected outcome, the decision rule is called the greedy rule. This decision rule will preclude the possibility of exploring other possible alternatives and thus prevent learning process if the first choice gives a near optimal outcome. To incorporate exploration behaviour into decision making, a probabilistic decision rule under some distribution assumption shall be specified.
Timmermans et al. (2003a) use a generalization of probabilistic decision rule under the assumption of Gibbs distribution (Sutton and Barto, 1998) as an example. The probability of action \( a \) being chosen at time \( t \) is (also known as the Boltzmann model) equals:

\[
\Pr(a|t) = \frac{e^{Q(t,a)/\tau}}{\sum_a e^{Q(t,a)/\tau}} \tag{2.25}
\]

where \( \tau \) is a positive parameter. When \( \tau \) becomes infinitely large, the probability of all actions becomes equal. All the learning models described above falls in line with this generalization.

**Bayesian learning**

Bayes theorem naturally represents inference and learning process with belief updating. From a Bayesian perspective, let \( P(A) \) be the degree of belief, or subjective probability, in \( A \). If one believes there is causal connections between \( A \) and \( B \), then Bayes theorem says :

\[
P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{2.26}
\]

where, \( P(A|B) \) represents the posterior belief of \( A \) given knowledge about \( B \).

\[P(B) = \int_A P(B|A)P(A)dA\] is the marginal distribution of \( B \).

One thing noteworthy mentioning is that reinforcement learning typically deals with learning averages about choice alternatives’ attributes, whilst Bayesian learning mostly concerns the uncertain distribution of states of a variable. Rather than better estimating attributes of choice alternatives by reducing the variance as
in reinforcement learning, Bayesian learning tries to learn the “true” distributions of the inherent uncertain nature of the choice alternative.

Findings in cognitive research have provided evidence that human learning process may be consistent with Bayes theorem. For example, Gopnik et al. (2004) in their experiments found that 2 to 4 years old children construct new causal maps and that their learning is consistent with Bayes net formalism. These findings provide a basis on which travel-related learning process can be modeled using Bayesian models. Work along these lines is still scarce but has emerged rapidly in recent years.

Jha et al. (1998) modeled learning of routes’ mean travel time as a Bayesian updating process. The expected travel time is updated by combining it with the received travel information. After experiencing travel time, post-trip updating occurs. Bayesian principles are used to update the previously expected travel time to a new expected travel time using the newly experienced travel time. Advantages of this kind of modeling are that information from various sources can be combined, with the additional benefit of being able to explicitly capture the reliability of these information sources.

Chen and Mahmassani (2004) also used Bayesian updating to model how people learn from experience. Their approach differs from that of Jha et al. (1998) in that the updating process does not takes place after every new experience. Rather, a update trigger mechanism is used. Under this trigger mechanism, updating is based on the difference between the perceived experienced travel time and the mean updated travel time, relative to the updated travel time. This rule states that “users update selectively only for travel times that are considered salient, with the difference between the experienced and updated travel times relative to the updated
travel times as the measure of salience”. Apart from this update-triggering rule, they did not include a travel information component as Jha et al. did.

Chorus et al. (2006b, 2007, 2008) applied a Bayesian learning model in their studies on the use of travel information. Additional to mean travel time, the variance term of travel time is incorporated into their model so that gradually the traveler’s belief of travel time variance approaches the true travel time variance as more observations are made. The model further assumes that travelers may learn that travel times on different (nearby) routes are likely to be correlated. Thus, a full covariance matrix is incorporated into the model. This implies that travelers update the full covariance matrix associated with multiple routes’ travel times, together with their means using the Bayesian updating rule. Their numerical simulations show that the model behaves consistently with intuitions regarding actual traveler behavior, e.g., travelers learn the travel time distribution more quickly for routes with a low level of travel time variability.

2.5. Heterogeneity in travel decisions

Individual travelers may behave differently under similar situations. The manifested heterogeneity in their travel decisions is either due to their personal characteristics or depends on underlying preferences and/or traits and attitudes. Incorporating and understanding heterogeneity will provide information on the distributional effects of resource use decisions or on differential policy impacts. Generally, two types of heterogeneities can be distinguished: heterogeneous preferences that capture different tastes of individuals for choice alternative attributes and heterogeneous risk attitudes that capture the difference in risk attitudes of individuals in uncertain situations.
2.5.1 Heterogeneous preferences

The first type of heterogeneity in decision making behavior is the systematic variance in preferences on choice alternatives. To model this heterogeneity in preference, some studies include demographic variables in the utility function (e.g., Pollack and Wales, 1992) whereas others stratify decision makers into several segments and estimate models for each stratum.

Recently, researchers have employed random coefficients or mixed logit models to explicitly account for heterogeneity by allowing model parameters to vary across individuals (Train, 1997, 1998; Srinivasan and Mahmassani, 2003). While these models incorporate and account for heterogeneity, they somehow lack the ability to explain the sources of heterogeneity. Although a distribution of parameters can be obtained in this model and thus be interpreted as a population property, the relation to individual socio-demographic characteristics is not explicitly linked with the estimation results.

Another way of tackling heterogeneity involves the use of latent class approaches to consider traveler segments (e.g., Goulias, 1999; Boxall and Adamowicz, 2002; Lee et al., 2003). The latent class approach explicitly stratifies individuals into a finite number of segments and the link between segment determinants and individual characteristics is addressed by specifying membership functions.

2.5.2 Heterogeneous risk attitudes

Generally, risk attitude can be defined on a continuous range from risk aversion to risk seeking. A decision maker displays risk aversion if and only if he strictly prefers a certain consequence to any risky prospect whose expected outcome equals the certain amount in choice situations involving monetary outcomes; or a decision maker is said to be risk-averse if and only if he strictly refuses to
participate in fair games (i.e. games with an expected net outcome of zero). He is said to be a risk seeker if and only if he strictly prefers the above mentioned risky prospect to its certain consequence. He displays risk neutrality if and only if he is indifferent between the risky prospect and the certain consequence. On the one hand, risk attitude can be viewed as a stable personal trait that stays stable within individual but differs across individuals; on the other hand, the manifested heterogeneous behavior towards risk in different situations can be seen as a reaction to different choice settings. Thus, individuals may show systematic risk attitude in similar choice situations.

When viewing risk attitude as a personal trait, it is usually measured either by drawing upon cardinal utilities and subjective beliefs, approaches derived from the expected utility framework, mainly in finance and marketing researches, or by psychometric approaches, such as scales and questionnaires in psychology. Cardinal utilities reflect preferences over lotteries with known probability distributions, and capture risk attitude by the curvature of the utility function (Keeney and Raiffa, 1976) and the distortion of probability functions (Tversky and Kahneman, 1992). Psychometric approaches directly attempt to measure risk attitude by asking respondents to indicate how much they agree with a set of statements and derive measurements of the tendency of risky behavior as a result.

In transportation research, several studies have explicitly taken heterogeneous risk attitude into consideration. For example, (Nakayama et al., 2002) have used a risk parameter in their travel time model. Travel cost of a particular route is conceptualized as the sum of average travel time experienced and the riskiness of this route. The riskiness is defined as the product of risk attitude and the range of travel time the travel has experienced. They found that travel has various choice patterns rather than only rational behavior. However, the results reported are based on numerical simulation rather than empirical data. Palma and Picard (2005)
developed an ordered probit model to address risk attitude in an ordinal rather than cardinal manner. This configuration does not preclude the use of non-expected utility theories. The basic assumption is that whatever their preference and probability weighting functions, all respondents should agree on the ranking of some prospects. Based on this ranking, the most risk-averse individuals choose the least risky prospects. i.e., consider a lottery experiment with two prospects, X and Y, if X is more risky than Y and individual i is indifferent between X and Y, then another individual j prefers X to Y if and only if j is less risk-averse than i. Their results show that for trips made by transit users, blue collars travelers and trips for business appointments are more risk-averse.

In the standard psychometric field, general risk attitude is defined as an individual’s current tendency to take or avoid risks. Constructs such as risk attitude are measured by asking a respondent to indicate the extent to which (s)he (dis)agrees with a set of statements. Nunnally and Bernstein (1994), Kunreuther and Ginsberg (1978), Maccrimmon and Wehrung (1986) and Shapira (1995), amongst others, conducted large-scale surveys and interviews investigating risk preferences using psychometric scaling procedures. Many researchers developed risk attitude scales and tested their psychometric properties in different research disciplines (e.g., Miller et al., 1982; Childers, 1986; Weber et al., 2002). However, there is no scale considering the domain of activity-travel risks faced by travelers yet.

When considering systematic risk attitude differences on lottery games that consist of different prospects with probability distributions, non-expected utility theories are generally applied. Many studies in transportation research, especially in route choice, found that travelers’ route choice is consistent with prospect theory. In a route choice experiment Katsikopoulous et al. (2002) found the risk attitude of people to be in line with prospect theory. Bogers and Van Zuylen (2004) arrived at
similar findings, showing that people were risk-averse when they could choose between a short and uncertain alternative and a longer but more certain one. Avineri and Prashker (2004) found that stated preferences of travelers faced with one-shot risky situations violate the EUT assumptions, and may be better captured by prospect theory. These results indicate that travelers are not necessarily utility maximizers. Nonetheless, these studies do not stratify individuals into segments or incorporate socio-demographic attributes as explanatory variables. Thus, to some extent these studies have limited applicability for managerial and marketing purposes.

A recent attempt to integrate both aspects, heterogeneity of risk attitude within and across individuals, in a single model, though not in transportation research, was made by Bruhin et al. (2007) who combined prospect theory and a finite mixture model to find the distribution of risk taking types in a set of gambling games. Their reported results show promising usability of the combination of the finite mixture model and prospect theory in identifying heterogeneous groups within a population. Their model found that 20% of their subjects followed expected utility maximization behavior in the sense that their value function and probability weighting function are approximately linear. The second group consisted of the remaining 80% of subjects that demonstrated prospect theory behavior in the sense that they exhibit an inverted S-shape probability weighting function. The classification is clear and unambiguous.

2.5.3 Context dependency

Although personal characteristics may be correlated with different travel decision styles, it has also been argued that variability in decision outcomes under uncertainty may be systematically related to context (e.g., Swait et al., 2002). Under this complex view, human behavior is regarded as locally conditioned to a
given situation. Typically, behavior is adaptive; it depends on the context and transitory perceptual conditions.

To the best of our knowledge, research on such context dependency is scarce. A relatively related theory is Fuji and Takemura (2003)’s contingent focus theory. They proposed a contingent focus model based on the assumption that contextual factors play a more important role in risk attitude than personal characteristics. In the contingent focus model, the key to explaining framing effects is the focusing hypothesis, which states that the extent of focusing on possible outcomes and probabilities determines risk attitudes. The results of their study indicate that the effect of outcome emphasis on decision making is consistent with their theory, but they failed to find evidence of the effect of probability emphasis. Thus, the authors tentatively argued that it is not the emphasis on probabilities, but the emphasis on the outcomes that has an impact on decision making. Although contingent focus theory to some extent tackles the decision situation effects on risk attitudes, it focuses on a single decision rather than on complex sequential decisions as one will usually confront in activity-based modeling. Thus, it has no components to take the full activity-decision context into account.

2.6. Discussion and conclusion

This brief review covers some disperse topics which are relevant to this PhD research project. The purpose of this review is not to give the reader a full overview of previous research, but rather an introduction to main concepts, theories and modeling approaches that are required to understand and position operational decisions, models and findings pertaining to this study.

This overview has demonstrated that the topic area, travel information and activity-travel decisions under uncertainty, has rapidly increased its importance due to new technological developments that allow planners and service providers to generate
dynamic and personalized information about the state of the transportation system and the state of the environment. Moreover, it allows giving advice/recommendations to individual travelers and the public at large, pre-trip and en-route. In that sense, the provision of travel information and recommendation is expected to be one of the main transport and urban planning management tools.

The success of such tools in improving the functioning of the urban and the transportation system depends on the validity and reliability of models and tools that predict consumer response to information provision: how do travelers adapt their activity-travel patterns in time and space when information is provided and recommendations are given. This literature review has shown that our current knowledge about this process is still quite limited. First, virtually none of the studies have dealt with effects of travel information on comprehensive activity-travel patterns as opposed to single facets such as for example route choice and departure time. Secondly, uncertainty has been mainly focused on a single source of uncertainty, but in reality travelers often deal with multiple sources of uncertainty, that may also differ in terms of their time window. Thirdly, relatively few studies have examined dynamics, especially learning effects and to the extent they did, only attribute learning has been examined in more detail. Fourthly, heterogeneity in decision styles in activity-travel decisions has not drawn enough attention in current studies although it has been explored in single facet models and fields other than transportation research. Thus, in the remainder of this thesis our goal is to develop a general and flexible framework for modeling activity-travel decisions under uncertainty and information provision and to model heterogeneous decision styles within such a framework.
3. Framework: representation of knowledge, inference, learning and information

3.1. Introduction

As discussed in the previous chapter, although many studies have been concerned with travel information, the impact of travel information on activity-travel schedules has hardly received any attention at all. How do travelers manage the uncertainty that is involved, how do they assess the credibility of the information source, what is the relationship between the nature of travel time and the credibility of ATIS information, how do they deal with multiple sources of uncertainty? These and other questions all require more research, not only in isolation but especially how they are linked. This chapter intends to develop a general framework to address these issues, elaborating the framework proposed by Arentze and Timmermans (2004a, b).

In their proposed model, the value of information is conceptualized as the extent to which information about travel time (or any other relevant state of the system) improves activity-travel scheduling decisions at the beginning of the day and during execution of a schedule. The measure of information value they propose is sensitive to several factors. First, since information is used for scheduling and re-scheduling decisions, the complete activity travel pattern of the day is taken into account. Secondly, the perception of the credibility of the information source and the existing uncertainty are explicitly represented. Thirdly, they argue that the value of information depends on dynamic causal knowledge. Information on causally related events or states is assumed to be updated each time a trip is implemented. Their framework is based on expected utility theory and Bayesian principles of belief updating and structural learning.
The purpose of this chapter is twofold. First, the framework will be briefly summarized to encompass belief updating, information evaluation, and other aspects relevant for scheduling and rescheduling activity-travel patterns under multiple sources of uncertainty. The decision problem is modeled as a decision tree representing all paths of possible decisions and outcomes of uncertain events. It is important to be aware, however, which rescheduling decisions need to be made at any given point in time and which can be delayed to some later moment when more information has become available. An answer to this question may provide a (partial) solution to the problem of combinatorial explosion of the decision tree with an increasing number of uncertain events that need to be taken into account. The objective of the elaboration, therefore, is to specify rules to identify the relevant events to be included in decision tree construction at any given moment in time. The second objective of this chapter is to derive theoretical implications of the model based on numerical experiments.

To this end, this chapter is structured as follows. First, Section 3.2 briefly describes the conceptual and modeling framework that we use and the issue of constructing efficient decision trees. Section 3.3 then introduces the numerical simulation settings. Next, Section 3.4 considers the results of the numerical simulations that were conducted to derive theoretical implications from the model. Finally, we summarize major conclusions and discuss possible ways of future research.

3.2. Knowledge, inference, learning

3.2.1 Basic concepts

The type of decisions considered concerns the choice of an activity-travel schedule for some time horizon (e.g., a day). An important concept in the model is the decision moment, $t$. The first decision moment is the beginning of the day where the individual generates a schedule. The next decision moments are moments
during execution of the schedule where the individual has the possibility to change the schedule for the time remaining. Each time the individual arrives at a node of the network or has completed an activity he may consider revising the existing schedule in some way or to continue implementing the existing schedule. We assume that re-considering the existing schedule is relevant only under certain conditions, namely when, due to an unforeseen event, the end time of the last (activity or travel) episode differs from the scheduled end time or when the individual receives new information (from some source) regarding future events (conditions, circumstances).

When the individual makes scheduling decisions, he/she may be uncertain about the outcomes of some events that are relevant for the utilities of different schedule decision options. To give some examples: the duration of an activity may depend on various uncertain conditions; the duration of travel on a link may depend on uncertain congestion conditions; whether or not the car is available may depend on uncertain decisions of others, and so on. In the following, we will use the term ‘event’ and ‘outcome’ to refer to any uncertain state of the system that is relevant for a scheduling decision. In dealing with uncertainty, we assume that an individual uses a scenario-based approach. That is to say, for each uncertain and relevant system state, the individual uses his knowledge and the information he/she has about specifies scenarios. A scenario defines a possible outcome and a probability representing the individual’s belief of how likely it is that the scenario will be true. We use the symbols $Y$ to refer to the (uncertain) event, $y_i$ to refer to a possible outcome and $P^t(y_i)$ to denote the individual’s belief in $Y = y_i$ at decision moment $t$.

To generate choice alternatives at each decision moment the model assumes some (re-)scheduling heuristic. How the heuristic is specified is not important in the present context. The model assumes that the individual generates an (optimal) schedule for each possible scenario. We use the symbol $S_i^t$ to refer to the schedule
that is optimally adapted to outcome $y_i$. At the moment of decision making, the individual is still uncertain about what the true outcome will be and, hence, to evaluate the schedule alternative, he has to take into account all possible other outcomes as well. Therefore, for each main variant $S_i'$ the heuristic is applied to generate another set of schedules representing subvariants. We use the symbol $(S_i' \mid y_j)$ to refer to the subvariant that is first optimized for outcome $y_i$ and next adapted would it turn out that $y_j$ is the true state. Technically, $(S_i' \mid y_j)$ is obtained by combing the results of two runs of the scheduling decisions under conditions of: 1) current moment is $t$ and $y_i$ is the outcome occurring at $t'$ and 2) current moment is $t'$ and $y_j$ is the outcome occurring at $t'$ (where $t'$ is the moment the uncertain state is relevant). Thus, the section of the schedule in interval $[t, t')$ is based on assumption $y_i$ and the section of the schedule in interval $[t', ET]$ is based on assumption $y_j$ (where ET is the schedule end time, i.e. and of the day in case of a schedule for a day).

The expected utility of each schedule main variant is defined as:

$$EU(S_i') = \sum_j U(S_i' \mid y_j) P(y_j)$$  

(3.1)

where $t$ is the decision moment, $U(\bullet)$ is the utility derived from a schedule, $S_i'$ is the main schedule variant, $(S_i' \mid y_j)$ the subvariant and $P(y_j)$ the perceived probability of $y_j$. The expected utility of the best choice at decision moment $t$ then is defined as:

$$EU' = \max_j \left\{ \sum_j U(S_i' \mid y_j) P(y_j) \right\}$$  

(3.2)

The value of a piece of information is conceptualized as the extent to which having the information improves the decision. The model assumes that the individual holds beliefs about the credibility of a given information source. The perception of
credibility of information regarding event $Y$ is represented by conditional probabilities of the form $P(Y' \mid Y)$ where $Y = \{y_1, y_2, ..., y_n\}$ are the possible outcomes for the event and $Y' = \{y'_1, y'_2, ..., y'_n\}$ are outcomes as revealed by the information. In the following, we will refer to $Y'$ as the message received’. The perception of full credibility is represented as the special case where $P(y'_k \mid y_j) = 0$, if $k \neq j$, and $P(y'_k \mid y_j) = 1$, if $k = j$ and the perception of zero credibility as the special case where the messages are completely random or $P(y'_k \mid y_j) = 1/n, \forall k,j$. The expected utility after having received message $y'_k$ then becomes:

$$EU_{k'}^{++} = \max \left\{ \sum_j U(S'_i \mid y_j)P(y_j \mid y'_k) \right\}$$

(3.3)

The conditional probabilities $P'(y'_k \mid y_j)$ are derived from $P(y'_k \mid y_j)$ by backward reasoning (using Bayes theorem). To determine the individual’s willingness to pay for the information, the expected value of information prior to receiving the information is relevant and can be found as:

$$EIV' = \sum_k P'(y'_k)EU_{k'}^{++} - EU'$$

(3.4)

The individual’s prior belief, $P'(y'_k)$, of receiving message $y'_k$ is derived from his prior beliefs $P'(Y)$ and conditional probabilities $P'(y'_k \mid y_j)$.

Two properties of the above conceptualization deserve attention. First, the scheduling heuristic and the utility function are considered a black box in the model framework. This means that any scheduling model could be used to specify these components. It is important, however, that the heuristic and the utility function are consistent in the sense that the heuristic uses the same utility function in searching for the best schedule. AURORA (Joh et al., 2002, 2003), is an example of a scheduling model that meets this requirement. Secondly, the variables
of type $Y$ have discrete states, whereas in reality relevant events, such as travel time, may have outcomes on a continuous scale. The assumption here is that even in case the variable has a continuous character, the outcomes are represented in terms of discrete values in the perception of the individual. For example, in case of travel time, outcomes may refer to rounded values (e.g., travel time is approximately 15 minutes) or ranges (e.g., travel time is somewhere in the range of 15 to 20 minutes). There is some evidence that uncertain travel times are indeed represented in this way (e.g., Bonsall, 2001).

### 3.2.2 Causal knowledge

Apart from using information, an individual may also reduce uncertainty using knowledge about situational factors. For example, the probability of a certain travel time on a certain link may depend on time of day, day of the week, traffic volumes earlier that day, etc. An individual’s causal knowledge can be represented by belief structures of the form $P^t(Y \mid X)$ where $X = \{x_1, x_2, \ldots, x_m\}$ are the possible states of some situational variable having an influence on $Y$. If there is more than just one factor, the structure is extended as $P^t(Y \mid X_1, X_2, \ldots)$, etc. To account for the impact of causal knowledge on expected utility, Equation (3) can be extended as follows (assuming a single causal factor):

$$ EU'' = \sum_k P^t(y_k' \mid x_h) \max_j \left\{ \sum_j U(S'_j \mid y_j, x_h) P^t(y_j \mid y_k', x_h) \right\} \quad (3.5) $$

The term $P^t(y_k' \mid x_h)$ expresses the notion that the expected content of the message ($Y'$) may depend on the situational variable $X$. The dependence may not arise from a direct influence, but rather through the impact $X$ has on true outcome $Y$. Second, the structure $U(S'_j \mid y_j, x_h)$ takes into account that $X$ may have a direct influence on the optimal schedule, in addition to an indirect influence through $Y$. 

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Equation (5) represents a relatively simple case where only one situational variable is considered, the state of which is known with certainty at the decision moment. More extensive and complex causal knowledge structures can be represented efficiently and intuitively by means of a Bayesian Belief Network.

### 3.2.3 Multiple events

Under the general framework, when there are more uncertain events $Y_1, Y_2, \ldots, Y_r$ the individual has to consider all combinations of these events, the joint probability, in his decision. It is not unlikely that multiple events are relevant in reality. For example, the travel times on different links may be independent and uncertain or combinations of activity and travel durations may be uncertain. The generalization to the multiple event case is straightforward if we redefine scenarios as unique outcome configurations of multiple events, i.e. $Y = Y_1 \times Y_2 \times \ldots \times Y_r$. Given that interpretation of a scenario, $S_t^i$ represents the schedule adapted to a combination of outcomes and $P_t(y_i) = P_t(y_{1i}, y_{2i}, \ldots, y_{ri})$ denotes the probability associated with the scenario. Using these definitions, the same equations apply for calculating expected utilities. However, information sources often relate to a single event and their credibility may differ. The expected utility after reception of message about the $q$-th event $Y_q = y_{qk}$ is defined as:

$$EU_{qk}^{\text{eq}} = \max \left\{ \sum_j U_j(S_t^i | y_{1j}, y_{2j}, \ldots, y_{rj}) P_t(y_{qi} | y_{qk}) \prod_{s \neq q} P_s^i(y_{qs}) \right\}$$ (3.6)

Needless to say that the number of scenarios grows exponentially with the number of events considered. Several ways of simplification are possible. First, not all uncertain states that are relevant for the schedule as a whole are also relevant at the moment of decision making. Secondly, individuals may use heuristics to reduce the set of all possible outcomes to a manageable subset that suffices to identify the most important choice alternatives. Finally, the time horizon may be limited such
that uncertainties occurring later in the schedule are left out of consideration at the decision moment.

3.2.4 Parameter learning

The probabilities representing an individual’s beliefs are not static. Each time an event is experienced during the implementation of the schedule beliefs are updated. Specifically, this pertains to the perceived credibility of an information source, $P(Y \mid Y)$, and causal knowledge $P(Y \mid X)$. Since the present model represents beliefs as probability distributions, single-value updating methods applied in reinforcement learning frameworks are not applicable here. To update full probability distributions, we use a method derived from Bayesian principles. The method is straightforward and can be described as follows for any belief structure of the form $P(Y \mid X)$ (Spiegelhalter et al., 1993):

$$P^{i+1}(y_i \mid x_k) = \frac{P'(y_i \mid x_k)W'(x_k) + w'}{W'(x_k) + w'} \quad (3.7)$$

$$P^{i+1}(y_j \mid x_k) = \frac{P'(y_j \mid x_k)W'(x_k)}{W'(x_k) + w'} \quad \forall j \neq i \quad (3.8)$$

$$W^{i+1}(x_k) = W'(x_k) + w' \quad (3.9)$$

$$P^{i+1}(y_j \mid x_l) = P'(y_j \mid x_l) \quad \forall j, l \neq k \quad (3.10)$$

$$W^{i+1}(x_k) = W'(x_k) \quad \forall j, l \neq k \quad (3.11)$$

where $y_i$ is the observed state of $Y$, $x_k$ is the observed state (or state configuration) of $X$, $w_t$ is the weight assigned to the $t$-th case and $P^{i+1}(y \mid x)$ is the probability representing the individual’s updated belief in $Y = y$ given that $X = x$. As implied by
the equations, the method assumes that, besides a probability for each possible state \( y \), the subject also stores a running total, namely \( W^t \), in memory. This total can be seen as a measure of the amount of experience that has accumulated until time \( t \). The larger this amount, the smaller the impact of the present case on the belief will be, given its weight \( w^t \). If all cases are given equal weight than \( w^t = 1 \). In non-stationary systems it is rational to assign more weight to more recent cases and, then, \( w^t \) should be set according to a decreasing function of time.

3.2.5 Rules for decision tree construction

Equations (3.2) and (3.3), which define the expected utility (without and with information), can be represented as a decision tree of the problem, as shown in Figure 3.1 for a case where there are three possible outcomes of some event \( Y \).

Since a decision tree grows exponentially with the number of possible outcomes, it is important to specify rules for ‘pruning’ a tree. This section describes situations in which the decision tree representation will partly collapse into a simpler form. Merging or collapsing of subtrees occurs if two or more schedule alternatives are identical in the section defined by the interval \([t, t']\) (where, as before, \( t \) is the decision moment and \( t' \) the moment where the uncertain event occurs). Because section \([t', ET]\) is optimized for each possible outcome of the event, being the same in the pre-event section means that the schedule alternatives are also the same in the post-event section for each outcome. Formally, schedule alternatives \( S^t_i \) and \( S^t_k \) are equivalent iff:

\[
(S^t_i | y_j) = (S^t_k | y_j) \quad \forall j
\]  

(3.12)

If this is the case, then there is no need to make a choice between the alternatives before the event occurs. The outcome of the event has only an impact on the optimal post-event section of the schedule, so that a re-scheduling decision can be
delayed until after the event when the outcome is known. In other words, whenever
the individual is able to reschedule his remaining activities and shift to the other
schedule groups after experiencing the outcome, the uncertainty at that decision
moment is not relevant to the decision process because he can always wait until the
event has happened and then re-schedule the rest of the activities according to the
known outcome.

The conclusion is that there is a need to choose between any two choice

Figure 3.1 Example of a decision tree representation of a re-schedule decision problem
alternatives $S_i$ and $S_j$ only if they are different regarding the pre-event section. Such collapsing may occur very frequently since the different outcomes of an event have an impact on the pre-event section of a schedule only in cases where re-sequencing occurs or a destination, route or transport mode choice need to be made before the actual travel time is experienced. We expect, therefore that tree collapsing will lead to substantial pruning of the decision tree in many cases.

3.3. Numerical simulation

To illustrate and explore the behavior of the model, this section discusses results of numerical experiments that were carried out. Before discussing the results we will describe the case considered and the basic settings of parameters of the system.

3.3.1 Situational settings

We set up a Java based simulation environment using the NeticaJ package, the Java API for Netica, to simulate the inference and learning process of a hypothetical individual. Conceptually, the simulation can be viewed as consisting of two separate parts: the traveler and the traffic-environment system. The system represents the real travel environment in which a traveler tries to learn both the real travel time distribution and the credibility of some travel-time information service, which we will call information travel agency or in short ITA. The traveler carries a Bayesian belief network representing his (conditional) beliefs about travel times and the credibility of ITA. It also acts as an inference engine at the same time. The system supplies the traveler with real traffic times, ATIS messages with a certain degree of credibility and possibly situational information such as time of day.

The traveler repeatedly implements the same set of activities for an indefinite number of subsequent days. Each time the traveler receives ATIS information about the travel time, considers re-scheduling decisions, experiences the real traffic situation afterwards and then updates his belief of travel time and ATIS credibility.
accordingly. The system generates the travel times, messages, and situational information based on the simulated true distributions of the variables. In sum, parameters of the system include assumed true distributions related to travel time and credibility of ATIS and parameters of the individual include the initial beliefs related to travel time and credibility, the initial level of prior experience and presence of causal knowledge. Note that zero prior experience means that $W^0 = 0$ and $P = 1/3$ for all outcomes. System as well as individual parameters are varied across runs to investigate their impact on the variables of interest. The latter include the (expected) value of information, choice behavior and the utility derived from activity-travel patterns.

3.3.2 Basic settings

In the simulation, a simple four-activity schedule, home-work-shopping-home, was used and the uncertain event is the travel time from work to the shopping location. The work activity has a given, fixed location, begin time and duration. The shopping activity is flexible in terms of including the activity in the schedule (yes or no), position in the schedule (before or after the work activity) and location. With respect to location, there are three alternatives. Shop1 and Shop2 are on the same route from home to work. Shop1 is nearer to home and Shop2 is nearer to the work location. Shop3 is not on the same route between work and home. Rather to reach Shop3 the traveler has to make a 10 minutes detour. Shop3 has no closing time constraint. Under normal conditions, the traveler prefers to shop after work at Shop1.

The case further assumes that there are three possible outcomes of the travel time from Work to the location where Shop1 is situated, namely, short, middle and long. For each possible travel time, the traveler has an optimal schedule as following:

$(S_1 | y_1)$: Home----------Work--------Shop1--Home

$(S_2 | y_2)$: Home----------Work--Shop2----------Home
Under each optimal schedule, the traveler also formulates a group of variants which are adapted to different possible outcomes of the travel time as experienced. If travel time is medium or long it is not possible to reach Shop1 before closing time and, hence, choosing the first schedule under that condition would mean that the shopping activity has to be skipped. If the travel time is short or medium it is possible to reach Shop2 before closing time. However, if travel time is long the shopping activity must be canceled. Canceling shopping means that more time can be spent at home, but this does not fully compensate for the loss in utility caused by skipping the shopping activity. Note that a choice between $S_1$ and $S_2$ could be postponed till the end time of the work activity. The choice between $S_1$ and $S_2$, on the one hand, and $S_3$ on the other, however, should be made at the beginning of the day.

Table 3.1 shows details about the utility function assumed. The base utility is set to 100 units for the best case, i.e. a short travel time and shopping in Shop1. The short, middle and long travel times are defined as a 0, 15 and 30 minutes delay, respectively. The shopping activity can be conducted either for the full duration or be skipped, and the penalty of skipping is –100. Shop1 and Shop3 have the same attractiveness and are preferred over Shop2. The perceived loss of utility of Shop2 is –20. The traveler has a preference for shopping in the afternoon. Since Shop3 is a feasible option only for shopping in the morning, its perceived utility loss is set to –30. The penalty of reducing the duration of being at home is –1/min and extra travel time reduces total utility with –1/min.

A relatively high level of credibility of ATIS is defined as the level where about 80 percent of the messages are correct. This is defined by the settings: $P(y_k' \mid y_j) = 0.8$, if $k = j$ and $P(y_k' \mid y_j) = 0.1$, if $k \neq j$. On the other hand, zero credibility is defined as
Two sets of possible traffic situations were used in the simulation, a usual one, where $P(Y) = \{0.6,0.25,0.15\}$ and a completely random one, i.e. $P(Y) = \left\{\frac{1}{3},\frac{1}{3},\frac{1}{3}\right\}$, corresponding to short, middle and long.

### 3.4. Results and findings

#### 3.4.1 Learning

As it appears less than 250 time steps (i.e., days) are enough to learn the true distribution and credibility of the information source starting from zero experience. The graphs of Figure 3.2 show how the expected value of information evolves over time for different settings of the true distributions of travel time and ATIS credibility. Intuitively, we would expect that the more random the nature of the real traffic environment is, the higher the information value will be.

<table>
<thead>
<tr>
<th>Schedule</th>
<th>Utility</th>
<th>Duration of shopping</th>
<th>Penalty of skipping shopping</th>
<th>Extra travel time delay</th>
<th>Penalty of reduce home duration (per min)</th>
<th>Location preference</th>
<th>TOD preference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(S_1</td>
<td>y_1)$</td>
<td>100</td>
<td>60</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$(S_1</td>
<td>y_2)$</td>
<td>-15</td>
<td>0</td>
<td>-100</td>
<td>15</td>
<td>-30</td>
<td>0</td>
</tr>
<tr>
<td>$(S_1</td>
<td>y_3)$</td>
<td>-52.5</td>
<td>0</td>
<td>-100</td>
<td>30</td>
<td>-15</td>
<td>0</td>
</tr>
<tr>
<td>$(S_2</td>
<td>y_1)$</td>
<td>80</td>
<td>60</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>$(S_2</td>
<td>y_2)$</td>
<td>42.5</td>
<td>60</td>
<td>0</td>
<td>15</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>$(S_2</td>
<td>y_3)$</td>
<td>-72.5</td>
<td>0</td>
<td>-100</td>
<td>30</td>
<td>-15</td>
<td>20</td>
</tr>
<tr>
<td>$(S_3</td>
<td>y_1)$</td>
<td>45</td>
<td>60</td>
<td>0</td>
<td>10</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>$(S_3</td>
<td>y_2)$</td>
<td>7.5</td>
<td>60</td>
<td>0</td>
<td>25</td>
<td>25</td>
<td>0</td>
</tr>
<tr>
<td>$(S_3</td>
<td>y_3)$</td>
<td>-30</td>
<td>60</td>
<td>0</td>
<td>40</td>
<td>40</td>
<td>0</td>
</tr>
</tbody>
</table>
P = \{0.6,0.25,0.15\} travel time distribution, high credibility

P = \{0.8,0.1,0.1\} travel time distribution, high credibility

Figure 3.2 Beliefs of travel times and credibility of ATIS as a function of time
The graphs show this trend in the information value. This implies that the hypothetical traveler is willing to pay more for an ATIS facility when he believes or finds out that the real travel time is random. He will expect a high utility gain under this circumstance. A counterintuitive finding may be that in the initial stage, before stabilizing, the information value displays a tendency to increase, at least in the first two graphs, whereas one would expect a decreasing trend if uncertainty decreases as a consequence of learning. We should realize, however, that learning does not necessarily decrease uncertainty. If the true distributions are highly random then learning means that uncertainty will persist. The large fluctuations in the initial stage of the curves are caused by the fact, that when the individual starts with zero experience, the first observations will have a strong impact on beliefs and, hence, also on the perception of uncertainty and value of information.

3.4.2 Value of information and experienced utility

The illustrations considered in this section highlight the functional relationships between variables for a certain moment in time in the simulation when convergence of beliefs has settled in. The graphs in Figure 3.3 plot the results of a series of runs where the level of credibility of ATIS and randomness in real travel time distribution were varied and the value of information (after sufficient learning) and utility of implemented schedules are monitored. It appears that the value of information decreases almost linearly with a decrease in credibility. Furthermore, as expected, the value increases with increasing randomness of travel times, but the effect is non-linear. The marginal value seems to increase over the range from high randomness to low randomness of the distribution of travel time. It means that in strong stochastic environments credibility is less critical. The impact on utility is also clearly visible and approximately linear.
Figure 3.3 The impact of credibility of information and true travel time distributions on perceived information value (upper graph) and utility (lower graph)
3.4.3 The impact of causal knowledge

Causal knowledge is introduced by including a time-of-day variable as a parent node of the travel-time variable. Two states are distinguished for the new node, namely Peak and Off-Peak. The following settings were applied in three simulation runs that were conducted to show the impact of acquiring causal knowledge through learning. All three scenarios assumed that \( P(\text{peak}) = 0.2, P(\text{off peak}) = 0.8 \) and that the real travel time distribution equals \( P = \{0.60, 0.25, 0.15\} \) for the off-peak period and \( P = \{0.15, 0.25, 0.60\} \) for the peak period. The credibility was assumed to be 0, 80% and 90% in the three scenarios respectively. An interesting question is how contradictory information between ATIS and time of day will affect the beliefs of the traveler as a function of credibility.

In the 80% credibility case, when the PITA gives a long travel time prediction and the time of day is Off-Peak, the traveler will always ignore the PITA suggestions except in the very beginning when he still did not know much about the traffic situation and the credibility. When the credibility increased to 90%, the traveler will follow the PITA guidance again. This phenomenon indicates that if the traveler has some other highly influential source of information, the PITA service will sometimes be doubted. It is possible to find the critical point of credibility beyond which the traveler will always take the PITA instructions given the availability of other information sources.

3.5. Discussion and conclusion

This chapter introduced and elaborated Arentze and Timmermans’ general framework to model the use and value of travel information in the context of scheduling and re-scheduling activity-travel decisions of individuals. The specific strength of the approach is that the broader scheduling implications of information and decisions are taken into account. In addition, the Bayesian belief updating
mechanism incorporated makes sure that beliefs regarding travel times or any other uncertain event are updated each time information is received and real outcomes are experienced. Hence, in the model both the perception of the credibility of the information source and existing uncertainties change through learning over time. Taking the broader schedule context into account makes the model more sensitive to re-scheduling effects, but also introduces the problem of combinatorial explosion. When uncertainty relates to multiple events spread across the day, the number of possible scenarios to be considered soon becomes intractable. A theoretical analysis showed, however, that in many cases insignificant branches of the decision tree can be pruned, i.e. ignored. Only in case the outcomes of an event have consequences for the optimal schedule in the pre-event section, the alternative schedules need to be taken into account. In all other cases, a decision can be postponed to a later decision moment.

A second purpose of this chapter was to illustrate and derive theoretical implications from the model. For this purpose, the model system was implemented in a micro-simulation system. The system simulates the perceptions, cognitive processes and choice behavior of an individual in an uncertain traffic environment. Several conclusions can be drawn. First, according to their model, learning a traffic environment based on experience does not necessarily mean that the value of information (and hence the willingness to pay for information) decreases over time. Rather, the value of information is a function of the degree of uncertainty and only if uncertainty decreases with learning the value will show a decreasing trend. In strongly stochastic environments the uncertainty will persist and with it also the value of information will remain high. Second, the (perceived) credibility of information tends to have a strong impact on the value of information. It should be emphasized that it is not the credibility as such, but the difference between the entropy in probability distributions with and without information or, in other words, the (expected) information gain. Information gain is not a sufficient condition. At
the same time, the impact of the uncertain outcomes on perceived utility determines the value of information and, hence, the inclination of using information. We conclude, therefore, that the nature of the transport system, the schedule context, preferences for decision alternatives and the individual’s perceptions and ability to learn, all should be taken into account in generating valid estimates of the value of information. The implementation showed that the model generates well-interpretable outputs.

Yet this framework does not incorporate the element of risk attitude which is found a common phenomenon in travel behavior under uncertainty. In the next chapter, we will develop a decision model that captures heterogeneity in risk attitude in an attempt to relax the current rational decision making assumption, implied by the use of expected utility in evaluating alternatives.
4. Heterogeneity in risk attitude

4.1. Introduction

The decision tree based decision model incorporating sequential decisions and perception evaluations that was introduced in chapter 3 is based on expected utility theory (EUT). It assumes that travelers use a scenario-based approach to evaluate choice alternatives at each decision moment taking into account all possible outcomes for next decisions and events where choice alternatives are evaluated together with corresponding probabilities based on the traveler’s perceptions based on EUT. At each decision moment, the traveler builds up a full decision tree to evaluate all possible scenarios. This decision tree in its basic form represents a fully rational evaluation process. However, different travelers may have a different risk attitude, and this kind of heterogeneity is not captured in the previously developed model, described in chapter 3. It implies a need to further modify the representation of the decision tree in such a way that it allows representing other risk attitudes besides rational behavior, or in other words, to model travelers’ heterogeneous risk attitudes.

Heterogeneous behavior is often modeled by mixed logit model/random coefficient model by allowing model parameters to vary across individuals. As introduced in chapter two, mixed logit models or random coefficient models, though capable of incorporate and account for individual differences in preference, to some extent lack interpretability in explaining the source of heterogeneity (Boxall and Adamowicz, 2002). Another approach, the latent class model, which segments decision makers into different segments, is increasingly used in discrete choice studies (e.g., Boxall and Adamowicz, 2002; Greene and Hensher, 2003; Lee et al., 2003). With the latent class model, researchers are free from possibly strong or unwarranted distributional assumptions about individual heterogeneity (Greene and Hensher, 2003). Further, the discrete nature of the LC model makes it extremely
useful for identifying market segments and providing within-segment share predictions which is crucial to managerial parties and policy makers. It is thus chosen as our main modeling approach in representing activity-risk heterogeneities.

Thus, in this chapter, we will introduce different risk attitudes by further developing the framework introduced in chapter 3 with two extensions. First, we assume travelers use different decision heuristics that lead to different decision styles under different uncertain events. Three types of risk attitudes will be distinguished, namely, risk avoiders, risk takers and risk neutral individuals. In uncertain situations, as we conceptualize it, a risk avoider uses only the worst case scenario to make decisions, a risk taker uses the most likely outcome and a risk neutral individual uses expected utility to evaluate his/her alternatives and their associated outcomes.

Second, travelers may differ in their preferences toward travel information as well, or taking traveler’s preference on information as his/her willingness to pay for information, travelers may differ in their willingness to pay for information as the information acquisition involves costs (monetary and mental). Therefore, we may argue that the willingness to pay for information can be a proxy of traveler’s propensity of reducing uncertainty against costs. In this chapter, we will develop a second model, willingness to pay model, in line with this argument. In this model, instead of pre-defining risk attitude classes, we use the goodness of fit of the model to select the appropriate segmentations.

We further elaborate the framework by introducing discounting behavior into scheduling decisions, in the sense that the further away the event is in time from the current decision, the weaker its impact on the current decision will be. This means when the traveler makes a decision, events farther away in time will be weighted less than the immediate subsequent event. We assume that discounting
behavior is a means of simplifying the complexity of the decision-making in the sense that the travelers are either limited in capacity to consider all possible outcomes in the future or are reluctant to spend too much mental effort on future events too far away from current decision thus underweight the utility of future outcomes.

Another purpose of this chapter is to develop an empirical model estimation procedure and explore the model property using numerical simulation to validate the estimation approach. The configuration of willingness to pay model follows the conventional latent class specification for which the estimation procedure is more or less standard. Thus, a numerical simulation test was carried out only on the heuristic model to explore its identifiability and validity.

4.2. Principles: utility and tree structure

Figure 4.1 gives a graphical representation of the decision problem. As before, each node in the tree structure is either a nature node or a decision node. A nature node is a node that has uncertain outcomes whilst a decision node has several possible states as its decision alternatives/options. Let \( r \) denote the time decay factor with \( 0 < r \leq 1 \) meaning the further the node from the root, the weaker its effect. Notation \( \{H\} \) is used to represent a node in general in a decision tree, \( H \) is a list representing the path from the root to the current node. Then \( \{H,i\} \) denotes a node at the next level to node \( \{H\} \), that is, the \( i-th \) child of \( \{H\} \). Given the decision tree representation, the structural utility of individual \( n \) experiencing outcome \( i \) at node \( \{H\} \) can be expressed as follows.

If node \( \{H\} \) is a nature node:

\[
v_{\{H,i\}} = v^0_{\{H\}} + \sum_{j} p_{\{H,i\}|j} v_{\{H,i,j\}}
\]  

(4.1)
If node \{H\} is a decision node:

\[
v_{(H)} = v_{(H)}^0 + r \max_i \left( v_{(H,i)} \right)
\]

where \(p_{(H,i)}\) denotes the probability of the \(i\)-th outcome at node \{H\} of the tree, \(v_{(H,i)}\) denotes the utility associated to the \(i\)-th outcome of \{H\}, \(v_{(H)}^0\) denotes the base utility of the state represented by node \{H\} itself and \(r\) is a future discount actor (\(r = [0,1]\)). These general utility functions allow the individual to evaluate the expected utility at each node in a given tree under uncertain situations.

One way of reducing the uncertainty is to acquire information. As described above, upon acquiring information, individuals update their perception of the uncertain

---

![Figure 4.1 Example of a decision tree representation of a simple decision problem](image-url)

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event so that their updated perceptions more closely reflect the true state of that event (given that the source has a positive credibility). In our model, options to acquire information are treated not differently from other choices. Thus, from a decision maker’s point of view, besides one decision tree that links to travel itself, he/she has to evaluate another decision tree representing information acquisition effects, that is, the same tree structure but with updated probabilities for each uncertain event, based on the information he/she got and the perceived credibility of the information. That is to say, the message an individual will get is itself an uncertain event with possible messages as the possible outcomes and probabilities determined by a-priori beliefs. Expected information value then becomes the difference in expected utility at the root node between these two decision trees. Thus, if node \( \{H\} \) is a node representing information acquisition, it has the same form as equation (4.1), whereby the base utility is specified as:

\[

\nu_{(H)}^0 = \beta_{infoprice} Price

\]

(4.3)

where \( \beta_{infoprice} \) is a price parameter and \( Price \) is the price for acquiring one piece of information from source referred to by node \( \{H\} \). The sum term on the RHS of equation (4.1) then represents the perceived expected value of information.

The discount factor \( r \) represents the extent to which the individual is myopic (in the sense of assigning less weight to the future). Since the equation is recursive, the weight of utility reduces progressively with increasing length of the path from the current node, according to the series \( r \) (next level), \( r_2 \) (two levels deep), \( r_3 \) (three levels deep), etc. If \( r = 0 \), the individual does not take the future into account at all and evaluates the choice alternatives for the current decision based on base utilities \( \nu_{H}^0 \). If \( r = 1 \), the future utility weighs as much as the current decision.
4.3. Heuristic latent class model

Risk attitude in heuristics

This basic conceptual framework can be extended by introducing different risk attitudes. Different heuristics can be introduced to allow modeling different decision styles under multiple uncertain events. Three types of risk attitudes will be distinguished, namely, risk avoiders, risk takers and risk neutral individuals. They are defined here as follows. In uncertain situations, a risk avoider consistently uses the worst case scenario to make decisions – i.e. evaluates decision alternatives always under the worst outcome, a risk taker evaluates decision alternatives under most likely outcomes (i.e., ignoring probabilities of other less likely outcomes) and a risk neutral individual uses expected utility to evaluate his/her alternatives and their associated outcomes. Apart from being influenced by personal traits, the decision style chosen may vary in different situations as well for example depending on the amount of risk involved. The decision styles can be represented in the decision tree model as follows. Let $C$ denote the total number of classes representing decision styles. Then, equation (4.1) can be extended as follows:

\[ v_{(H)c} = v_{(H)0} + v_{(H)c1} \]  

(4.4)

where $c$ is an indicator of class membership ($c=1$ is risk avoider, $c=2$ is risk taker and $c=3$ is risk neutral traveler). In this equation, the utility $v_{(H)c1}$ is defined as class dependent, shown as follows:

\[ v_{(H)c1} = \min_i (v_{(H),i}) \]  

(4.5)

\[ v_{(H)c2} = v_{(H),k} \quad k = \arg \max_i (p_{(H),i}) \]  

(4.6)

\[ v_{(H)c3} = \sum_i p_{(H),i} v_{(H),i} \]  

(4.7)
The risk aversive traveler defined in equation (4.5) always evaluate his/her choices based on the minimum outcome, worst case, risk taking traveler defined in equation (4.6) always evaluates his/her choice based on the maximum outcome and risk neutral traveler in equation (4.7) use expected utility to evaluate his/her choice outcomes.

**A model for data analysis**

From the perspective of the analyst, there are unobserved attributes of the choice alternatives in each decision. As we assume the choice alternative with the highest utility is always chosen, following random utility theory, we specify the utility of each type of decision alternatives in the decision tree depending on whether it has uncertain outcomes or is followed by a next decision as follows. If the alternative has uncertain consequences and, hence, the node \( \{H\} \) representing the alternative is a chance node, then the utility function is defined as:

\[
U_{\{H\}|c} = v_{\{H\}}^0 + v_{\{H\}|c}^1 + \varepsilon_{\{H\}|c}
\]  

(4.8)

and if the alternative is followed by a next decision and, hence, the node \( \{H\} \) representing the alternative is a decision node, the utility function is defined as:

\[
U_{\{H\}|c} = v_{\{H\}}^0 + rE\left(\max_i \left(U_{\{H,i\}|c}\right)\right) + \varepsilon_{\{H\}|c}
\]  

(4.9)

where \( U_{\{H,i\}|c} \) denotes the utility of class \( c \) given its \( i \)-th outcome of \( \{H\} \), and, as before, \( v_{\{H\}}^0 \) denotes the base utility of the choice alternative represented by the node itself, \( v_{\{H\}|c}^1 \) denotes the class-dependent outcome-related utility and \( \varepsilon_{\{H\}|c} \) is an unobserved error term.
The error term $\varepsilon_{(H)ce}$ is class dependent, which implies that (i) unobserved errors consists of two parts, a class dependent constant and a random effect which is unknown; (ii) random effects across trials and decisions made by one individual are independent of each other. This is justified because the error term in the early decision stage has already been conceptually “realized”, thus its associated error term does not affect later choice alternatives anymore. Under this assumption, the expected maximum utility of next level alternatives can be replaced by a logsum function:

$$U_{(H)ce} = v_{(H)}^0 + r \ln \sum \exp(U_{(H)ce}) + \varepsilon_{(H)ce}$$

(4.10)

Furthermore, we assume the error term $\varepsilon_{(H)ce}$ of choice alternatives to be i.i.d.-extreme value distributed. This gives a logit form for the choice probability for each decision alternative.

In this specification, we assume that the parameters for observable variables are the same throughout the population and the unobservable classes in risk attitudes lead to possible differences in systematic utility components. One individual is assigned to one class explicitly. The way that distinguishes individuals with different decision styles is the heuristic that is used to evaluate outcome utilities and corresponding probabilities or, in other words, how an individual chooses to combine the utility and probabilities. Thus, the population consists of a set of mutually exclusive and exhaustive homogeneous subpopulations, different risk attitude groups.
4.4. Willingness to pay model

Heterogeneity in willingness to pay

In this model, we assume the heterogeneity in risk attitude may affect travelers’ preferences for information acquisition. For example, risk-aversion means higher willingness to pay for reducing the risk and hence higher willingness to pay for information given the perceived value of information. Based on this consideration, we assume that individuals have different preferences for information price, in line with the willingness to pay concept. Further, we assume there is a finite number of groups/categories of preferences for information. Travelers belonging to the same group of people have approximately the same preference for information whilst preferences differ across groups. As in the heuristic model, let $C$ denote the total number of classes. Then, equations (4.1) and equation (4.2) can be expressed as follows regarding interclass differences: If node $\{H\}$ is a nature node:

$$v_{\{H\}|c} = v^0_{\{H\}} + \sum_i p_{\{H,i\}}v_{\{H,i\}|c}$$

(4.11)

If node $\{H\}$ is a decision node:

$$v_{\{H\}|c} = v^0_{\{H\}} + \max_i \left( v_{\{H,i\}|c} \right)$$

(4.12)

where $v_{\{H\}|c}$ denotes class-specific utility.

If node $\{H\}$ is a node representing information acquisition, it has the same form as equation(4.11), and the utility is specified by equation (4.3) becomes

$$v^0_{\{H\}|c} = \beta_{\text{infoprice}c} \cdot Price$$

(4.13)
where $\beta_{\text{infoprice}}$ is class specific parameter of information price, \textit{Price} is the price for acquiring one piece of information (i.e., consulting the information source). The sum term on the RHS of equation (4.11) then represents the perceived information value.

\textit{A model for data analysis}

From the perspective of the analyst, there are unobserved attributes of the choice alternatives in each decision. As we assume the choice alternative with the highest utility is always chosen, following random utility theory, we specify the utility of each type of decision alternatives in the decision tree depending on whether it has uncertain outcomes or is followed by a next decision as follows. If the alternative has uncertain consequences and, hence, the node \{H\} representing the alternative is a chance node, then the utility function is defined as:

$$U_{(H|c)} = v_{(H|c)}^0 + \sum U_{(H,i|c)} P_{(H,i)} + \epsilon_{(H|c)}$$  \hspace{1cm} (4.14)

and if the alternative is followed by a next decision and, hence, the node \{H\} representing the alternative is a decision node, the utility function is defined as:

$$U_{(H|c)} = v_{(H|c)}^0 + E\left(\max_i \left(U_{(H,i|c)}\right)\right) + \epsilon_{(H|c)}$$  \hspace{1cm} (4.15)

where $P_{(H,i)}$ denotes the probability of its $i-th$ outcome at node \{H\} of the tree, $U_{(H,i|c)}$ denotes the utility of class $c$ given its $i-th$ outcome of \{H\}, $v_{(H|c)}^0$ denotes the base utility of the choice alternative represented by the node itself, $\epsilon_{(H|c)}$ is an unobserved error term.
The error term $\epsilon_{(H)_{i|e}}$ is class dependent, which implies that (i) unobserved errors consists of two parts, a class dependent constant and a random effect which is unknown; (ii) random effects across trials and decisions made by one individual are independent of each other. As argued in heuristic model, this is justified because the error term in the early decision stage has already been conceptually “realized”, thus its associated error term does not affect later choice alternatives anymore. Under this assumption, the expected maximum utility of next level alternatives can be replaced by a logsum function:

$$U_{(H)_{i|e}} = v^0_{(H)} + \ln\sum \exp(U_{(H,i)_{i|e}}) + \epsilon_{(H)_{i|e}}$$  \hspace{1cm} (4.16)

Furthermore, we assume the error term $\epsilon_{(H)_{i|e}}$ of choice alternatives to be i.i.d.-extreme value distributed. This gives again a logit form for the choice probability for each decision alternative.

4.5. Model estimation

In this section, we will develop general empirical estimation procedure for the two models developed in previous sections that allow us to estimate the parameters of interest and, in particular, the decision styles based on choice observations that are collected under experimentally controlled conditions.

4.5.1 Specification

In the heuristic model, we do not use class specific parameters in our framework, rather, we use different decision heuristics to distinguish the classes from each other. Therefore, the difference across classes is represented by different utility functions used by travelers that are using different risk heuristic. The willingness to pay model on the other hand resembles the standard latent class model in the sense
that it uses class specific parameters and all classes use the same form of utility function. However, this difference appears only in the node utility functions in the decision tree. When considering data analysis from an analyst’s perspective, the way an individual’s choice contributes to the likelihood function of the whole dataset is identical. In that sense, we can derive a general estimation procedure that allows us to estimate the parameters of behavior based on choice observations for both models and substitute the underlining individual choice utility functions for each model accordingly.

The estimation procedure is based on the maximum likelihood function. Assume we have $N$ individuals, each of them belonging to one of the $C$ classes. Each individual makes $T$ trials of sequential choices, each sequence of choices consists of $S$ decisions, each decision has $J$ alternatives. We define the probability of individual $n$ choosing alternative $j$ at decision $s$ in trial $t$ when this individual belongs to class $c$ as:

$$P_{nts} (j) = \text{Prob}(y_{nts} = j | \text{class} = c)$$

(4.17)

where $y_{nts}$ denotes the choice made. Further, we define the probability of individual $n$ choosing choice alternative $j$ in trial $t$ making the $s-th$ decision given the class of this individual in logit form following the earlier assumption of the i.i.d.-extreme value distributed form of the error terms:

$$P_{nts} = \frac{\exp(v_{nts})}{\sum_{k=1}^{J} \exp(v_{nts})}$$

(4.18)

The contribution of this individual to the likelihood of the model is the joint probability of decision sequence $y_n = \{y_{n1}, y_{n2}, ..., y_{nT}\}$, defined as:
\[ P_{nic} = \prod_{i=1}^{T} \prod_{j=1}^{s} P_{nic} \]  \hspace{1cm} (4.19)

or

\[ P_{nic} = \prod_{i=1}^{T} \prod_{j=1}^{s} P_{nic}^{\delta_{j}}, \]  \hspace{1cm} (4.20)

where \( \delta_{j} = 1 \) if the \( j \)-th alternative is chosen and 0 otherwise.

Let \( \alpha_{nc} \) denote the probability that individual \( n \) belongs to class \( c \). Then the membership function is defined as:

\[ \alpha_{nc} = \frac{\exp(z_{n}\theta_{c})}{\sum_{c=1}^{C} \exp(z_{n}\theta_{c})}, c = 1...C, \theta_{c} = 0 \]  \hspace{1cm} (4.21)

where \( z_{i} \) denotes a set of observable attributes that may be psychological constructs or socio-economic characteristics. \( z_{i} \) in this format is known as “concomitant variable” or “covariate variable”. \( \theta_{c} \) denotes the unknown class parameters. Equation (4.19) represents a general approach in latent class modeling. We keep this form simply for convenience and future use because such covariates do not exist in our model at this moment but may be introduced into our model later on. At this moment, our only interest is to find the proportion of each class. Thus, \( \alpha_{aq} \) is simply a constant. Therefore, we adopt a single attribute in \( z_{a} \) and set this attribute to a constant “1”, and the latent class probabilities would sum up to 1 by construction.
The likelihood function for individual $n$ across all classes is the weighted sum of the class specific contributions:

$$P_n = \sum_{c=1}^{C} \alpha_{nc} P_{n|c}$$  \hspace{1cm} (4.22)

The log likelihood function for all observations is:

$$LL = \sum_{n=1}^{N} \ln P_n = \sum \ln \left( \sum_{c=1}^{C} \alpha_{nc} \left( \prod_{j=1}^{J} \prod_{i=1}^{I} P_{n|j} \right) \right)$$  \hspace{1cm} (4.23)

where $P_{n|j}$ in likelihood function is $\prod_{j=1}^{J} P_{n|j} \delta_{j}$, where $j \in J$ indicates a choice alternative.

The assumption that, given the class an individual belongs to, the decisions made by that individual are independent across cases implies there are no learning effects. In the cases we consider when the individual makes repeated choices, the decisions made before do not have impacts on later choices. Although Greene and Hensher (2003) argued that this maybe a strong assumption in their experiment setting, it has been alleviated however by the controlled nature of the experiment design (Chapter 5). In the controlled interactive experiment, the uncertain events are generated randomly from a finite set of uncertain magnitudes, thus rather a uniform distribution in form. In doing so, participants are facing basically a new situation in each trial and it is hard to form beliefs about these uncertainties.

### 4.5.2 Estimation using EM algorithm

Maximization of this log likelihood function regarding structural parameter vectors, $\beta$ and the C-1 latent class parameter values $\theta_j$ is a standard likelihood maximization problem. But maximization of the logarithm of a sum is relatively difficult even if it is feasible in principle (McLachlan and Peel, 2000). It is
especially so when we embed the decision tree evaluation in the probability derivation. The log likelihood function in equation (4.23) does not yield an explicit solution for the unknown parameters. Newton type of methods proved to give numerical difficulties in stability due to the nonlinear form of the log likelihood function and multi mode-nature of the function curve. Therefore, an expectation-maximization (EM) algorithm was developed and applied (e.g., Redner and Walker, 1984; Rost and Langeheine, 1997).

The EM algorithm is an iterative optimization approach to estimate parameters given that part of the data is “missing” or “hiding”. It has enjoyed its popularity in estimating latent class models for years due to its stability, simplicity and ease of implementation. For a full description, readers are referred to Dempster (1977). Let \( \Theta \) denote all parameters to be estimated, consisting of \( \beta \) and \( \theta_c \), \( \Theta = (\beta, \theta_c) \), \( X \) denote observed data and \( C \) be the underlying latent class. \( X \) is called “incomplete data” and is observable. \( Z = (X, C) \) is then assumed as “complete” data set, which has the following joint density function:

\[
p(z | \Theta) = p(x,c | \Theta) = p(c | x, \Theta) p(x | \Theta) \tag{4.24}
\]

Then, we can derive two likelihood functions; observed data likelihood:

\[
L_{obs} = P(X | \Theta) = \prod_{n=1}^{N} P(x_n | \Theta) = \prod_{n=1}^{N} \sum_{c=1}^{C} P_c (x_n | \Theta_c) \tag{4.25}
\]

and a complete data likelihood function:

\[
L_{complete} = P(X, C | \Theta) = \prod_{n=1}^{N} P(x_n, c_n | \Theta) = \prod_{n} P_{cn} (x_n | \Theta) \tag{4.26}
\]
where \( c_n \in \{ 1, \ldots, C \} \) denotes classes. The summation over classes now has disappeared in the complete data likelihood function because of the assumption of knowing which class it belongs to. The target of finding \( \Theta = \arg \max_{\Theta} P(X \mid \Theta) \) is hard since it contains products of sums, whereas the finding \( \Theta = \arg \max_{\Theta} P(X, C \mid \Theta) \) would be relatively easier if we know \( C \) (class). The idea of EM is to zigzag between maximizing \( \Theta \) with \( C \) fixed and calculate the completions \( C \) based on best guesses given \( \Theta \), the posterior.

Thus, starting from some sort of guess for \( \Theta \), the algorithm combines two steps alternately. These steps are known as E and M-step and are specified as follows:

E-step: calculate completions \( P(C \mid X, \Theta') \), given a currently fixed \( \Theta \)

Let \( \alpha_n \) be the latent class distribution, then using Bayes’ rule, the completions become:

\[
P(c_n \mid x_n, \Theta) = \frac{\alpha_n \hat{P}_{n\mid c}(x_n \mid \Theta)}{\sum_{k=1}^{C} \alpha_k \hat{P}_{n\mid c}(x_n \mid \Theta)}
\]  

(4.27)

This represents the posterior probability of each individual belonging to each class conditional on observed data, given \( \alpha \) and \( \hat{P}_{n\mid c} \) as known.

M-Step: given fixed completions \( P(C \mid X, \Theta') \), maximize

\[
Q_i(\Theta \mid \Theta) = E[\log P(X, C \mid \Theta) \mid C, \Theta] = \sum_{c} P(C \mid X, \Theta) \log P(X, C \mid \Theta)
\]

(4.28)

with respect to \( \Theta \).
After some transformation, we get:

\[
Q_c(\Theta | \Theta') = \sum_c P(C | X, \Theta') \log P(X, C | \Theta) = \sum_c^{C} \sum_{n=1}^{N} p(c | x_n, \Theta) \log(\alpha_c p_c(x_n | \theta_c))
\]

\[
= \sum_c^{C} \sum_{n=1}^{N} \log(p_c(x_n | \theta_c)) p(c | x_n, \Theta') + \sum_c^{C} \sum_{n=1}^{N} \log(\alpha_c) p(c | x_n, \Theta')) (4.29)
\]

in which \( p_c(x_n | \theta_c) \) is \( P_{n;c} = \prod_{t=1}^{T} P_{n;tc} = \prod_{j=1}^{J} \prod_{t=1}^{T} P_{n;jtc} \), \( \alpha_c \) is

\[
\alpha_c = \frac{\exp(\delta_c)}{\sum_{c=1}^{C} \exp(\delta_c)}
\]

Substituting into the equation above, we get

\[
Q_c(\Theta | \Theta) = \sum_c^{C} \sum_{n=1}^{N} \sum_{i=1}^{I} \log(P_{n;ilc}) p(c | x_n, \Theta') + \sum_c^{C} \sum_{n=1}^{N} \log(\alpha_c) p(c | x_n, \Theta'))
\]

\[
= \sum_c^{C} \sum_{n=1}^{N} (\sum_{i=1}^{I} \sum_{j=1}^{J} \delta_{ij} \log(P_{n;ilc})) p(c | x_n, \Theta') + \sum_c^{C} \sum_{n=1}^{N} \log(\alpha_c) p(c | x_n, \Theta')) (4.30)
\]

These two parts can be maximized separately because they are independent of each other. The second part of this equation allows us to derive analytically \( \tilde{\alpha}_l = \frac{1}{N} \sum_{n=1}^{N} p(l | x_n, \Theta') \). The EM algorithm alternates the above two steps until convergence.

### 4.6. Numerical simulation

To explore the behavior and properties of the developed model, in this section, we set up a numerical simulation which first generates a hypothetical data set and then estimates the model using the customized EM algorithm as specified in the previous section. Since the willingness to pay model is to some extent a conventional latent class model in a form for which the EM algorithm has been
applied as a standard estimation procedure, we focus our attention in this section only on the heuristic model which distinguishes itself from the normal latent class model by using different utility functions. For the illustration and testing purpose, we tested two simple models in terms of sample size, variance in probabilities across outcomes and number of decisions each individual has to make.

4.6.1 Binary choice case

In this simulation, we mainly focus on the basic behavior of the heuristic model, in terms of identifiability, considering sample size and variance in uncertainty. The question is how sample size and variance in uncertainty affect parameter estimation. Due to the slow convergence property of the EM algorithm, we tested a simple binary choice model using our decision style heuristics to explore the basic characteristics of this decision heuristic model.

The basic setting is as follows: N individuals each making M decisions. Each decision has two alternatives with each alternative having 3 possible outcomes. Each alternative has three attributes X. Individuals are stratified into 3 decision styles at the beginning of each test according to class proportion parameter \( \alpha \). We use randomly generated values for X in the experiment from a uniform distribution. For the uncertain outcomes in each trial for each individual, we designed three settings: (i) probabilities drawn from fixed set \( \{0.7,0.2,0.1\} \), (ii) probabilities drawn from three distributions: \( \{0.7,0.2,0.1\} \), \( \{0.8,0.1,0.1\} \), \( \{0.4,0.3,0.3\} \), in the simulation, one of these candidates was picked up randomly, and (iii) random generated probabilities based on the Dirichlet distribution with the shape parameter equal to 2 for all possible outcomes. Marginal utilities for all test cases are specified as \( \beta = (-0.7, 0.8, 0.3) \). Parameter \( \alpha \) denotes class proportions.
Simulations are conducted as follows: first, generation of choice data. For each individual simulated, choice attributes $X$ and outcome probabilities are randomly drawn based on previous mentioned distributions. Then, the individual makes his/her choice regarding the attributes and uncertainty using the risk heuristic model. This process is repeated $M$ times for one individual, then for the next individual until $N$ individuals all have made their choices. Second, the recorded data sets are estimated using the customized EM algorithm.

The test results indicated that the variation in probabilities is crucial (Table 4.1). For example, the first two test cases with less variance in probabilities do not estimate back the original parameters. Sample size affects the estimation as well. Test round 4,5,7,8 with sample size 100,500,100,200 respectively do not yield

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<th>Sample size N</th>
<th>Decisions per trial M</th>
<th>Initial parameters</th>
<th>Estimated $\alpha$</th>
<th>Estimated $\beta$</th>
<th>loglik convergence</th>
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<td>-6717.176 Yes</td>
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close estimates to original parameters, whilst, sample size larger than 500 and with larger variance in this simulation provides close estimation results, e.g. test round 3, 6, and 9. Hence, these results imply that given adequate sample size and enough variation in outcome probabilities, the parameters can be accurately estimated. The requirement of a large sample size and large variation in probabilities can partially be explained by the fact that different styles will lead to the same choice probabilities especially in cases where only few probability levels are used, which therefore are not very informative.

4.6.2 A shopping decision case

Given the results of last numerical simulation and estimation, we further tested the heuristic model and estimation procedure under a more realistic situation. The hypothetical case concerns a shopping decision regarding possible travel delays.

Settings and Utility Functions

The traveler is located at the city centre and has to buy groceries for dinner planned at 6 PM with a friend at his home. Thus, ideally, the traveler should return home before 6 pm. The route back home from grocery shop has a certain given probability of congestion and the traveler knows the probability before hand, for example, obtained from consulting an information source. The traveler has to decide to do a full length shopping or to do a quick shopping to avoid congestion or compensate delay time by the congestion. However, a quick shopping reduces the shopping utility. If he/she decides to do a full length shopping and turns out being home late, his utility for dinner also decreased.

Again we test different uncertainty settings, in terms of fixed levels of delay probability or random generated probability based on the Dirichlet distribution. The normal travel time from shop to home for each decision of each individual in each trial, is randomly selected from a set \{10,15,20\} minutes and the delay time is
randomly drawn from the set \{0,5,10\} minutes. The traveler has to decide either to
do full length shopping, taking the risk of being home late or to do a quick
shopping without full satisfaction to shopping requirement.

Let \( N \) denote the sample size, \( M \) denote the number of decisions each individual
made, \( \alpha \) denote the initial proportion of classes, and \( \beta \) denote marginal utilities.
Travelers are randomly assigned to one of the aforementioned risk-attitude classes
and each traveler repeatedly makes \( M \) times this choice. The decision to do quick
shopping or not is modeled as a decision node, \( D_{\text{hurry}} = \{1,0\} \), with utility function:

\[
    v_{\text{hurry}} = D_{\text{hurry}} \beta_{\text{hurry}} + v_{\text{travelback}}
\]

where \( \beta_{\text{hurry}} \) is marginal utility of doing quick shopping, \( v_{\text{travelback}} \) denotes utility of
applying different heuristics on possible travel time outcomes.

Travel time outcome is modeled as a nature node with following utility function for
each delay outcome:

\[
    v_{\text{travelback}} = \beta_{T_{\text{normal}}} T_{\text{normal}} + \beta_{T_{\text{delay}}} T_{\text{delay}} + v_{\text{dinner}}
\]

where \( \beta_{T_{\text{normal}}} \) and \( \beta_{T_{\text{delay}}} \) denote marginal utility for normal travel time and travel delay
time due to congestion, \( T_{\text{normal}} \) and \( T_{\text{delay}} \) denote normal travel time and travel delay
time. \( v_{\text{dinner}} \) denotes the penalty of being late for dinner conditioned on the arrival
time compare to preset dinner time.
\[ v_{\text{dinner}} = \{0, \beta_{\text{late}}, \beta_{\text{midlate}}, \beta_{\text{verylate}}\} \]  \hspace{1cm} (4.33)

where \(\beta\)'s denote different penalties of being late for dinner at different time. We set 4 levels of penalty for being late for dinner, zero if in time, \(\beta_{\text{late}}\) if 10 minutes late, \(\beta_{\text{midlate}}\) if 20 minutes late and \(\beta_{\text{verylate}}\) if late more then 30 minutes. Using different sample size and starting values, we tested several cases using different combinations. In our tests, if the simulation did not converge in 2000 iterations, the estimation was stopped manually.

**Results**

We tested several cases with different class proportions parameters and different probability variations but using the same marginal utility parameters set and same sample size 1000. Results are shown in Table 4.3.

The results in Table 4.3 confirm the simulation results, described in last section. Given enough variation in probability levels, the decision tree model parameter estimations can be very close to the original parameters. As discussed before, one possible reason for the model requiring enough variation in probability may be that the particular probabilities used in our simulation are not sufficiently informative to distinguish between individuals based on decision styles. This requires that the experiment is carefully designed and suggests the need for a set of pilot tests to ensure that the profiles in the experiment are informative. In doing so, it may be

<table>
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<td>Quick shopping</td>
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<td>Very late for dinner (&gt;30m)</td>
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feasible to use a smaller sample size and/or less varying probabilities to estimate the parameters.

Simulations and estimations were implemented using R and C++. For a case with 1000 individuals each making 10 decisions, the estimation took more than 20 hours in R. To accelerate the estimation speed so that it can handle more pragmatic decisions scenarios, the final EM estimation was implemented in C++ via a dynamic link library upon which R makes function calls. This reduced the estimation time for our test case to one to two hours roughly.

### 4.7. Discussion and conclusions

In this chapter, two alternative models accounting for heterogeneity in risk attitudes under uncertain travel situations were formulated: a heuristic model that assumes travelers use heuristics when making travel decisions and a willingness to pay model that uses information price as an indicator of heterogeneity in risk attitudes. In the heuristic model, we differentiated between three classes of risk attitudes labeled as risk-averse, risk-taking and risk-neutral decision making. By using

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different heuristics, individuals in different classes may choose different alternatives given the same amount of uncertainty. A risk avoider uses only the worst case scenario to make decisions, a risk taker uses the most likely outcome and a risk neutral individual uses expected utility to evaluate his/her alternatives and their associated outcomes.

In the willingness to pay model, travelers are stratified in terms of their preference for information price. It is assumed that a higher utility (the utility is negative) in information price preference implies a higher willingness to reduce uncertainty in risky situations. The segments in the sample will be determined by comparing the goodness of fit across models with different segment numbers.

To explore the estimation of the heuristic model, we developed an estimation method, based on a customized EM algorithm. The results of numerical experiments indicated that the model under this specification is able to identify the three heuristic types. It also shows the importance of sample size and variations in uncertainty. This provides evidence of face validity for the heuristic model. Results also suggest that under a right set of conditions, this algorithm can be used for parameter estimates. The properties of the experiment should satisfy these conditions.

In next chapter, a web-based activity travel simulator is designed and implemented to collect data for empirically testing these models developed in this chapter.
5. Experiment

5.1. Introduction

In the previous chapter, we described the development of two activity-travel decision models that account for heterogeneity, a latent class heuristic model and a willingness to pay model. They represent heterogeneity in activity-travel decisions using heuristics and heterogeneous information preference respectively. To estimate the parameters of these models, we need data on how individuals change their activity-travel patterns when receiving travel information. In general, there are two data collection approaches to estimate such models: revealed preference and stated preference approaches. Both have been extensively used in travel behavior research (Polak and Jones, 1993; Hensher, 1994; Polak and Jones, 1997; Polydoropoulou and Ben-Akiva, 1998). Revealed preferences data involve data of actual behavior collected in real markets or real travels. In contrast, stated preference data involve data collection about people’s preferences or choice behavior under hypothetical situations. Either approach has its intrinsic advantages and disadvantages. In brief, the stated preference approach, also known as conjoint preference/choice analysis in marketing research, gives full control to the experimenter in designing hypothetic choice options that do not yet exist in real markets or that reflect the necessary and sufficient conditions to estimate the parameters of an assumed (choice) model. However, the external validity of the stated preference approach may be problematic in the sense that choice behavior in real markets may differ from choice behavior under hypothetical circumstances. In contrast, the revealed preference approach is not hampered by this kind of validity, but it is more expensive and labor intensive to conduct. Moreover, observed behavior does not always reflect underlying preferences only, and therefore the predictive ability of revealed preference models has often been debated.
In view of the lack of empirical data, revealed preferences data are not an option in the present study. We need to rely on stated preference methods. However, the usual experimental design data are also problematic in that we are dealing with multiple sources of uncertainty and sequential decisions, which are not easy to capture in traditional experimental designs. Computer based travel simulations offer an alternative. This approach has been adopted in several research projects (e.g., Chen and Mahmassani, 1993; Adler and Mcnally, 1994; Koutsopoulos et al., 1995; Walker and Ben-Akiva, 1996). Abdalla et al. (2006) used a travel simulator representing a realistic network with real historical congestion levels to collect data in order to examine the impacts of different travel information provision scenarios on travel times. A recent application in the field of travel information that uses a travel simulator is Chorus et al. (2007). In his experiment, a laboratory hypothetical experimental environment was set up to collect stated responses to traveler’s information acquisition behavior when making repetitive decisions. It was another application of the Travel Simulator Laboratory (TSL) developed by Hoogendoorn at the Delft University of Technology (De Groot and Hellendoorn, 2004; Bogers and Hoogendoorn, 2005; Hoogendoorn, 2008).

One main advantage of a hypothetical, simulated experimental environment is that it seems to be the only feasible way to collect particular types of data concerning the decision process, under full control of the researchers. They need not to rely on behavioral outcomes observed in specific environments, but rather the researcher can design these environments with full control and then observe how respondents state they would behave under such circumstances. The disadvantage is that these laboratory simulators normally require inviting people to be present in person to conduct the experiment, which induces extensive time constraints, financial costs and work. Further, it suffers from the same criticisms raised against the stated preference approach that behavior in hypothetical simulated experiments is not necessarily the same as behavior in the real world.
The cost of laboratory simulation experiments encourages researchers to develop web-based simulators. The immense number of web-based surveys in various domains suggests this approach of data collection is cheaper, easier (if well designed), and that more honest responses will be collected. Web-based experiments have also been introduced in transportation research (e.g., Bogers and Hoogendoorn, 2004; Bos, 2004), but in most cases the experiments and involved tasks were simple.

In this chapter, to empirically test the framework defined in previous chapters, the data collected has to reflect the effect of information, risk attitude towards uncertainty, activity chaining, etc. A fully controlled laboratory experiment seems to fit these requirements since in a laboratory experiment, the settings of different situations can be varied as designed such that certain effects of information service can be observed. To allow a larger sample at lower costs, a web-based simulation was chosen as our data collection method.

It should be emphasized from the start that this does not mean that web-based simulators are without problems. For example, it is difficult to filter respondents, it is hard to tell whether the responses are serious choices or casual random inputs, and since there is no personal guidance during the experiment, very clear instructions without ambiguity shall be provided.

To empirically estimate the two models developed in previous chapters, activity-travel behaviors and responses to travel information at each decision stages have to be collected. To this end, neither travel diary nor stated preferences serve this purpose. Travel diaries lack the means to record the travel environment status in terms of uncertainty, while the stated preference approach cannot capture the sequential nature of activity-travel decisions. Thus, in the following section, a hypothetical activity-travel simulator is developed for collecting empirical data. It
is designed to identify choice and information use behavior in an activity-schedule context (reveal the influence of activity schedule context variables on information value, for instance) and different risk attitudes. In terms of the latter, the experiment is designed to be able to identify different styles based on the outcomes: i.e., risk takers would make different choices than risk avoiders in similar situations, etc. The hypothetical settings of the experiment, the experimental design and the implementation of the web-based travel simulator will be discussed and a brief summary of response data will be presented in following sections.

5.2. Activity simulator

5.2.1 Structure of the web-based experiment

The experiment consists of three parts: in part one, a short online survey prompts respondents to provide information about personal and household characteristics and about aspects of their travel behavior. The socio-demographic information of respondents includes attributes such as gender, age, household size, household composition, and car ownership. Information about their travel behavior include the frequency of car use, public transportation use, etc. After this short survey, the second part is the core part of the experiment: the activity-travel simulator. The activity-travel simulator presents hypothetical travel situations to respondents and asks them to make choices based on the given storyline and current travel situation. The choices made are recorded by the simulator. The third part is a questionnaire concerning the respondent’s stated risk attitude, time perspective, information acquisition attitude and information acquisition frequency under different situations.

Figure 5.1 shows the composition of the web experiment.
After finishing the first questionnaire, based on information about transport mode usage, respondents are categorized into 3 groups: car users, mixed car-public mode users and public transport users. This categorization is also applied in step three: the questionnaire on risk attitude and information acquisition behavior. Next, the respondents enter the second phase: the activity-travel simulator. The activity-travel simulator has two similar versions of hypothetical situations, emphasizing different aspects, namely simultaneous multiple uncertain events and sequential uncertain events. Details are given in the following sections. The respondent is randomly assigned to one of these two experiments by the simulator.

The web survey about risk attitude and information acquisition behavior (questionnaire two) will be introduced and discussed in chapter 7. In the following sections, only information about the experiments with the activity-travel simulator is explained in detail.
5.2.2 Activity-travel context and hypothetical settings

The web-based interactive computer experiment/travel simulator is designed to collect data of respondents’ activity rescheduling and information acquisition behaviors. That is, data about how respondents reschedule their activities and/or collect travel information for a set of hypothetical travel situations is collected. Two experiments, each consisting of two uncertain events, labeled as delay 1 and delay 2, under similar activity context and geographical settings were designed. In experiment I, the two uncertain events happen sequentially over time, whilst in the second experiment II uncertain events occur concurrently. Figure 5.2 and Figure 5.3 show the hypothetical travel environment used in our experiment. In both experiments, travel information on two possible delays is supplied. Respondents can acquire information on either delay event at a certain cost. The information is not always perfect which means information service predicts delay times wrongly in some occasions. The reliability of information service is defined as the percentage of correctly predicted delay times out of all predictions.

![Figure 5.2 Hypothetical map used in Experiment I](image)
Unlike stated preference and choice experiments, the subject interacts with the (virtual) environment and the context of the decision process is critical in interactive computer experiments. That is, respondents are invited to make choices on the basis of a narrative or storyline, implement these choices and receive feedback. The web-based simulator can be viewed as a state-dependent machine that presents situations to respondents according to current system states. It keeps a record of the respondent’s decision history, current time, current location information and conditional on these, the simulator generates choice alternatives available for the current situation and gives feedback after implementing choices.

**Narrative**

Experiment I
Assume you live in a city and work at the fringe of the city. The layout of the city is shown on the screen. There may be traffic jams on the highway routes (delay 1) from work to the roundabout. Assume there is a farewell party for one of your colleagues from 4:30 to 5 pm, while in the evening you are invited to join a dinner/banquet with your friends. You have to change dress and refresh yourself before heading to the dinner/banquet place together with your spouse. The invitation asks you to arrive between 6:45 to 7 pm at the dinner/banquet. Because you wish to bring a gift, you plan to buy some flowers in the inner city shop on your way back home. Normally, this will take 20 minutes, but there is a chance that you will spend more time as you need to find parking space, there may be a queue before the cashier, etc. (delay 2).

Hence, if no delays happen then the schedule is as follows:
4.30 – 5.00 pm: farewell party of colleague (30 minutes)
5.00 – 5.30 pm: travel work to roundabout (30 minutes)
5.30 – 6.10 pm: buy flowers inner city (20 minutes)
6.10 – 6.40 pm: change dress and relax a bit (20 + 10 minutes)
6.40 – 7.00 pm: travel to dinner place (20 minutes)

7.00 pm: start dinner

There are three decisions you have to make. First, you could skip the farewell party and leave work earlier in order to have enough time for shopping and traveling. By doing so, you will miss the opportunity to express your good wishes to your colleague. After arrival at the roundabout, you can choose to go to the inner city and buy the flowers, or you can skip this in order to be on time.

In short, decisions you have to make:

1. *Leave earlier at 4:30 pm and skip the farewell party or leave normal at 5 pm*
2. *Go to flower shop in the inner city or skip buying flowers*
3. *Have a rest at home or skip it*

Beside these decisions, you can always choose to buy travel information that predicts whether a delay will happen or not at particular locations (highway and inner city), before you depart from work place.

For the farewell party, there are two situations possible. In one case, the farewell party is hold for the colleague from another department. In the other case, the farewell party is hold for a colleague from your own group. For the dinner, there are two possible situations too. In one case, you and your spouse are the only guests invited by your friend and in the other case, also other guests are invited. The colleague for whom the farewell party is held and the dinner situation are changed time by time, please read the descriptions on the screen carefully.
**Experiment II**

This experiment shares most of the features with Experiment I except: there are two routes from work to the roundabout (highway and provincial road), and uncertain events (delay1 and delay2) are associated with these routes respectively. There is no uncertain event at the inner city for shopping. In this experiment, it is possible that either the farewell party or dinner or both are absent from the activity context.

In both experiments, delay1 refers to possible delays that may happen on the highway from work to roundabout. Delay2 refers to a possible delay at inner city in Experiment I and a possible delay on the provincial road in Experiment II. Respondents may choose to buy information before leaving work either before or after the farewell party. Experiment I is intended to look at schedule adaptation decisions regarding sequential uncertain events, whilst experiment II concerns more with baseline preferences, i.e. simultaneous delays that are more related to immediate action, with which respondents will face two uncertain events simultaneously and have to make a choice between two uncertain alternatives.
Delays are consistently presented with probabilities and magnitudes in minutes. Respondents are informed that the delay probabilities are independent of each other and that they reflect their knowledge about the routes. En-route information is not available in our experiments, so it is not possible to acquire any information during travel.

In both experiments, transportation mode is assumed to be car; however, public transportation mode users identified in the first part survey are not excluded from the experiments.

There are two configuration differences other than uncertain events in experiment II comparing to experiment I. First, the farewell party activity and dinner activity may not exist in experiment II. That is to say, there are situations that there is no farewell party at the workplace. Then, the traveler does not need to make a decision on leaving party early or not. There are also situations that no dinner is planned; then the buy flower activity is not a choice consideration and the schedule ends at home. Second, as shown in Figure 5.3, in experiment II, there is an alternative route from work to roundabout, a provincial road. The additional route (provincial road, indicated by the yellow line) available from work to the roundabout in addition to highway in the second experiment is included to accommodate the use of two concurrent uncertain events.

Thus, these differences imply that an additional route choice decision after leaving work (early or normal) has to be made compared to Experiment I. Furthermore, there are situations without time pressure on the activity schedule. For example, if no dinner is planned, there will be no shopping activity, and delay time on the route back home may play a minor role in route choice. Figure 5.2 and Figure 5.3 show the hypothetical activity-travel environments for the two experiments.
Task
Given this narrative, the task for the respondent is to organize his/her activities given different situations (different delay times, delay probabilities, for whom the farewell party is held, with whom to have dinner together, etc) generated by the simulator by making choices at different decision moments. After each decision, the simulator executes a respondent’s choice. The status (current time, current location, etc.) of the hypothetical travel environment will then be changed based on the choice made, and feedback (e.g., how much time is spent on which route, how long the delay is, etc.) will be given to a respondent. Figure 1 shows the way the situations were presented for the two experiments. In Experiment I, delay 1 may happen on the way from work to roundabout on highway (red line) due to traffic jams. The other possible delay may happen at the city center in the flower shop due to queuing or finding a parking place. Travel time on each route is annotated in minutes. Shopping time and dress up time are also marked on the map.

In experiment I, delay one may happen on the way from work to roundabout on highway (red line) due to traffic jams, the other possible delay may happened at the city center in the flower shop due to queuing or finding part places. Travel time on each route is annotated by minutes. Shopping time and dress up are also marked in the map.

In the second experiment, an additional route, provincial road (yellow line) is available from work location to roundabout aside to highway. It has an associated possible delay (delay 2) as well. The shopping activity then is assumed to have a fixed time period with certainty, that is, no possible delay involves at this location.

5.2.3 Pilot tests
Before finalizing the final research design, two rounds of pilot tests were carried out to investigate how the hypothetical situation could be appropriately represented.
In pilot test one, aspects such as activity settings, travel times for each route, delay times and delay probabilities, geographical layout of the hypothetical city, graphical user interface layout, etc. were tested and revised during and after each pilot test. Pilot test one used a desktop application to simulate the web GUI to be used. Pilot test two uses the implemented web based activity-travel simulator to check its functionality.

A desktop application was scratched up with basic GUI layout for pilot test one using Python, wxpython and wxGlade. Figure 5.4 and Figure 5.5 are screen shots of GUI used in the first pilot tests. After this pilot test, the factor levels, travel context and transportation network had been adjusted according to respondent’s comments and applied to the second pilot test and final web based experiments.

The second pilot test was conducted in the final web based version after revision on factor settings, activity-travel context, transportation network settings, etc., based on the result form first pilot test. All experiment contents were translated into Dutch in the second pilot test as respondents are mainly Dutch speaking people. This test focused on fine tuning the instructions, amenity of GUI and question items in the third part of the web survey on risk attitude and information acquisition behavior.

Parallel to testing factor levels and GUI layouts, etc., mentioned in the last section, by conducting these two pilot tests, information of time spent to complete the experiments, how difficult it is to evaluate the choice alternatives, how sensitive the situational configuration is, etc., was collected.

In the first pilot test, 16 respondents were recruited. Each respondent conducted both experiments and each experiment consisted of 16 profiles (situations). It took about 50 minutes to 1 hour on average to finish both experiments. These results
from pilot test one suggested that completing both experiments by a single respondent does not seem feasible, considering respondents’ fatigue effects.

Figure 5.4 Screen shot of pilot test one

Figure 5.5 Screen shot of experiment II during pilot test
A possible consequence of having farewell party activity is that it may mangle the risk attitude observation with weight balance between farewell party and dinner, especially in the first experiment. However, this can be alleviated by the fact that in the second experiment, there are situations with only a dinner or a farewell party, in which the choice concerns only two uncertain choice alternatives.

Comments such as “probability of 0.05 is too small that it is nearly always considered as zero”, “no route from roundabout to home seems unrealistic”, etc., led to changes in the spatial configuration of the hypothetical city, variable levels and time settings.

Based on these results, the final experiment was set such that each respondent completed one (randomly assigned) experiment. Each experiment consists of 14 situations among which the first two situations are trials for respondents to explore and to get familiar with the simulator.

After reducing the length of the experiment by assigning one experiment to one respondent, the second pilot was tested by 7 respondents using the intended final web-based experiment environment. Reported times to complete the experiment and web survey ranged from 45 minutes to more than one hour.

5.2.4 Experimental design

As shown in Table 5.1 and Table 5.2 there are 8 control variables (factors) in both experiments: farewell party at work, dinner with friends, delay time 1, delay time 2, delay probability 1, delay probability 2, information price, and information reliability. Experiment I involves two levels for both party and dinner, which implies that there is always a farewell party and a dinner planned but circumstances differ. Delay time zero implies that no delay will happen. Although in conventional stated preference and choice experiments, orthogonal or optimal designs are used
to systematically vary the experimental factors, these properties are lost in this experiment due to sequential decisions and feedback. Furthermore, multi-way interactions are to be expected between the information variables, on the one hand, and all other variables, on the other, so that on that level efficiency gains by taking a fraction are not feasible. Therefore, we decided to derive the experimental conditions from a randomized experimental design that uses the permutation of all variables as profiles. For experiment I, 6144 profiles were generated, while for experiment II, 12194 profiles were generated.

Table 5.1 Control variables in experiment I

<table>
<thead>
<tr>
<th>Control variable</th>
<th>levels</th>
<th>state</th>
</tr>
</thead>
<tbody>
<tr>
<td>Party</td>
<td>2</td>
<td>Planned party, only your couple are invited</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Planned party, other friends are also invited</td>
</tr>
<tr>
<td>Dinner</td>
<td>2</td>
<td>Farewell party for colleague from other department</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Farewell party for a colleague from your group</td>
</tr>
<tr>
<td>Delay time 1</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>50 min</td>
</tr>
<tr>
<td>Delay time 2</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>10 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>20 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30 min</td>
</tr>
<tr>
<td>Delay 1 probability</td>
<td>4</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.667</td>
</tr>
<tr>
<td>Delay 2 probability</td>
<td>4</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.5</td>
</tr>
<tr>
<td>Information reliability</td>
<td>2</td>
<td>80</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>Information price</td>
<td>3</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td></td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>150</td>
</tr>
</tbody>
</table>
Table 5.2 Control variables in experiment II

<table>
<thead>
<tr>
<th>Control variables</th>
<th>levels</th>
<th>state</th>
<th>No party planned</th>
<th>Planned party, only your couple are invited</th>
<th>Planned party, other friends are also invited</th>
</tr>
</thead>
<tbody>
<tr>
<td>Party</td>
<td>3</td>
<td>0</td>
<td></td>
<td>No farewell party</td>
<td>Farewell party for colleague from other department</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td></td>
<td>Farewell party for a colleague from your group</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dinner</td>
<td>3</td>
<td>0</td>
<td></td>
<td>No farewell party</td>
<td>Farewell party for colleague from other department</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td></td>
<td>Farewell party for a colleague from your group</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delay 1 time</td>
<td>4</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>20 min</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>30 min</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>50 min</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delay 2 time</td>
<td>4</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>10 min</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>20 min</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>30 min</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delay 1 probability</td>
<td>4</td>
<td>0.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.667</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delay 2 probability</td>
<td>4</td>
<td>0.1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.33</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information reliability</td>
<td>2</td>
<td>80</td>
<td>80%</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>100</td>
<td>100%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information price</td>
<td>3</td>
<td>50</td>
<td>Euro cents</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>100</td>
<td>Euro cents</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>150</td>
<td>Euro cents</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.3. Implementation

5.3.1 Internal control flow

This section gives the details of internal control flow of the activity-travel simulator. The simulator can be conceptually considered as a state-dependent machine that presents situations to respondents according to current system states (current time, current location, completed activities, remaining tasks, etc.). It keeps a record of the respondent’s decision history, current time, current location information and conditional on these state status, the simulator generates choice alternatives available for the current situation.
Figure 5.6 shows the simulator internal control flow for one respondent. In experiment I, respondents make their choices at all three locations: work, roundabout and home. Whilst for experiment II, in some situations when there is not a planned dinner or no planned farewell party, the choices at location roundabout or home may disappear.

Upon the entrance of a respondent into the simulator, he/she will be randomly assigned one of the two experiments. Then, 14 profiles are randomly picked from the profile database based on the assigned experiment. For each profile, the simulator presents the situation to the respondent and upon receiving the choice, the simulator updates its state (location, time, decision history) after each decision, based on the hypothetical configuration (travel times, shopping time, and refresh time) and profile (control variables or factors, delay times, occurrence of delays, etc.). When all 14 profiles have been executed, the respondent is diverted to the third part of experiment: a web survey on risk attitude and information acquisition behavior.

Figure 5.7 shows the detail control flow at the work location. The elements in dashed shape indicate they are not part of the experiment I, but of experiment II. The simulator examines the system state (e.g., conditions in gray diamond shapes on the left) and displays choice alternatives accordingly. If information has not been bought yet, then a choice option of buying information is added to the choice panel to be shown to this respondent. If the decision of leaving early (or join farewell party) has not been chosen yet, which is reflected by condition “D_leave early done” equaling to “No”, then the simulator will add these two options to the choice panel. Only after one of the two choices related to the farewell party has been chosen, the simulator displays the route choice options in case of experiment II.
Figure 5.6 System control flow for one respondent
Figure 5.7 Decisions at work place
After the respondent chooses “leave early” or “joint party” in experiment I or route choice in experiment II, the ‘real’ delay time on highway or provincial road is taken from the profiles and added to the current time, additional to the normal travel time. This delay information is also shown in the feedback panel in the simulator.
Figure 5.8 shows the control flow at the roundabout, inner city, home and dinner locations. In contrast to Figure 5.7, in this graph, dashed shape “delay 2” is of experiment I only, because experiment II does not have a possible delay for shopping activity.

5.3.2 Implementation based on Ruby on Rails framework

The simulator was implemented using Ruby on Rails, a web application framework. Started in 1993, Ruby was mainly used inside Japan as a minor flavor of general purpose scripting language until the framework Ruby on Rails (ROR) appeared. After ROR was out of the box, it gained a boom in the web design world. Features such as flexibility, easiness to use, naturally embedded Ruby language inside the web framework, etc., give web developers an extremely powerful tool to develop rapid web applications.

The web surveys were implemented in a questionnaire system\(^2\). With this system, one does not need actual programming skills to develop a web-based questionnaire system. The activity-travel simulator was also prototyped as part of this system and was customized to fit the required settings. The targeted group is Dutch households living in Eindhoven. Thus, the questionnaires and simulator GUI had to be translated into Dutch before launching the web application.

Figure 5.9 and Figure 5.10 show the appearance of the first two pages of the first part of the web survey, as an example. It shows that every page has one or more questions. Answers can be provided with the standard types of responses. Respondents can scroll back and forth through the web-pages. Every time their answers are checked in the sense that they should fall within a certain range. These checking options will likely improve the reliability of the data.

\(^2\) developed by A.J. Jessurun
Figure 5.9 First page of questionnaire one

Figure 5.10 Second page of questionnaire one
Figure 5.11 shows the main interface of the web simulator. All the contents are in Dutch. Inside the web browser, a gray bar at the top indicates the current number of situations (profiles). Next, a table shows the detailed current situation, including detailed information of the 8 control variables. In this figure, the farewell party is held from 16:30 to 17:00 for a colleague from another department, dinner is planned at 19:00 and only the respondent and his/her spouse are invited, the delay probability on the highway is 66.7% with a delay time of 20 minutes, delay at the inner city has a 10% chance with a delay time of 10 minutes. Information cost is 1 euro for each piece (this means that it will cost 2 euros if information is bought for both possible delays.) Shopping duration and refresh and dressing up time are also shown in the table.

The second part is the graphical component. At the top, one line of text indicates the current location and current time. The graphical part is divided into left and right in two panels. The left panel displays the hypothetical city layout with all information regarding to the profile being used. Pie charts show the delay probability in red with annotation of delay time and probability to its right, while normal travel times on each route are shown in black text. A blue arrow indicates the current location. On the right panel, information about delay predicted by the travel information service is shown only if the respondent chose to buy information in previous choice stages. At the bottom of right panel, an analogue clock shows the current time again to make the time imagination easier for some respondents who are more used to analogue clock perception of time.

The third section is the feedback component. Information about what has been done and what happened after each decision are shown here. In this figure, it is stated that the respondent attended the farewell party and on his way from work to roundabout, he has experienced a 20 minutes delay.
The last part is the choice component. Options available to the current location and time are shown here. The respondent has to check one of these options and click at “next” to proceed to the next stage. When cursor hovering occurs on locations to make decisions, pie charts, routes with possible delays, an information box will pop up and show the detailed information about this location. For example, in
Figure 5.11, the cursor is located on the work location, the information tip box displays the information about when and for whom the party was held as a replica of the information in the table at the top.

5.3.3 Information services

The hypothetical information service is available in the simulator and provides two types of information: fully reliable and 80 percent reliable. In the fully reliable case, the information service will accurately predict the future delays. That is to say, the predicted delay is always consistent with the real situation later on after traveling. In the case of 80 percent reliability, when a real delay happens during travel, the information service provider will correctly predict the occurrence of delay 8 times out of ten, if the respondent acquires information before his travel.

Upon starting an experiment, two real delay states are drawn from two random draws based on the delay probability control variables. Information prediction is randomly drawn, conditionally on real delay occurrence and information reliability. First, the real occurrence (true or false) of a particular delay is randomly drawn based on real inherent delay probability $p_i$, where $i$ denote the $i$-th delay. Second, the information prediction is randomly drawn based on the information reliability. For example, if the real occurrence is true and the information reliability is 80%, the prediction of delay will be a random draw from distribution (0.8, 0.2) which has 80% probability of being true and 20% of probability of being false.

5.4. Sample

5.4.1 Study area and reward schemes

The study area was chosen in the south west of Eindhoven, the Netherlands. The area does not evenly spread spatially to avoid overlapping with other ongoing projects that also involved recruiting people and recently finished projects that had
recruited people in Eindhoven within our group. Incentives were used in our experiments with different reward schemes. Respondents could choose from different reward schemes with different amounts of money with different probabilities. There are five reward schemes in lottery form with different probabilities of winning: 10 Euros for certain, 80% chance winning of 12.5 Euros, 50% chance of winning 20 Euros, 20% chance of winning 50 Euros, and 10% chance of winning 100 Euros as shown in Table 5.3.

<table>
<thead>
<tr>
<th>Rewards</th>
<th>Probability</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 Euros</td>
<td>0% chance</td>
<td>10 Euros</td>
</tr>
<tr>
<td>12.5 Euros</td>
<td>50% chance</td>
<td>12.5 Euros</td>
</tr>
<tr>
<td>20 Euros</td>
<td>20% chance</td>
<td>20 Euros</td>
</tr>
<tr>
<td>50 Euros</td>
<td>10% chance</td>
<td>50 Euros</td>
</tr>
<tr>
<td>100 Euros</td>
<td>0% chance</td>
<td>100 Euros</td>
</tr>
</tbody>
</table>

This inevitably brings in bias since the sample may contain a large proportion of monetary sensitive respondents. Despite the possibility of inherent bias in this recruiting approach, the very low response rate (2~5%) of other web-based experiments encouraged the use of incentives.

Figure 5.13 shows the study area where invitation cards were sent. Figure 5.14 shows the invitation card used in the experiments. The light gray colored areas in Figure 5.13 defines the study area in which invitation cards are randomly distributed to its contained districts, while darker gray and black areas are districts where invitation cards were distributed. In total, 6000 invitation cards were put into the households’ mail box (Figure 5.14).
Figure 5.12 Map of Eindhoven (from Google maps)

Figure 5.13 Study area
5.4.2 Responses

The invitation cards were distributed between February 22, 2008 and April 8, 2008. In total, 776 respondents entered the website. This may be a little higher than the actual number of different respondents as we did not issue a personalized code and therefore there may have been multiple entries from one respondent. Among these 776 entries, 635 finished the first short survey and entered the hypothetical simulation experiments.

In the hypothetical simulation experiments, each respondent was asked to make choices in 14 different situations (activity-travel and information condition settings). Upon completion of this simulation experiments, respondents proceed to the second web survey. All respondents that entered the second survey are counted as valid data inputs to model estimation, given the fact that by reaching the third part of the experiment, data on activity-travel behavior has been collected and is ready to be used in estimating the models.
Table 5.4 Summary statistics of respondents

<table>
<thead>
<tr>
<th></th>
<th>Absolute number</th>
<th>proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>male(1)</td>
<td>215</td>
<td>51.56%</td>
</tr>
<tr>
<td>female(0)</td>
<td>202</td>
<td>48.44%</td>
</tr>
<tr>
<td><strong>age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;27</td>
<td>88</td>
<td>21.10%</td>
</tr>
<tr>
<td>[28 -50]</td>
<td>230</td>
<td>55.16%</td>
</tr>
<tr>
<td>&gt;50</td>
<td>99</td>
<td>23.74%</td>
</tr>
<tr>
<td><strong>education level</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-Basisonderwijs, lager onderwijs</td>
<td>16</td>
<td>3.84%</td>
</tr>
<tr>
<td>2-vmbo</td>
<td>9</td>
<td>2.16%</td>
</tr>
<tr>
<td>3 mavo</td>
<td>17</td>
<td>4.08%</td>
</tr>
<tr>
<td>4 havo</td>
<td>23</td>
<td>5.52%</td>
</tr>
<tr>
<td>5 vwo/atheneum/gymnasium</td>
<td>33</td>
<td>7.91%</td>
</tr>
<tr>
<td>6 mbo</td>
<td>71</td>
<td>17.03%</td>
</tr>
<tr>
<td>7 hbo</td>
<td>137</td>
<td>32.85%</td>
</tr>
<tr>
<td>8 Universiteit</td>
<td>111</td>
<td>26.62%</td>
</tr>
<tr>
<td><strong>has job</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>yes</td>
<td>306</td>
<td>73.38%</td>
</tr>
<tr>
<td>no</td>
<td>111</td>
<td>26.62%</td>
</tr>
<tr>
<td><strong>work hour per week</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;20</td>
<td>47</td>
<td>11.27%</td>
</tr>
<tr>
<td>20-40</td>
<td>253</td>
<td>60.67%</td>
</tr>
<tr>
<td>&gt;40</td>
<td>8</td>
<td>1.92%</td>
</tr>
<tr>
<td><strong>household size</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>145</td>
<td>34.8%</td>
</tr>
<tr>
<td>2</td>
<td>159</td>
<td>38.1%</td>
</tr>
<tr>
<td>3</td>
<td>52</td>
<td>12.5%</td>
</tr>
<tr>
<td>4</td>
<td>40</td>
<td>9.6%</td>
</tr>
<tr>
<td>5</td>
<td>13</td>
<td>3.1%</td>
</tr>
<tr>
<td>6</td>
<td>6</td>
<td>1.4%</td>
</tr>
<tr>
<td><strong>Household car number</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>94</td>
<td>22.54%</td>
</tr>
<tr>
<td>1</td>
<td>241</td>
<td>57.79%</td>
</tr>
<tr>
<td>2</td>
<td>75</td>
<td>17.99%</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>0.96%</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>0.48%</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>0.24%</td>
</tr>
<tr>
<td><strong>driving license</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>yes</td>
<td>360</td>
<td>86.33%</td>
</tr>
</tbody>
</table>

3 This is a Dutch education system.
Web survey two counted 417 valid entries. Among these respondents, 190 respondents were assigned to experiment I and 227 respondents were assigned to experiment II. Among the 417 respondents who have finished the simulator experiment, 397 respondents completed the second survey on risk attitude and information acquisition behavior, and thus completed the whole experiment. As a

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4 Discount cards for public transportation in The Netherlands.
matter of fact, the drop-out rate (4.8%) is very low at this stage although there were people who did quit the experiment for various reasons.

Based on different transport mode use frequency, respondents were categorized into car users, public transport mode users and mixed car/public transport mode users. This information will be used later in the third part of the experiment, the web survey about informational acquisition and risk attitudes, described in Chapter 7.

The age group frequencies indicate that the respondents were distributed across different ages: about half of the respondents were located in range 28-50 years of age and a quarter below 27 and above 50 respectively. Most respondents have an education level higher or equal to “mbo”. Differences between genders are small. Only 22.5% of the households do not have a car; 34.8% and 38.1% respectively of the households are single person households and two-person households.

5.5. Discussion and conclusions

This chapter described the development and implementation of an interactive web-based simulation environment for collecting activity-travel data in the context of information acquisition and uncertain events. Activity-travel data were collected using the simulator by presenting hypothetical travel situations to the respondents and recording the choices made by respondents for each varied situation. Two experiments were implemented. In activity-travel experiment I sequential uncertain events in activity settings were presented, whereas in experiment II uncertain events were presented simultaneously. Using the developed activity-travel simulator, field data were collected in Eindhoven, the Netherlands in 2008.

Despite the low, but not uncommon, response rate, the collected sample shows diversity in composition of gender, education level, and household type attributes.
There are several issues that may affect the reliability of our sample. Firstly, by using a web-based approach, we did not filter or stratify the sample. However, the availability of computers and internet connections filtered out those people who do not have access to internet. This is not necessarily a bias; only if these people would react differently than those not included in the sample it would, and of course we do not know.

Secondly, monetary incentives used in the experiments may lead to a sample consisting mostly of monetary sensitive respondents. This can, however, not be justified in light of the low response rate, even with rewards.

Thirdly, the time required to complete the experiment is relatively long and the repetitive choice situations may lead to fatigue, and thus uncooperative responses. As we stated before, the total time to conduct the whole experiment, either being assigned to experiment I or experiment II plus questionnaire, was roughly 45 minutes to more than one hour during our pilot tests.

In the next chapter, models developed in chapter four will be estimated using the collected data.
6. Data Analysis

6.1. Introduction

In chapter 5, we described the development of a web-based travel simulator and how it was used to collect data on activity-travel rescheduling behavior of respondents, living in Eindhoven, the Netherlands. The data collection basically aimed at empirically testing the developed decisions framework and risk attitude models, described in Chapter 4. In this chapter, we report the estimation results based on these data.

In the following sections, the activity-travel decision process in each experiment will be described, and the results of the estimation of the heuristic latent class model and willingness to pay model will be reported.

6.2. Decision process

6.2.1 Experiment I

Decision sequence

Figure 6.1 shows the decision sequences of respondents in experiment I. Basically four types of decisions had to be made by each respondent: buy information (at work location), leave early or join farewell party (at work location), go shopping or go home (at roundabout), rest or no rest (at home). Oval shapes indicate the feedback from uncertain events, delay 1 and delay 2, after implementing a decision that is associated with uncertainty.

Based on the activity pattern shown in this flow chart, a decision tree can be constructed with as deep as 7 levels, e.g., The deepest branch (“buy information for delay one” \( \rightarrow \) “buy information for delay two” \( \rightarrow \) “leave early or not” \( \rightarrow \) “buy flowers or not” \( \rightarrow \) “have a rest at home or not”) has 5 decisions; adding two uncertain
outcome levels, the decision tree becomes 7 levels in depth. At the initial stage at the work location, there are 4 choices: buy information about highway delay, buy information about shopping delay, leave early (skip the farewell party) and join the farewell party. If the buy information choice is made, the next decision stage will have 3 decisions: the option of buying information for the other uncertain event, leave early and join farewell party options. Thus, the decision tree of information branch is nested with the remaining options which themselves are decision trees as well.

Figure 6.1 Decisions in experiment I
One possible simplification of this decision tree is to eliminate the decision of having a rest or not. As described in chapter 5, there is no uncertainty involved in the decision “have a rest or not”. A respondent does not “need” to make this decision since he/she already knows the current time and the fixed travel time ahead to the dinner place. One possible use of this choice data is to trace uncooperative respondents, for example, if a respondent chooses “to have a rest” at home when it is already late for dinner (taking travel time to dinner into account) several times. This respondent is probably “uncooperative” or he/she does not value social activities that much. We did not put effort on this elimination though since that was not our intention. Based on this argument, we removed this decision level from our model so that less parameters need to be estimated, which will speed up the estimation without loosing much information. This simplification applies to experiment II as well.

Decision tree representation
As an example, Figure 6.2 shows the constructed decision tree for experiment I.

![Decision tree](image)
The dashed shapes in the decision tree indicate that the further branches attached to this node are not displayed for clarity. Thus, this partial decision tree only shows a few branches, illustrating how the full tree can be constructed. Square nodes are decision nodes and circles outcome chance nodes.

Figure 6.3 shows the decision tree at the roundabout after the decision to leave early or join the party has been made and executed. Either decision, leave early or join party, will lead to travel from work to the roundabout and to experience possibly a real delay time on the highway, as described above and in chapter 5. At the roundabout, two choice alternatives are available: to go to the inner city to buy flowers or to go back home directly and skip the shopping activity. Although this decision tree is identical as a branch of the previous decision tree, it represents a decision evaluation stage by itself and thus also forms a standalone decision tree (with root node). Note that this decision tree has no rest choices, as previously discussed.

6.2.2 Experiment II

Experiment II focuses more on basic preferences about route, travel time, delay time, disutility of missing a colleague’s farewell party, disutility of being late at dinner with friends and risk attitudes towards simultaneous uncertainties. The flow chart of the decisions involved in this experiment is shown in Figure 6.4.
In experiment II, two control variables (party and dinner), each with 3 states, as shown in chapter 5, imply nine possible combinations (party and dinner variables have only two levels in experiment I). In an activity context their states can be compressed into two (“has” and “has not”). For example, the variable ‘dinner’ has three states: 0-no dinner planned, 1-dinner with only you and your spouse, 2 - dinner with also other friends being invited. From an activity aspect, the dinner is either planned or not, and hence the decision chain will be different with respect to these states accordingly. If there is no dinner planned, then the shopping activity is
not necessary. Thus, travel delay time only matters in the sense that it may affect travel time preferences and the disutility of possible waiting times due to congestion. The party situation can be viewed from the same viewpoint. Thus, in total there are four activity configurations in experiment II:

<table>
<thead>
<tr>
<th>Situation</th>
<th>Farewell party</th>
<th>Dinner</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>yes</td>
<td>Yes</td>
</tr>
<tr>
<td>B</td>
<td>yes</td>
<td>No</td>
</tr>
<tr>
<td>C</td>
<td>no</td>
<td>Yes</td>
</tr>
<tr>
<td>D</td>
<td>no</td>
<td>No</td>
</tr>
</tbody>
</table>

The decisions in the first situation in experiment II are shown in Figure 6.4. Figure 6.5 gives the remaining three (B, C, D) decision flow chart diagrams.
Figure 6.5 Decisions in three situations 1-no party 2-no dinner 3-no party no dinner in experiment II
Figure 6.6 Decision tree (partial) at work place in experiment II

Figure 6.6 shows the constructed decision tree for experiment II.

### 6.2.3 Information effect

Only before departing from the work place, a respondent can acquire information about possible delay events. That is, in experiment I, the respondent can acquire highway delay information or delay information for the city center, while, in experiment II, the respondent can acquire information about the state of traffic at the highway or the provincial road. As the information source is not always fully reliable, this introduces the evaluation effort of judging the quality of the information and predicting consecutive uncertain events. If information is fully reliable, there will no further uncertainty in the successive decisions. In case of non-perfect information, the probability of information turning out to be delay or no delay depends on both information reliability and the inherent probability distribution of true delay.
In the decision tree representation, on branches where a piece of information is acquired, delay probabilities corresponding to this information have to be updated accordingly. We assume that respondents update their belief on delays upon received information based on Bayes’ theorem:

\[
P(A | B) = \frac{P(B | A)P(A)}{P(B)} \quad (6.1)
\]

\[
P(B) = P(A \cap B) + P(A^c \cap B) = P(B | A)P(A) + P(B | A^c)P(A^c) \quad (6.2)
\]

where \( A^c \) denotes the complementary event of \( A \), also known as “not \( A \)”. Let \( A \) denote delay events in reality, and \( B \) denote predicted delay events. Upon receiving a piece of information \( B \), the perceived probability of delay \( A \) is updated as:

\[
P(A | B) = \frac{P(B | A)P(A)}{P(B)} = \frac{P(B | A)P(A)}{P(B | A)P(A) + P(B | A^c)P(A^c)} \quad (6.3)
\]

where \( A^c \) means “no delay”.

This update mechanism applies to both delay events in both experiments.

6.3. Observed choices

In the experiments, on average, respondents bought in formation about delay 1 (delays on highway in both experiments) 2.1 times, about delay 2 (delays at inner city in experiment I and delays on provincial road in experiment II) 1.1 times out of 14 trials (see Table 6.1). On average, respondents chose to leave early and skip the farewell party 3.4 times, had been late to the dinner 2.7 times, for a total of 46.6 minutes later than planned for dinner.
The average total delay time experienced by a respondent is 78.9 minutes on delay 1 and 36.3 minutes on delay 2. The choices (information acquisition) and experiences (delay times, being late for planned dinner) of respondents in the experiments varies considerably, as indicated by the standard deviations in Table 6.1. Table 6.1 shows the aggregate statistics for the sample.

Late \( N \) denotes how many times a respondent has been late for dinner, late \( T \) denotes the total time of being late, ds1 denotes the cumulative delay time on delay 1, i.e., the total experienced delay time of delay 1 in all trials, for a respondent, ds2 denotes the cumulative experienced delay time on delay 2, leave_early \( N \) denotes for how many times this respondent choose to leave early when there is farewell party, buyinfo1 \( N \) and buyinfo2 \( N \) denotes for how many times the respondent choose to buy information, for delay event one and delay event two respectively.

### 6.4. Heuristic latent class model

In chapter 4, we have developed a heuristic latent class model to capture heterogeneity in travelers’ risk attitudes towards uncertainty. The model assumes that travelers evaluate their activity-travel choices using heuristics. Three types of risk attitudes, namely, risk-averse, risk taking and risk neutral are identified in this model. A risk-averse traveler will evaluate his/her choice alternatives applying worst-case scenario or, in other words, using the least utility of uncertain outcomes.
as the outcome of this alternative. A risk taking traveler uses most likely outcomes of uncertain events as the outcome of choice alternative and a risk neutral traveler will use the expected utility approach to evaluate his/her choice alternatives.

6.4.1 Recap of model specification

As discussed in Chapter 4, at decision node \( \{ H \} \), the utility equals:

\[
v_{\{H\}|c} = v^0_{\{H\}} + v^i_{\{H\}|c}
\]  

(6.4)

where \( c \) is an indicator of class membership (\( c = 1 \) is a risk avoider, \( c = 2 \) is a risk taker, and \( c = 3 \) is a risk neutral traveler). In this equation, the utility \( v^i \) is defined to be class dependent as follows:

\[
v^i_{\{H\}|1} = \min_i (v_{\{H,i\}})
\]  

(6.5)

\[
v^i_{\{H\}|2} = v^i_{\{H,k\}}, \quad k = \arg \max_i (p_{\{H,i\}})
\]  

(6.6)

\[
v^i_{\{H\}|3} = \sum_i p_{\{H,i\}} v_{\{H,i\}}
\]  

(6.7)

where \( v_{\{H,k\}} \) denotes the utility of outcome \( k \), and \( p_{\{H,i\}} \) denotes the probability of the \( i \)-th outcome.

From the perspective of the analyst, the utility function of a chance node is defined as:

\[
U_{\{H\}|c} = v^0_{\{H\}} + v^i_{\{H\}|c} + \epsilon_{\{H\}|c}
\]  

(6.8)
and the utility function of a decision node is defined as:

\[ U_{(H|c)} = v^0_{(H)} + rE\left(\max_i\left(U_{(H|c)_i}\right)\right) + \varepsilon_{(H|c)} \]  \hspace{1cm} (6.9)

where \( U_{(H|c)_i} \) denotes the utility of class \( c \) given its \( i \)-th outcome of \( H \), and, as before, \( v^0_{(H)} \) denotes the base utility of the choice alternative represented by the node itself, \( v^i_{(H|c)} \) denotes the class-dependent outcome-related utility and \( \varepsilon_{(H|c)} \) is an error term. \( E\left(\max_i\left(U_{(H|c)_i}\right)\right) \) denotes the expected maximum utility of later decisions. Note that these utility functions are class specific in their structure; the parameters are the same across all individuals. Heterogeneity is captured by travelers applying different heuristics in evaluating their alternatives and the error terms.

The error term \( \varepsilon_{(H|c)} \) is class dependent, which implies that (i) unobserved factors consists of two parts: a class dependent constant and a random effect which is unknown; (ii) random effects across trials and decisions made by the same individual are assumed independent of each other. Under this assumption and assuming error terms are i.i.d. Gumbel distributed, the expected maximum utility of next level decisions can be replaced by a logsum function:

\[ U_{(H|c)} = v^0_{(H)} + \ln \sum \exp(U_{(H|c)_i}) + \varepsilon_{(H|c)} \]  \hspace{1cm} (6.10)

Furthermore, we assume the error term \( \varepsilon_{(H|c)} \) of choice alternatives to be i.i.d.-Gumbel distributed. This gives a logit form for the choice probability of each decision alternative.
6.4.2 Model estimation

Node utility

We identify two types of decisions at the work location: buy information or not, leave early or join party. At the roundabout, the decision is go shopping or go home directly. The deterministic part of utilities for these nodes can be specified as follows. For experiment I, nodes next to leave early or join party are outcomes of delay one, and thus

\[ V_{\text{leave early}_c} = \beta^{\text{leave early}}_c D^{\text{party}}_c + f_c(v_{\text{leave early}_c}, \ldots, v_{\text{leave early}_c}, p_{\text{leave early}_c}) \]  

(6.11)

\[ V_{\text{join party}_c} = f_c(v_{\text{join party}_c}, \ldots, v_{\text{join party}_c}, p_{\text{join party}_c}) \]  

(6.12)

For experiment II, nodes next to leave early or join party are route choice decisions, and thus

\[ V_{\text{leave early}_c} = \beta^{\text{leave early}}_c D^{\text{party}}_c + \ln \sum \exp(v_{\text{leave early}_c}) \]  

(6.13)

\[ V_{\text{join party}_c} = \ln \sum \exp(v_{\text{join party}_c}) \]  

(6.14)

where \( \beta^{\text{leave early}}_c \) denotes the parameter (the node constant) for choice alternative leaving early from work, where \( j \in \{1,2\} \), \( j=1 \) denotes the party is held for a colleague from another department, while \( j=2 \) indicates it is for a close colleague from the same group. \( D^{\text{party}}_c \) is a dummy variable indicating the situation of farewell party. \( f_c \) denotes evaluation heuristics defined in equations (6.5)(6.6)(6.7) and has the same meaning in the following equations.
\[ V_{\text{buyinfo}} = \beta_{\text{infoprice}} \text{Price} + f_c \left( v_{\{\text{buyinfo}\},i} \cdot p_{\{\text{buyinfo}\}} \right) \]  
(6.15)

Information acquisition is considered a general choice as other decisions. The same heuristic applies to information acquisition decision node outcomes. \( \beta_{\text{infoprice}} \) denotes the parameter for information price.

In experiment I, the decision of buying flowers is followed by uncertain outcomes of delay two, and thus

\[ V_{\text{buyflower}} = f_c \left( v_{\{\text{buyflower}\},i} \cdot p_{\{\text{buyflower}\}} \right) \]  
(6.16)

\[ V_{\text{nobuyflower}} = \beta_{\text{nobuyflower}} D_{\text{nobuyflower}} + f_c \left( v_{\{\text{nobuyflower}\},i} \cdot p_{\{\text{nobuyflower}\}} \right) \]  
(6.17)

In experiment II, there are no further decisions (note choice of having a rest at home has been ignored as discussed before) after this buying flowers choice. Thus,

\[ V_{\text{nobuyflower}} = \beta_{\text{nobuyflower}} D_{\text{nobuyflower}} \]  
(6.18)

where \( \beta_{\text{nobuyflower}} \) denotes the parameter (the node constant) for not buying flowers for dinner, where \( j \in \{1,2\} \) \( (j = 1 \text{ if only respondent and his/her spouse are invited}; \ j = 2 \text{ if other friends have been invited}) \).

The information outcomes, either delay or no delay, are followed by decisions based on updated belief. The value of information is calculated as:

\[ V_{\text{infodelay}} = \ln \sum \text{Exp} \left( v_{\{\text{infodelay}\},i} \cdot p_{\{\text{infodelay}\}} \right) \]  
(6.19)
\[ V_{\text{infonodelay}c} = \ln \sum \text{Exp}(v_{\text{infonodelay},c}, p_{\text{infonodelay},c}) \]  \hspace{1cm} (6.20)

In experiment II, route choice alternatives highway and provincial road have probabilistic outcomes, thus travelers evaluate their outcomes using the defined heuristics. This results in:

\[ V_{\text{highway}c} = \beta_{\text{highway}} + f_c \left( v_{\text{highway},c}, p_{\text{highway},c} \right) \]  \hspace{1cm} (6.21)

\[ V_{\text{provincialroad}c} = f_c \left( v_{\text{provincialroad},c}, p_{\text{provincialroad},c} \right) \]  \hspace{1cm} (6.22)

where \( \beta_{\text{highway}} \) denotes a base preference (the node constant) for highway compared to provincial road.

Nodes of uncertain outcomes have the following utility forms:

\[ V_{\text{traveldelay}c} = \beta_{\text{traveldelay}} T_{\text{traveldelaytime}} + \ln \sum \text{Exp}(v_{\text{traveldelay},c}, p_{\text{traveldelay},c}) \]  \hspace{1cm} (6.23)

\[ V_{\text{travelnodelay}c} = \ln \sum \text{Exp}(v_{\text{travelnodelay},c}, p_{\text{travelnodelay},c}) \]  \hspace{1cm} (6.24)

\[ V_{\text{shoppingdelay}c} = \beta_{\text{shoppingdelay}} T_{\text{shoppingdelaytime}} + \ln \sum \text{Exp}(v_{\text{shoppingdelay},c}, p_{\text{shoppingdelay},c}) \]  \hspace{1cm} (6.25)

\[ V_{\text{shoppingnodelay}c} = \ln \sum \text{Exp}(v_{\text{shoppingnodelay},c}, p_{\text{shoppingnodelay},c}) \]  \hspace{1cm} (6.26)
where $\beta_{\text{traveldelay}}$ and $\beta_{\text{shoppingdelay}}$ denote the base utilities of travel delay time and shopping delay time. $T_{\text{traveldelaytime}}$ denotes travel delay time, $T_{\text{shoppingdelaytime}}$ denotes shopping delay time.

$$V_{\text{dinner}} = \beta_{\text{late}k} L_{\text{late}} + \beta_{\text{latedif}lk} L_{\text{late}} \text{Dinner}$$ (6.27)

where $\beta_{\text{late}k}$ denotes the disutility of being late in $k$-th time range for dinner when the dinner is planned for only the respondent and his/her spouse, $k \in \{1,2\}$, $k = 1$ denotes being late but less than 15 minutes, $k = 2$ denotes being late more than 15 minutes. $L_{\text{late}}$ is a dummy variable indicating being late or not for the dinner. $\beta_{\text{latedif}lk}$ denotes an additive term on disutility $\beta_{\text{late}k}$ in the situation when other friends are also invited to dinner. $\text{Dinner}$ denotes a dummy variable indicating whether other friends has been also invited for dinner. Parameters to be estimated are

$\beta_{\text{infoprice}}$, $\beta_{\text{leaveearly}}$, $\beta_{\text{nobuyflower}}$, $\beta_{\text{highway}}$, $\beta_{\text{traveldelay}}$, $\beta_{\text{late}k}$, $\beta_{\text{latedif}lk}$.

Note that the parameter for buying flowers is specified as a disutility of not buying flowers for dinner, to be in line with the specification of utility for leaving work early (skipping the farewell party) which is also modeled as a disutility. Acquisition of information is treated as a normal choice. This generalizes the structure of decisions making process so that information acquisition decisions can be evaluated as other decisions.

**Model**

Now, assume we have $N$ individuals, each of them belonging to one of the $C$ classes. Each individual makes $T$ trials of sequential choices, each sequence of
choices consists of $S$ decisions, each decision has $J$ alternatives. We define the probability of individual $n$ choosing alternative $j$ at decision $s$ in trial $t$ when this individual belongs to class $c$ as:

$$P_{nsc}(j) = P(y_{ns} = j \mid \text{class} = c) \quad (6.28)$$

where $y_{ns}$ denotes the choice made. Further, we define the probability of individual $n$ choosing choice alternative $j$ in trial $t$ making the $s$-th decision given the class of this individual in logit form following the earlier assumption of the i.i.d.-Gumbel extreme value distributed form of the error terms:

$$P_{njts c} = \frac{\exp(v_{njts c})}{\sum_{j=1}^{J} \exp(v_{njts c})} \quad (6.29)$$

The contribution of this individual to the likelihood of the model is the joint probability of decision sequence $y_n = \{y_{n1}, y_{n2}, \ldots, y_{nT}\}$, defined as:

$$P_{nsc} = \prod_{t=1}^{T} \prod_{s=1}^{S} \prod_{j=1}^{J} P_{njts c}^{\delta_j} \quad (6.30)$$

where $\delta_j = 1$ if the $j$-th alternative is chosen and 0 otherwise.

Let $\alpha_{nc}$ denote the probability that individual $n$ belongs to class $c$. Then the membership function is defined as:

$$\alpha_{nc} = \frac{\exp(z_n \theta_c)}{\sum_{c=1}^{C} \exp(z_n \theta_c)} \quad c=1\ldots C, \theta_c = 0 \quad (6.31)$$

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where $z_i$ denotes a set of observable attributes that may be psychological constructs or socio-economic characteristics. $z_i$ in this format is known as “concomitant variable” or “covariate variable”. $\theta_i$ denotes the unknown class parameters related to person attributes.

Equation (6.31) represents a general approach in latent class modeling. We keep this form simply for convenience and future use because such covariates do not exist in our model at this moment but may be introduced into our model later on. At this moment, our only interest is to find the proportion of each class. Thus, $\alpha_{aq}$ is simply a constant. Therefore, we adopt a single attribute in $z_n$ and set this attribute to a constant “1”, and the latent class probabilities would sum up to 1 by construction.

The likelihood function for individual $n$ across all classes is the weighted sum of the class specific contributions:

$$ P_n = \sum_{c=1}^{C} \alpha_{ac} P_{nlc} $$

(6.32)

The log likelihood function for all observations is:

$$ LL = \sum_{n=1}^{N} \ln P_n = \sum \ln \left( \sum_{c=1}^{C} \alpha_{ac} \left( \prod_{j=1}^{J} \prod_{i=1}^{S_j} P_{nijlc} \right) \right) $$

(6.33)

where $P_{nijlc}$ in likelihood function is $\prod_{j=1}^{J} P_{ijnlc}^{x_{ij}}$, where $j \in J$ indicates a choice alternative.
6.4.3 Estimation results

Since experiments I and II are special cases of a single decision tree structure, the data for the two experiments can be merged to estimate the structure. Three estimations have been conducted. The first estimation used data set of respondents (190 in total) who have completed experiment I. The second estimation used data set of respondents (227 in total) who have completed experiment II, while the third estimation used the pooled data set of all respondents (417 in total). Table 6.2 gives the estimated parameters and their \( t \) statistics, goodness of fit measures, AIC (Akaike Information Criterion of goodness of fit measure), BIC (Bayesian information criterion of goodness of fit measure, also known as Schwarz Criterion) and McFadden’s Rho square. As discussed, the EM algorithm was used in the estimations.

All three model estimations give correct parameters signs. For example, the price parameter is negative, indicating the disutility of paying. The parameter for leaving is also negative, suggesting a penalty for skipping the farewell party. Similarly, not buying flowers for the dinner has a negative sign, also indicating a penalty in the utility function. Finally, the parameters for the delays (travel delay or shopping delay) also have negative signs. Thus, the signs of all estimated parameters are consistent with expectations, giving face validity to the results.

The magnitudes of estimates seem in line with expectations. The penalties for leaving early when the farewell party is held for a colleague of another department (-0.928, -0.725, -0.758) are not as bad as skipping the farewell party for a colleague from the own group (-2.547, -2.752, -2.568). Being very late (more than 15 minutes) for the dinner has a much higher penalty than being late (later than planned time but less than 15 minutes), namely -2.054 vs. -0.389 in Experiment I, -0.812 vs. -0.297 in Experiment II and -1.371 vs. -0.295 in the pooled data set.
**Table 6.2 Estimation results**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>exp1 estimates</th>
<th>exp1 t-value</th>
<th>exp2 estimates</th>
<th>exp2 t-value</th>
<th>Pooled data estimates</th>
<th>Pooled data t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_{\text{infoprice}} )</td>
<td>-0.024</td>
<td>-45.371</td>
<td>-0.031</td>
<td>-54.227</td>
<td>-0.028</td>
<td>-73.457</td>
</tr>
<tr>
<td>( \beta_{1}^{1} )</td>
<td>-0.928</td>
<td>-14.220</td>
<td>-0.725</td>
<td>-8.948</td>
<td>-0.758</td>
<td>-15.141</td>
</tr>
<tr>
<td>( \beta_{2}^{2} )</td>
<td>-2.547</td>
<td>-26.059</td>
<td>-2.752</td>
<td>-23.326</td>
<td>-2.568</td>
<td>-34.623</td>
</tr>
<tr>
<td>( \beta_{\text{highway}} )</td>
<td>0.000</td>
<td></td>
<td>0.136</td>
<td></td>
<td>0.030</td>
<td>0.532</td>
</tr>
<tr>
<td>( \beta_{\text{nobuyflower}} )</td>
<td>-1.636</td>
<td>-21.631</td>
<td>-1.967</td>
<td>-19.235</td>
<td>-1.993</td>
<td>-31.245</td>
</tr>
<tr>
<td>( \beta_{\text{traveldelay}} )</td>
<td>-0.026</td>
<td>4.325</td>
<td>0.000</td>
<td></td>
<td>-0.043</td>
<td>-8.481</td>
</tr>
<tr>
<td>( \beta_{\text{shoppingdelay}} )</td>
<td>-0.389</td>
<td>-2.791</td>
<td>-0.297</td>
<td>-2.556</td>
<td>-0.295</td>
<td>-3.507</td>
</tr>
<tr>
<td>( \beta_{\text{late1}} )</td>
<td>-0.015</td>
<td>-0.074</td>
<td>0.065</td>
<td>0.521</td>
<td>0.066</td>
<td>0.654</td>
</tr>
<tr>
<td>( \beta_{\text{latedif1}} )</td>
<td>-2.054</td>
<td>-13.945</td>
<td>-0.812</td>
<td>-4.024</td>
<td>-1.371</td>
<td>-11.605</td>
</tr>
<tr>
<td>( \beta_{\text{late2}} )</td>
<td>0.017</td>
<td>0.096</td>
<td>-0.573</td>
<td>-2.686</td>
<td>-0.028</td>
<td>-0.206</td>
</tr>
</tbody>
</table>

Class 1: risk averse 0.278 0.197 0.210
Class 2: risk taking 0.000 0.069 0.058
Class 3: risk neutral 0.722 0.734 0.732

Loglik NULL model -7968.648 -12258.49 -20227.13
Loglik -4789.41 -6483.412 -11323.5
AIC 9602.82 12990.82 22671
BIC 9683.089 13075.25 22761.84
McFadden's R-sq 0.3990 0.4711 0.4402
McFadden's R-sq adjusted 0.3975 0.4701 0.4396

*Note: t-values are calculated using the Hessian matrix (Fisher’s observed information matrix), by numerical derivation of the log likelihood function at its maximum, which is approximated by the EM algorithm. Other t-values are calculated using the same approach.*
On the other hand, the estimates do indicate that being invited or not together with others at the dinner does not matter very much, as the disutility of skipping buying flowers ($\beta_{nobuyflower}$) for two situations (dinner with spouse only and dinner with other friends) nearly has the same magnitude (-1.636 vs. -1.697 in Experiment I; -1.967 vs. -1.706 in Experiment II and -1.993 vs. -1.868 in the pooled data). Further, the additive terms of being late for dinner, which indicates how much the second situation differs from the first, are small and are not significant in Experiment I and in the overall model, while only one parameter is significant in Experiment II: the additive term for being very late.

Class estimates shows that 27.8% of the respondents in Experiment I adapted a worse case scenario heuristic to evaluate their choice alternatives, while the remaining percentage seems to have used an expected utility evaluation heuristic. None of the respondents exhibited risk taking behavior in this experiment. The corresponding proportion of risk avoiders in Experiment II and the pooled data is reduced to 19.7% and 21% respectively. Again, only a very small fraction of the respondents showed evidence of risk-taking behavior.

If we take $\beta_{infoprice}$ as an indicator of willingness to pay for travel information, the higher the value (near to zero), the more the respondent is willing to pay for information, given the specific value of information for the given activity-travel situation, risk attitude of the person and credibility of the source. Comparing estimates for Experiment I and Experiment II suggests that respondents who participated in Experiment I tend to be more willing to pay for information than respondents involved in Experiment II, after correction for possible differences in information value. The results are consistent across all three model estimations in terms of parameter signs and magnitudes, giving further face validity to the model as one would indeed expect a same willingness to pay after correction for
information value.

6.4.4 Risk heuristics and observed choices

The latent class estimation gives the probabilities of class membership. Comparing estimated membership with descriptive statistics of choice data Table 6.1, we found that the risk-averse class has a positive correlation with buying information and leaving early, whilst it correlates negatively with the number of times of being late and the total time of being late for dinner. In contrast, risk neutral membership correlates positively with the number of times being late and the total time being late, but negatively with buying information. This is consistent with expectations and suggests a substantial difference in traveler’s preference of buying information (higher information value and, hence, higher willingness to pay when risk avoider).

The correlation results are shown in Table 6.3. V1, V2, V3 are memberships obtained from model estimation which is defined as probabilities of a traveler belong to each class, where V1 is the membership probability of the risk-averse class, V2 is the membership probability of traveler of risk taking class and V3 is the membership probability of traveler of risk neutral class.

<table>
<thead>
<tr>
<th></th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>Late N</th>
<th>lateT</th>
<th>ds1</th>
<th>ds2</th>
<th>Leave Early N</th>
<th>buyinfo1 N</th>
<th>buyinfo2 N</th>
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<tbody>
<tr>
<td>V1</td>
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<tr>
<td>V2</td>
<td>-0.324**</td>
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<td>0.231**</td>
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<tr>
<td>ds1</td>
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<td>-0.022</td>
<td>0.290**</td>
<td>0.451**</td>
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</tr>
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<td>-0.041</td>
<td>0.127*</td>
<td>0.425**</td>
<td>0.465**</td>
<td>0.093</td>
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</tr>
<tr>
<td>leave early N</td>
<td>0.213**</td>
<td>-0.046</td>
<td>-0.212**</td>
<td>-0.182**</td>
<td>-0.179**</td>
<td>0.132**</td>
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<tr>
<td>buyinfo1 N</td>
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<td>-0.414**</td>
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<td>buyinfo2 N</td>
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<td>-0.193**</td>
<td>-0.606**</td>
<td>-0.072</td>
<td>-0.034</td>
<td>0.02</td>
<td>0.062</td>
<td>0.065</td>
<td>0.485**</td>
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</tr>
</tbody>
</table>

** significant at p < .01 level  
*significant at p < .05 level
6.5. Willingness to pay model

Travelers may have differing needs for travel information depending on how they wish to cope with uncertainty. This source of heterogeneity could or should be incorporated in models of information acquisition. The effect of this source of heterogeneity is modeled and examined in this section in the context of a route choice and activity rescheduling problem involving multiple uncertain events. As the estimation results in the last section suggest, information acquiring behavior can be significantly different across travelers. People may differ in their attitudes towards risk or uncertainty, thus the heterogeneity in risk attitude may affect their preferences for information acquisition.

A different conceptualization of risk-aversion, therefore, is willingness to pay for information (to reduce uncertainty). This alternative way of conceptualization is closer to the traditional interpretation of risk-averseness in economic theory. For example, risk-aversion in that theory means higher willingness to pay for reducing the risk and hence higher willingness to pay for information given the perceived value of information. Therefore, it is also meaningful to estimate a model that takes into account heterogeneity in information preference. The assumption then is that an individual who is risk-averse will be more willing to pay for information to reduce the uncertainty he is facing, whilst a risk neutral or risk taking individual is less willing to pay for information. Based on this consideration, the willingness to pay model assumes that individuals have different preferences for information price which is in line with the willingness to pay concept. Further, we assume that there is a finite number of groups/categories of preferences for information. Travelers belonging to the same group of people have approximately the same preference for information whilst preferences differ across groups. This model assumes homogeneity in terms of the way decision options are evaluated, i.e., based on expected utility.
6.5.1 Recap of the model specification

The willingness to pay model developed in chapter 4 also assumes that the utility of a node in decision tree regarding interclass differences depends on the nature of the node. If node \( \{H\} \) is a nature node, the utility equals

\[
v_{\{H\}|c} = v_{\{H\}|c}^0 + \sum_i P_{\{H\},i} v_{\{H,i\}|c}
\]  

(6.34)

If node \( \{H\} \) is a decision node, the utility equals:

\[
v_{\{H\}|c} = v_{\{H\}}^0 + \max_i \left( v_{\{H,i\}|c} \right)
\]  

(6.35)

where \( v_{\{H\}|c} \) denotes class-specific utility, and \( C \) denote the total number of classes.

If node \( \{H\} \) is a node representing information acquisition, the alternative-specific utility is specified as

\[
v_{\{H\}|c}^0 = \beta_{\text{infoprice}c} \cdot \text{Price}
\]

where \( \beta_{\text{infoprice}c} \) is a class-specific parameter of information price, \( \text{Price} \) is the price for acquiring one piece of information (i.e., consulting the information source). The sum term on the RHS of equation (6.34) represents, as before, the perceived expected information value.

From the perspective of the analyst, there are unobserved attributes of the choice alternatives in each decision. Again, we assume that the choice alternative with the highest utility is always chosen, following Random Utility theory. If the alternative has uncertain consequences and, hence, the node \( \{H\} \) representing the alternative is a chance node, then the utility function is defined as:

\[
U_{\{H\}|c} = v_{\{H\}|c}^0 + \sum_{i} v_{\{H,i\}|c} P_{\{H,i\}} + \varepsilon_{\{H\}|c}
\]  

(6.36)
and if the alternative is followed by a next decision and, hence, the node \( \{H\} \) representing the alternative is a decision node, the utility function is defined as:

\[
U_{\{H\}c} = v^0_{\{H\}} + rE\left(\max_i \left(v_{\{H\}i|c}\right)\right) + \varepsilon_{\{H\}c}
\]  

(6.37)

where \( p_{\{H\}i} \) denotes the probability of its \( i \)-th outcome at node \( \{H\} \) of the tree, \( v_{\{H\}i|c} \) denotes the utility of class \( c \) given its \( i \)-th outcome of \( \{H\} \), \( v^0_{\{H\}} \) denotes the base utility of the choice alternative represented by the node itself, \( \varepsilon_{\{H\}c} \) is an error term.

The error term \( \varepsilon_{\{H\}c} \) is class dependent, which also implies that (i) unobserved errors consist of two parts, a class dependent constant and a random effect which is unknown; (ii) random effects across trials and decisions made by one individual are independent of each other. Under this assumption, the expected maximum utility of next level alternatives can be replaced by a logsum function if we assume the error term \( \varepsilon_{\{H\}c} \) of choice alternatives is i.i.d. Gumbel distributed:

\[
U_{\{H\}c} = v^0_{\{H\}} + \ln \sum \exp(U_{\{H\}i|c}) + \varepsilon_{\{H\}c}
\]  

(6.38)

This gives a logit form for the choice probability for each decision alternative.

6.5.2 Model estimation

Node utility

The utility of nodes in decisions trees are specified in a similar way as in the heuristic model. For experiment I, nodes next to leave early or join party are outcomes of delay one, and thus
\[ V_{\text{leave early} | c} = \beta_{\text{leave early} | c} + \sum \left( v_{\text{leave early} | j, c}, p_{\text{leave early} | j, c} \right) \]  
\[ (6.39) \]

\[ V_{\text{join party} | c} = \sum \left( v_{\text{join party} | j, c}, p_{\text{join party} | j, c} \right) \]  
\[ (6.40) \]

For experiment II, nodes next to leave early or join party are route choice decisions, and thus

\[ V_{\text{leave early} | c} = \beta_{\text{leave early} | c} + \ln \sum \exp \left( v_{\text{leave early} | j, c} \right) \]  
\[ (6.41) \]

\[ V_{\text{join party} | c} = \ln \sum \exp \left( v_{\text{join party} | j, c} \right) \]  
\[ (6.42) \]

where \( \beta_{\text{leave early} | c} \) denotes the parameter (the node constant) for choice alternative leaving early from work., where \( j \in \{1, 2\} \), \( j =1 \) denotes the party is held for a colleague from another department, while \( j = 2 \) indicates it is for a close colleague from the same group. \( D_{\text{party} | j} \) is a dummy variable indicating the situation of farewell party.

For the buying information alternative, the willingness to pay model assumes that travelers have different preferences about information price, and thus

\[ V_{\text{buy info} | c} = \beta_{\text{info price} | c} \text{Price} + \sum \left( v_{\text{buy info} | j, c}, p_{\text{buy info} | j, c} \right) \]  
\[ (6.43) \]

where \( \beta_{\text{info price} | c} \) denotes the class specific parameter for information price.
In experiment I, the decision of buying flowers is followed by uncertain outcomes of delay two, and hence

\[
V_{\text{buyflower}} = \sum (v_{\{\text{buyflower}_i\}} \cdot p_{\{\text{buyflower}_i\}})
\]

\(\text{(6.44)}\)

\[
V_{\text{nobuyflower}} = \beta_{\text{nobuyflower}} D_{\text{nobuyflower}} + \sum (v_{\{\text{nobuyflower}_i\}} \cdot p_{\{\text{nobuyflower}_i\}})
\]

\(\text{(6.45)}\)

In experiment II, there are no further decisions (note: choice of having a rest at home has been ignored as discussed before) after this buying flowers choice. Thus,

\[
V_{\text{nobuyflower}} = \beta_{\text{nobuyflower}} D_{\text{nobuyflower}}
\]

\(\text{(6.46)}\)

where \(\beta_{\text{nobuyflower}}\) denotes the parameter (the node constant) for not buying flowers for dinner, where \(j \in \{1, 2\}\) (\(j = 1\) if only respondent and his/her spouse are invited; \(j = 2\) if other friends have been invited).

The information outcomes, either delay or no delay, are followed by decisions based on updated beliefs, and hence

\[
V_{\text{infodelay}_c} = \ln \sum \text{Exp}(v_{\{\text{infodelay}_i\}} \cdot c \cdot p_{\{\text{infodelay}_i\}})
\]

\(\text{(6.47)}\)

\[
V_{\text{infonodelay}_c} = \ln \sum \text{Exp}(v_{\{\text{infonodelay}_i\}} \cdot c \cdot p_{\{\text{infonodelay}_i\}})
\]

\(\text{(6.48)}\)

In experiment II, route choice alternatives highway and provincial road have probabilistic outcomes, thus travelers evaluate their outcomes using expected utility perceptions. Thus,
\[ V_{\text{highway}} = \beta_{\text{highway}} + \sum (v_{\ldots, \text{highway}, i}, p_{\ldots, \text{highway}, i}) \quad (6.49) \]

\[ V_{\text{provincialroad}} = \sum (v_{\ldots, \text{provincialroad}, i}, p_{\ldots, \text{provincialroad}, i}) \quad (6.50) \]

where \( \beta_{\text{highway}} \) denotes the preference (the node constant) for highway compared to provincial road.

Nodes of uncertain outcomes have the following utility forms:

\[ V_{\text{traveldelay}} = \beta_{\text{traveldelay}} T_{\text{traveldelaytime}} + \ln \sum \text{Exp}(v_{\ldots, \text{traveldelay}, i}, p_{\ldots, \text{traveldelay}, i}) \quad (6.51) \]

\[ V_{\text{travelmodel}} = \ln \sum \text{Exp}(v_{\ldots, \text{travelmodel}, i}, p_{\ldots, \text{travelmodel}, i}) \quad (6.52) \]

\[ V_{\text{shoppingdelay}} = \beta_{\text{shoppingdelay}} T_{\text{shoppingdelaytime}} + \ln \sum \text{Exp}(v_{\ldots, \text{shoppingdelay}, i}, p_{\ldots, \text{shoppingdelay}, i}) \quad (6.53) \]

\[ V_{\text{shoppingmodel}} = \ln \sum \text{Exp}(v_{\ldots, \text{shoppingmodel}, i}, p_{\ldots, \text{shoppingmodel}, i}) \quad (6.54) \]

where \( \beta_{\text{traveldelay}} \) and \( \beta_{\text{shoppingdelay}} \) denote the base utilities of travel delay time and shopping delay time. \( T_{\text{traveldelaytime}} \) denotes travel delay time, \( T_{\text{shoppingdelaytime}} \) denotes shopping delay time.

\[ V_{\text{dinner}} = \beta_{\text{latek}} L_{\text{late}} + \beta_{\text{latek} \text{h} \text{late}} L_{\text{late}, \text{Dinner}} \quad (6.55) \]

where \( \beta_{\text{latek}} \) denotes the disutility of being late in \( k \)-th time range for dinner when the dinner is planned for only the respondent and his/her spouse, \( k \in \{1, 2\}, \ k = 1 \)
denotes being late but less than 15 minutes, $k = 2$ denotes being late more than 15 minutes. $L_{late}$ is a dummy variable indicating being late or not for the dinner. $\beta_{late|_i}$ denotes an additive term on disutility $\beta_{late|_i}$ in the situation when other friends are also invited to dinner. Dinner denotes a dummy variable indicating whether other friends has been also invited for dinner.

Note that only node utilities that may appear before the information acquisition decision are class specific. Nodes without further information acquisition choices use the same parameters across all individuals.

**Model**

The difference between two models is how utility is defined for each class. In heuristic latent class model, risk attitudes are distinguished by using different utility function forms for different heuristics, whilst in WTP model, heterogeneity is represented by different preferences on information price. The same form of likelihood function can be used for both models. Thus, the model estimation of WTP model follows the same procedure as heuristic latent class model in section 6.4.

**6.5.3 Estimation results**

The estimation was conducted by utilizing the EM algorithm, using pooled data of experiment I and experiment II. Three different models, varying the number of latent classes, were estimated. Table 6.4 shows the results of the estimation. The AIC, BIC (smaller) and McFadden’s R-square adjusted (bigger) measures all suggest that a 3 class model better fits the data than a model with 2 or 4 classes. Thus, the 3 class model was chosen as the final model estimation result.
<table>
<thead>
<tr>
<th></th>
<th>2 classes</th>
<th>3 classes</th>
<th>4 class</th>
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</thead>
<tbody>
<tr>
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<td>t-value</td>
<td>t-value</td>
<td>t_value</td>
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<tr>
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<tr>
<td>$\beta_{\text{infoprice4}}$</td>
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</tr>
<tr>
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<tr>
<td>McFadden’s R-sq adjusted:</td>
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<td>0.4751</td>
</tr>
</tbody>
</table>
The three class model estimates have correct parameters signs. For example, the class-specific price parameters are negative, indicating the disutility of paying. The parameter for leaving is also negative, suggesting a penalty for skipping the farewell party. Similarly, not buying flowers for the dinner has a negative sign also indicating a penalty in the utility function. Finally, the parameters for the delays (travel delay and shopping delay) also have negative signs (note: after correction for their possible consequences of arriving late at dinner). Thus, the signs of all estimated parameters are consistent with expectations, giving face validity to the results.

The magnitudes of estimates seem intuitively correct. The penalties for leaving early when the farewell party is held for a colleague of another department (-0.723) are not as bad as skipping the farewell party for a colleague from the own group (-2.501). Being very late (more than 15 minutes) for the dinner has a much higher penalty than being late (later than planned time but less than 15 minutes late), -1.676 vs. -0.318 in the dataset. The estimation results indicate that dinner situations in this experiment do not differ very much, as the disutility of skipping buying flowers ($\beta_{\text{nobuyflower}}$) for two situations (dinner with spouse only and dinner with other friends) nearly have the same magnitude (-1.664 vs. -1.766). Furthermore, the additive terms of being late for dinner, which indicates how much the second situation (with others invited) differs from the first (without others invited), are small and only one additive term for being very late is significant.

Class estimates show that 18.5% of the respondents are clustered in class one, 39.7% are clustered in class two and 41.8% are clustered in class 3. This classification will only be meaningful after examination of the class specific parameter estimations. If we take $\beta_{\text{infoprice}}$ as an indicator of willingness to pay for travel information, the higher the value (near to zero), the more the respondent is
willing to pay for information (after correcting for expected information value). Comparing estimates for 3 classes suggests that respondents who are labeled as class one (-0.011) tend to be more willing to pay for information than respondents in class 2 (-0.124) and class 3 (-0.0264). Respondents in class 2 are very reluctant to pay for information compared to class 1 and class 3, whilst respondents in class 3 are somewhere in between. In that sense, Class 1 can be labeled as risk averse and Class 2 as risk taking in comparison to an average.

Comparing estimated membership probabilities with descriptive statistics of the choice data, as shown in Table 6.5, we find that class one has positive correlations with buying information, whilst class 2 has strong negative correlations with buying information. This confirms the substantial difference in traveler’s preference of buying information relative to the perceived information value which is also reflected in our model by the marginal utility of information price. Only class 1 is significantly (0.01 level) and positively correlated with total experienced delay time on delay 1, only class 2 is significantly (0.05 level) and negatively

Table 6.5 Correlation between membership and choices

<table>
<thead>
<tr>
<th></th>
<th>V1</th>
<th>V2</th>
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<th>Late N</th>
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</tr>
</tbody>
</table>

** significant at p < 0.01 level
* significant at p < 0.05 level
V1, V2, V3 are membership obtained from latent class model estimation.
correlated with total experienced delay time on delay 2. Nonetheless, the correlations are low. The membership probabilities are not correlated with total time of being late and frequency of being late, and the frequency of leaving early.

6.6. Discussions and conclusions

In this chapter, two models that account for risk heterogeneity using different concepts, a heuristic latent class model and a willingness to pay model were empirically estimated using data collected using the activity-travel simulator. The heuristic latent class model is based on the assumption that individual travelers evaluate uncertain outcomes differently using the heuristic base approach. The willingness to pay model, on the other hand, treats individual heterogeneity in risk attitude as the manifest effects of the differences in information price preference. Willingness to pay classes differ in terms of travelers’ preference for information as a means of reducing risk. In general, the higher the value (negative) of information price preference, the higher the willingness to pay for information.

The results of these experiment estimations provide evidence of face validity for both models as the signs of the estimated parameters were consistent with a priori expectations and the relative magnitudes of estimated parameters are interpretable. The two models use different conceptualizations of risk attitudes. According the conceptualization assumed in the heuristic latent class model, the percentage of risk-takers in the sample is negligible, while the percentage of risk avoiders is much higher. According the conceptualization assumed in the willingness-to-pay model, on the other hand, risk-aversion versus risk-taking refers to a tendency to use information, given the value of it, and, hence, willingness to pay for information. In willingness to pay model, the 3-class solution found provides evidence for a three-way classification of risk attitudes. The three classes are all clearly distinguishable in the sample and can be interpreted as risk aversion versus risk seeking in this more classical economic sense. The estimation results confirm
the existence of heterogeneity in activity-travel decisions. It can be attributed to either decision styles (heuristic model) or to different preferences for information price (willingness to pay model).

As far as the estimation results and behavior patterns are concerned, several conclusions can be drawn. First, in both model estimations, risk-averse travelers, either defined by decision style in the heuristic latent class model or by information price preference in the willingness to pay model, tend to buy more information whereas risk seeking travelers tend to buy less. Second, risk-averse travelers in the heuristic latent class model tend to avoid being late for participating in planned activities while risk neutral travelers have the opposite tendency. In the willingness to pay model, however, risk-averse travelers do not show a tendency of avoiding being late for planned dinner or experiencing less delays.

The negligible portion of risk taking travelers in the estimation results of the heuristic latent class model may have two implications: first, there are very few travelers who apply a risk taking decision style in activity-travel decisions and if so, the heuristics defined in the heuristic latent class model can be simplified into two decision styles: risk-averse and risk neutral. Second, it maybe the case that risk taking travelers evaluate their alternatives based on other rules rather than based only on taking the most likely outcomes into account. Either the first or the second implications call for reconsideration of decision rule definitions. Third, it may be attributed to the experimental design that the experiments may be not sensitive enough to risk taking heuristics. Though the numerical simulations conducted in chapter 4 suggested that the heuristic latent class model is capable of capturing all three decision styles, the complexity of activity-travel decisions and the complete random experimental design together may diminish the model’s identifiability for risk taking behaviors. Therefore, our finding suggests that individuals generally do take risks into account in making choices.
In the willingness to pay model, risk attitudes are defined by traveler’s preferences for information price as we assume acquiring information is a means of reducing uncertainty. The estimation results are, not surprisingly, correlated with information acquisition behavior; risk-averse travelers tend to buy more information and risk taking travelers tend to do the opposite. However, the correlations with other aggregated choice statistics are either not significant or low in magnitude. The expectation that a risk-averse traveler in general will participate in planned activities on time and experience less delays in travel is thus not achieved by acquiring information. Hence, we may argue that acquiring information may be not the only indicator of risk-averse attitude. Or, in other words, risk attitude in complex decision situations such as activity-travel may be intrinsically multi-dimensional and thus cannot be measured by a single measurement.
7. Travel risk attitude scale

In this chapter, a travel risk attitude scale was developed and validated against survey data. The relationship between this scale and a general risk attitude of recreational risk scale developed by Weber et al. (2002) and a future oriented time perspective scale by Zimbardo et al. (1997) is examined as well. A sequential equation model is fitted at the end as a confirmatory test for the relationship between the proposed travel risk attitude scale and these general risk measurement scales.

7.1. Introduction

Several studies have demonstrated the importance of risk attitude in traveling decisions (e.g., Parkany et al., 2004; Ben-Elia et al., 2008). In many travel situations, people can be stratified based on the travel risk attitude they purport. Bus and taxi companies may look for non-risk taking employees with non-risk taking travel behavior. Policy makers may want to know who the travelers are that will change their travel patterns with increased or decreased uncertainty induced by new policies.

Travel risk attitude may be closely linked to travel information acquisition behavior. As travel information is assumed to be able to reduce uncertainty, a risk-averse traveler may choose to consult travel information sources more frequently than a risk taking traveler. Thus, information service providers may want to identify their potential customers.

In the context of transportation research, risk attitudes are assumed to impact travel decisions of individual travelers in uncertain travel environments and are often modeled using expected utility theory and its variants. However, in the expected utility (EU) framework and non-EU theories including prospect theory (Kahneman
and Tversky, 1979), risk attitude is nothing more than a descriptive label for the shape of the utility function and weighted probability function presumed to underlie a person’s choices (Weber et al., 2002). Weber therefore argued the conceptualization of risk attitudes in general form does not depict the whole view of a risk spectrum.

In psychological research, scales are widely used to measure individual’s coherent traits. Henson et al (2006) argued and provided evidence that risk attitudes are domain-specific rather than general. Weber et al. (2002) developed a set of domain-specific scales to measure risk attitudes. More specifically, they developed a psychometric scale that assesses risk taking in five different content domains: financial decisions (separately for investing and gambling), health/safety, recreational, ethical, and social decisions. In their research, Weber and his co-workers concluded that “conventional risk-attitudes, i.e. risk attitudes inferred from behavior either directly or via utility functions that are derived from risky choices, are also domain-specific rather than reflections of a stable attitude or trait.”

Researchers found that the time perspective plays an important role in people’s risky behavior. In their present time perspective scale, Zimbardo et al. (1997) linked attitudes towards the present and future time perspective to risky behavior. The results suggested a strong correlation between risky driving behavior and attitudes on the time perspective. Generally, the time perspective refers to the relative temporal orientation that motivates (i.e., guides and influences) an individual’s typical actions and goals. Zimbardo and Boyd’s (1999) Time Perspective Inventory (ZTPI) assesses individual differences in terms of attitudes believed to identify persons of past, present or future orientation. According to Zimbardo, this inventory identifies tendencies towards a Hedonistic Present (living the present life in enjoyment), a Fatalistic Present (perceiving one’s own life under the control of external events), a Positive Past (an orientation towards pleasant past
memories), a Negative Past (living a past of unpleasant and painful events), and Future Orientation (the tendency to plan and anticipate events) and can be summed to past, present, and future-oriented time perspective. In general, the present time perspective refers to a primary orientation to the here-and-now, and an inclination to form goals and adopt behaviors that meet immediate desires. There are two components of the present time perspective that are theorized to operate differently, such that (a) a hedonistic time perspective which evokes immediate, pleasure-oriented goals, whereas (b) a fatalistic time perspective is characterized by general pessimism and self-destructive behavior. Independent of the present time perspective, the future time perspective represents one’s tendency to abstain from immediate pleasure in order to obtain long-term rewards. The inventory was applied and examined in other studies and the results showed convincing consistency (e.g., D'Alessio et al., 2003). Zimbardo and his colleagues (1997) in their studies reported that the shorter version of ZTPI had proven to be an important predictor of risky driving behavior. They further argued that the dynamic process of a time perspective was also important in the decision to engage in a variety of risk-taking behaviors.

As Weber argued, risk attitude and risky behavior are essentially domain-specific. Therefore, a scale successfully measuring risk behavior in one domain may fail to capture risk behavior in others. It is logical to argue that risk attitude towards travel is different from risk attitude toward entertainment activities under the assumption that risk attitude itself is context-specific. Existing risk attitudes scales developed in psychologic research are not designed for a travel context specifically and to the best of our knowledge there is no existing psychometric scale to measure travel risk attitude. The only risk scale with some linkage to travel behavior we found is Zimbardo et al. (1997), but it is specifically concerned with driving behavior. Thus, there seemingly is a need to develop a risk-behavior scale for travel behavior that can quickly and easily identify travelers’ risk attitudes.
The purpose of this chapter is twofold. First, the goal is to develop a scale that can consistently measure travel-related risk attitudes in an activity-travel context in particular. Second, we wish to check the relationships between this travel risk scale, a recreational risk attitude scale, the future-oriented time perspective and stated travel information acquisition behavior, which also provides a validity check of the developed scale.

In the following sections, we propose and test a scale which specifically measures travel risk attitudes in an activity-travel context concerned with travel information provision. First, we discuss the items comprising the scale and reduce these to a smaller, consistent set based on their internal consistency. Second, the validity and reliability of the refined scale will be examined. Finally, a confirmatory analysis using a structural equation model is conducted to check the relationship between the developed travel risk scale and general purpose risk scales. Two general purpose risk scales were selected in this analysis: the recreational risk attitude scale from Webers’ domain-specific risk scales as it concerns recreational activity engagement and the future-oriented time perspective scale from ZTPI inventory, as it links to some extent to planning behavior which is crucial in activity-travel decisions.

7.2. Administration

The scale was constructed as a uni-dimensional research instrument regarding travel behavior under uncertainty. In the third part of our web-based experiment (see Chapter 5), three groups of survey questions about activity risk attitudes were devised and administered. They measure travel risk attitudes (see Appendix A for item details) for different travel mode users, namely, car users, public transport users and mix car and public transport mode users. Multivariate measurement data on future oriented time perspectives from Zimbado’s time perspective inventory
and recreational risk attitudes items from Weber’s domain specific scales were collected as well. These two psychometric measures are to some extent related to activity and travel behavior. At the end, stated frequencies of information acquisition behavior data under different situations were collected as well. Five point Likert scales were used throughout the questions when applicable.

In total, 397 respondents out of the 417 who completed the travel simulator experiment completed the questionnaires. Among these, 194 were females and 203 were males. The average age is 38.2 with a standard deviation of 14.4. Based on transport mode use revealed in the first part of the questionnaire, three segments were identified: car users (176), car-public transport mixed mode users (127), and public transport users (94).

**Travel risk scale**
Travel risk attitude is measured by a set of items about travel risk attitudes and activity time planning attitudes. The items concern route choice, departure time choice, activity and scheduling choice under uncertainty. For different mode users, the questions are adjusted to suit the travel context according to the mode used. Those items irrelevant for a particular travel mode were filtered out (see Appendix A for the list of questions). The number of items varies between 11 (car and public transport users), 9 (car users) and 8 (public transport users) due to the adjustments to travel context for travel modes. Participants were asked to indicate using a 5-point Likert scale ranging from 1 (extremely untypical) to 5 (extremely typical) how they would act when they engaged in risky travel decisions. Sample items are: If there is a probability of delay then I always incorporate a sufficient margin in my appointments with others (activity scheduling decision for all mode users); If it is really necessary to be on time then I rather take two trains than one train earlier (public mode users); I will always avoid a route of which I cannot assess well how long the journey will take (car users).
General risk scale

The relationship between the developed travel risk scale and general risk scales provides a test of convergent validity (Devellis, 1991). The recreational activity risk attitude items of Weber’s domain specific risk scale and Zimbardo’s time perspective inventory (ZTPI)-future oriented were adopted in our survey, measured by a 5-point Likert scale for each item.

7.3. Scale development

In this section, the proposed items of the travel risk scale are assessed in terms of their internal consistency and convergence. Based on factor analysis results, a final set of items for the travel risk scale is formulated. The goal is to find a coherent uni-dimensional scale that is able to capture activity-travel risk attitudes under uncertainty. The full sample (N=397, 194 females and 203 males) was randomly split into two parts. Sample I consists of 190 respondents (97 females and 93 males) and a slightly bigger portion (Sample II) consists of 217 respondents (97 female and 110 males). 176 car users, 127 car-public mixed mode user and 94 public transport users comprise the full sample. Sample I consists of 90 car users, 50 mixed mode users and 50 public transport mode users. Sample II consists of 86 car users, 77 mixed mode users and 44 public transport mode users. The first sample is used for exploratory factor analysis to check the dimensionality and internal consistency and the second sample is used for confirmatory factor analysis to examine the scale validity.

7.3.1 Item elicitation

To construct a uni-dimensional scale measuring the activity-travel risk attitudes, we used item-total correlation and exploratory factor analysis for purification of the initial item pool for different travel modes. Psychometric theory suggests 0.30 as the minimum item-total correlation for discriminating items (Nunnally and Bernstein., 1994) and Cronbach coefficient alpha exceeding 0.7 as an acceptable
reliability of internal consistency. For each transport mode group, items with high item–total correlation scores (> 0.3) were selected as the final scale items. All items had been re-aligned into the same direction to avoid negative correlations.

**Car users**

After removing items that have a lower item-total correlation than the threshold, a total of 6 items is left for constructing the scale for car users to measure their risk attitude towards uncertainty (Table 7.1). Table 7.1 shows the item-total correlations of the selected items and Cronbach’s alpha without this item. The overall Cronbach alpha is 0.71, which is above the suggested acceptance level. The eigenvalues of the factor analysis suggest that the scale is uni-dimensional, as shown in Table 7.4.

<table>
<thead>
<tr>
<th>Item</th>
<th>Item-Total Correlation</th>
<th>Alpha Without</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>I will always avoid a route of which I cannot assess well how long the journey will take</td>
<td>0.38</td>
<td>0.71</td>
<td>176</td>
</tr>
<tr>
<td>If I have to be somewhere in time and there is a probability of delay than I always incorporate a sufficient safety margin</td>
<td>0.58</td>
<td>0.65</td>
<td>176</td>
</tr>
<tr>
<td>If it is really necessary to be in time then I rather take a route where the probability of a delay is smallest even if the travel distance then is considerably larger</td>
<td>0.43</td>
<td>0.69</td>
<td>176</td>
</tr>
<tr>
<td>If I evaluate a route then I always look at how long the trip will take in the worst case</td>
<td>0.48</td>
<td>0.68</td>
<td>176</td>
</tr>
<tr>
<td>If there is a probability of delay then I always incorporate sufficient margin in my appointments with others</td>
<td>0.58</td>
<td>0.65</td>
<td>176</td>
</tr>
<tr>
<td>If there is a probability of delay, then I take it as it happens</td>
<td>0.31</td>
<td>0.73</td>
<td>176</td>
</tr>
</tbody>
</table>

5 Alpha without denotes Cronbach alpha without this item.
Table 7.2 Item-total correlations and Cronbach’s alpha without for mixed mode users

<table>
<thead>
<tr>
<th>Item</th>
<th>Item-Total Correlation</th>
<th>Alpha Without</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>If I have to be somewhere in time and there is a probability of delay than I always incorporate a sufficient safety margin</td>
<td>0.46</td>
<td>0.68</td>
<td>127</td>
</tr>
<tr>
<td>If I have to be in time somewhere then I always take a train earlier</td>
<td>0.58</td>
<td>0.65</td>
<td>127</td>
</tr>
<tr>
<td>If it is really necessary to be in time then I rather take two trains than one train earlier</td>
<td>0.44</td>
<td>0.70</td>
<td>127</td>
</tr>
<tr>
<td>If I evaluate a route then I always look at how long the trip will take in the worst case</td>
<td>0.39</td>
<td>0.68</td>
<td>127</td>
</tr>
<tr>
<td>If there is a probability of a delay then I always incorporate a sufficient margin in my appointment with others</td>
<td>0.55</td>
<td>0.66</td>
<td>127</td>
</tr>
<tr>
<td>If there is a probability of a delay then I take it how it happens</td>
<td>0.33</td>
<td>0.71</td>
<td>127</td>
</tr>
</tbody>
</table>

Table 7.3 Item-total correlations and Cronbach’s alpha without for public transport mode users

<table>
<thead>
<tr>
<th>Item</th>
<th>Item-Total Correlation</th>
<th>Alpha Without</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>If I have to be somewhere in time and there is a probability of delay then I always incorporate sufficient margin</td>
<td>0.63</td>
<td>0.75</td>
<td>94</td>
</tr>
<tr>
<td>If there is a probability that I miss a connecting train and it is important to arrive in time then it depends strongly on how big the probability is whether I take a train earlier</td>
<td>0.41</td>
<td>0.78</td>
<td>94</td>
</tr>
<tr>
<td>If it is really necessary to be in time then I rather take two trains than one train earlier</td>
<td>0.49</td>
<td>0.77</td>
<td>94</td>
</tr>
<tr>
<td>If I evaluate a trajectory then I always look at how long the trip will taken in the worst case</td>
<td>0.53</td>
<td>0.76</td>
<td>94</td>
</tr>
<tr>
<td>If there is a probability of delay then I always incorporate sufficient margin in my appointments with others</td>
<td>0.5</td>
<td>0.77</td>
<td>94</td>
</tr>
<tr>
<td>If there is a probability of delay, then I take it as it happens</td>
<td>0.45</td>
<td>0.78</td>
<td>94</td>
</tr>
</tbody>
</table>
Table 7.4 Eigenvalues of travel risk scales for different types of mode users

<table>
<thead>
<tr>
<th></th>
<th>Comp.1</th>
<th>Comp.2</th>
<th>Comp.3</th>
<th>Comp.4</th>
<th>Comp.5</th>
<th>Comp.6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car users</td>
<td>2.56</td>
<td>0.99</td>
<td>0.83</td>
<td>0.67</td>
<td>0.59</td>
<td>0.32</td>
</tr>
<tr>
<td>Mixed mode users</td>
<td>2.56</td>
<td>0.90</td>
<td>0.78</td>
<td>0.74</td>
<td>0.55</td>
<td>0.47</td>
</tr>
<tr>
<td>Public transport mode users</td>
<td>2.63</td>
<td>0.98</td>
<td>0.82</td>
<td>0.71</td>
<td>0.51</td>
<td>0.35</td>
</tr>
</tbody>
</table>

Table 7.5 Item-total correlations and Cronbach’s alpha without for the final travel risk scale

<table>
<thead>
<tr>
<th>Item</th>
<th>Item-Total Correlation</th>
<th>Alpha Without</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>If I have to be somewhere in time and there is a probability of delay then I always incorporate sufficient margin</td>
<td>0.55</td>
<td>0.66</td>
<td>190</td>
</tr>
<tr>
<td><strong>Car</strong>: If it is really necessary to be in time then I rather take a route where the probability of a delay is smallest even if the travel distance then is considerably larger</td>
<td>0.44</td>
<td>0.70</td>
<td>190</td>
</tr>
<tr>
<td><strong>Mixed</strong>: If it is really necessary to be in time then I rather take two trains than one train earlier</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Public</strong>: If it is really necessary to be in time then I rather take two trains than one train earlier</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Car</strong>: If I evaluate a route then I always look at how long the trip will taken in the worst case</td>
<td>0.55</td>
<td>0.65</td>
<td>190</td>
</tr>
<tr>
<td><strong>Mixed</strong>: If I evaluate a route then I always look at how long the trip will take in the worst case</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Public</strong>: If I evaluate a trajectory then I always look at how long the trip will taken in the worst case</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>If there is a probability of delay then I always incorporate sufficient margin in my appointments with others</td>
<td>0.53</td>
<td>0.66</td>
<td>190</td>
</tr>
<tr>
<td>If there is a probability of delay, then I take it as it happens</td>
<td>0.38</td>
<td>0.71</td>
<td>190</td>
</tr>
</tbody>
</table>

Car and public transport mixed mode users

After removing items with item-total correlations lower than the threshold, a six items scale is left (Table 7.2). Cronbach’s alpha of 0.72 suggests a good
consistency of the resulting risk attitude scale for mixed mode users. The eigenvalues for the selected items shown in Table 7.4 suggest a uni-dimensional scale.

Public transport users
After removing items with an item-total correlation less than 0.3, a total of 6 items remains for this scale, as shown in Table 7.3. Cronbach’s alpha for this scale is equal to 0.73. The eigenvalues reported in Table 7.4 support the uni-dimensionality of the constructed scale.

<table>
<thead>
<tr>
<th>Table 7.6 Eigenvalues of final travel risk scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Comp.1</td>
</tr>
<tr>
<td>2.43</td>
</tr>
</tbody>
</table>

Final scale
Items for all three travel modes appeared to be uni-dimensional, with good item-total correlations and evidence of internal consistency. The final scale uses the 5 common items for all three transport modes. Cronbach’s alpha for this final scale is equal to 0.72. Again, eigenvalues shown in Table 7.6 suggest that the final travel risk scale has good internal consistency and is uni-dimensional.

A composite travel risk attitude scale was formed by averaging the items. This composite is used when assessing the relationship with other general risk scales to examine the convergent validity of the scale.

7.3.2 Confirmatory factor analysis
Confirmatory factor analysis (CFA) can give further evidence of the validity of a developed psychometric scale. In scale development, CFA can confirm the structure of a scale for a new sample, either a second portion of the same sample,
or a second independent sample. Another useful application of CFA is to provide a strong test of one’s model by testing various models against one another rather than simply testing a single model. In this section, a simple CFA was used to examine the overall goodness-of-fit of the developed travel risk scale.

The adequacy of model fit is measured by fit indices. The following goodness-of-fit indices are widely used to assess the degree of fit between the model and the sample data: Chi square, Goodness-of-fit (GFI), adjusted goodness-of-fit (AGFI), Tucker Lewis Index (TLI; >.90 acceptable, >.95 excellent) (Tucker and Lewis, 1973), the Comparative Fit Index (CFI: >.90 acceptable, >.95 excellent) (Bentler and Bonett, 1980; Bentler, 1990), and Root Mean Square error of approximation (RMSEA; <.08 acceptable, <.05 excellent) (Brown and Cudeck, 1993). Basically, they can be classified into three types: the absolute or stand-alone indices, the comparative or incremental fit indices, and the information-theoretic, model comparison approach of Browne and Cudeck (Brown and Cudeck, 1993). Absolute fit indices address the degree to which the variances and covariances implied by the specified model match the observed variances and covariances. The main indice of this type is chi-square. The chi-square fit index tests the hypothesis that an unconstrained model fits the covariance/correlation matrix. A problem with this test is its sensitivity to sample size, i.e., the larger the sample size, the more likely the rejection of the model and the more likely a Type II error. Another main absolute fit index is GFI, which indexes the relative amount of the observed variances and covariances explained by the model, and varies from zero to 1. AGFI is the Adjusted Goodness of Fit Index, which is akin to an adjusted R-squared in multiple regression. It is a variant of GFI that uses mean squares instead of total sums of squares in the numerator and denominator of 1 – GFI, and varies from 0 to 1 as well. Chi-square and GFI indices will favor more complex models, which is contradict the parsimony requirement by researchers. Thus, when comparing alternative models, some parsimony-corrected fit index, such as the AGFI togeth
with GFI and chi-squared, are more suitable. Comparative fit indices compare the model in question to a baseline model in which the covariances among all the variables are assumed to be zero. CFI and TLI are of this type. CFI indexes the relative lack of fit of a target model versus the independence baseline model and varies from zero to 1. Tucker-Lewis Index (TLI), also called the NNFI (nonnormed fit index), is simply another way to compare the lack of fit of a target model to the lack of fit of a baseline independence model. However, unlike the CFI, the TLI is moderately corrected for parsimony by considering the relative improvement per degree of freedom over a baseline model.

The most widely used index in the third type, the information-theoretic model comparison approach, is RMSEA, the root mean square error of approximation, which measure the error of approximation. As the TLI, it indexes discrepancy per degree of freedom, and hence is parsimony-adjusted. As some researchers pointed out, one has to be very careful when interpreting CFA or SEM results using fit indices (Hu and Bentler, 1998; 1999; MacCallum and Austin, 2000). Researchers prefer particular fit indices to others. For example, Hu and Bentler (1998) recommended against the usage of some common indices such as GFI and AGFI. MacCallum and Austin (2000) strongly recommended to use RMSEA. McDonald and Hu (2002) recommended the CFI and RMSEA and the reporting of these two indices together, along with the chi-square, has become somewhat standard.

The CFA results on the second sample \((N = 217)\), with goodness-of-fit index of 0.99, adjusted goodness-of-fit index of 0.96, an adjusted root mean square error of approximation of only 0.049, TLI index of 0.97, Bentler CFI index of 0.99, and a Chi-square of 7.46 with \(p = 0.189\), indicate very good model fit.

The item loadings are shown in Table 7.7. The loadings on items have implications on how well this indicator represents the underlying psychological construct. For
example, a loading of 0.85 on item “If there is a probability of delay then I always incorporate a sufficient margin in my appointments with others” suggests that this item is very representative of the travel risk attitude. Item “If there is a probability of delay, then I take it as it happens” indicates a lower representation of the underlying travel risk attitude.

7.4. Relationship between travel risk scale and general scales

7.4.1 Re-test of general risk scales

Despite the fact that Weber’s recreational risk attitude scale and Zimbardo’s future oriented time perspective scale have been tested and applied in other studies (D’Alessio et al., 2003; Henson et al., 2006), their applicability in a Dutch context

| Items                                                                 | Loadings | Std Error | z value | Pr(>|z|) |
|-----------------------------------------------------------------------|----------|-----------|---------|----------|
| If I have to be somewhere in time and there is a probability of delay then I always incorporate sufficient margin | 0.61     | 0.072     | 8.6     | 0.0e+00  |
| Car: If it is really necessary to be in time then I rather take a route where the probability of a delay is smallest even if the travel distance then is considerably larger |          |           |         |          |
| Mixed: If it is really necessary to be in time then I rather take two trains than one train earlier | 0.44     | 0.077     | 5.7     | 9.5e-09  |
| Public: If it is really necessary to be in time then I rather take two trains than one train earlier |          |           |         |          |
| Car: If I evaluate a route then I always look at how long the trip will taken in the worst case |          |           |         |          |
| Mixed: If I evaluate a route then I always look at how long the trip will take in the worst case | 0.54     | 0.074     | 7.3     | 2.0e-13  |
| Public: If I evaluate a trajectory then I always look at how long the trip will taken in the worst case |          |           |         |          |
| If there is a probability of delay then I always incorporate sufficient margin in my appointments with others | 0.85     | 0.073     | 11.6    | 0.0e+00  |
| If there is a probability of delay, then I take it as it happens | 0.36     | 0.076     | 4.8     | 2.0e-06  |
still has to be tested, given the argument that these psychometric constructs are in most cases domain-specific and rely heavily on testing context. Two shorter forms of the recreational risk scale and future oriented time perspective were abstracted from their original items based on their correlation with other items for two reasons. First, the exploratory factor analysis indicated that multi-dimensionality exists for both scales. Thus, shorter forms with only strongly correlated items may comprise coherent uni-dimensional psychometric measures. Second, if a construct can be accurately assessed with a smaller number of items, it could reduce response burden.

Rather than using the originally proposed items for both scales, four items from the recreational risk scale and five items from the future oriented time perspective were examined. The validity of these shorter forms of Weber’s recreational risk scale and Zimbardo’s future oriented time perspective inventory were examined as well. Following conventional practice in developing scales, the dimensionality and internal consistency of both scales were examined. This resulted in a four items recreational risk scale and a five items future oriented time perspective scale as shown in Table 7.8 and Table 7.10 with good internal consistency. Cronbach’s alpha of the shorter version of recreational risk scale is 0.78. The eigenvalues, reported in Table 7.9, suggest that the scale is uni-dimensional.

Table 7.8 Item-total correlations and Cronbach’s alpha without of the final recreational risk attitude scale

<table>
<thead>
<tr>
<th>Item</th>
<th>Item-Total Correlation</th>
<th>Alpha Without</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Going on a safari in Kenya</td>
<td>0.45</td>
<td>0.80</td>
<td>397</td>
</tr>
<tr>
<td>Going whitewater rafting at high water in the spring</td>
<td>0.65</td>
<td>0.69</td>
<td>397</td>
</tr>
<tr>
<td>Periodically engaging in a dangerous sport (e.g. mountain climbing or sky diving)</td>
<td>0.69</td>
<td>0.67</td>
<td>397</td>
</tr>
<tr>
<td>Trying bungee jumping</td>
<td>0.56</td>
<td>0.74</td>
<td>397</td>
</tr>
</tbody>
</table>
When examining the future oriented time perspective, the items “If things don’t get done on time, I don’t worry about it” and “Before making a decision, I weigh the costs against the benefits” had very low item-total correlations (0.08 and 0.21 respectively) and were therefore deleted. The resulting scale has a Cronbach alpha of 0.72. As shown in Table 7.11, the eigenvalues of the factor analysis on the remaining items suggest that the scale is uni-dimensional.

<table>
<thead>
<tr>
<th>Item</th>
<th>Item-Total correlation</th>
<th>Alpha Without</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>When I want to achieve something, I set goals and consider specific means for reaching those goals</td>
<td>0.48</td>
<td>0.68</td>
<td>397</td>
</tr>
<tr>
<td>Meeting tomorrow’s deadlines and doing necessary work comes before tonight’s play</td>
<td>0.44</td>
<td>0.70</td>
<td>397</td>
</tr>
<tr>
<td>I complete projects on time by making steady progress</td>
<td>0.46</td>
<td>0.69</td>
<td>397</td>
</tr>
<tr>
<td>I am able to resist temptations when I know that there is work to be done</td>
<td>0.56</td>
<td>0.65</td>
<td>397</td>
</tr>
<tr>
<td>I keep working at difficult, uninteresting tasks if they will help me get ahead</td>
<td>0.48</td>
<td>0.68</td>
<td>397</td>
</tr>
</tbody>
</table>

In the subsequent sections, these shorter forms of the recreational risk attitude scale and the future oriented time perspective were used.

<table>
<thead>
<tr>
<th>Comp.1</th>
<th>Comp.2</th>
<th>Comp.3</th>
<th>Comp.4</th>
<th>Comp.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.39</td>
<td>0.74</td>
<td>0.70</td>
<td>0.63</td>
<td>0.54</td>
</tr>
</tbody>
</table>
7.4.2 Relationship between travel risk attitude, recreational risk attitude and future oriented time perspective

To verify the validity of the derived activity-travel risk scale, the relationship between the activity-travel risk scale and the other two risk scales was explored. First, three composite latent construct variables were constructed for each individual by taking the average of item scores for each scale. The correlations among these three variables are shown in Table 7.12. Note, the recreational risk scale has been realigned to have the same direction as travel risk scale and future oriented time perspective scale. Thus, after re-alignment, a high risk-attitude score indicates acceptance of large risks (and vice versa) and a high future-orientation score indicates a high awareness of future time (and vice versa).

As shown in Table 7.12, travel risk attitude is positively correlated with recreational risk attitude and positively correlated with the future oriented time perspective. Both relations are significant at the 0.01 level. Travel risk attitude has a stronger correlation with future oriented time perspective than with recreational risk attitude. Recreational risk attitude and future time perspective have very weak non-significant correlation.

Table 7.12 Correlations among travel risk, Weber's risk and time perspective

<table>
<thead>
<tr>
<th></th>
<th>Travel attitude</th>
<th>recreational risk attitude</th>
<th>Future oriented time perspective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel risk attitude</td>
<td>1</td>
<td>0.252**</td>
<td>0.348**</td>
</tr>
<tr>
<td>Recreational risk attitude</td>
<td>0.252**</td>
<td>1</td>
<td>0.065</td>
</tr>
<tr>
<td>Future oriented time perspective</td>
<td>0.348**</td>
<td>0.065</td>
<td>1</td>
</tr>
</tbody>
</table>

**significance at 0.01 level
**SEM models**

Structural Equation modeling, or SEM, is a powerful statistic tool that has advantages compared to correlation analysis, multiple regression analysis and ANOVA. Factor analysis, path analysis and regression all represent special cases of SEM. It is one of the most used approaches for confirmatory analysis. Rather than explanatory factory analysis, SEM is mostly used to determine whether a hypothetical model is valid or not. However, SEM can be used in explanatory analysis as well. In most SEM applications, several model comparisons are made to determine the favored model.

Basically, SEM model consists of two elements, a structural model and measurement model. The measurement model captures the relationship between observed variables, indicators and latent constructs, which are hypothesized to be measured. The structural model captures the internal relationships among the latent variables. Most attention in SEM modeling is often devoted to latent constructs. They measure abstract concepts that are not directly measurable, such as attitude, satisfaction, willingness, etc. Their effects can be only observed by manifest variables or indicators. There are two types of variables in structural equation models, exogenous variables that are the independent variables in any equations in the system and endogenous variables that are dependent variables in at least one equation in the system and these endogenous variables may themselves be independent variables in other equations.

SEM provides several advantages over other analytic techniques in that it allows the specification of causal relationships between observed variables and latent constructs while simultaneously accounting for item-level measurement error (Bryant and Yarnold, 1995) when applying it in scale development. For the validity of developed scale, SEM can be used to examine the extent of their similarity with other similar scales. This represents a test of convergent validity. To explore
possible underlying relations, comparing different conceptualizations of the factor structure among three scales, a series of SEM models was fitted using the full sample data. These models include the following (see Figure 7.1):

1. A null model that assumes the activity-travel risk scale, the recreational risk scale, and the future oriented time perspective are unrelated. As the statistics already show these scales are indeed related, and thus this model serves as a base-line model with which other models can be compared.

2. A one factor model that assumes all items from the three scales are governed by a universal latent risk attitude variable. Individuals do not differentiate different risk contexts or domains, and their risk attitudes can be best represented by a uni-dimensional factor rather than three.

3. A causal model that assumes recreational risk attitude and future oriented time perspective are more general than activity-travel risk attitude. Thus, in this model, activity-travel risk attitude is assumed to be dependent on the other scales.

4. A hierarchical model that assumes a higher order factor representing general risk attitude exists. All three risk attitude factors are subscales of this general risk attitude. This model is observationally indistinguishable with a model that all three factors are correlated to each other, the loadings on three factors from higher order factor can be accounted for equally well by correlations among three factors. Support of this model suggests the developed travel risk model is a valid construct that measures a different domain from the recreational risk scale and the time perspective scale.

Table 7.13 shows that model fit increases from the null model to the hierarchical model. The best fitting model is the hierarchical/correlated model: goodness-of-fit is 0.963, Tucker Lewis Index is 0.967, the Comparative Fit Index is 0.974, and Root Mean Square error of approximation is 0.034.

When choosing the final model, not only the fit indices have to be taken into account, theoretical soundness and plausibility are also important for model selection (Noar, 2003). As indicated by Table 7.13 and Figure 7.2, the hierarchical/correlation model outperforms the other models, although only
marginally better than the causal model, in which the time perspective and recreational activity risk attitudes are considered more general and have causal effects on travel risk attitudes. Despite the fact that the hierarchical/correlated model fits slightly better than the causal model, the correlation between future oriented time perspective and recreational risk attitude is very weak (0.09) and not significant ($p = 0.165$), which agrees with the correlation results shown in Table 7.12. Hence, based on the assumption that travel risk attitude is more specific and influenced by other more general risk attitudes, the causal model is chosen as the final model.

Figure 7.2 shows the hypothesized model structure that represents the relationships

![Figure 7.1 Hypothetical models]
between travel risk, recreational risk attitude and future oriented time perspective for causal model and hierarchical/correlated model. In the causal model, the loading from recreational risk attitude to travel risk is 0.39 at the 0.01 significance level. The loading from future oriented time perspective to travel risk attitude is 0.58 at the 0.01 significance level. In terms of convergent validity, given the significant relations to the other two constructs, results indicate that those who are more risk taking in considering future oriented time effects are more likely to endorse a risk taking strategy in travel choices. Likewise, those who are risk taking in recreational activities are more likely to be risk seeking in travel choice as well.

The results shown in Table 7.14 indicate that the constructs of travel risk attitude, recreational risk attitude and future time perspective are closely correlated to their corresponding items (all item loadings are significantly higher than 0.3 at 0.01 significance level).

<table>
<thead>
<tr>
<th>Table 7.13 Model fit indices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null model</td>
</tr>
<tr>
<td>$\chi^2$</td>
</tr>
<tr>
<td>df</td>
</tr>
<tr>
<td>$p$</td>
</tr>
<tr>
<td>Goodness-of-fit</td>
</tr>
<tr>
<td>Adjusted goodnness-of-fit</td>
</tr>
<tr>
<td>RMSEA</td>
</tr>
<tr>
<td>Bentler-Bonnett NFI</td>
</tr>
<tr>
<td>Tucker-Lewis TLI</td>
</tr>
<tr>
<td>Bentler CFI</td>
</tr>
<tr>
<td>SRMR</td>
</tr>
<tr>
<td>BIC</td>
</tr>
</tbody>
</table>
Causal model  
Hierarchical/correlated model

Figure 7.2 Estimates of Causal model and Hierarchical/correlated model

Table 7.14 Factor loadings of hierarchical latent variable risk model

| Factor | Estimate | Std Error | z | Pr(>|z|) |
|--------|----------|-----------|---|---------|
| **Recreational risk scale** |          |           |   |         |
| 1. Going on a safari in Kenya | 0.50     | 0.052     | 9.7 | 0.0e+00 |
| 2. Going whitewater rafting at high water in the spring | 0.77     | 0.048     | 16.2 | 0.0e+00 |
| 3. Periodically engaging in a dangerous sport (e.g. mountain climbing or sky diving) | 0.82     | 0.047     | 17.6 | 0.0e+00 |
| 4. Trying bungee jumping | 0.67     | 0.049     | 13.9 | 0.0e+00 |
| **Future oriented time perspective** |          |           |   |         |
| 1. When I want to achieve something, I set goals and consider specific means for reaching those goals | 0.59     | 0.054     | 11.0 | 0.0e+00 |
| 2. Meeting tomorrow’s deadlines and doing necessary work comes before tonight’s play | 0.52     | 0.054     | 9.6  | 0.0e+00 |
| 3. I complete projects on time by making steady progress | 0.58     | 0.054     | 10.8 | 0.0e+00 |
| 4. I am able to resist temptations when I know that there is work to be done | 0.68     | 0.053     | 13.0 | 0.0e+00 |
| 5. I keep working at difficult, uninteresting tasks if they will help me get ahead | 0.57     | 0.054     | 10.6 | 0.0e+00 |
| **Travel risk scale** |          |           |   |         |
| 1. If I have to be somewhere in time and there is a probability of delay then I always incorporate sufficient margin | 0.55     | 0.046     | 11.9 | 0.0e+00 |
2. **Car:**
   If it is really necessary to be in time then I rather take a route where the probability of a delay is smallest even if the travel distance then is considerably larger

**Mixed:**
If it is really necessary to be in time then I rather take two trains than one train earlier

**Public:**
If it is really necessary to be in time then I rather take two trains than one train earlier

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.38</td>
<td>0.046</td>
<td>8.3</td>
<td>2.2e-16</td>
</tr>
</tbody>
</table>

3. **Car:**
   If I evaluate a route then I always look at how long the trip will taken in the worst case

**Mixed:**
If I evaluate a route then I always look at how long the trip will take in the worst case

**Public:**
If I evaluate a trajectory then I always look at how long the trip will taken in the worst case

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.49</td>
<td>0.045</td>
<td>10.9</td>
<td>0.0e+00</td>
</tr>
</tbody>
</table>

4. If there is a probability of delay then I always incorporate sufficient margin in my appointments with others

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.61</td>
<td>0.048</td>
<td>12.8</td>
<td>0.0e+00</td>
</tr>
</tbody>
</table>

5. If there is a probability of delay, then I take it as it happens

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0.31</td>
<td>0.046</td>
<td>6.8</td>
<td>1.1e-11</td>
</tr>
</tbody>
</table>

7.5. **Travel risk attitude and information acquisition behavior**

Self-reported information acquisition behavior data were also collected in this survey. In the web-based survey, respondents were asked to indicate which source of travel information they usually consult and the frequencies with which they acquire travel information in different situations. Four information sources were considered in the experiments: teletext, radio, telephone, SMS and internet.

Table 7.15 shows that respondents acquire travel information mostly through the internet (97.7%), radio (86.4%) and teletext (80.9%). Only 61% of the respondents use telephone, whilst 61.2% use SMS. Internet has the highest rate in this sample, given the fact that the internet are widely available at the present time.
Respondents were asked to indicate how often they acquire travel information in different situations (familiar, unfamiliar) and at which stage (during planning stage, before departure stage and in execution stage) of the travel (see Appendix A-4).

Table 7.16 Frequency of acquiring information at different stage in different situations

<table>
<thead>
<tr>
<th></th>
<th>Unfamiliar route</th>
<th>Familiar route</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>plan</td>
<td>departure</td>
</tr>
<tr>
<td>Never</td>
<td>38</td>
<td>65</td>
</tr>
<tr>
<td>Sometime</td>
<td>77</td>
<td>151</td>
</tr>
<tr>
<td>Generally</td>
<td>127</td>
<td>126</td>
</tr>
<tr>
<td>Always</td>
<td>155</td>
<td>55</td>
</tr>
</tbody>
</table>

Table 7.16 shows the behavior under different situations. In an unfamiliar travel context, 90% of the respondents will acquire information at least sometimes during the planning stage, whilst only 41% choose to acquire information in familiar travel situations. At the departure time, 83.6% respondents choose to acquire information in unfamiliar travel situations and 56% will do so in familiar travel situations. During the execution (en-route) stage, 45% of the respondents choose to acquire information in unfamiliar travel situations, while 36% acquire information in familiar travel situations. Thus, respondents tend to acquire information more in unfamiliar travel situations than do they in familiar situations. The information acquisition frequency decreases from the travel planning stage to the execution stage.
7.6. Risk scales and revealed activity-travel risk attitudes

The membership estimated for heuristic latent class model and willingness to pay (WTP) mode model provide information about the probability of a traveler belonging to a particular category. The correlations between the travel risk scale (composite) and activity-travel risk memberships of two models are shown in Table 7.17 and Table 7.18.

Table 7.17 Correlation between heuristic latent class model membership and risk scales

<table>
<thead>
<tr>
<th></th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>Travel</th>
<th>Weber</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1</td>
<td>1</td>
<td>-0.324**</td>
<td>-0.966**</td>
<td>-0.046</td>
<td>-0.078</td>
<td>-0.086</td>
</tr>
<tr>
<td>V2</td>
<td>-0.324**</td>
<td>1</td>
<td>0.067</td>
<td>0.103*</td>
<td>-0.008</td>
<td>-0.028</td>
</tr>
<tr>
<td>V3</td>
<td>-0.966**</td>
<td>0.067</td>
<td>1</td>
<td>0.02</td>
<td>0.085</td>
<td>0.098</td>
</tr>
<tr>
<td>Travel</td>
<td>-0.046</td>
<td>0.103*</td>
<td>0.02</td>
<td>1</td>
<td>-0.252**</td>
<td>0.348**</td>
</tr>
<tr>
<td>Weber</td>
<td>-0.078</td>
<td>-0.008</td>
<td>0.085</td>
<td>-0.252**</td>
<td>1</td>
<td>-0.065</td>
</tr>
<tr>
<td>TP</td>
<td>-0.086</td>
<td>-0.028</td>
<td>0.098</td>
<td>0.348**</td>
<td>-0.065</td>
<td>1</td>
</tr>
</tbody>
</table>

V1, V2, V3 denote the class membership (probability). As the results show, correlations between risk scales and memberships of both models are low and not significant, one exception is that V2 and travel risk scale in the heuristic model estimation are significantly correlated, however, given the negligible proportion of

Table 7.18 Correlation between WTP model membership and risk scales

<table>
<thead>
<tr>
<th></th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>Travel</th>
<th>Weber</th>
<th>TP</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1</td>
<td>1</td>
<td>-0.429**</td>
<td>-0.345**</td>
<td>-0.065</td>
<td>-0.002</td>
<td>-0.076</td>
</tr>
<tr>
<td>V2</td>
<td>-0.429**</td>
<td>1</td>
<td>-0.700**</td>
<td>0.026</td>
<td>-0.062</td>
<td>-0.012</td>
</tr>
<tr>
<td>V3</td>
<td>-0.345**</td>
<td>-0.700**</td>
<td>1</td>
<td>0.024</td>
<td>0.066</td>
<td>0.073</td>
</tr>
<tr>
<td>Travel</td>
<td>-0.065</td>
<td>0.026</td>
<td>0.024</td>
<td>1</td>
<td>-0.252**</td>
<td>0.348**</td>
</tr>
<tr>
<td>Weber</td>
<td>-0.002</td>
<td>-0.062</td>
<td>0.066</td>
<td>-0.252**</td>
<td>1</td>
<td>-0.065</td>
</tr>
<tr>
<td>TP</td>
<td>-0.076</td>
<td>-0.012</td>
<td>0.073</td>
<td>0.348**</td>
<td>-0.065</td>
<td>1</td>
</tr>
</tbody>
</table>
risk taking class, the correlation does not necessarily imply. The failure to find significant correlations between revealed activity-travel risk attitude and stated travel risk attitude measured by the travel risk scale may have several implications. First, it suggests that revealed activity-travel risk attitude is different from what travelers perceive and state they will do in the stated risk attitude survey. Second, risk attitude seems to be intrinsically domain-specific. In the activity-travel simulator experiments, a respondent not only needs to evaluate explicit risk in travel outcomes, but also needs to prioritize different activities. Whilst in the travel risk survey, risk concerns only travel outcomes. Thus, risk attitude captured in the activity travel simulator experiments may be different from risk attitude measured in travel risk survey. Third, attitude is strongly situational dependent and situational dependence is not taken into account by the scales: they lead the respondents to think about an overall average of their behavior. In the experiment they can take into account the characteristics of the situation. If the situation has a large influence then one would see a strongly suppressed correlation and that may be in fact what we see here.

7.7. Stated risk attitude and revealed monetary choices

At the end of the experiments, participants were asked to choose how they prefer to receive their rewards, tickets that can be used in many shops in Eindhoven. There are five reward schemes in lottery form with different probabilities of winning, namely, 10 Euros for certain, 80% chance winning 12.5 Euros, 50% chance winning 20 Euros, 20% chance winning 50 Euros and 10% chance winning 100 Euros. Of the 397 respondents who participated in this study, 392 indicated that they would like to receive a reward. Their choices are shown in Table 7.19. It shows that the majority manifested risk aversive behavior.
Of the 392 participants, 290 chose 10 Euros for certain which accounts for 74% of all participants. However, of the remaining participants who preferred an uncertain outcome, 13.8% chose 100 Euros with a 10% probability of winning, 7.4% preferred winning 20 Euros with a probability of 50%, while the remaining options (12.5 Euros with 80% and 50 Euros with 20% probability) together accounted for 4.8% of all participants who indicated they wish to receive a reward. Participants who choose uncertain rewards manifested risk seeking attitudes. Most of respondents who indicated a lottery preferred a high reward level with low probability. Only few chose the 80% chance of winning 12.5 Euros. The results show that those people who choose for a lottery have a higher preference for a lower probability of a higher reward (10%, 100Euros).

The results are consistent with much evidence suggested by prospect theory, especially the probability weighting function, which implies (i) an overweighing of small probabilities implying that decision makers tend to be risk-seeking in situations when offered low-probability, high-reward lotteries, and (ii) an extreme underweighing of high probabilities, which are very close to certain outcomes, making certain positive outcomes very attractive.

The correlations among rewards choices (treated as a 5-level ordinal variable ranging from low to high risk) and stated risk attitudes are shown in Table 7.20. Rewards choices are only weakly positively correlated with recreational risk attitude.

<table>
<thead>
<tr>
<th>Table 7.19 Rewards probability and volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 Euros</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>290</td>
</tr>
<tr>
<td>74.0%</td>
</tr>
</tbody>
</table>
Despite that answers to monetary rewards indicate a risk-averse pattern, these attitudes are not reflected in the correlation table, which either implies an inconsistency between revealed behavior and stated risk preference or implies that risk attitudes towards monetary choices are different from risk attitude towards other choice types as travel, recreational activity and time perspectives. This has also been pointed out by Weber et al. (2002) who argued that risk attitude towards monetary or gambling decisions are different from risk attitudes to social or recreational choices. This result may also suggest that special attention has to be paid when applying general descriptive decision models in specific domains like travel decisions, since most of these theories including prospect theory were developed based on and for lottery games and therefore their applicability in other domains may be limited.

### 7.8. Discussion and conclusion

In this chapter, a five items travel risk scale concerning activity-travel choices in uncertain travel environments was developed. The initial item pool was reduced to the final five items by removing items with low item-total correlations. The internal consistency reliability associated with the final scale is good, judged by common standards. The final scale was then checked using confirmatory factor analysis, and again results were positive. In addition, construct convergent validity was assessed using a structural equation model against a recreational risk scale and
a future oriented time perspective of Zimbardo’s time perspective inventory. Finally, the relationship between the developed travel risk scale and self-reported travel information acquisition behavior and monetary reward choices were examined.

SEM models and confirmatory analysis suggest that a causal relationship exists among recreational risk attitude, future oriented time perspective and activity-travel risk attitude. That is, the travel risk attitude is correlated positively with future oriented time perspective and with recreational risk attitude.

Some findings have not been entirely conclusive and deserve further exploration. For example, despite the fact that the travel risk scale is internally consistent and valid in terms of convergent validity, it does not correlate with self-reported information acquisition behaviors. Similar findings were obtained for the correlation test between risk scales and revealed monetary reward choices. The interesting reward results show that when facing real monetary choices, the majority of our participants show risk-averse behavior. These results and the failure of finding strong correlations between travel risk and heterogeneous activity-travel risk attitudes together may imply that risk attitudes are indeed domain-specific. Thus, when applying some descriptive decision theory from another domain, one has to be careful about its applicability to the new domain.
8. Discussion and conclusion

In daily activity-travel decisions, travelers face a dynamic and, most of the time, uncertain travel environment. Unexpected delays come from congestion, accidents, off-schedule bus and train connections, etc. Travelers have to make their activity-travel choices in the context of these unexpected disturbances and adjust their original plans accordingly during the implementation of their activity-travel plans. Gradually, travelers will accumulate knowledge about their travel environment and formulate their beliefs about the transportation network and surrounding environments, and make decisions based on their learned and adjusted beliefs. The widely available travel information, which is likely to increase in years to come, allows travelers to get easily acquainted with the transportation network and hence reduce risk in making travel decisions. Travelers may however manifest heterogeneity in their travel choices under uncertainty. In similar situations, travelers with purporting different risk attitudes may behave differently. Risk-averse travelers may schedule their activity plans under a worst case scenario, risk neutral travelers may carefully calculate the payoff of possible alternatives in a rational way, while risk taking travelers may disregard the possibilities of outcomes with lower probabilities.

Most research on travel information has either dealt with the importance of travel information in reducing uncertainty and the corresponding willingness to pay or with the effects of travel information on simple, mostly uni-dimensional travel choices. The goal and innovative contribution of this research project is to better understand the perceived value of travel information and the impact of travel information on comprehensive activity-travel patterns as opposed to single facet choices under multiple uncertain events as opposed to single events. This work is motivated by the belief that only by considering this increased complexity
ultimately dynamic activity-based models that also take travel information, route choice and activity rescheduling behavior into account can be developed.

In this thesis, to capture multiple uncertain events and activity (re)scheduling choice options, a utility-tree based activity-travel decision framework has been developed. Learning effects were incorporated in terms of a Bayesian belief network representation. In this framework, travelers are assumed to make activity-travel decisions using scenarios, assuming that travelers specify possible outcomes of uncertain events as scenarios based on their beliefs and acquired information. Thus, this framework is capable of representing activity-travel choices, rescheduling decisions, learning, causal knowledge under uncertainty and perceived credibility of the information source. Numerical simulation provided further validation of this conceptual framework. The numerical simulation showed the framework generates interpretable results.

As people may have different attitudes towards travel risk and different willingness to acquire travel information, two latent class models were developed. The first model captures travelers’ heterogeneity in terms of their attitudes towards uncertain events. A heuristic approach was used in this model. Basically, this model assumes that travelers evaluate their travel choice alternatives using heuristics when facing uncertain outcomes. The heterogeneity is then represented by the different heuristics applied by travelers. Three types of heuristics were identified: risk-averse travelers who evaluate their alternatives using a worst case heuristic which is based on the lowest utility outcomes of uncertain events; risk-taking travelers who evaluate alternatives using the most likely outcome of uncertain events as the basis of their choices, and rational travelers who make travel choices based on expected utility. A second model focuses on the willingness to pay of travelers for travel information. It assumes that travelers evaluate their travel choice alternatives
based on the concept of expected utility. Heterogeneity in willingness to pay is captured by heterogeneous preferences for the price of travel information.

To collect empirical data, an interactive-web based travel simulator was developed. It was used as a platform for dynamic, interactive computer experiments. In the experiments, respondents were told a storyline and based on this storyline they were asked to make activity-travel decisions, related to activity rescheduling, route choice and information acquisition. The simulator recorded changes in the states of the simulated system, updated information and provided relevant feedback to respondents, and dynamically showed relevant choice options. Two versions of the experiment were created, which differed in terms of the timing of uncertain events. One experiment involved simultaneous multiple uncertain events, while another was concerned with sequential multiple uncertain events.

The two heterogeneity models were estimated using the data collected in the interactive computer experiments. The results of these estimations provide evidences of face validity for both models, as the signs of the estimated parameters of both models were consistent with a priori expectations and interpretable in relative magnitude of estimated parameters. In case of the heuristic latent class model, the percentage of risk-takers in the sample is negligible, while the percentage of risk avoiders is much higher. In the willingness to pay model, a 3-class solution was found. All three classes are clearly distinguishable in the sample and can be interpreted on a dimension of risk aversion versus risk taking.

Finally, a psychometric scale was developed to measure the travelers’ activity-travel risk attitudes to increase our understanding of travel behavior from a different aspect. A five items scale was elicited with good internal consistency and good convergent validity. Using a structural equations model, the relationship of this activity-travel risk scale with two other risk scales (a recreational risk scale and
a future oriented time perspective scale) was explored. The results of the analysis indicated that correlation exists in that the activity-travel risk scale is correlated with the recreational risk attitude scale and the future oriented time perspective. However, findings of non-correlation between the travel risk scale and other risk related behavior and measurements, e.g., activity-travel risk attitude, information acquisition behavior, and choices of monetary lottery, implies that risk attitudes are probably domain-specific and situation dependent.

The specific strength of the general framework is that the broader scheduling implications of information and decisions are taken into account, making the model more sensitive to re-scheduling effects in terms of both perceived value and impact of information. Activity-travel decisions are represented by a decision tree structure, implying that the interdependencies in activity-schedules are captured naturally by the tree structure. Uncertainties are represented by chance nodes in the decision tree.

Compared to other activity-based models, the models developed in this study represent an attempt to integrate many elements in activity-travel behavior into one comprehensive modeling framework, including (re)scheduling, route choice, departure time choice, destination choice, inference, learning effects, uncertainty, risk attitudes and information (reliability) effects. This is achieved by combining approaches including decision tree representation, Bayesian learning, discrete choice, heuristic decision rules, and latent class modeling. The flexibility of the general framework allows the substitution of its decision components. For example, the heuristic latent class model uses heuristics to make activity-travel choices rather than utility-maximization decision rules.

The findings of both the heuristic latent class model and the willingness to pay model have some policy and managerial implications. The results show that travel
information does not only reduce uncertainty in travel situations but in doing so will also lead to activity rescheduling decisions. It means that route choice and activity-based models should be adjusted to relate to entire days as short-term simulations likely tell only part of the story. It also implies that in designing scenarios for information provision, the consequences for activity rescheduling should be taken into consideration by policy makers. This is even more critical if the focus is on optimal control strategies.

This study has added the findings that propensity to use information also depends on decision style. Acquiring travel information seems less relevant for risk-takers and risk-neutral travelers. Especially the latter group seems to make up a substantial share of the travelers. It means that when targeting different segments of the population, it would be most efficient, effective and cost-saving if the group of risk-avoiders could be better targeted. Of course, this will be difficult in general, but if decision style would be systematically related to socio-demographics characteristics, marketing efforts could be improved.

As many complex models, the models developed in this study suffer the difficulty of trading-off between model complexity and practical feasibility. The explicit representation of uncertainties in the decision tree raises the problem of combinatorial explosion. Although the empirical analysis suggests that it is feasible to incorporate two uncertain events as shown in Chapter 6, it is not straightforward to extend the models to handle a large number of uncertain events. This remains a problem when the activity-pattern becomes more complex. In realistic situations, when activity-travel decisions involves many activity types with multiple destinations, multiple departure time possibilities and multiple route alternatives, how to confine the model to arrive at a practically feasible model deserves further attention. A possible solution is to develop tree pruning rules to remove those un-influencing branches in the decisions tree. To derive these pruning rules, one has to
closely check the detailed tree structure to find those branches that can be removed without affecting the decision results.

When considering activity-travel data collection, the interactive web based travel simulator forms a flexible virtual laboratory for collecting activity behavioral data dynamically. With information provision components, it becomes a test-bed for different information provision strategies in the context of activity-travel behavior. Based on the internet, it enables us to reach respondents with relatively less costs.

The final psychometric activity-travel risk scale explored travel risk attitude from different aspects and thus forms a complementary part of the developed framework and provides a concise and easy method to assess travelers risk attitudes. The failure of linking this risk scale to risk attitudes membership revealed in hypothetical activity-travel experiments is not necessarily an implication to invalid either measure; rather, it may imply: (i) either a subtle difference existing between revealed activity-travel risk attitude and stated risk attitude in activity planning behavior. Or, (ii) risk attitude captured in the experiments and risk attitudes measured in travel risk scale belong to different risk domain hence they are domain-specific.

Although the general framework and derived models presented in this thesis contribute to activity-based modeling, several issues deserve further consideration in future research. First, the assumption of travelers using scenarios to evaluate their choice alternatives under uncertainty introduces the problem of combinatorial explosion. When uncertainty relates to multiple events spread across the day, the number of possible scenarios to be considered soon becomes intractable. However, we have shown that in many cases insignificant branches of the decision tree can be pruned. Only, in case the outcomes of an event have consequences for the optimal schedule in the pre-event section, alternative schedules need to be taken
into account. In all other cases a decision can be postponed to a later decision moment. However, there remains the empirical question which simplifying strategies individuals use under what circumstances. Will they exhibit myopic behavior, or will they select only a subset of attributes or some combination of these strategies? Will they exhibit heterogeneity in terms of their myopic behavior? When operationalising the suggested approach for large scale applications, the multiple uncertain events representation still deserves additional research.

Second, an interesting question is whether travelers’ decision styles are related to personal traits or to situational factors or to some combination of both. Besides the manifested heterogeneity in traveler’s activity choices under uncertainty caused by personal traits’ differences, the manifested heterogeneity may relate to situational factors as well. That is to say, the same traveler may show different risk attitudes in different activity-travel environments given the same amount of uncertainty. In this sense, trip purpose, time pressure and status of activity schedule play important roles in risk attitude. The assumption then is that individuals are homogeneous in risk perception and evaluations, but they are sensitive to situational settings when making risk travel choices. Existing theoretical frameworks and models applied in transportation research to the problem of the impact of travel information, such as studies applying cumulative prospect theory and regret theory, seem to have ignored this issue, and if it is relevant, the findings of these studies may have been biased.

Third, the socio-demographic attributes did not play a role in the modeling efforts, described in this thesis. Given the fact that many studies had evidenced the influencing effects of socio-demographic attributes on risk attitudes, the incorporation of such elements constitutes another potentially relevant analysis of future research.
Fourth, as the models become increasingly more complex especially when dealing with multiple uncertainties, it will also be meaningful to compare a simpler choice model against the proposed hierarchical decision tree representation of activity-travel model to explore the effects of degree of complexity of models. However, finding a simpler model that is capable of addressing the activity-travel decisions regarding multiple uncertainties remains a challenging task.

Finally, although the learning effect was modeled in the general framework developed in this study, it did not appear in the empirical analysis. The current experimental design does not allow the exploration of such effects. Dedicated experiments specifically focusing on activity-travel learning or sophisticatedly designed experiments that are able to capture both heterogeneity and learning effects would be a useful complementary study to the current work. However, in order to study these effects simultaneously, sophisticated experimental designs are required. This issue constitutes a relevant research topic in its own right. Or alternatively, the same experiment as reported here can be used as a starting point of such experiments, where the probabilities of delay outcomes are not presented in each treatment, but rather learned across treatments by the respondent based on feedback.

Overall, although further extensions and improvements are required, the use of web based experiments yielded satisfactory data collection results, the numerical simulation and empirical estimation results provide evidence of the validity of the framework, while the activity-travel risk scale forms a concise and easy measure for travel risk attitudes. The general framework for activity-travel decisions under information provision and uncertainty and two derived models that capture risk attitude heterogeneity in activity travel decisions provide useful modeling approaches. The empirical results and findings in this study suggest that these models offer feasible and valuable tools for policy makers. All these developments
contribute to the knowledge in the activity-based modeling paradigm both in theoretical and empirical aspects and thus enrich our understanding of how individuals make rescheduling decisions and how their activity-travel patterns evolve under uncertainty with travel information provided. Hopefully, this study will trigger further developments in activity-travel research.
9. Bibliography


Ben-Akiva, M. (1973), Structure of Passenger Travel Demand Models, PhD, Cambridge, MA, MIT


Bonsall, P. (1991), Using an Interactive Route-Choice Simulator to Investigate Drivers' Compliance with Route Guidance Advice, 6th International Conference on Travel Behavior, International Association for Travel Behavior, Quebec, Canada.


Appendices

Appendix A: Recreational risk scale

The following 1 to 5 rating scale is applied:

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zeer onwaarschijnlijk</td>
<td>Enigermate</td>
<td>Onzeker</td>
<td>Enigermate</td>
<td>Zeer waarschijnlijk</td>
</tr>
<tr>
<td>Extreme unlikely</td>
<td>Onwaarschijnlijk</td>
<td>Not sure</td>
<td>Waarschijnlijk</td>
<td>Extremely likely</td>
</tr>
<tr>
<td>Unlikely</td>
<td>Not sure</td>
<td>Likely</td>
<td>Likely</td>
<td></td>
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</table>

1. Verkennen van een onbekende stad of onbekend deel van een stad
Exploring an unknown city or section of town
2. Wild kamperen
Going camping in the wild.
3. Op safari gaan in Kenia
Going on a safari in Kenya
4. Op een tweeweekse vakantie gaan in het buitenland zonder van te voren een hotel te boeken
Going on a two-week vacation in a foreign country without booking accommodations ahead
5. Wildwater kano varen met hoog water in de lente
Going whitewater rafting at high water in the spring
6. Reizen met een commercieel vliegtuig
Traveling on a commercial airplane
7. Af en toe deelnemen aan een gevaarlijke sport (bijv. mountain biken of delta vliegen)
Periodically engaging in a dangerous sport (e.g. mountain climbing or sky diving)
8. Bungee jumping proberen
Trying bungee jumping
9. Een tornado achterna gaan met de auto om foto’s te nemen die je aan een krant kan verkopen
Chasing a tornado by car to take photos that you can sell to the press
10. Een skipiste nemen die te moeilijk of dicht is
Going down a ski run that is too hard or closed
Appendix B: Zimbardo’s time perspective-future orientation

The following 1 to 5 point scale is applied:

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<tr>
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<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Zeer niet typerend</td>
<td>Enigszins niet typerend</td>
<td>Onzeker</td>
<td>Enigszins typerend</td>
<td>Zeer typerend</td>
</tr>
<tr>
<td></td>
<td>extremely untypical</td>
<td>Slightly untypical</td>
<td>Not sure</td>
<td>Slightly typical</td>
<td>Extremely typical</td>
</tr>
</tbody>
</table>

1. Ik denk dat de dag van een persoon elke ochtend gepland zou moeten worden
I believe that a person’s day should be planned ahead each morning

2. Als dingen niet op tijd gebeuren, dan maak ik me daar geen zorgen over
If things don’t get done on time, I don’t worry about it.

3. Als ik iets gedaan wil hebben, dan stel ik doelen en bedenk ik bepaalde manieren om die doelen te bereiken
When I want to achieve something, I set goals and consider specific means for reaching those goals

4. Voldoen aan deadlines op de volgende ochtend en het doen van noodzakelijk werk komt voor ontspanning ‘s avonds
Meeting tomorrow’s deadlines and doing necessary work comes before tonight’s play

5. Te laat komen op een afspraak stoort mij
It upsets me to be late for appointments

6. Ik kom mijn verplichtingen aan vrienden en gezaghebbenden op tijd na
I meet my obligations to friends and authorities on time

7. Ik neem elke dag zoals die is in plaats van het helemaal te plannen
I take each day as it is rather than try to plan it out

8. Voordat ik een beslissing neem weeg ik de kosten af tegen de opbrengsten
Before making a decision, I weigh the costs against the benefits

9. Ik maak projecten op tijd af door gestaag vorderingen te maken
I complete projects on time by making steady progress

10. Ik maak lijstjes van dingen die ik moet doen
I make lists of things to do

11. Ik kan verleidingen weerstaan wanneer ik weet dat er werk gedaan moet worden
I am able to resist temptations when I know that there is work to be done

12. Ik blijf werken aan moeilijke, oninteressante taken als deze mij helpen verder te komen
I keep working at difficult, uninteresting tasks if they will help me get ahead

13. Er zal altijd wel tijd zijn om werk in te halen
There will always be time to catch up on my work
Appendix C: Travel Risk attitudes scale

The following are initial item pools of activity-travel risk scale for three travel mode, car users, car public transport mixed users and public transport mode users. In the web survey, respondents were asked to indicate at each proposition to what extent these are typical for them, providing a rating from 1 to 5 using the following scale:

<table>
<thead>
<tr>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zeer niet typerend</td>
<td>Enigszins niet typerend</td>
<td>Onzeker</td>
<td>Enigszins typerend</td>
<td>Zeer typerend</td>
</tr>
<tr>
<td>extremely untypical</td>
<td>slightly untypical</td>
<td>Not sure</td>
<td>slightly typical</td>
<td>Extremely typical</td>
</tr>
</tbody>
</table>

Car and public transport users:

2. Als ik een route kan kiezen die gemiddeld sneller is maar waar wel kans is op file dan hangt het sterk af van hoe groot die kans is of ik die route zou kiezen

If I can choose a route which on average is faster but has probability of a queue, then it depends strongly on how big that probability is whether I would choose that route

3. Ik zal altijd een route vermijden waarvan ik niet goed kan inschatten hoe lang de reis gaat duren

I will always avoid a route of which I cannot assess well how long the journey will take

5. Als ik ergens op tijd moet zijn en er is kans op vertraging dan bouw ik altijd een voldoende veiligheidsmarge in

If I have to be somewhere in time and there is a probability of delay than I always incorporate a sufficient safety margin

6. Als ik in een file kan komen dan houd ik daar geen rekening mee bij het bepalen hoe laat ik van huis vertrek als de kans op file klein is, ook niet als ik op tijd moet aankomen

If I can end up in a queue then I don’t take that into account in determining what time I leave from home if the probability of a queue is small even not if I have to arrive in time

8. Als ik ergens op tijd moet zijn dan neem ik altijd een trein eerder

If I have to be in time somewhere then I always take a train earlier

9. Als de kans bestaat dat ik een aansluitende trein mis en het is belangrijk om op tijd te komen dan hangt het af van hoe groot die kans is of ik een trein eerder neem

If there is a probability that I miss a connecting train and it is important to arrive in time then it depends strongly on how big the probability is whether I take a train earlier

12. Als er op een traject wel eens een trein uitvalt dan is dat voor mij geen reden om een andere route te kiezen

If on a traject a train drops out every once and a while then that for me is not a reason to choose another route
13. Als het echt noodzakelijk is om op tijd te zijn dan neem ik liever twee treinen eerder dan een trein eerder
   If it is really necessary to be in time then I rather take two trains than one train earlier
14. Als ik een route beoordeel dan kijk ik altijd naar hoe lang in het slechtste geval de reis zou duren
   If I evaluate a route then I always look at how long the trip will take in the worst case
16. Als er kans op vertraging bestaat dan bouw ik altijd voldoende marge in in mijn afspraken met anderen
   If there is a probability of a delay then I always incorporate a sufficient margin in my appointment with others
17. Als er kans op vertraging bestaat, dan neem ik het zoals het komt
   If there is a probability of a delay then I take it as it happens

---

Car users:

2. Als ik een route kan kiezen die gemiddeld sneller is maar waar wel de kans op file bestaat dan hangt het
   sterk af van hoe groot die kans is of ik die route zou kiezen
   If I can choose a route which on average is faster but has probability of a queue, then it depends strongly
   on how big that probability is whether I would choose that route
3. Ik zal altijd een route vermijden waarvan ik niet goed kan inschatten hoe lang de reis gaat duren
   I will always avoid a route of which I cannot assess well how long the journey will take
5. Als ik ergens op tijd moet zijn en er bestaat kans op vertraging dan bouw ik altijd een voldoende
   veiligheidsmarge in
   If I have to be somewhere in time and there is a probability of delay than I always incorporate a sufficient
   safety margin
6. Als ik in een file kan komen dan houd ik daar geen rekening mee bij het bepalen hoe laat ik van huis
   vertrek als de kans op file klein is, ook niet als ik op tijd moet aankomen
   If I can end up in a queue then I don’t take that into account in determining what time I leave from home if
   the probability of a queue is small even not if I have to arrive in time
9. Als er kans bestaat op vertraging en het is belangrijk om op tijd te komen dan hangt het af van hoe groot
   die kans is of ik eerder van huis vertrek
   If there is a probability of a delay and it is important to arrive in time then it depends on how big that
   probability is whether I will leave earlier from home
13. Als het echt noodzakelijk is om op tijd te zijn dan neem ik liever een route waar de kans op vertraging het
   kleinist is ook als de reisafstand dan een stuk groter is
   If it is really necessary to be in time then I rather take a route where the probability of a delay is smallest
   even if the travel distance then is considerably larger
14. Als ik een route beoordeel dan kijk altijd naar hoe lang in het slechtste geval de reis zou duren
   If I evaluate a route then I always look at how long the trip will taken in the worst case
16. Als er kans op vertraging bestaat dan bouw ik altijd voldoende marge in in mijn afspraken met anderen
   If there is a probability of delay then I always incorporate sufficient margin in my appointments with others
17. Als er kans op vertraging bestaat, dan neem ik het zoals het komt
   If there is a probability of delay then I take it as it happens
Public transport users:

2. Als een traject gemiddeld sneller is maar wel de kans heeft dat een trein uitvalt dan hangt het sterk af van hoe groot die kans is of ik dat traject zou kiezen.

   If on average a trajectory is faster but has the probability that a train drop outs then it depends strongly on how big that probability is whether I would choose that trajectory.

5. Als ik ergens op tijd moet zijn en er is kans op vertraging dan bouw ik altijd een voldoende veiligheidsmarge in.

   If I have to be somewhere in time and there is a probability of delay then I always incorporate sufficient margin in my appointments with others.

8. Als ik ergens op tijd moet zijn dan neem ik altijd een trein eerder.

   If I have to be somewhere in time then I always take a train earlier.

9. Als er kans bestaat op het missen van een aansluitende trein en het is belangrijk om op tijd te komen dan hangt het af van hoe groot die kans is of ik een trein eerder neem.

   If there is a probability that I miss a connecting train and it is important to arrive in time then it depends strongly on how big the probability is whether I take a train earlier.

13. Als het echt nodzakelijk is om op tijd te zijn dan neem ik liever twee treinen eerder dan een trein eerder.

   If it is really necessary to be in time then I rather take two trains than one train earlier.


   If I evaluate a trajectory then I always look at how long the trip will taken in the worst case.

16. Als er kans op vertraging bestaat dan bouw ik altijd voldoende marge in in mijn afspraken met anderen.

   If there is a probability of delay then I always incorporate sufficient margin in my appointments with others.

17. Als er kans op een vertraging bestaat, dan neem ik het zoals het komt.

   If there is a probability of delay, then I take it as it happens.
Appendix D: Questionnaire for travel information acquisition behavior

Wilt u in de onderstaande situaties aangeven hoe vaak het voorkomt dat u reistijd informatie inwint en op welk moment u dat doet?
(We want you to indicate in the situations mentioned below how frequently you acquired travel time information and at what moment you do that)

Train users and public transport users:

<table>
<thead>
<tr>
<th></th>
<th>Vaak</th>
<th>Regelmatig</th>
<th>Zelden</th>
<th>Nooit</th>
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<tbody>
<tr>
<td>Hoe vaak komt dit voor?</td>
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<tr>
<td>How frequent this is occurring?</td>
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<tr>
<td>Hoe vaak maakt u gebruik van een informatiedienst in die gevallen?</td>
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<tr>
<td>How frequently do you inquire travel information?</td>
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<tr>
<td>Bij plannen van de reis</td>
<td>Altijd</td>
<td>Meestal</td>
<td>Soms</td>
<td>Nooit</td>
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<td>At plans of travel</td>
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<td></td>
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<tr>
<td>Vlak voor vertrek</td>
<td>Altijd</td>
<td>Meestal</td>
<td>Soms</td>
<td>Nooit</td>
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<td>At departure</td>
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<tr>
<td>Tijdens de reis</td>
<td>Altijd</td>
<td>Meestal</td>
<td>Soms</td>
<td>Nooit</td>
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<td>During travel</td>
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<th>Vaak</th>
<th>Regelmatig</th>
<th>Zelden</th>
<th>Nooit</th>
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<td>Hoe vaak komt dit voor?</td>
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<tr>
<td>How frequent this is occurring?</td>
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<tr>
<td>Hoe vaak maakt u gebruik van een informatiedienst in die gevallen?</td>
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<td>How frequently do you inquire travel information?</td>
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<td>Bij plannen van de reis</td>
<td>Altijd</td>
<td>Meestal</td>
<td>Soms</td>
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<tr>
<td>At plans of travel</td>
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<tr>
<td>Vlak voor vertrek</td>
<td>Altijd</td>
<td>Meestal</td>
<td>Soms</td>
<td>Nooit</td>
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<tr>
<td>At departure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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Car users:

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