Measuring mental representations underlying activity-travel choices

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Measuring Mental Representations Underlying Activity-Travel Choices

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Preface

I can still recall the day when Tommy Gärling, the supervisor of my master thesis, forwarded me an email in which a vacant PhD position was offered. The only sentence Tommy Gärling added was "Wouldn't that be something for you?!". The original sender of this email was a Harry Timmermans from Eindhoven, a name I recognized from journal articles I had read during my studies. I was certainly amused by this suggestion. "Did Tommy Gärling really think that I am the right person for doing a PhD? He must have been wrong!", so were my thoughts. I ignored the forwarded email for some weeks and did my business as usual. Still, the imagination of doing a PhD had entered my mind and my curiosity was finally stronger than my self-doubts. So, I replied to that Harry Timmermans and showed slight interest in his offer. What I first learned about Professor Timmermans was his quick response time. Only two minutes later I received his reply inviting me to come to Eindhoven.

Now this is almost six years ago and in the meantime I have learned much more than accepting challenges and writing pragmatic emails. The core of the acquired knowledge of these years is printed between these book covers and the essence of the acquired experiences is stored in my personality. Therefore, it is time to wipe the slate clean and to express my gratitude to a number of persons who helped me on the way up to this day.

An initial "Tack så mycket" goes to Professor Tommy Gärling for encouraging me to start a PhD. Next, I want to express my gratitude to Professor Harry Timmermans for giving me the opportunity to do this project. With his unconventional and effective way of communication he was almost always available whenever there was need for help and supervision. Moreover, Harry and his lovely wife Ria did not forget to enhance the social relationships among all members of the Urban Planning Group.

A special thanks owes to Dr. Theo Arentze in the role of my daily supervisor. In his modest and helpful manner he was the biggest support and mental driving force of my PhD project. Even though he supervised many PhD students at the same time I had always the feeling that he was 100% aware of what I was doing. Together with Professor Benedict Dellaert in the role of my co-promotor, he gave me a lot of mental input and scientific foundation to push on my work successfully. Thanks to Benedict I got a broader view on my project in the context of consumer decision making and thanks to his creative ideas and his manifold contacts I benefited from his co-promotion in several ways. Harry, Theo en Benedict: Hartelijk bedankt voor jullie steun! Likewise I am glad that Professor Martin Dijst, Professor Cees Midden, and Professor Frank Witlox were willing to function as committee members for my dissertation.

A work like this has however much more contributors who helped me to cope with the challenges of my project in uncountable small but decisive situations. As such, a warm "Dankuwel" goes to all secretaries from the Urban Planning Group for their courteous organizing abilities. Also, I want to name Joran Jessurun without whose profound programming skills my online interview program would barely have turned out as a successful measuring tool. In the same breath I need to mention all colleagues and students from the Faculty of Architecture, Building and Planning who assisted me in the setup of a semantic database and who served as test respondents for my interview. Outstanding work in collecting and translating Dutch synonyms was done by my student assistant Rianne Wolters. Likewise, I am grateful that CentERdata, Tilburg, gave me the opportunity to conduct my survey by making use of its LISS panel. This meant a big relief for me in time and effort. Nevertheless, I am aware of the fact that the success of this work relies heavily on the voluntary support by several hundreds of respondents who participated in one of the interview waves. Thank you all very much for your contribution to science.

Living abroad for four years is of course more than just a business trip. After some start problems I got finally acquainted with the Dutch language and the way of life in the Netherlands. It goes without saying that the feeling of being an Eindhovenaar necessitates friends and joint social activities. Thanks to my colleagues and sport mates I had an unforgetable time also outside university. In this vein I want to name representatively Aida, Ana, Anastasia, Brano, Carolina, Christina, Daniel, Dave, Erik, Gamze, Gordon, Gustavo, Ioana, Linda, Marloes, Nicole, Pauline, Pierre and Vincent. It was me a pleasure to be your "Chief of Social Affairs" in the PhD network.

Above that I want to thank my housemate Sascha for the positive pressure he set on me for moving together, his unshakable pragmatism and his genial cooking and party attacks. I enjoyed the time we spent together with his friends as much as my friends perceived him as a gain of entertainment.

Den letzten Abschnitt des Vorwortes möchte ich gern meiner Familie und meinen Freunden zu Hause und in Schweden widmen. Ich weiß, dass sie in den zurückliegenden Jahren oft auf mich verzichten mussten. Besonders möchte ich mich bei meinem guten Freund Jonas bedanken, der trotz der räumlichen Entfernung immer für mich da war, wenn ich entmutigt von Rückschlägen Zuspruch nötig hatte. Nicht zuletzt durch ihn haben sich für mich die Wege eröffnet, die ich bis hierher gegangen

bin. Mein größter Dank gebührt aber meinen Eltern und Großeltern, die mir immer Rückhalt bei meinen Entscheidungen geboten und meinen Werdegang voll unterstützt haben. So ist das vorliegende Resultat meiner Arbeit auch ihr Verdienst. Danke vielmals!

Oliver Horeni
Dresden, June 2012

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Acronyms

APT – Association Pattern Technique

CNET – Causal Network Elicitation Technique

HL – Hard Laddering

HVM – Hierarchical Value Map

MR – Mental Representation

SL – Shopping Location

TM – Transport Mode

TS – Time of Shopping

1

Introduction

1.1 Motivation

It is widely known and often reported that the increased (car) traffic causes a lot of threats for the urban and natural environment (Gärling and Steg 2007). Likewise there exist many different strategies on how to cope with these threats. After years of attempts to adapt the environment to the needs of the increased (car) traffic, politicians and planners changed their mind and developed strategies to manage the traffic with the available transport infrastructure by reducing or changing private car use (e.g. Steg and Gifford 2005). According to Bamberg *et al.* (2011) these so-called travel demand measures can be divided into *hard* measures such as prohibition or prizing and *soft* measures such as personalized travel plans and travel awareness-campaigns. Despite the fact that sometimes the soft measures are explicitely called psychological and behavioural strategies (Fujii and Taniguchi 2006) also hard measures aim at changing individual (choice) behaviour. Therefore, in order to implement successful travel demand measures it is essential to understand how individuals will react to them. As a consequence, different theories have been developed in behavioural science in order to explain individual choice behaviour for urban/transport planning.

The issue of heterogeneity in urban transport demand analysis is thereby of considerable importance. Conventional transport models assume that all travelers of the same socio-economic characteristics demonstrate the same type of most behaviour. Models are based on averages and thus do not capture any behavioural differences. Scholars are dealing with this issue in different ways. One stream of research, focusing on mixed logit models (Hensher and Greene 2003), is estimating the parameters with some distribution for each parameter in order to reflect heterogeneity with regard to the effect of explanatory variables on the dependent variable of interest. Such models, however, still assume that the nature of the relationships between the explanatory variables and the dependent variable is the same for all respondents. A second approach identifies latent classes, each class having a different utility function; for example, depending on socio-demographic or context variables (Ben-Akiva *et al.* 1997). Although both these approaches break down the choice problem into subproblems by segment respectively content, within each breakdown the assumption of homogeneous responses/behaviour still holds.

Thus, regardless of their sophistication and relative success, all these approaches are fundamentally limited in the sense that some degree of aggregation is still used. From a truly behavioural perspective, however, individuals and households face a different space-time environment in which they need to cope with a different set of constraints in satisfying their needs and organising their activities. They have different experiences and hence will have different mental or cognitive maps of their built environment, the transportation system and the institutional context. They will vary in terms of their perception of the environment, which will be incomplete and partially incorrect. They hold different beliefs with regard to the most effective strategy of coping with constraints. Arguably, modelling such individual variability could provide further insight in individuals' decision-making and, therefore, would be an important research goal to pursue. This line of reasoning could further be extended to also capture the fact that besides individual differences, mental representations may also differ for one and the same individual depending on the specific situation that he or she faces. This would be realistic if individuals' pursued benefits and perception of relevant attributes differ depending on their goals in a given situation. Hence, mental representations of joint activity-travel decision problems underlie individual and contextual variability. Rapid developments in cognitive agent-based systems and progress in data fusion suggest that incorporating processes of mental construction of reality in behavioural models may be feasible in the not too distant future (Rossetti and Liu 2005).

In addition to various research questions on the nature of mental representations and its relationship to spatial behaviour and its links to properties of the built environment, the question *how to collect valid and reliable data of mental representations* is a research issue in its own right.

To collect such data, a semi-structured interview protocol called CNET (Causal Network Elicitation Technique) has been developed and tested by Dellaert *et al.* (2008) and Arentze *et al.* (2008). Using this technique, mental representations are modeled as causal networks consisting of decision variables, attributes, benefits, situational variables and causal linkages between them. These components are elicited in a stepwise manner in a face-to-face interview through targeted questions. However, the

CNET interviews turned out to be very time-consuming and personal-intensive. Large scale applications and a quantitative collection of mental representations are, thus, impossible with the CNET interview.

Related advances such as the association pattern technique (APT) (ter Hofstede *et al.* 1998) and (online) "hard" laddering (HL) (Russell *et al.* 2004b) have allowed for such large scale data collections for the price of possibly influencing respondents by their administration. What facilitates the successful large scale application of these methods is, namely, their reliance on aided recall (i.e. the full set of relevant components is presented directly to respondents). This circumstance is, however, likely to dampen the method's sensitivity to measure context effects since all attributes and benefits are presented to respondents up front.

Only recently, research has emphasized that depending on the context with which decision makers are faced different aspects in such attribute-benefit chains may be more or less prominently activated (Dellaert *et al.* 2008, Srivastava *et al.* 1981, Rathneshwar *et al.* 1997). For example, researchers have shown that the relative emphasis on benefits vs. attributes may vary based on psychological distance (Trope and Liberman 2003) and that depending on the consequences of the activity task, the number of aspects may vary between contexts (Dellaert *et al.* 2008). These types of variations may, thus, be difficult to capture with online hard laddering and the association pattern technique.

This chapter started with *the issue of heterogeneity*. If this is the long-term goal in transport analysis then the tools for attaining that goal must be able to capture this issue. The existing techniques and methods do not fulfill this requirement. A promising avenue for an efficient data collection on individual MRs is hence the combination of features from the above mentioned techniques. The consequence is the adaptation of the CNET protocol towards a computerized interview.

1.2 Objective

In light of the above, the objective of this research is to develop and test an online method for measuring MRs for large-scale applications in a flexible and open-ended elicitation process that maintains the scalability of the known approaches but possesses the sensitivity to measure shifts in MRs caused by contextual effects on the decision situation.

This objective is therefore connected with the following expectations: An online application of the CNET interview protocol is able to measure mental representations more accurately or equally accurately than comparable proven techniques that work with revealed lists of variables. Moreover, in line with the idea of situation-dependent heterogeneity of mental representations, online CNET is assumed to be sensitive for measuring shifts in MRs which are caused by situational factors of the decision context. Finally, CNET is expected to deliver more interesting insights in the underlying driving forces of decision making and choice behaviour than the structured interview techniques. These insights might be of valuable importance for policy making and model development.

1.3 Thesis outline

This thesis reports the development of an online data collection tool for measuring mental representations and explorative and model-based analyses of survey data of a daily activity-travel task. Therefore, this thesis is organised into six chapters. Following this introductory chapter, chapter 2 summarizes different approaches for transport choice modelling with emphasis on activity-based approaches. Accordingly, the link to decision making and mental representations is outlined. As bottom line it will be worked out that a logical next step in the improvement of transport modelling will be the investigation of mental representations. Chapter 2 closes with a brief overview of existing techniques for measuring these mental representations.

The insight into the shortcomings of such measurement techniques led to the set up of technical and organisational requirements for the development of an online instrument for measuring mental representations. This development process including a comprehensive pilot study will be outlined together with the technical features of the instrument and the two techniques that were applied to it in chapter 3.

Chapter 4 is the most comprehensive part of this thesis. As empirical part it will not only describe two waves of data collection for five experimental manipulations of a daily activity-travel task but it will also report on the analysis of the collected data material. While the explorative part investigates mental representations structurally and substantially, the last part of chapter 4 highlights the performance of the data collection tool in light of the interaction with respondents.

Chapter 5 presents a formal model for the activation of mental representation components. Accordingly, model parameters are estimated with the MR data collected with CNET. The chapter closes with insights gained from the estimated activation parameters for contextual shifts.

As conclusion of this thesis, chapter 6 gives a brief summary of all important sections and discusses the most important findings and experiences with measuring mental representations critically. A final outlook into future research gives an indication of the steps to be undertaken to make the online measurement tool a widely accepted convenient and successful data collection method on mental representations.

2

Theory

2.1 Transport choice modelling

When trying to understand today's endeavors to model travel-activity planning, it is essential to consider it in the context of transport modelling in which it is integrated. This section will provide an overview of the scientific management of the phenomenon *transport*. This overview will however be limited to the most relevant model approaches for the description and computation of transport demand.

2.1.1 From aggregated to disaggregated models

The reconstruction of destroyed cities along with new standards in urban planning in Western Europe after World War II coincided with economic upswing. This was also visible in transport and in travel behaviour of the population. The car became a symbol of the spreading welfare in the nineteen fifties when the higher living standard promoted the motorization of the population (Zemlin 2005). This development faced urban and transport planners with the challenge to adapt the reconstruction of cities with the requirements of increased car traffic. For the dimensioning of the future infrastructure mainly two thoughts played a central role: On the one hand the estimation of the expected transport volume and on the other hand its distribution on the transport system between the particular locations of origin and destination. These thoughts are the groundwork of the so-called aggregated (transport demand) models.

One property of these models is the segmentation of the planning area into cells covering an urban zone with homogenous characteristics such as its population and number of workplaces. Besides a location factor these characteristics are considered as determinants of the transport volume in the cell according to longtime empiric findings. Another property of the aggregated models is their computation process in four steps.

The model step of computing the above mentioned transport volume is called *trip generation* and is nothing else than estimating the number of trips originating from cell *i* or terminating in cell *j*, respectively. After repeating this step for all cells of the planning area one needs to establish origin-destination relations of all trips in the so-called *trip distribution*. In other words, the originating transport volume is split up and allocated to possible destination cells. As each originating trip must also terminate somewhere the total originating transport volume of the planning area equals the total terminating transport volume of the area over a closed period of time. What is labeled trip distribution in the four-step model will later in this thesis appear from a completely different approach under the label *location choice*. The trip distribution in the four-step model does however not regard decision making and choice behaviour of individuals. Rather, the allocation of the origin and destination cell to traffic flows is ascribed to time and distance resistances regardless whether individuals really consider these attributes.

Also the third step of the four-step model will return later in this thesis from a completely different perspective. In the aggregated models the *mode choice* determines the assignment of the trips to one of the competing transport modes in the planning area. As for trip distribution also the distribution on the available travel modes is based merely on empirical structural data of the planning area and possibly characteristics of the transport system. The focus is thus on the aggregated outcome of mode choice but not on its underlying causes.

After the mode choice has successfully been accomplished, the car trips need to be assigned to routes on the street network, the public transport users to bus and tram lines and the pedestrians to walking paths. This final step is called *route or traffic assignment* which is determined again by resistances in terms of characteristics of the infrastructure such as its capacity, speed limitations, ban on turns, frequency of public transport service, travel times etc.

Depending on the sequence of the four steps the aggregated models can either be classified as trip-end models when the mode choice precedes the trip distribution or as trip-interchange models when the steps are in the order as described above. The latter group of models has the advantage that also characteristics of the transport system such as the travel time are taken into consideration for the mode choice whereas trip-end models compute mode choice only on the basis of structural characteristics of the planning cells.

The biggest shortcoming of both model types is however the lack of behavioural heterogeneity. As a consequence of the computation process only with empirical data the human traveler remains in the background and appears merely as trip. Rather, the models impute homogenous and generally valid behavioural patterns, i.e. inter-individual margins in the travel behaviour and local, temporal and situational variations are ignored or considered as being outbalanced at best. It is due to this fact that these models are called aggregated models. Causal conclusions on the acceptance of travel demand measures cannot be drawn by them. However, in the time when these models were developed the common believe was that the infrastructure could be adapted to the travel demand and not vice versa.

Even today after the attitudinal change towards transport policies the four step model is still a widely used instrument for transport planners. Yet, over time computer programs have appeared for transport planners which incorporated already some sort of disaggregation in single steps of the four step model by applying probabilistic approaches (e.g. VISEVA, Schnabel and Lohse 1997). It is especially the mode choice that deserved most attention by representators of this new class of disaggregated or behavioural transport models, respectively.

The disaggregated models owe their naming to the assumption on individual behaviour as a result of utility maximization (Ben Akiva and Lerman 1985). With regard to mode choice travelers are assumed to make a rational choice from a finite set of transport alternatives. Hereby travelers are assumed to choose the mode that promises the subjectively highest utility. As travelers do not possess about all information of the transport alternatives and the search for any additional information is connected with (mental) costs, too, it is assumed that they do not necessarily choose the objectively best alternative but a satisfying suboptimal alternative instead. This concept is called bounded rationality.

Random utility models suppose therefore that the utility *U* for a choice alternative *j* consists of a deterministic part *u* and a probabilistic error term ε:

$$U_j = u_j + \varepsilon_j \qquad \text{(Equation 2-1)}$$

The deterministic part u_j is expressed as a linear function comprising characteristics of alternative *j* such as travel time, travel cost, comfort etc. which thus serve as explanatory variables. These part-worth utilities X_{jk} are weighted by the parameter β_k:

$$u_j = \sum_k \beta_k X_{jk} \qquad \text{(Equation 2-2)}$$

According to assumptions about the distribution of the aggregated error term ε different approaches exist to compute the probability for choosing alternative *j*. Given a binary choice between alternatives *j* and *l*, the linear probability model assumes a uniform distribution of ε over an interval *[-D,D*] (Schnabel and Lohse 1997):

$$P(j) = \begin{cases} 0 & when \quad u_j - u_l < -D \\ \dfrac{u_j - u_l + D}{2 \cdot D} & when \quad -D \le u_j - u_l \le +D \\ 1 & when \quad u_j - u_l > +D \end{cases}$$ (Equation 2-3)

A somewhat more realistic approach is realized by the Probit model which assumes the utility difference between two alternatives *j* and *l* to be normally distributed. In the binary case one would hence expect the alternative having the higher utility to be chosen. By aggregating both alternative utilities to $U = u_j - u_l$ the probability of choosing alternative *j* is hence the probability of *U* being positive (2-4).

$$P(j) = P(U > 0) = \int_0^\infty f(U) \cdot dU = 1 - F(0)$$ (Equation 2-4)

In multinomial cases the solution of multiple integrals is required for the computation of the choice probability making this approach mathematically demanding. Furthermore, the standard deviation σ must be known for the analysis.

The most common model to compute the choice probability of an alternative is the multinomial logit model which is based on similar assumptions as the probit model but much easier in handling. The aggregated error term *ε* is however assumed to be independently and identically Gumbel distributed. When the choice alternatives are independent from each other, the choice probability for alternative *j* can be calculated as the quotient of an evaluation function for the utility of alternative *j* over the sum of evaluation functions for the utilities of all alternatives *t*:

$$P(j) = \frac{\exp(u_j)}{\sum_t \exp(u_t)}$$ (Equation 2-5)

More sophisticated approaches use nested logit functions for modelling interdependies between choice alternatives or mixed logit to allow for random taste variation (Hensher and Greene 2003). Others aim at disaggregating the transport demand by applying different utility functions for latent classes (Ben-Akiva *et al.* 1997). A similar approach was chosen by Yagi and Mohammedian (2007) who incorporated socio-demographic characteristics of the decision maker or the household into the utility functions. Despite of their efforts in better modelling heterogeneity, all disaggregate models have in fact two inherent shortcomings; they do not provide an explanation of individual choice behaviour and they assume a common valid bundle of attributes for which each decision maker evaluates the choice alternatives in question.

2.1.2 Attitude models

Historically, the development of attitude-oriented models went along with a shift in transport planning during the nineteen seventies when the user group of transport models changed gradually from pure transport planners to transport managers who aimed at steering the transport volume more effectively on the existing infrastructure. This shift in transport policy also caused a shift in the perception of the individual traveler. It was not any longer believed that people act according to a simple stimulus-reaction-scheme on the basis of objective characteristics. Rather, the attitude-oriented models suppose a direct link between subjective attitudes and behaviour. Hence, any perceived stimulus is being assessed with the attitudes of the decision maker before a behavioural intention is formed. As it is furthermore assumed that behavioural intentions lead to realized behaviour one could conclude on the (travel) behaviour when the attitude towards several travel modes is known.

In order to understand the role of attitudes for determining a behaviour, Fishbein and Ajzen (1975) developed the Theory of Reasoned Action. According to this theory, beliefs about the expected outcome of a certain behaviour determine the attitude towards it. Likewise, people have beliefs about the opinion of people close to them towards performing that behaviour. These beliefs form the subjective norm of an individual which determines together with the attitude an intention to perform (or not perform) a certain behaviour. Both factors are weighted by relative importance factors. Therefore, it is possible that people holding the same attitude and the same social norm towards a behaviour form different behavioural intentions. If no external restrictions hinder the individual, the intended behaviour will be realized (Figure 2-1).

The transport mode choice is a quite suitable case to illustrate the attitude theory exemplary. An individual might hold positive beliefs about going by bus. He might esteem meeting other people, reading while travelling or believe that it is environmentally friendly. Thus, he might hold a positive attitude *A* towards going by bus. Yet, all his neighbors and colleagues might go by car to work. This observation might lead to the subjective norm *SN* that his private environment expects him also to drive to work. Depending on what weighs more on his internal value scale (*w*), the attitude or the subjective norm, he either establishes the intention *I* to go by bus or by car to work. If both modes are available, he is assumed to perform the intended

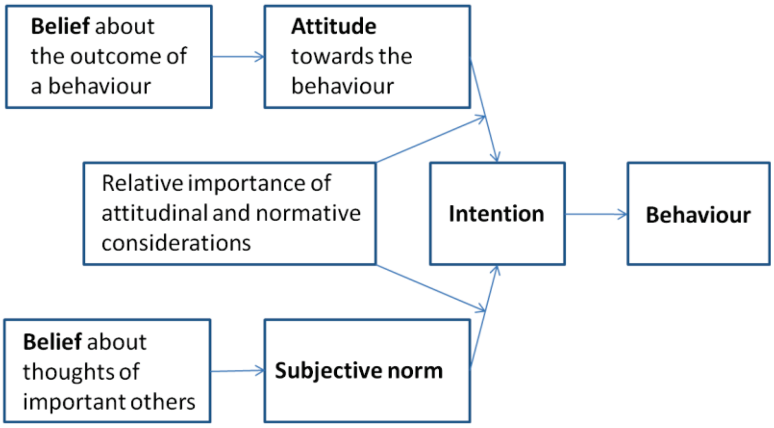

Figure 2-1. Factors determining a person's behaviour. (From Ajzen and Fishbein 1980)

behaviour. In the successor of the Theory of Reasoned Action, the Theory of Planned Behaviour, Ajzen (1985) included perceived behaviour control *PBC* as a determinant of the behavioural intention. That means for our example that the individual also considers whether the sought outcome is likely before establishing an intention. If the individual traveler perceives taking the bus as too risky or too weather-dependent for being in time then his intention is probably to take the car, provided that he perceives a higher behavioural control for the car trip. Equation (2-6) summarizes the discussed factors that determine a behavioural intention according to the Theory of Planned Behaviour.

$$I = w_A A + w_{SN} SN + w_{PBC} PBC \qquad \text{(Equation 2-6)}$$

Ajzen and Fishbein (1980) emphasize that only the attitude towards a certain behaviour has the power to predict behaviour. Attitudes towards objects and people may fail to predict behaviour reliably. Still, it is more than attitudes, subjective norm and perceived behavioural control that influences behaviour. Although personality traits and demographic variables are not regarded explicitly in the model, it is assumed that they influence the beliefs and the relative importance of attitudes and norms. For instance, fearful people might rather believe that going by public transport is not safe against crime compared to individuals having a stronger self-confidence.

Already in the nineteen seventies Gilbert and Foerster (1977) composed transport choice models including attitudinal variables next to travel time, travel cost and convenience as independent variables. These models were tested with data collected in a household survey in Chapel Hill, North Carolina after a public bus system had been implemented. Besides socio-demographics and travel data respondents had to rate twelve attitude items of which five where chosen from Lovelock (1973), four from Johnson (1974) and three from Gilbert and Foerster themselves. Several regression models were built to test the explanatory power of the attitudes. The significance of the difference in explanatory power was tested by F-statistics manifesting that Johnson´s attitudes are not important for mode choice decisions whereas including Lovelocke´s attitudes results in an significant increase of explanatory power. Other successful mode-choice models were developed by Pez (1998) who connected attitude-oriented ideas with the model of graded choice possibilities or Bamberg and Schmidt (1993) who explained mode choice by the intention to perform the behaviour under consideration which in turn is determined by attitudes, social norm and perceived behavioural control according to the Theory of Planned Behaviour (Ajzen 1991). Yet, Bamberg and Schmidt included also the past travel behaviour as a predictor of future mode choice in their model. Their results showed that the behavioural intention to use a certain mode increases with a positive attitude towards it. Thus, they supported the Theory of Planned Behaviour for transport mode choice.

2.1.3 Activity-based models

The model classes listed above caused some critics over the years (McNally and Rindt 2008) or turned out to be not appropriate as planning instruments. One common shortcoming of them is that they view transport mode choice as a decision process detached from its context. "Interdependencies between transport mode choice and other decisions underlying the organization of activities of individuals and households in time and space are lacking." (Verhoeven 2010). The insight into this shortcoming is as simple as obvious as most trips are not undertaken for the sake of travelling per se. Rather, the need for transport is derived from other needs which require overcoming of spatial distance. Hence, behaviourists embedded transport into the context of daily activity agendas and built thus holistic models where transport related choices are majorly based on activity participation on individual or household level. The interdependency of household members in their activity pattern and as a result also in their travel behaviour is only one advantage activity-based models show over conventional transport models. Still, also this class of models can further be sub-classified into constraint-based models, utility maximizing models, computational process models and micro simulation models (Timmermans *et al.* 2002).

The **constraint-based models** pick up ideas from time geography (Hägerstrand 1970) in that the performance of human activities is constrained by spatial and temporal characteristics. These models compute whether certain activity patterns can be performed in a particular time-space environment. However, the transport mode choice is not explicitly modeled but transport mode characteristics are used as assessment criterion for the feasibility of activity patterns instead. Examples for constraint-based models are PESASP (Lenntorp 1976), CARLA (Jones *et al.* 1983), BSP (Huigen 1986) or approaches for multiple agents as proposed by Neutens *et al.* (2007).

The basic idea of the **utility maximizing models** has already been outlined for the mode choice as disaggregated model. Each choice alternative is considered as a bundle of attributes each providing a part-worth utility. The total utility of any alternative can then be expressed as a linear function. As described above for estimating the probability of choosing any alternative the multinomial logit model is an appropriate solution. Choices where some alternatives are more similar than others can better be modeled with nested-logit as it allows for a more realistic contention between alternatives. The difference to conventional random utility models is that transport mode choice is not considered isolated for a trip but integrated in each tour of the activity agenda instead. Activity-based models underlying utility maximization are, for instance, the daily activity model (Ben-Akiva *et al.* 1996), the HCG model (Ettema *et al.* 1997), COBRA (Wang and Timmermans 2000), the g-Logit household time-use model (Zhang *et al.* 2002), and more recently a dynamic activity scheduling model for weekend activities (Habib 2010).

The **computational process models** arose because scholars criticized the concept of the rational decision maker in the utility maximizing models. They argued that individuals would rather apply context-dependent heuristics in terms of "If-then-rules" for activity-travel scheduling. These rules determine the behaviour under a set of context conditions. In these models the context is described by characteristics such as number of cars per household, availability of transport modes, availability of a driving license and the interaction with other household members, just to name a few. By knowing the settings of these conditions rules are applied to determine the travel behaviour the simulated respondents would show in order to perform the activities on their given agendas. What these rule-based models usually do not take into account are rather latent conditions of the context such as individual needs, mood, well-being, motivations and attitudes. Nevertheless, these models are put in an activity-based context and regard the interaction with other individuals. Examples of computational process models are SMASH (Ettema *et al.* 1995), ALBATROSS (Arentze and Timmermans 2000) and TASHA (Miller and Roorda 2003).

Finally, the **micro simulation models** are in fact a more data driven variant of computational process models such as ORIENT (Sparmann 1980), RAMBLAS (Veldhuisen *et al.* 2000), and MATSim (Balmer *et al.* 2008). The latter model is a transformation of TRANSIMS (Wagner and Nagel 1999) into a Multi-Agent Transport Simulation (MATSim) working in an iterative procedure for route, time, mode and location choice.

2.1.4 Conclusions

This section presented several model classes for modelling transport with the focus on transport mode choice. The aggregated four step model provided a trip-based approach from trip generation over distribution and mode choice till route assignment based on empirical values and is a widely-used instrument among transport planners still nowadays. The determinants of travel are considered universally valid for all trips, individuals, neighborhoods, and times. Very much related to this lack of heterogeneity is the criticized handling of the incentive-reaction scheme which the modeled individuals are assumed to show. Personal variation or inter-individual interactions are ignored. The aggregated model describes, hence, only what the status quo of a system is or extrapolates it for a future state. It does not try to understand why it is as it is.

The disaggregation of travel demand towards focusing on individual choice behaviour was captured by probabilistic approaches in the class of disaggregated models. These models assume an evaluation of a finite set of characteristics of choice alternatives by all individuals. While the approach with the logit function has often been applied, the disaggregated models lack in general explanation power on the motivation or purpose of an individual's trip. They are neither incorporated in a broader frame of planning decisions nor do they regard much individual and contextual heterogeneity in the utility equations.

The attitude-oriented models attempt to explain how individuals decide in certain ways. Besides attitudes it is subjective norms and perceived behavioural control which are held responsible for choice outcomes. Although some studies could prove the effect some attitudes have on the choice, much of the variety cannot be explained. In the theory of planned behaviour (Ajzen 1985) inter-individual interaction, context-variation and all other less stable factors are summarized under the label perceived behavioural control. What exactly individuals aim to control remains fuzzy or is determined by the modeler, respectively. Hence, heterogeneity is only incorporated in terms of the evaluation of attitudes and subjective norms. Besides this improvement attitude models give little answer to the question why individuals decide in the way they do and how the need for travel is derived. The latent concepts of attitudes and subjective norm take much room in these models whereas deterministic characteristics of the choice environment and rational considerations deserve barely attention which does not make these models to appropriate instruments for transport policy makers.

The activity-based models put transport planning in the context of daily activity-patterns under consideration of other household members. Travelling is hence perceived as a means to be able to conduct activities. Therefore, the activity-based models start modelling the choice process much earlier than the other model classes, namely with the stimulus of any trip. Context and inter-individual dependencies are also widely regarded by the activity-patterns and household characteristics. Yet, besides all attempts to allow for more heterogeneity also these approaches are fundamentally limited in the sense that some degree of aggregation and generalisation is still used. There are barely models using different sets of variables for different individuals. From a truly behavioural perspective, however, individuals and households face a different space-time environment in which they need to cope with a different set of constraints in satisfying their needs and organising their activities. They have different experiences and hence will have different mental or cognitive maps of their environment, the transportation system and the institutional context. They will vary in terms of their perception of the environment, which will be incomplete and partially incorrect. They hold different beliefs with regard to the most effective strategy of coping with constraints. Arguably, the incorporation of such individual variability is a consequential step in the history of transport modelling.

2.2 Decision making

The previous section gave a brief overview of the historical development of the classes of transport models and their different approaches. What all these models have in common is their purpose to model and forecast characteristics of the transport system prevalently transport mode choice. The variety of models uses, however, different determinants to explain the choice outcomes. Hence, in order to understand and measure what exactly underlies human decision making it is inevitable to view the decision process from the cognitive perspective. This section will therefore introduce different types of human decision making.

In general, it is assumed that any choice behaviour (transport mode choice, route choice, location choice, etc.) is preceded by an internal cognitive, motivational or emotional process which is invisible for an external observer (Zemlin 2005). This decision making process is triggered by an internal or external incentive and includes information search and evaluation of different courses of action. Arentze *et al.* (2011) state that decision processes are determined by an individual's needs which lead to the definition of targets the choice alternatives are evaluated on. Once a behavioural intention has been found it will be realized as (choice) behaviour if no external constraints prevent it. According to the level of cognitive control one can group the whole decision making process into impulsive decisions, habitual decisions, limited decisions and extensive decisions (Katona 1951, Howard and Sheth 1969). Impulsive decisions lack cognitive control and will thus not be further pursued in this work. The three remaining types of decisions can be translated as habitual, script-based and rational decision making.

Habitual choices have only little cognitive control. They result in fact from rational past decisions which led to satisfying choice outcomes. If the decision maker faces similar stable decision situations time and again the response to the incentive becomes automated, i.e. the habit is eventually formed. Aarts and Dijksterhuis (2000) speak about habitual behaviour as automatic goal-directed behaviour as the repetitive performance of an action strengthens the link between it and the goal which is attained by performing the action (Kusumastuti 2011). From a mental perspective, habitual choices are a very efficient behaviour as they lead to satisfying solutions by minimized cognitive load (Baumeister *et al.* 1998).

Similar to habitual choices and therefore difficult to separate is script-based behaviour. Even in science there is disagreement about the definition of the latter. According to some researchers such as Svenson (1990) and Fujii and Gärling (2003) script-based behaviour is the manifestation of links between repeatedly performed actions and activated parts of the mental representation of the choice task for given situations. If certain contextual characteristics are given, then a certain action will be performed. This IF-THEN relation is in fact the underlying principle of script-based behaviour. Other possible actions will not be considered by the decision maker and, thus, mental effort be reduced. The difference between script-based and habitual behaviour is, as Kusumastuti (2011) works out, that "*the first represents a knowledge structure whereas the latter resembles a response program*".

The most deliberate decision process with a high level of cognitive control is rational decision making for infrequent or novel decision tasks where previous experience does not provide a readymade solution. In those cases, the decision problem needs to be explored and the solutions need to be evaluated actively (Hayes-Roth and Hayes-Roth, 1979). Human decision makers must hence have a simplified image of reality in mind which allows them to evaluate their available actions of choices and oversee the potential consequences. Craik (1943) postulated that the mind constructs 'small-scale models' of reality that are used to anticipate events, to reason, and to underlie explanation. This 'small-scale model' has later been put forward as mental representation (MR) by Johnson-Laird’s mental model theory (1983). The next section will introduce the concept of mental representations and how it is affected.

2.3 Mental Representations

According to Johnson-Laird (1983) an MR is a temporary result of individual perception being stored in working memory for the moment of consideration. Building MRs depends on the individual’s experiences and long-term knowledge from which relevant information is retrieved, reordered or translated into other forms (Kearney and Kaplan 1997, Cox 1999).

Mental representations consist of different components such as attributes and benefits (Myers 1976) but also situational variables and causal relations between them. Depending on the point of view also the decision itself can be considered as a variable of the MR. While attributes relate to physically observable states of the considered choice options, benefits describe outcomes in terms of dimensions of more fundamental needs. Situational variables describe states of the system which cannot be influenced by the decision maker or they result from a far-reaching decision in the past. Kusumastuti (2011) refers to attributes as instrumental and to situational variables as contextual aspects. Anyhow, as MRs represent causal knowledge of the environment, i.e. complex IF-THEN relations under different circumstances, they can be mapped as causal networks with nodes as variables and unidirectional arrows as causal links. This structure allows for an application as Bayesian Decision Network with additional parameters for conditional probabilities and utilities and facilitates the simulation of the decision process. Figure 2-2 shows a MR for an exemplary activity-travel task depicted as causal network.

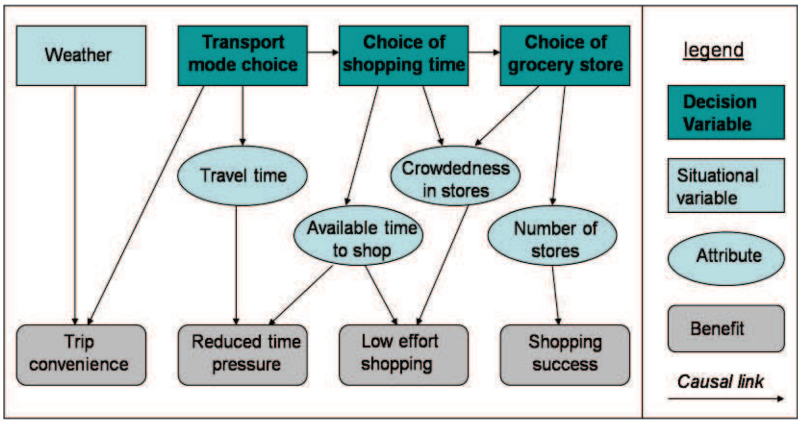

Figure 2-2. Mental representation for an activity-travel task.

More formally, Arentze *et al.* (2008) define an MR_i as a decision network DN_i, where i is the triggering task-situation. The DN_i in turn consists of a directed acyclic graph G_i and conditional probability P_i and utility U_i parameters. However, as this thesis is not pursueing measuring these parameters the formal description can be limited to the directed acyclic graph G_i which is defined as $G_i = (V_i, L_i)$. L_i is a set of directed links in terms of cause-effect relationships between the set of variables V_i of the system being represented. A link is denoted as (X, Y) where Y undergoes a direct influence of X. Therefore, the following links are permitted to occur in an MR: $L = \{(S, S), (A, A), (B, B), (D, A), (D, B), (S, A), (S, B)\}$ with D as decision variables, S as situational variables, A as attributes and B as benefits. Nevertheless, not all of these possible links will be captured by the measuring techniques presented later on in this thesis.

Introducing MRs for rational decision making does not necessarily mean that individuals represent the real world genuinely. Due to the limited capacity of the working memory individuals will experience limitations on the amount of information that can be represented (Anderson 1983). Consequently, MRs will generally involve a significant simplification of reality and are, thus, tailored to the specific task and contextual setting under concern (Johnson-Laird and Byrne 1991).

Limited cognitive capacity is not the only determinant for the construction of MRs. It was already stated above that the considered attributes and benefits depend largely on respondents' experience and information stored in long-term memory (Kearney and Kaplan 1997). Taking just these two determinants into consideration MRs would barely differ between different contexts. Recently however, research has emphasized that depending on the context with which decision makers are faced different aspects in the attribute-benefit chains may be more or less prominently activated (Dellaert *et al.* 2008, Srivastava *et al.* 1981, Rathneshwar *et al.* 1997). In other words, contextual circumstances and the state of the person activate different needs which in turn cause the individual to define targets the choice alternatives should meet (Arentze *et al.* 2011). Nijland *et al.* (2010) stated, for instance, that for daily recurring location and travel choices an individual's needs for time saving, entertainment and convenience etc. vary across situations depending on the individual's state and contextual settings. External influences like advertisement and fashion on the one hand and internal psychological processes on the other hand are also considered as source of need activation (Rathneshwar *et al.* 1997).

In terms of contextual settings of a decision task different influences on the activation of needs and eventually on the construction of MRs have been discovered. The Construal Level Theory (Trope and Liberman 2003) proposes that people's mental representation of future events changes with temporal distance. The relative emphasis on benefits vs. attributes would increase with the temporal distance of the events. This effect of temporal distance between the decision maker and the considered task would also hold for other sorts of psychological distances like spatial or inter-personal distance (Liberman and Trope 2008).

Next to the time horizon for which the decision is considered also the importance of the (anticipated) consequences of the activity task affects the variation of the number of represented attributes and benefits and their causal interlinking (Dellaert *et al.* 2008). Trivial decisions are considered as less complex than decisions whose consequences have implications for a longer period of time or are perceived as severe or uncertain (Payne *et al.* 1993). The latter type of decisions is hence likely to result in higher mental effort. Payne argues further that individuals are able to adjust the required mental effort according to the desired accuracy of MRs.

Moreover, the choice set per se is likely to influence the size of MRs. Not only the number of choice alternatives might influence the number of considered attributes (Tversky 1972), but also the (dis)similarity between the possible courses of action determines the mental effort which the decision maker needs to find the optimal solution (Shocker *et al.* 1991). Thus, the quality and quantity of choice alternatives are assumed to influence the construction of MRs.

Sections 2.2 and 2.3 have built the connection between choice behaviour and the preceding decision process. Three different types of choice behaviour have been introduced and the concept of mental representations has been outlined. Attention was paid to the determinants and processes that influence the construction of mental representations. The next section will introduce existing techniques for measuring these mental representations or similar cognitive constructs.

2.4 Measuring mental representations

After mental representations have been introduced in the previous section, this section will focus on techniques for measuring them. Before delving into different existing approaches and the difficulties connected with the measurement the relation to other mental constructs will be outlined.

Since similar mental constructs exist in related scientific disciplines and streams it might be worthwhile to clarify the frame of mental representations this work is referring to before introducing measuring and causal mapping techniques for MRs underlying activity-travel choices. In the area of spatial behaviour, for instance, the research interest is on individuals' way finding and spatial learning (Gärling and Evans 1991, Golledge 2003, Tversky 2003). Spatial knowledge is stored and represented in mental or cognitive maps. According to Gärling *et al.* (1979) cognitive maps are "*long-term stored information about the relative location of objects and phenomena in the everyday physical environment*". Hannes *et al.* (2006) in turn prefer the terminology mental map which they define as "*a representation of spatial knowledge and spatial understanding in the memory of human beings*". Yet, mental maps do not have much in common with mental representations of activity-travel related decision problems.

A more similar concept are mental models in the field of human-system interaction (Hegarty and Just 1993). When interacting with some (technical) device or system, individuals construct a mental model that allows them to mentally simulate it. Although mental models are also used to assess the likely consequences of actions there are some differences to mental representations for activity-travel choices. First of all, MRs are constructed for the moment of decision making and stored in working memory. For mental models however there is disagreement among researchers about their storage in memory. Cañas *et al.* (2001) pointed out some researchers refer to mental models as a representation stored in working memory while others use the term for the knowledge of the structure and the operation of the physical system in long-term memory. According to the latter definition one would expect mental models to be more durable and stable compared to MRs. This has also implications on the consciousness of mental models for the individual. They might not only be easier retrieved than MRs, they can also be checked on consistency and completeness as they are comparable to the real-world system. Nevertheless, also mental models underlie simplifications. Gentner (2002) assumed analogue reasoning for the simplification of both mental models and representations. According to him individuals might use (simpler) systems which superficially resemble the actual systems for reasons of familiarity.

Conceptually completely different than MRs but methodologically interesting for the experimental part of this work are the hierarchical value maps (HVMs) from means-end-chain theory (Gutman 1982). Means-end chains serve in marketing research to understand consumers' positioning of products free of any decision context and emphasize differences in personal values between consumers. The commonality between MRs and HVMs is their mapping as causal network. Means and attributes are rather concrete components which are causally linked to the more abstract level of benefits and ends. Hence, the methods for measuring means-end-chains should also be applicable for measuring MRs.

Measuring such mental constructs is not as easy as measuring any physically observable value. It is complicated by mainly three facts. First, mental representations are latent constructs being stored in working memory. For the outside researcher this is a kind of black box. In order to get access to it the active cooperation of the human individual under investigation is necessary. Still, a second related difficulty herewith is that humans are not necessarily fully aware of their exact mental representations. Often the MRs need to be rendered consciously before they can be measured. For this reason, we speak also about eliciting mental representations instead of measuring. The third complicating factor is the dynamic character of mental representations. As they are constructed each time an infrequent cognitive task (such as a choice problem) is faced they are not stable over time but influenced by varying factors like the framing situation or need activation. Furthermore, the individuality and subjectivity with which they are constructed have implications on the size and complexity of the mental representation. A mental model of a technical system, for instance, is quite limited in the number of considered concepts as the technical system consists only of a limited amount of elements. Hence, it is quite easy to verify which of the technical elements are part of the mental model and which are not. A mental representation of a choice task in contrast can consist of any conceivable attribute and benefit. During the elicitation process of mental representations it is hence difficult to estimate and verify the completeness and integrity of MRs.

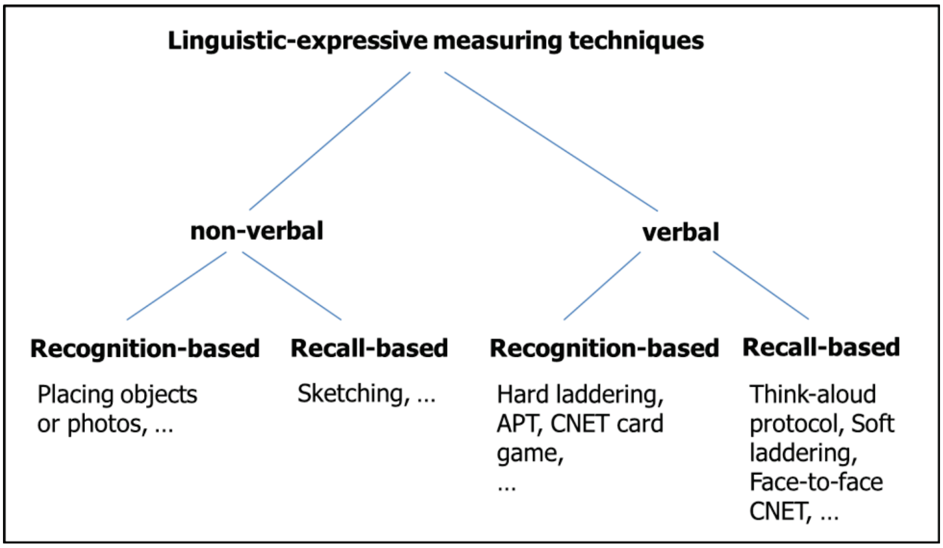

Figure 2-3. Overview of existing techniques for measuring mental representations.

After this little discourse into the variety of mental concepts that are somehow of interest for this work the focus will switch now to the approaches which exist to elicit or measure any of the presented types of mental constructs. It has previously been stated that mental constructs are latent so that the active cooperation of the individual is required for the elicitation process. Passive techniques on the neuro-psychological level such as functional magnetic resonance imaging (fMRI) (Engel 1999) are not applicable for measuring highly complex mental representations of decision problems. Thus, only techniques that work on a linguistic-expressive response level are appropriate for this purpose. Figure 2-3 gives an incomplete graphical overview of the most important and applied eligible techniques.

According to Figure 2-3 it can be distinguished between techniques that base on verbal responses such as written or spoken language on the one hand and techniques that make use of non-verbal means of expression on the other hand. Nonetheless, even for non-verbal techniques the use of (written) language is mostly unavoidable. In such cases, verbal responses serve however mainly for clarification or as an additional channel of expression. The presentation of techniques further below will shed more light on that issue. Next to the nature of responses there is another dimension by which the techniques can be categorized, namely the memory retrieval process which is called for: recognition and recall (MacDougall 1904).

The non-verbal techniques are predominantly used to elicit mental or cognitive maps, respectively. A common and widely adopted recall-based approach in this regard is to ask respondents to draw a map of their city or any other spatial environment under investigation on a blank piece of paper (e.g. Lynch 1960, Shemyakin 1962). By means of these **sketches** it can be concluded on their mental or cognitive map, respectively. Their relying on non-verbal dimensions make these techniques applicable to population groups with linguistic restrictions such as young children, illiterates or people with little (native) language skills. The mental load would switch from recall towards recognition when, for instance, photos of landmarks would be presented to the respondent with the task to identify them or with the intention to trigger more precise information from the respondent (Gärling 1989). Although all sketching techniques work in-fact completely non-verbally respondents often think-aloud while sketching their maps or state written comments on the map such as street names or landmarks etc. Thus, in reality the non-verbal techniques are often accompanied by a verbal dimension. For the investigation of spatial knowledge such sketching techniques are often sufficient and necessary. For the investigation of causal knowledge, i.e. mental representations for choice tasks, non-verbal elicitation techniques are, however, no appropriate means of measurement. The attributes and benefits being part of a mental representation are mostly too abstract than being expressible by sketches or drawings. Hence, only verbal techniques come into question for measuring mental representations of activity-travel decisions.

On the side of verbal measuring techniques many approaches exist of which only the most prominent ones will be presented here. As stated above, mental representations and hierarchical value maps from means-end-chain theory (Gutman 1982) show structural similarities as both can be mapped as causal networks. In order to measure means-end-chains several techniques proved to work and could hence also be adapted for measuring MRs. A widely used qualitative technique in this regard is **laddering** (Reynolds and Gutman 1988). The original laddering technique is a structured face-to-face interview for understanding consumer's values (ends) and how they are trying to attain them (means). The interviewer would start by asking respondents to name the most important attributes of some choice products which are subject to investigation. For each mentioned attribute they would then be asked why they consider it. Ideally, the responses can be classified as *consequences.* Accordingly, the interviewer would continue asking why these consequences are important for the respondent until a satisfying level of ends has been attained. The resulting ladder or means-end-chain does hence consist of more than two levels of abstractness. The exact number of levels depends on the interview depth and the desired precision determined by the interviewer. So, consequences can for instance also be grouped into the more concrete physical consequences and the next highest level of psychosocial consequences. A laddering interview performed in the described manner would not provide support in the memory retrieval process in terms of revealed attributes, consequences and values. Thus, laddering can be classified as recall-based technique.

Since the emergence of a recognition-based variant of laddering (Botschen and Thelen 1998) both versions are distinguished as soft (the recall-based version) and hard (the new version) laddering. Hard laddering presents hence predefined attributes, consequences and values from which respondents are asked to select the relevant ones. The sequence of the interview in the laddering format remains however the same. Next to soft laddering Russell *et al.* (2004a,b) applied a paper-and-pencil and a computerized version of hard laddering in an experiment on mothers' opinions of the role of breakfast on their children's physical and psychological well-being. In contrast to what was stated above about soft laddering Russell asked his respondents to select one to three important attributes from a list. Consequences and values were however elicited without auxiliaries by recall. The results showed that the hard laddering techniques yielded more ladders than soft laddering; a fact which is attributed to differences in participants' cognitive processing (recall vs. recognition). While Russell *et al.* (2004a) recommend hard laddering if the focus of the research is on investigating strong links between certain pre-determined elements, soft laddering would be more appropriate for gaining a fuller picture of participants' cognitive structure. Yet, the drawbacks of a face-to-face interview remain which make soft laddering not suitable for large-scale surveys.

Ter Hofstede *et al.* (1998) suggested another measurement technique, called the **association pattern technique (APT)**. Similar to the hard laddering variants respondents are faced with revealed attributes, consequences and values. The difference is only that the variables are not shown in list format and that the ladders are not elicited one-by-one. Rather, APT consists of two matrices (one for attributes and consequences and one for consequences and values) where respondents can indicate causal links by ticking off the corresponding cells. Hence, all ladders are elicited simultaneously which makes this technique quite difficult. The high complexity of the matrix format with which respondents might struggle can hardly be outweighed by the short interview duration. The advantage of APT is due to its simple analysis the convenience it brings for the researcher. Thanks to the predefined labelling of variables no post-processing of the responses is necessary, thus, making responses conveniently comparable. Yet, the downside of this convenience is, that respondents are limited in their response freedom and possibly influenced by the revealed presentation of attributes, consequences and values. Furthermore, APT does not allow for a variation of the level of abstractness of the means-end-chains.

In order to scrutinize mental models many more techniques and modifications exist that work with revealed variables. Rowe and Cooke (1995), for example, applied among others **Relatedness ratings** and **Diagramming** to investigate Air Force technicians' mental models of a troubleshooting job for an airborne electronic equipment system. Both methods investigated however only how respondents represented the relations between the predefined set of limited components of the electronic equipment system. Eliciting components from respondents is not possible with these methods.

In their work Rowe and Cooke (1995) applied also **Think-Aloud and Verbal Troubleshooting** to the same respondents. This little sophisticated technique is a completely unstructured recall-based technique which is in fact also applicable to measure MRs underlying choice problems. Usually, respondents are instructed to express all their thoughts loudly when considering a cognitive task. During the session respondents will not be interrupted or corrected by the researcher. The Think-Aloud session will only stop when the task was solved or the respondent gave up or when the time limit elapsed. Despite of the general applicability for measuring MRs the Think-Aloud technique has limitations in the sense that the responses are unstructured. Higher levels of abstraction or rather subconscious components of the MR might be forgotten to consider by respondents.

In order to collect data on MRs underlying decision tasks, a semi-structured interview protocol has been developed and tested in face-to-face sessions (Arentze *et al.* 2008, Dellaert *et al.* 2008). The so-called causal network elicitation technique (**CNET**) starts by confronting the respondents with the decision variables in a random arrangement. They are asked to select them in the sequence in which they prefer to deal with them, assuming they were to make decisions. Next, the interview proceeds through the list of decision variables in the order indicated by the respondent and, for each variable, the respondent is informed about the decision alternatives and asked "What are your considerations when faced with these alternatives?". From a list of predefined attributes and benefits, that is not visible to the respondent, those variables are identified that correspond to the response. If the response variable is not on the predefined list, the new attribute or benefit will be added. In any case, it is verified whether the respondent agrees with the classification and determined whether the attribute or benefit is causally linked to the decision variable. In case of doubts, these links are checked with the respondent. Having identified the variable, the next step depends on the variable type. If the variable is an attribute, the interview proceeds with the question "*Why* is this variable influential in this case?". This "why" question generally results in the identification of an underlying benefit generated by the attribute, in which case no further "why" questions are needed. If another attribute is mentioned, the "why" question gets repeated until an underlying benefit emerges. When the originally mentioned variable is a benefit, the interview proceeds with the question "*How* is this variable influenced?" and this "how" question leads to the identification of other situational or alternative attributes. The causal links are also established and verified if in doubt. Further considerations are prompted by repeating this procedure until the respondent has no further considerations to mention. After the first decision variable is processed, the entire procedure is repeated for the next decision variable, and so on, until all decision variables are processed. Ultimately, this procedure leads to a completed representation of the attributes and benefits involved in respondents' MR of the decision problem, as well as the causal links among these attributes and benefits and the action variables involved in the decision. Finally, after the MR is completed, the respondent is asked to select, for each decision variable, the alternative that he or she would choose in the given scenario.

This protocol implies already that the interview is quite intensive and time-consuming. Each variable is processed step-by-step so that all components of the MR are captured. However, the repeated prompts for consideration might possibly evoke too much deliberation on the respondent's side so that he or she gives answers only in order to satisfy the interviewer. A somewhat tricky property of CNET is connected to its response freedom. Because respondents are not instructed in the labeling of the predefined variables the interpretation of their responses is subject to the interviewer. Still, a common set of variable labels is necessary to enable comparing MRs between individuals. The possibility to include even not predefined variables makes the MRs however strongly individually tailored.

Originating from the semi-structured CNET protocol Kusumastuti *et al.* (2009, 2011) developed modifications in order to measure MRs underlying leisure-shopping trip decisions. Her first modification is called **CNET card game** as it works with revealed variables printed on cards. Instead of eliciting the components of the MR by recall the interviewee indicates thus the relevant variables from card stacks which he goes through one by one with the interviewer. The second modification is a computerized version of the card game (**CB-CNET**).

Although the presented techniques proved to work mainly under laboratory conditions for small samples, they are not very convincing for applications in large-scale surveys for the elicitation of MRs underlying activity-travel choices. Hence, there is a need for an interview technique that works automatically without impacts by interviewers or revealed variables. Furthermore, the structured techniques such as HL and APT do not allow skipping layers of the MR. It is, however, not uncommon that some cognitive subsets lack attributes. A less structured interview technique would, thus, come closer to respondents' unbiased and individually tailored MRs. The precise requirements and conditions of the new technique will be outlined in the next chapter.

3

An Instrument for Measuring Mental Representations

3.1 Requirements and conditions for measuring MRs online

Based on the experiences with the techniques described above and the underlying research purpose the general conditions for the development of an instrument for measuring mental representations are basically given. These conditions and specifications will be discussed in this section.

Ideally, a tool for measuring MRs should serve the following three purposes:

1) Eliciting genuine data without impacting the respondent

2) Being attractive and accessible for (almost) all respondents

3) Being easily and economically applicable for researchers

The first mentioned point might be taken for granted when developing a scientific tool. However, by taking a deeper look into the existing techniques one will discover quite quickly that some of them give reason to the assumption that the elicited mental representations are impacted by several factors. All techniques that work in a face-to-face setting are likely to be exposed to an interviewer impact. So might the interviewer trigger certain thoughts by suggestive questions or might introduce a subjective element by misinterpreting responses, respectively. Furthermore, respondents might not give true answers when being embarrassed by the interviewer or the research subject itself. Hence, they might state socially desired responses instead in order to satisfy the interviewer. The interviewer impact becomes even another dimension when several interviewers are involved in one project in that data elicited from different interviewers become gradually less comparable. Due to these circumstances it is a premise for the development of the new instrument to run automatically without an interviewer.

Still, it is not only the interviewer who possibly influences the respondent in the consideration process. Also characteristics of the methodology itself might have an impact on the responses. Methods that work with revealed response options such as the association pattern matrix (ter Hofstede *et al.* 1998) or paper card techniques (Kusumastuti *et al.* 2009) are recognition stressed whereas methods in open format such as the laddering interview (Reynolds and Gutman 1988) are based on recall. What these two mental processes involve has been outlined in the previous chapter. The biasing risk being inherent to recognition stressed techniques is that showing response options may activate thoughts in respondents' consideration process. For example, might respondents be seduced to indicate any plausible response option as underlying consideration although it is not part of the mental representation and would thus not be recalled. Hence, we believe that recall based techniques are able to measure mental representations in a more sensitive and accurate way. In how far recall and recognition based techniques differ in measuring mental representations will be part of the empirical research analysis of the instrument to be developed. Consequently, two versions of the instrument will be developed in order to allow for comparative conclusions.

The second reason for developing a new instrument is that some of the existing techniques or their methodological circumstances are not considered attractive for respondents. The interactive setting of the face-to-face like methods requires the physical presence of both the interviewer and the interviewee at the same location. The travel effort and time exposure connected with that might be perceived as a burden by some potential respondents who, thus, refrain from participating. An online survey instrument which is available 24 hours and not place bound is due to its flexible applicability believed to be much more attractive for respondents. This way, respondents can participate in the survey from their familiar environment at the point in time they prefer most. Moreover, the anonymity inherent to online surveys might encourage people's response willingness making embarrassment responses, thus, more unlikely.

Still, what mostly has been criticized by respondents of interactive face-to-face methods is their long interview duration. Kusumastuti *et al.* (2010) report interview settings of more than one hour. This does not only lead to fatigue among respondents but also to a diminished willingness to participate in follow-up sessions. A premise for developing the new survey instrument is hence to shorten the interview duration to an acceptable level.

Besides a more precise way of measuring mental representations and a higher attractiveness for respondents, the development of the new survey instrument is also driven by economical considerations on the researcher's side. Most of the field work that was done so far in measuring mental representations did not exceed sample sizes of a few hundred respondents. Yet, for large-scale applications a lot of the existing methods fail for economic reasons. The personnel effort which is necessary to conduct hundreds of qualitative face-to-face interviews (or other supervised methods) is just too costly not to mention the time needed for training and performing interviews. Further, all non-computerized techniques require post-experimental coding work in order to enable electronic data processing. The recruitment of respondents for sessions which require physical presence is also complicated by two facts. Firstly, the geographical radius from which potential respondents can be invited is naturally limited by travel distance. Secondly, the recruiting process itself with sending invitations and scheduling of appointments is due to its interactive procedure for both parties a burden which not seldomly results in a lower response rate. In contrast, inviting respondents by email to a web-based survey and providing a hyperlink to the respective experiment saves much of organizational effort. An instrument that works automatically without an interviewer would thus not only save a lot of (research) money but would also facilitate the preparation, performing and processing of data collection for the researcher considerably.

Having discussed the drawbacks of existing techniques and the objectives connected with measuring mental representations, the general requirements for the development of an instrument for measuring mental representations can be summarized as follows:

- Automated
- Web-based
- Support of electronic data processing
- User-friendly (accessibility, interview duration, comprehensibility)
- Support of recall and recognition stressed elicitation processes

The following section will introduce the new instrument along with its development and the technical components being necessary for a successful application.

3.2 Development of the online interview instrument

This section elaborates on the development of the measuring instrument and its technical components. First the online CNET application and its inherent technical characteristics are outlined, being followed by the equivalent presentation of the HL application.

The origins of the new instrument were the general conditions listed in the previous section and the semi-structured interview protocol from Arentze *et al.* (2008) and Dellaert *et al.* (2008). It has however to be noted that the original interview protocol contains additional interview phases in order to determine conditional probability and utility tables. These steps are completely disregarded for the development of the new instrument as its intention is merely the elicitation of the components of mental representations and their causal relationships. The development on an operational level is based widely on experiences in measuring mental representations underlying activity-travel choices collected by researchers from the Urban Planning Group of Eindhoven Technical University prior to this project (den Hartog *et al.* 2005). It is not only for this reason why the exemplarily applied decision task during the whole development and testing stage of the instrument is an activity-travel scheduling task. Still, an additional original demand was that the instrument is flexible with regard to the application and manipulation of the subject of investigation.

3.2.1 The course of an online CNET interview

The semi-structured CNET interview protocol from Arentze *et al.* (2008) has been translated into a Nassi-Shneiderman-Diagram (NSD) in order to be programmable (Figure 3-1). For the sake of simplification it is assumed that only causal links as shown in Figure 2-2 are measured. Higher level mental representations with interlinked attributes are not part of this investigation.

The interview starts with the introduction (step 1) where respondents are informed about the procedure and their experimental task. Respondents' first task consists of sorting the decision variables being part of the underlying complex choice task (step 2) according to their preferred order. (This step is redundant when the choice task consists only of one decision variable.) The subsequent interview steps 3 to 6 are then performed for each decision variable separately in the indicated rank order. The actual elicitation of the mental representations starts by asking for the first

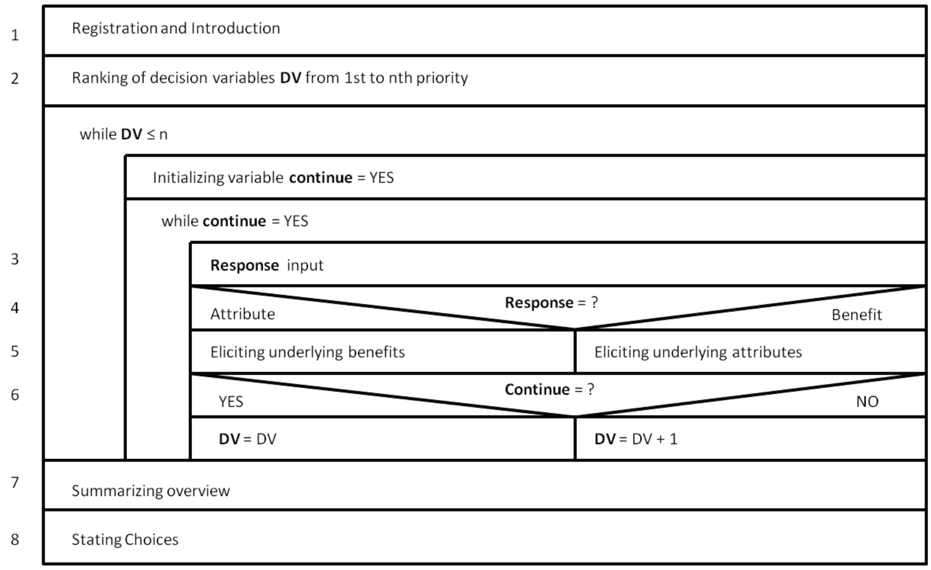

Figure 3-1. Nassi-Shneiderman-Diagram for the original CNET interview protocol (Arentze *et al.* 2008, Dellaert *et al.* 2008).

consideration for the first decision variable (step 3). The response is then categorized as attribute or benefit, respectively (step 4). In the former case, the interview proceeds by eliciting the underlying benefits. Consequently, the underlying attributes are elicited in the latter case (step 5). In step 6, respondents are asked, if they have any further considerations for the decision at hand. If so, steps 3, 4 and 5 are repeated. If not, the next decision variable will be processed. When the whole mental representation has been elicited, respondents get an overview of the elicited mental representation with the last chance for modifications (step 7). Finally, respondents are asked to state their choices in step 8.

However, after first tests of the tentative online CNET application it turned out that the repetitive elicitation of attributes and benefits one by one is too cumbersome and irritating for respondents. Hence, the interview protocol has been modified (see Figure 3-2) so that all considerations underlying one decision are elicited at one time. In interview step 3 thus eight edit boxes are provided in which respondents are supposed to type their considerations (one per box). The number of edit boxes is based on previous research which showed that more than eight considerations per decision are unlikely. The categorizing step 4 works as in the original version (Figure 3-1). However, interview step 5 is skipped when the typed consideration is interpreted as benefit.

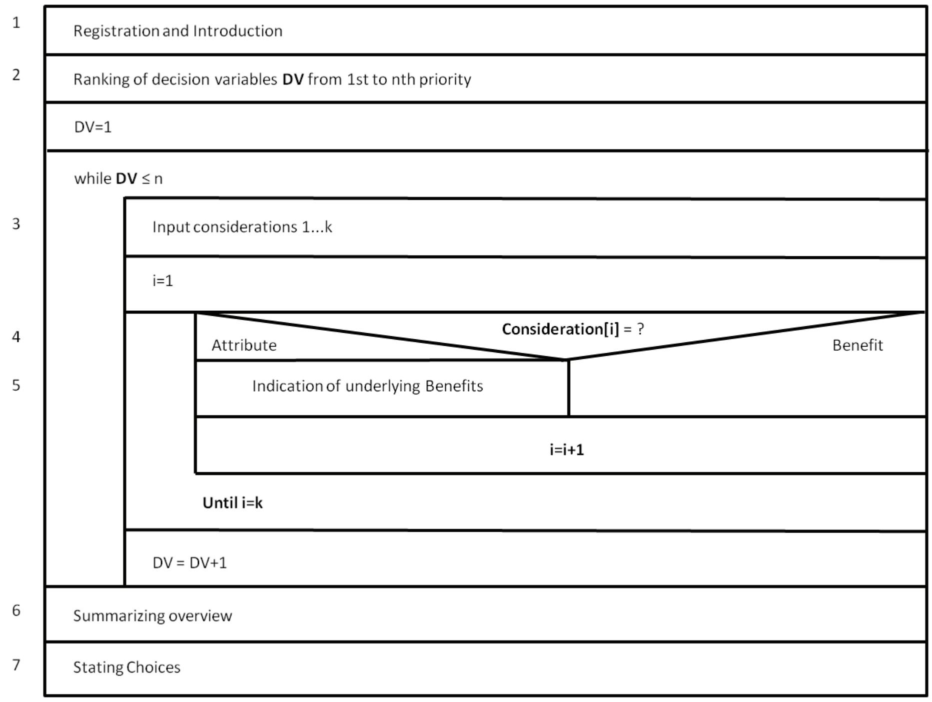

Figure 3-2. Nassi-Shneiderman-Diagram for the modified CNET interview protocol.

Furthermore, the course of the interview has been rationalized by skipping interview step 6 in which respondents were prompted to indicate whether they have any more considerations. The final interview steps 7 and 8 are not affected by the changes.

3.2.1.1 Technical characteristics

As programming language PHP 5.2.0 has been chosen as it allows for a convenient compatibility with MySQL as relational database management system which will be described below. For single applications of the programme JavaScript functions have been embedded, too. The ordering of decision variables in interview step 2 is such an example. When loading the page the decision variables appear in random order on the screen. Respondents are prompted to drop the decision variables with the mouse and drag them at the desired rank position. Only when at least one decision variable has been shifted, ranking numbers appear ahead of the decision variables and the continue button is activated.

Having completed the sorting task successfully interview step 3 starts for the highest ranked decision variable. Deviating from the face-to-face application, respondents are prompted to give written responses in up to eight edit boxes. All of them are buffered in the database during the subsequent interpretation process (interview step 4). This is in fact the most challenging part of the whole application as the human capabilities of understanding and interpreting language need to be taken over by a machine. In order to cope with that the machine gets two auxiliaries: a string recognition algorithm and a pre-defined list of attributes and benefits embedded in a topic-relevant lexical database. While the string recognition algorithm aims at capturing the human interviewer's cognitive capabilities of understanding and abstracting language, the database represents in fact his semantic knowledge. In that sense, the processing of the response by the machine (interview step 4) works quite in the same way as in the face-to-face interview by the human interviewer. Both look for keywords in the statement given in order to interpret the response on its content. If the content is ambiguous, the respondent is confronted with all possible interpretations and prompted to indicate the one he intended. Subsequently, the category of the indicated response is checked as it determines the further process of the interview (step 5).

The string recognition algorithm which has been developed for the online CNET application can be looked up in Appendix A. Firstly, the input string is parsed into word units. The so arisen array of strings is checked for a number of small words without information content such as frequently occurring words like articles or conjunctions. These words are excluded from further processing and the remaining words are considered as keywords. The consequent step is to check whether these keywords have matches in the corresponding database. Yet, comparing each remaining input string with each entry in the database can draw on quite some calculating capacity. Hence, for each database entry the Soundex value has been stored, too.

Soundex is a phonetic algorithm for encoding words according to their sound. It has been developed by Robert Russell and Margaret Odell (U.S. Patents 1261167 and 1435663). Firstly, Soundex assigns indices to consonants whereby similar sounding consonants get the same index. This allows for the recognition of slightly deviating spellings (e.g. *d* instead of *t*). The fact that vowels are not considered at all makes it even more tolerant towards typos. Furthermore, the four digit Soundex value presents only the first characters of a string so that e.g. two longer words sharing identical characters in the beginning have the same Soundex value. The advantage of this feature is that e.g. plural forms are recognized as match when compared to their singular. Although the PHP built-in Soundex function is based on English pronunciation, it can be applied to Dutch language, too, provided that it does not process spoken language. In online CNET it rather serves as information aggregation than as proper encoding of the sound.

Example: Computation of the Soundex value for the word *transport*

$$T = T, R = 6, A = \varnothing, N = 5, S = 2, PORT = \varnothing \Rightarrow T652$$

The string recognition process in online CNET goes on by calculating the Soundex values for all keywords from the response input. Next, a query is made to the database fetching all words with the same Soundex values as the keywords. For our example it would mean that all words with the Soundex T652 will be retrieved. This would not only include all words starting with *trans* but also apparently confusing matches such as *trams*, *terms*, *thermic*, etc. The reason is that they all share the same soundex value. Therefore, the string recognition algorithm needs an additional but more precise measure to find a match from the pre-selected result set. This is the point where the Levenshtein-distance (Levenshtein 1965) comes into play. It describes the minimal number of deletions, insertions and reversals being necessary to transform one string into the one it is compared to. Consequently, the string recognition algorithm would compute the Levenshtein-distance between the keyword (e.g. *transport*) and all its Soundex-matches (e.g. *transport, trams, terms, thermic*, etc.). The word with the least Levenshtein-distance (in this case it is 0 for *transport*) is likely to be the one the respondent intended. Next, the algorithm retrieves all variables from the database where this likely match points to and presents them to the respondent. As *transport* is a quite common term it could relate to numerous attributes and benefits the respondent is considering. Anyhow, by prompting the respondent to select the variable which comes closest to his consideration any doubt could be ruled out. The majority of responses consists however of several keywords (e.g. *transport* and *costs*). Hence, the described procedure will be performed for all other keywords as well. Before listing the possible matches it will, however, be checked whether *transport* and *costs* point to one common or multiple variables. In this example both would refer to the attribute with the label *travel cost* which would be presented to the respondent as top possible match.

It is then up to the respondent to agree or disagree with the presented label. In the latter case he is given the chance to retype his original input and applying it thus to the string search algorithm again or to continue the interview session with the unidentified input, respectively. The latter option is arguably critical as it provides a way to circumvent the interpretation and categorization of responses which consequently needs to be done later manually by the researcher. Misinterpretations can hence not be avoided completely. For the sake of user friendliness and last way out of that interview step this option needs, however, to be provided. The unidentified response would be stored and treated as an attribute for the remainder of the interview. The category of the identified variables in contrast is retrieved from the database in interview step 4 determining interview step 5. In the example, *travel cost* is stored as attribute so that it would be aimed at eliciting its underlying benefits subsequently. Having done this successfully, steps 4 and 5 are repeated for potential further input strings from step 3. The whole procedure will be gone through again for the remaining decision variables according to their ranking from step 2.

Essential changes had to be made to interview step 5 after first test rounds of the interview instrument suggested a modification. It turned namely out that respondents struggled in recalling underlying benefits for earlier mentioned attributes. This was however a necessary termination condition for the interview algorithm which only went on to the next consideration after a benefit had been found. Hence, it has been decided to elicit underlying benefits in step 5 deviating from the original CNET protocol (Arentze *et al.* 2008, Dellaert *et al.* 2008) not in open format but in revealed list format. This means that a selection of benefits tailored to the attribute at hand is shown to the respondent who then is prompted to indicate the one(s) underlying his considered attribute or type an additional benefit if it is not on the list. The limitation of the provided benefits to a selection only is caused by considerations for keeping the readability and user friendliness of the interview screen. Therefore, for each attribute being stored in the database the researcher needs to predefine the benefits that shall be listed with it. Not only required this variant of step 5 a change. The experiences made by initial tests suggested also not to query respondents for underlying attributes when the original consideration has been categorized as benefit in step 4. Hence, the elicitation of attributes is skipped under these circumstances and postponed to step 6.

The summarizing overview given in interview step 6 differs strongly from the one given to respondents in face-to-face CNET. In the latter one, respondents saw a graphical map of the elicited mental representation at the end of the interview and were given a chance for correction and additions. In online CNET the summary is not provided for the whole mental representation at once but for each elicited benefit separately. That means that it is indicated for each benefit which of the elicited attributes are linked to it and which not. By ticking off check boxes the latter attributes can still be linked to the benefit at hand. Furthermore, the option is provided to add attributes (or situational variables) which have not been mentioned during the whole interview and link them to the benefit under consideration. This stands in relation to the necessary change for interview step 5 described above.

Finally, respondents are directed to a webpage where they are asked to state their choices for the considered decisions. The choice alternatives are illustrated by small icons in the order of the decision ranking from interview step 2. Radio buttons ensure that only one choice per decision variable can be indicated. With that, the online CNET application ends officially. Nonetheless, acknowledgements and post-experimental evaluation questions of the interview instrument succeeded step 7 in the conducted surveys. Screenshots of all web pages from online CNET can be found in Appendix B.

3.2.1.2 The database

In the previous paragraphs it has been frequently mentioned that variables are retrieved or stored in a database. It is hence time to present the features and purposes of the applied relational MySQL database system (version 1.2.12). Figure 3-3 gives an overview of the data tables the online CNET interview is based on.

The relational database shown in Figure 3-3 consists of data tables with pre-defined information provided by the researcher (shaded tables) and data tables which

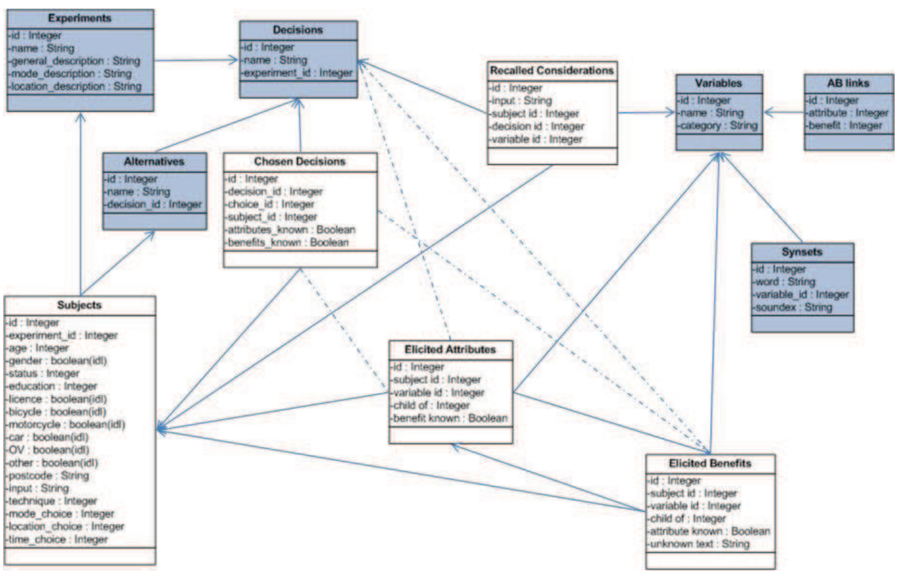

Figure 3-3. Schematic overview of the relational database online CNET is based on.

are filled during an interview depending on respondents' data (blank tables). The arrows and dashed lines between them represent their relations internally expressed by identifier variables in the data tables. In particular, the information is captured in the following way:

Experiments

This table includes the name of the experimental scenario and the experimental information being necessary before respondents are able to run the interview. This information is split up into three variables covering general, mode and location description and will appear on three consecutive web pages during the introduction.

Decisions

The names of the choices which are supposed to be considered by respondents are stored in this table depending on the underlying experiment. The experimental scenarios of the underlying work did however not differ in terms of the decision variables.

Alternatives

The table *Alternatives* covers the choice options for each decision variable depending on the experimental scenario. Except for one, all applied scenarios provided three choice alternatives per decision variable. Nevertheless, this number is generally scenario dependent.

Variables

The above mentioned pre-defined list of attributes and benefits interviewers used in face-to-face CNET is represented by the data table *variables* in the online version. It covers hence all potential variables that the researchers expect could be considered by the respondents for the underlying decision task. Besides their label, it is also stored whether they are defined as attribute or benefit. Technically, situational variables are treated as attributes.

AB links

In interview step 5, benefits are listed which might underlie the attribute identified in the previous interview step. As not all benefits being stored in table *variables* can be listed, only a selection of relevant benefits is shown. The data table *AB links* captures the information about the benefit selection tailored to each attribute.

Synsets

The biggest and most challenging data table to be filled by the researcher is aimed at substituting the interviewer's semantic knowledge, at least the vocabulary which is relevant for the decision task at hand. It is in fact an extension of the *variables* table as it covers synonyms and abstract descriptions for each pre-defined variable. Therefore, each entry is a string that respondents might use when entering their considerations. Next to it, a pointer variable is saved which links the string to one or more variables in the previously described table. For example, the word *rain* would be linked to the internal id of the variable *weather*. Also the soundex code of each entry is stored in the respective column. The above described string recognition algorithm is closely working together with the table *synsets* by retrieving all entries that have the same soundex value as the words in the response string. Words that are not stored in this table will thus not be understood by the interview instrument. It is hence a necessary pre-condition for running online CNET interviews successfully to collect and store as many as possible synonymous expressions for the variable labels and indicating their semantic relations by grouping synonymous words into synsets. The latter distinction gave the name to this data table. In fact, both the table *variables* and *synsets* form a small semantic network which under some circumstances could also be incorporated from external sources. For some languages such as English and German more or less accessible lexical databases exist (WordNEt, GermaNet) which cover the vocabularies and their inherent semantic relations. However, for the Dutch language which was chosen as experimental language no lexical database existed by the time of developing the instrument.

Subjects

The table *subjects* is filled throughout the course of the interview. When starting a session each respondent is assigned an internal ID to by which all his entries can be associated with him over all data tables. The id of the experimental scenario from table *experiments* is also stored automatically. Furthermore, all socio-demographic data surveyed in interview step 1 and the IDs of the chosen alternatives indicated in interview step 7 are saved in this table.

Chosen decisions

The second output table captures the ranking order of the decision variables as it is indicated by respondents in step 2 of the interview. Additionally, two Boolean variables keep track of the successful elicitation of attributes and benefits for each decision variable which is a necessary termination condition for the interview algorithm as shown in Figure 3-2.

Recalled considerations

This table covers all inputs from interview step 3 and links them with the variables as which they were interpreted by the string recognition algorithm. This allows for a possible post-experimental investigation of respondents' inputs. Furthermore, also this table supports the steering of the interview course. Only when all recalled considerations have been interpreted the next decision variable can be considered.

Elicited attributes

The responses from the table *recalled considerations* which have been identified as attributes are stored in the table *elicited attributes* together with the id of the decision variable for which they have been considered. The Boolean variable *benefit known* serves merely internal steering processes.

Elicited benefits

This table is the counterpart to the table *elicited attributes*. It keeps the IDs of all benefits elicited during an interview session. The column *child of* reveals whether the benefit at hand was recalled in interview step 3 and hence directly linked to the decision variable or whether it has been indicated to underlie an attribute in interview step 5.

3.2.2 The course of an online HL interview

Complementary to the development of online CNET a second application, hereafter called hard laddering (HL), has been implemented. As it combines features of the association pattern technique from ter Hofstede (1998) and hard laddering (Russell *et al.* 2004a,b) which both had been tested by computerized versions, it can be considered as a tested technique. The main consideration behind its implementation into the interview tool is therefore founded by comparative purposes. The course of an online HL interview and its technical characteristics are outlined analogously to CNET.

By comparing Figures 3-2 and 3-4 it is evident that the latter diagram consists merely of five interview steps, i.e. that the categorization of inputs and the summary of all elicited variables are not part of HL. This has good reasons. The introduction and ranking of decision variables does not differ from online CNET. Yet, the most essential difference between both applications is the way the attributes (and benefits) are elicited in step 3. While they were typed in by respondents in online CNET, HL works with revealed lists of attributes where the considered ones just need to be ticked off. These

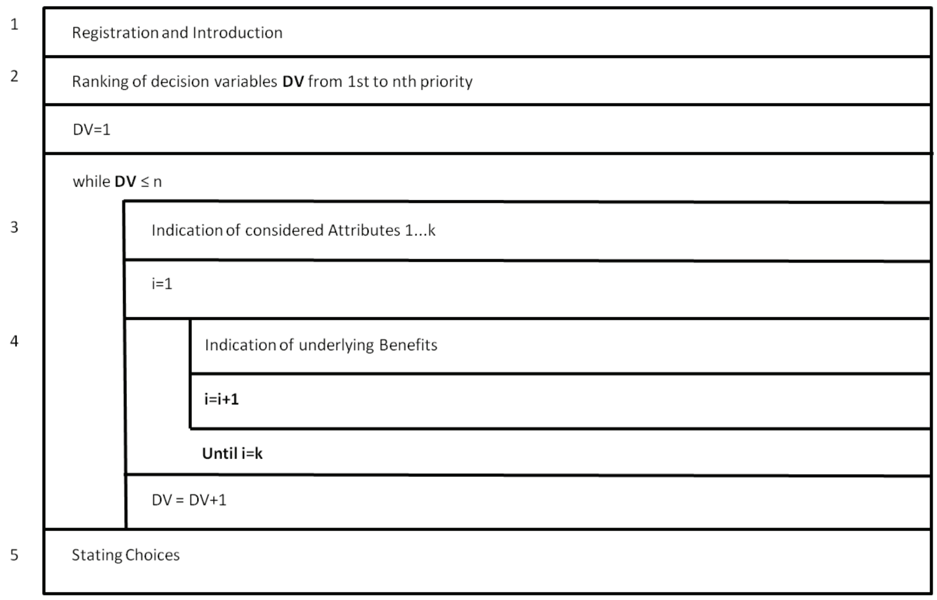

Figure 3-4. Nassi-Shneiderman-Diagram for the online HL interview protocol.

lists are tailored to the decision variable at hand. As only attributes are shown to the respondents in step 3, the categorization (and the whole string recognition procedure) becomes redundant. If however any consideration is not among the revealed attributes the possibility is provided to type it into an edit field which will be treated as an unidentified attribute. The consequential indication of underlying benefits (step 4) is performed in the same way as for online CNET: They are ticked off from a tailored list separately for each considered attribute. Steps 3 and 4 are then repeated for the remaining decision variables before respondents state their final choices in step 5. An overview of the elicited mental representation is not given to the respondent in HL as the chance of missing any variable or causal link is relatively small with this technique. The course of an online HL interview is illustrated by means of screenshots in Appendix C. (As the introduction is the same as in CNET Figures B-1 to B-3 are not repeated there.)

3.2.2.1 The database

Also online HL depends on a complex database (see Figure 3-5) which partly makes use of the same data tables as online CNET. The HL specific data tables are in particular:

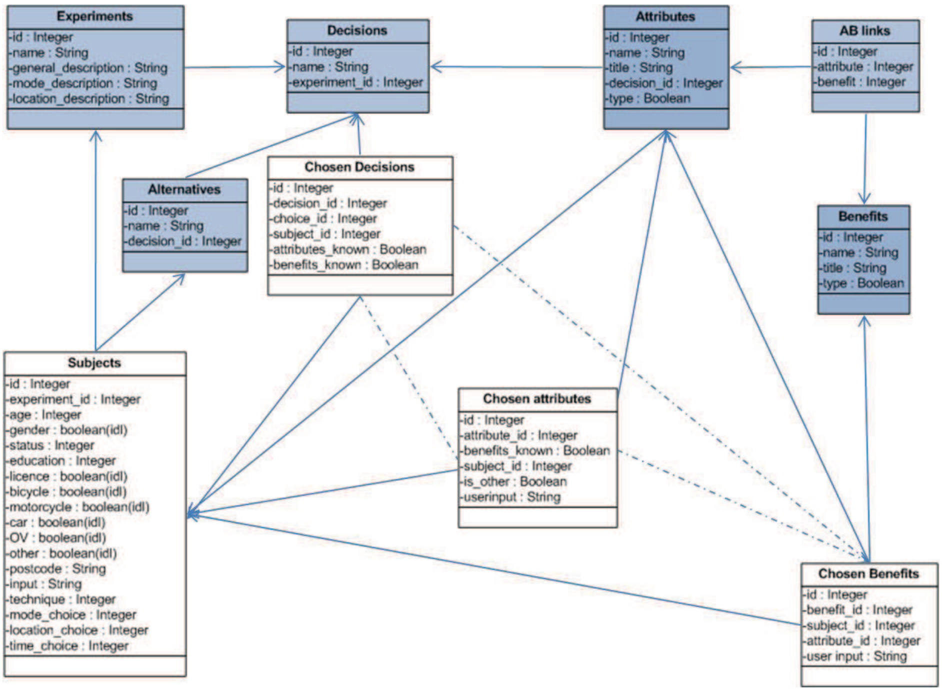

Figure 3-5. Schematic overview of the relational database online HL is based on.

Attributes

The pre-defined list of attributes respondents face in interview step 3 is generated from this data table. It is in fact a selection of attributes from the CNET table *variables*, i.e. both online HL and CNET use the same labels for variables. Furthermore, a short descriptive explanation is stored for each attribute in the column *title*. It will appear on screen as mouse-over effect to help respondents to grasp the content of the listed attributes. In the column *decision ID* it is specified for which decision variable the attribute will be listed.

Benefits

This data table is the counterpart of the table *attributes*. The information which determines which benefits will be revealed for the attribute at hand is however kept in the table *AB links*.

Chosen attributes

Attributes which were ticked off, i.e. which were indicated to be part of the mental representation, are stored in this table. The causal link to the decision variable is not stored explicitly but encrypted in the attribute ID. Whenever respondents type an additional attribute the input string is kept in this table, too.

Chosen benefits

Consequentially, the table *chosen benefits* keeps the benefit IDs that respondents indicated to underlie their considerations. The causal link to the attribute which the benefit is considered for is stored by the attribute ID and potentially added benefits are kept in the column *user input*.

3.3 Development of the case study

The previous section introduced the interview course of online CNET and HL and the database which both techniques are making use of. Before any data could be collected by the new instrument the shaded data tables shown in Figures 3-3 and 3-5 had to be filled. In particular, experimental scenarios had to be set up and their decision variables and choice alternatives specified. Furthermore, attributes, benefits and situational variables that the potential respondents might consider in the experimental choice situations had to be predefined. For CNET also synonyms for these variables had to be collected and entered in the table *synsets*. Finally, the possible causal relations between attributes and benefits had to be coded in the table *AB links*. This section will briefly outline these preparatory works.

Although the online interview instrument is not restricted to any specific research domain, the decision subject is represented by activity-travel related choices in this project. This is not only a research domain where insights into mental representations are of high scientific interest but also a domain where extensive field work by similar and different techniques has been done and can be used for the development and evaluation of experimental scenarios. As the underlying project is an extension of den Hartog's work (2005), also the basic idea of her complex activity-travel choice problem has been taken over. Yet, before it was applied to the interview instrument it had been adapted in several ways. Firstly, the scheduling task was modified to trip planning for daily grocery shopping and working in a fictive environment. Secondly, the complex decision task was reduced to three choices, namely for transport mode, shopping location, and time of shopping. Den Hartog's fourth choice for the sequence of the activities was skipped and integrated in the decision for time of shopping. Thirdly, the choice alternatives for each decision variable were organized in the following way:

- Transport mode choice: Car | Bicycle | Bus
- Shopping location: Supermarket | Corner store | Week market
- Time of shopping: Lunch break | After work | In the evening

These characteristics constitute the skeletal structure of the experimental task. Based on it different experimental scenarios were developed which differ in situational task characteristics. The scenarios will be outlined in the experimental part of this work.

Regardless of the modifications made to den Hartog's (2005) scheduling task her list of pre-defined and added variables was taken as origin for the data tables *variables* in CNET and *attributes* and *benefits* in HL. Hence, 30 attributes (including situational variables) and 20 benefits served as starting point. However, especially for CNET it seemed quite obvious that 30 attributes would not cover all potential considerations respondents might have for the activity-travel choices in the experimental scenarios. Furthermore, the interactive and open character of CNET required the presence of synonyms (or other circumscriptions) of the variable labels in the data table *synsets*. Hence, a pre-requisite for a successful CNET application was the qualitative exploration of the potential vocabulary respondents might use as it has been outlined in the previous section. Basically, three approaches have been used to collect as many (meaningful) considerations and their wordings as possible:

- Brainstorming
- Interviews
- Think-aloud protocols

A first round of brainstorming has been performed individually by six colleagues of the researcher. As all of them worked as PhD candidates in the urban planning group at Eindhoven University of Technology they can be considered as the round of experts. After an oral instruction each of them received a three-page questionnaire where conceivable considerations respondents might have in the experimental task could be filled in empty tables separately for attributes, benefits and situational variables. In a second column synonymous expressions could be stated. This task was repeated for each decision variable. The setting was rather common as scenario related information was not given. Owing to the fact that not all of the experts were native Dutch speakers this brainstorming group was performed in English. The brainstorming round served hence more as source for additional variables than synonymous expressions. Nevertheless, even the English synonyms have been translated and used where meaningful.

A second round of variable exploration has been performed by a native Dutch speaking student assistance. In the frame of a student job she collected considerations and different labels in a brainstorming manner by herself and by interviewing friends, family members and student colleagues. In any case, it was aimed at approaching people from different educational levels and age groups to cover differences in the social variety of language. Furthermore, dictionaries in online and printed version were consulted by the student assistant to find synonymous expressions for the brainstormed considerations. As starting point of her survey she was equipped with den Hartog's variable list and the results from the expert round, too.

Chronologically much later but still in advance of the official pilot tests, think-aloud protocols of CNET and HL test users have been recorded. Five native Dutch speaking third-year-students and two technical employees from the faculty of Architecture, Building and Planning at Eindhoven University of Technology were observed by the researcher while performing a tentative experiment by online HL or CNET, respectively. They were instructed to think-aloud and comment on their actions. While the main purpose of this test-round was checking aspects such as the comprehensibility of the task and the technical soundness under operational conditions, even respondents' considerations could be revealed and possibly missing variables detected. Whenever new linguistic expressions or even unseen considerations emerged they were added to the database.

The considerations collected by all three methods were analysed, summarized and categorized as attributes, benefits or situational variables, respectively. A common label has been chosen for each of them which then was stored in the database as variable name. All other expressions which refer to that variable were grouped in the data table *synset*s together with their Soundex values and linked to the ID of the variable they belong to. Finally, when the pilot experiments started there were 74 attributes (including situational variables) and 21 benefits in the table *variables* and 1344 entries in the table *synsets* (both CNET). Consequently, the table *benefits* (HL) consisted of the same 21 benefits as CNET. Somewhat more specified looked the organization of the table *attributes* in HL. Besides the name of the variable it has also been pre-selected for which decision variable it will be shown to respondents. Eventually, 11 attributes have been selected to appear for the transport mode decision, 16 for shopping location, and 14 for time of shopping. Some attributes were shown for more than one decision variable, for instance might *the crowdedness in the store* be considered both for choosing shopping location and time of shopping. However, no variables would be shown in HL that would not also be part of CNET. Appendix D shows the lists of variables however not in the state prior to the pilot survey as described here but in the state after the analysis being completed by additional variables discovered during the surveys.

The only data table from Figures 3-3 and 3-5 which was not discussed yet is the table *AB_links* specifying which benefits will be revealed to respondents in interview step 4 (HL) or 5 (CNET), respectively. The tailoring of benefits to the attribute under consideration is justified by a better readability of the webpage and the prevention of confusing respondents by showing benefits that are out of question. For example, it is very unlikely that anyone considers the attribute *costs for petrol* because the benefit *safety in the shopping location* would be impacted by it. According to this logic, for each attribute being stored in *attributes* (HL) and *variables* (CNET) meaningful causal links to underlying benefits were pre-specified. These pre-specified links are stored in the table *AB_links*. Nevertheless, in the unlikely case that respondents want to indicate causal links that were actually excluded they could do so by typing the benefit which was not among the revealed ones.

After the even presented preparatory steps had been fulfilled the whole system was tested by 41 Dutch speaking employees of Eindhoven University of Technology or people from outside the university who were acquainted with the author. In any case, none of them was involved in the previous variable exploration survey. These final tests served to check the technical soundness of the system, the proper storage of responses in the database, the clarity of the task instructions, the orthographic accuracy and respondents' opinions about the layout and background color of the webpage etc. After the advices had been analysed and implemented the interview instrument was considered ready for the pilot data collection being described in the next section.

3.4 Pilot testing

This section deals with the pilot survey which has been conducted prior to the actual surveys. As it was decided to use an existing national household panel for the survey there was room and reason to collect pilot data prior to the panel survey. Namely, panel members might have a higher interest to participate in and complete an interview. Otherwise their further panel membership or at least the benefits of their participation might be endangered. These circumstances would therefore bias conclusions about respondents' willingness to participate and complete an online CNET or HL interview. Also, the societal representativeness of the household panel would barely facilitate statements about any self-selection process of certain groups of the population. Expressed in other words, it would not become clear whether CNET and HL differ in their attractiveness and appropriateness for all groups of the population. Therefore, it has been decided to conduct a pilot survey with a sample drawn from a systematically approached but natural population. This pilot survey is described in the following.

3.4.1 Recruiting respondents

Respondents were invited to participate in the experiment by orange paper cards in A6 format (see Figure 3-6) which were systematically distributed in four neighbourhoods in Eindhoven, The Netherlands. These neighbourhoods were selected such as to avoid neighbourhoods previously selected by other research groups and to ensure diversification of respondents. Within these neighbourhoods all households were approached except the ones which explicitly excluded impersonal postings to their letterboxes. Besides the invitation text and the webaddress of the interview the invitation cards included the logo of the TU Eindhoven, the research subject, the name of the researcher and his email address. As incentive for participation a lottery was announced where 10 respondents would win shopping vouchers each worth €50. Furthermore, a date was mentioned by which the interview could be performed. Depending on the neighbourhood in which the addressed household was located this deadline amounted between one and three weeks.

Figure 3-6. Invitation card to participate in the pilot survey.

3.4.2 Experimental Design

Although the interview address of the survey on the invitation card (Figure 3-6) included the term *CNET*, also HL respondents started the interview with this link. Actually, the respondents were not informed at all that two different interview techniques were used in the survey. Neither did the names of the techniques appear anywhere. Rather, respondents started the interview in the belief that the conditions do not differ between respondents and sessions. Only after they enrolled successfully in interview step 1, a random generator determined the interview technique and the experimental scenario for their session.

Basing on the fundamental experimental decision task presented in section 3.3 three scenarios have been developed. The underlying activity-travel task is thus the same in each scenario. It consists of scheduling trips to work and grocery shopping for daily needs on a usual workday. Even a map of a fictive city with the locations of interest was provided in all scenarios. Respondents were asked to imagine that they had recently moved to the new city where they have started a new job. In the so-called *basic scenario* additional information about the travel times for the different transport modes was provided. Furthermore, it was assured that the daily groceries to be bought would be available at all shopping locations. The statements about the travel times and the product availability as well as about the weather situation were modified towards uncertain propositions in the second scenario which therefore is called *uncertainty scenario*. Finally, a third scenario has been developed aimed at generating some psychological distance between the respondent and the situation. The *distance scenario* introduces the basic activity-travel task for a fictive third person, called Laura. Respondents were hence not asked what their considerations are but what they think Laura considers.

The idea behind the development of several scenarios is to test whether CNET is able to measure shifts in mental representations as they are believed to exist. Yet, HL was only run with the basic scenario as HL merely served to benchmark CNET in the pilot survey. The theories behind and the expectations about the techniques' performance will be kept for the main survey in chapter 4.

3.4.3 Sample

From a total of 3945 households which were addressed 276 started the interview (≈7%). Yet, only 137 respondents (49.64%) finished the interview successfully which yields a net response rate of 3.47%. Possible explanations for the low response and the high dropout rate will be discussed in section 3.4.5.

Table 3-1. Descriptors of the pilot sample.

Characteristics		**HL basic**	**CNET basic**	**CNET uncertain**	**CNET distant**
N		38	32	35	32
Gender (% men)		60.5	59.4	60.0	46.9
Age (years) (M/SD)		47.5/17.6	48.1/17.2	44.7/13.8	42.1/16.5
Status (%)	Single	34.2	18.8	22.9	28.1
	Childless Couple	36.8	37.5	34.3	25.0
	Couple with child	23.7	37.5	31.4	28.1
	Lone parent	5.3	0.0	8.6	6.3
	Other	0.0	6.3	2.9	12.5
Education (%)	none	2.6	0.0	0.0	0.0
	secondary school	15.8	6.3	5.7	18.8
	MBO[1]	7.9	15.6	17.1	15.6
	University[2]	73.7	78.1	77.1	65.6
Driving licence (% YES)		100	100	100	31.25
Vehicle ownership (%)					
	Bicycle	92.1	96.9	88.6	87.5
	Scooter	2.6	0.0	8.6	6.3
	Motorcycle	2.6	6.3	5.7	3.1
	Car	78.9	84.4	91.4	59.4
Possession of PT passes (%)					
	40% discount card	31.6	43.8	25.7	40.6
	Annual ticket	7.9	6.3	5.7	6.3
	Route bound discount	0.0	3.1	5.7	9.4

[1] Middelbaar beroepsonderwijs = vocational training school
[2] Including HBO (Higher professional education)

Table 3-1 presents sample descriptors calculated from responses to questions concerning socio-demographic information. It shows that there are only little differences between the sub-samples. Statistical testing revealed that merely the possession of a driving licence and a car differed significantly on a *p*=.05-level between the CNET distant respondents and all other groups. This has a simple cause. For experimental reasons respondents without driving licence where assigned to the distant scenario as it was believed that suchlike respondents could have problems in considering car-related choices for themselves. The distant scenario, in contrast, where the activity-travel task was anyway considered for a third person, avoids this issue. As a logical consequence, also the car possession is significantly lower for CNET distant respondents.

Very striking is the high number of participants with a university degree (or a comparable qualification) between 65.6% and 78.1%. Although the survey took place in neighborhoods close to Eindhoven University of Technology, this finding does by far not reflect the distribution of the educational level in the population. Statistics Netherlands quantified the share of higher educated people in the Dutch population at about 25% in 2003 (http://www.cbs.nl [Accessed 25 February 2011]). Therefore, this finding indicates a greater appeal of scientific online surveys to higher educated people and a stronger interest in participation among this group.

3.4.4 Analysis

The data collected during the pilot survey will be analysed in three different ways. Firstly, some performance measures such as the interview duration and the dropout rate are examined. Secondly, the mental representations will be investigated in a quantitative dimension and, thirdly, in a rather qualitative manner by means of a frequent itemset analysis. The results will be presented in the following.

When analyzing respondents' performance it is first of all worth to know how many respondents dropped out untimely. Table 3-2 presents these numbers and additionally the dropout rate during interview step 1 (instruction part). While 27% of the HL respondents did not finish their session, this number is almost twice as high for the CNET scenarios. A Chi-Square test yielded significant results (χ^2=15.49, *df*=3, *p*=.001) for experimental group vs. finishers/dropouts. When investigating where exactly respondents dropped out it was striking that roughly spoken 50% of them gave up before the second interview task (ranking of decision variables) was completed. This may suggest that the instructions given in the introduction were not clear or too fatiguing or that the subject of research did not arouse interest among respondents. However, it may also mean that respondents struggled with the ranking task.

Table 3-2. Dropouts during the pilot survey.

	HL basic	CNET basic	CNET uncertain	CNET distant
starters	52	67	89	68
finishers	38	32	35	32
dropouts	14	35	54	36
dropout rate	27%	52%	61%	53%
dropout rate before step 2	15%	28%	27%	29%

The high number of higher educated respondents on the one hand and the high number of dropouts on the other hand gave cause to the suspicion that the cognitive demand of the survey has led to the dropout of lower educated respondents. A Chi-Square test for education level vs. dropouts/finishers could rule out this suspicion (χ^2=3.94, *df*=2, *p*=.139).

Respondents who completed the interview had the chance to comment on it in a final step. These comments were grouped into three categories: scenario related comments, technique related comments and personal comments. Typical scenario related comments regarded for instance elucidations of respondents´ activity-travel considerations or that the scenario did not match their real life situation. For these respondents, the comment box served mainly as a relief to finally express what could not be stated during the interview. The second group of comments regarded statements about technical or procedural features of the corresponding interview technique. Some respondents criticized for instance the abstract questions or the long instructions. Finally, a third group of comments comprises statements such as "interesting research" or "I would like to get informed about the outcomes of this study." Number of comments and their relation to respondents are shown in Table 3-3.

According to Table 3-3 the tendency to comment is slightly higher in CNET than in HL. As this could be expected for technique related comments, the difference for scenario related comments between HL and CNET basic is a bit striking as the given situations do not differ. Furthermore, the strong positive echo for CNET in terms of personal comments is even more surprising. However, statistical tests are not reliable as the observed frequencies are too little.

Table 3-3. Respondents' final comments.

		scenario	technique	personal
HL basic	Number of comments	4	3	2
	relative	11%	8%	5%
CNET basic	Number of comments	7	5	7
	relative	22%	16%	22%
CNET uncertain	Number of comments	5	3	2
	relative	14%	9%	6%
CNET distant	Number of comments	2	6	3
	Relative	6%	19%	9%

Table 3-4 presents means for the interview duration for each experimental group. Respondents from HL basic completed the interview quickest in 13min 33s whereas CNET distant respondents took most time to fill in their considerations (19min 55s). An analysis of variance (ANOVA) on interview duration between the four experimental groups showed significant results (F=3.046, df=3, p=.031). Bonferroni corrected post hoc tests indicate however a difference only between HL basic and CNET distant (p=.050).

Table 3-4. Means for interview duration per scenario.

	N	Mean	SD	Std. Error
HL basic	38	00:13:33	00:06:45	00:01:06
CNET basic	32	00:19:05	00:10:52	00:01:55
CNET uncertain	35	00:18:33	00:08:26	00:01:26
CNET distant	32	00:19:55	00:13:05	00:02:19
Total	137	00:17:36	00:10:08	00:00:52

Switching now the focus to the actual aim of the interview techniques, namely measuring mental representations, the first analysis concerns the ranking of decision variables. Table 3-5 presents means for each scenario. As HL and CNET basic did not differ methodologically up to that interview step their results were merged. The average rank scores for all decision variables are around 2, suggesting that the ranking is quite balanced. Nevertheless, it seems that the ranking in the basic scenarios are more outbalanced than in the uncertain and distant scenario which show a rank pattern of the form: time of shopping, transport mode, shopping location. It has however to be noted that actually only a few respondents ranked the transport mode choice second. Rather, number of respondents who ranked it first and third was almost equally large. Tests of significance did not show effects between scenarios and decision variables.

Table 3-5. Ranking of the decision variables (average rank scores).

Scenario	Basic	Uncertain	Distant
Transport Mode	1.99 (SD 0.86)	2.00 (SD 1.00)	2.06 (SD 0.95)
Shopping Location	1.97 (SD 0.72)	2.11 (SD 0.68)	2.09 (SD 0.69)
Shopping Time	2.04 (SD 0.88)	1.89 (SD 0.76)	1.84 (SD 0.81)

When the elicited mental representations were analysed six variables have been created whose means are reported in Table 3-5. *Cognitive subsets* counts all causal associations of the form decision variable – (attribute –) benefit. *Attributes* is the number of ticked off (HL), typed in (CNET) or added (HL) attributes. *Unknown attributes* counts added attributes (HL) and not-interpreted inputs (CNET). *Benefits* is the number of recalled (CNET), ticked off or added (HL and CNET) benefits. *Unknown benefits* counts all benefits which have been added (HL and CNET). *Benefits per attribute* is the ratio between number of benefits and number of attributes.

Table 3-6. Means of dependent variables for each experimental group.

Variable	HL basic	CNET basic	CNET uncertain	CNET distant	F	df	p
Cognitive subsets	41.66	22.13	22.80	28.88	4.117	3	.008
Attributes	11.71	6.31	5.97	7.09	19.163	3	<.001
Unknown attributes	0.21	2.16	1.97	3.19	14.356	3	<.001
Benefits	12.47	9.00	9.23	9.81	5.023	3	.002
Unknown benefits	0.82	0.31	0.51	0.50	1.208	3	.309
Benefits/attribute	1.09	1.56	1.63	1.50	7.852	3	<.001

An examination of Table 3-6 reveals that HL yields significantly different means than CNET for almost all variables. The number of cognitive subsets is almost twice as high for HL than for the CNET scenarios which might be caused by an induction effect of presenting variable lists to the respondent which CNET circumvents. It is conceivable that HL respondents indicated causal links between variables which they recognized as plausible reasons but which were not necessarily part of their MR. After the significant F-test (F=4.117, p=.008) Bonferroni corrected post hoc tests showed a significant difference between HL basic and CNET basic (p=.018) and CNET uncertain (p=.020).

Also number of attributes is roughly twice as high for HL than for CNET and, therefore, significantly different (F=19.163, p <.001) between scenarios. Post hoc tests showed that all CNET scenarios differ significantly (p <.001) from HL but not among each other. As for cognitive subsets this finding might be caused by an induction effect by the revealed handling of variables in HL. The same applies to number of unknown attributes which shows a significant difference between HL and all CNET scenarios (p ≤.001) in the post hoc test. The low value for HL (0.21) can have different reasons. On the one hand, it speaks to the completeness of the provided list of attributes in HL. On the other hand, this recognition-oriented methodology might hamper respondents in rendering their MR completely consciously, i.e. attributes which are not on the list are also not recalled. The higher values for CNET in turn do not necessarily speak to the incompleteness of the database. Rather, it might be caused by an imperfect performance of the string recognition algorithm. Whenever wordings were used for which no match could be found (or only matches for similar sounding words), the respondent could go on with the not interpreted input which was then treated as an unknown attribute. It does, however, not necessarily mean that this attribute is not already part of the database under a different label.

The significant difference in number of benefits (F=5.023, p=.002) is confirmed by the post hoc results between HL basic and CNET basic (p=.006), and HL basic and CNET uncertain (p=.010), respectively. The higher values for number of benefits among HL respondents might be a multiplication effect as also number of attributes was higher in this group. Hence, HL respondents were more frequently faced with the interview step aiming at eliciting benefits. The technique itself cannot be causal for this difference since respondents of both techniques were able to recognize benefits from a list. Consequently, number of unknown benefits does not differ significantly between the experimental groups.

When comparing the ratio of benefits to attributes, HL basic yields significantly (*p*=<.001) lower numbers than all CNET scenarios. While this ratio is almost 1:1 for HL, CNET yields around 1.5 times more benefits than attributes. The reason for this perhaps unexpected finding is, as mentioned above, the comparatively low number of recalled attributes to the high number of recalled (mean 0.73) and recognized benefits in the CNET scenarios.

Besides the structure of mental representations also their content, i.e. the nature of the cognitive subsets, has been examined by means of a frequent itemset analysis. The itemsets are in this case respondents' cognitive subsets. The latter are the smallest self-contained entities of a mental representation. Theoretically, a mental representation could consist only of one cognitive subset. For this work a cognitive subset or itemset, respectively, is defined as mental association between a decision variable and a benefit and a possibly interlinked attribute or situational variable. For the sake of completeness it has to be added that the association between a decision variable and a situational variable is not of causal character, i.e. the choice cannot influence the situation in which the decision takes places. Nonetheless, whenever a decision maker takes situational factors into consideration for a decision he establishes some sort of cognitive association between them. This association is thus captured in the itemsets, too. The frequent itemset analysis requires a threshold value determining whether an itemset is considered as frequent or not. This so-called minimal support value (minsupp) expresses the appearance of a certain itemset over the amount of all elicited itemsets as percentage. As any cognitive subset can be elicited only once per respondent, the minsupp value is the percentage of respondents who consider it in this study. Yet, since this study has a rather exploring character it is not aimed at determining an arbitrary threshold for frequency by defining random minsupp values. Rather, the support values were calculated for the most frequent itemsets in each scenario. Table 3-7 summarizes all itemsets which were considered by at least 20% of respondents in any CNET scenario. The listing is incomplete for HL basic as there were 72 cognitive subsets on which more than 20% of the respondents agreed.

According to Table 3-7 the cognitive subsets yield considerably higher support values in HL basic than in the CNET scenarios. This is not surprising when taking into consideration that also number of cognitive subsets is significantly greater in HL basic (Table 3-5). Owing to the limited and tailored lists of response variables it is hence very likely that the results suggest a higher agreement among HL respondents. Still, it can also be seen that all frequent CNET itemsets score high also in HL with two exceptions.

Table 3-7. Support values of frequently elicited cognitive subsets.

Cognitive subset	HL basic	CNET basic	CNET uncertain	CNET distant
SL - available assortment - shopping success	44.74 %	21.88 %	34.29 %	31.25 %
SL - price level – financial savings	42.11 %	31.25 %	17.14 %	18.75 %
SL – available assortment – diversity in choice	36.84 %	18.75 %	17.14 %	28.13 %
TM – amount of luggage – ease of travelling	50.00 %	21.88 %	20.00 %	12.50 %
TM – weather – travel comfort	39.47 %	12.50 %	20.00 %	15.63 %
SL – available assortment – ease of shopping	34.21 %	15.63 %	20.00 %	9.38 %
SL – distance – time savings	0.00 %	6.25 %	14.29 %	21.88 %
TM - % - environmental protection	0.00 %	12.50 %	0.00 %	21.88 %

SL=Shopping Location, TM = Transport Mode

Both cognitive subsets at the bottom of the table which were considered by 21.88% of CNET distant respondents did not appear in HL basic at all. While this could be caused by the scenario as well, the main reason is that the attribute *distance* was not among the response possibilities in HL basic. Still, respondents had the chance to type it if they really considered it. Skipping the attribute level was not possible in HL which explains the value for the *transport mode – environmental protection* itemset. CNET basic yields only three cognitive subsets which are supported by at least 20% of the respondents, while the other two CNET scenarios yield four each.

Some sort of agreement between the experimental groups exists for the cognitive subset *shopping location – available assortment – shopping success* which was considered by more than 20% of respondents of each group. Even though the CNET scenarios did not differ significantly for the structural variables in Table 3-6, here some interesting effects can be seen. The uncertainty about the available product assortment which was implied in the uncertain scenario is reflected by the highest support value of the respective cognitive subset among all CNET groups. Furthermore, the fact that the *transport mode – environmental protection* itemset was not elicited for CNET uncertain speaks to the insignificance of suchlike noble considerations when the uncertainty about the choice outcome forces respondents' focus to the more choice relevant considerations. Besides, it is also striking that all the listed itemsets are cognitive subsets for transport mode choice and shopping location choice. Cognitive subsets for *time of shopping* did not exceed support values of 12.5% for any CNET scenario. This means that decision makers differ strongly in their cognitive subsets when considering *time of shopping*.

3.4.5 Conclusions and implications for the main survey

First of all, the pilot study proved that CNET and HL can be brought online for large-scale surveys albeit with some concessions to the original interview protocols and some caveats like the low response and the high dropout rate. The complexity of online CNET is assumed not to be higher than for offline CNET. The threshold to drop out is in the anonymous online version only much lower.

It has also been experienced that the invitation to the online interview appealed mainly higher educated people. Hence, the second development goal listed under 3.1 could not be hold. As a logical consequence for the main survey it was aimed at finding another means for respondent recruitment which is able to attract potential respondents of all education levels and to decrease the dropout rate. As it will be described in section 4.4 the application of the electronic instrument to a household panel turned out to be a proper solution. Next to a better respondent accessibility it means also an extra easement for the researcher. An assessment of the economical effort for the researcher which also is aimed at being minimized by the new interview instrument would, however, be unjustified due to the extra effort caused by the pilot character.

In comparison to conventional face-to-face interviews the pilot survey yielded a strongly decreased interview duration. Dellaert *et al.* (2008) report an average interview duration of 55 minutes for their offline CNET version which is almost three times as long as for online CNET. Yet, it has to be added that their interview included an additional set of questions to reveal parameters of the causal network (i.e., conditional probabilities and utilities). Nevertheless, it is believed that the shorter interview duration contributes to a higher respondent friendliness.

The results of the study have clearly shown that MRs elicited by CNET are smaller than the MR elicited by HL. The number of cognitive subsets, number of attributes and number of benefits are all significantly smaller in CNET than in HL. The explicit a priori listing of variables in the latter technique might, thus, trigger mentioning attributes which are not necessarily part of the MR. In order to check how respondents evaluated their opportunities to indicate (all aspects of) their considerations a post-experimental question addressed this issue ("Could you indicate all your considerations?"). On a scale from 1 (never) to 7 (always) HL scored highest (5.83). The difference to CNET (5.25) is, however, not significant. There is no correlation between this post experimental rating and the number of times the string recognition could not find a match (r = -0.047 with p = .800).

Although the variables describing the structure of the mental representations differed significantly between HL and the CNET scenarios, there was no measurable effect among the three CNET scenarios. This leads to the tentative conclusion that the scenarios did not differ enough to measure a structural shift in the mental representations. For the main survey the descriptions and instructions were therefore revised. Besides small textual changes and a clearer presentation of the scenario relevant information the revision regards above all the distant scenario. The psychological distance which has been attempted to achieve by considering the activity-travel task for another but fictive person (Laura) will be substituted by a temporal (and spatial) distance from the respondent in the main survey. All scenarios will be described in detail in section 4.3. Although no structural shifts in MRs were found in the pilot study the examination of the frequent cognitive subsets showed indeed a substantive variation between all scenarios. This finding gives rise to optimism about CNETs ability to measure sensitively substantial changes in mental representations.

4

Measuring Individuals' Joint Choices of Shopping and Transportation

4.1 Introduction

In the previous chapter the online instrument for measuring mental representations with its two applied techniques has been described. The outcomes of a pilot study were despite some minor deficits encouraging for deeper investigation. In order to be able to draw conclusions on the applicability of online HL and CNET for measuring mental representations a broader survey has been considered necessary after the settings had been improved according to the discovered shortcomings. The settings concern a bigger and more representative sample on the one hand and more elaborate experimental scenarios on the other hand.

This chapter starts by outlining the technical and experimental expectations of the proposed scenarios and measuring techniques. Accordingly, the performance of the study and the sample are described. The subsequent analysis part reports how the experimental subsamples differ in their mental representations. The analysis is, in turn, split up into an explorative and a performance evaluative part.

4.2 Technical expectations

Before outlining the expectations linked to this survey it might be worthwhile to take a look back to the motivation of this project. In chapter 2 several techniques for measuring mental representations had been introduced. Some of them were criticized for being too suggestive by providing predefined answer options. Other completely open and unstructured techniques have the drawback of yielding barely comparable results. Originating from these extreme counterpoints CNET was developed and brought online with basically three intentions:

1) Eliciting genuine data without impacting the respondent

2) Being attractive and accessible for (almost) all respondents

3) Being easily and economically applicable for researchers

Undoubtedly, points 2 and 3 were also important issues for developing online CNET. For assessing CNET´s performance in measuring mental representations they are however considered as having negligible influence. Thus, merely the first issue is of concern in this regard.

What is aimed at being expressed by the awkward term "genuine data" is nothing else than unbiased mental representations. As the discussion will show later on this is a sublime aim which hardly can be attained. Nevertheless, by comparing the mental representations yielded by online CNET with mental representations elicited by a technique which already proved its consistency it is expected that CNET can firstly be validated and secondly demonstrate its advantage in having less technique specific impact on the outcomes. These two ambitions are believed to be accomplished by contrasting online CNET with the earlier outlined online HL. This technique is not only based on established on- and offline techniques such as computerized hard laddering (Russell *et al.* 2004a,b) and the association pattern technique (ter Hofstede *et al.* 1998) it also can be considered as a counterpart to CNET as it works with predefined answer options. Such it can be investigated whether mental representations measured with CNET are less impacted than mental representations from HL. Formulated differently, it is expected that showing attributes and benefits has an impact on the size of the mental representations as it has been reported by others for similar investigations (Russell *et al.* 2004a). Psychologically, this can be explained with the difference in the cognitive effort both techniques require. While HL stresses recognition CNET respondents are demanded to recall attributes and benefits. Hence, HL respondents might also indicate variables which are not necessarily underlying their considerations but are esteemed as plausible causes. On the other hand, CNET respondents might not mention attributes and benefits which they take for granted or obvious. Hence, next to a quantitative difference in the structure of mental representations it is also believed that their substance differs between techniques.

Depending on the variation in response freedom online CNET is believed to be more sensitive in measuring shifts in mental representations than online HL. If it is true that revealed a priori lists cause a higher indication of attributes and benefits it can be expected that this leads to an equalization of mental representations for different decision situations. This expected outcome might not only be caused by the fact that a recognition stressed technique such as HL rather measures causal knowledge than actual considerations but also by the limited amount of listed attributes and benefits. The open questions in CNET in turn are believed to lead to the rather necessary and choice relevant variables. As online CNET applies all (hidden) variables from the database as possible responses the variation between decision situations and individuals is believed to be much stronger. In order to test the expected higher sensitivity of online CNET five different experimental scenarios have been developed which are presented in the next section.

4.3 Experimental settings and expectations

According to the pilot experiment an activity-travel task has been chosen which was believed to be a familiar decision problem for respondents. It consisted of a scheduling task for working and grocery shopping on a usual workday in a fictive environment. More precisely, in interview step 1 (Figures 3-2 and 3-4) respondents were informed about their task and the situational settings on three subsequent webpages (see Figures B-1 to B-3 in Appendix B). The first page introduced the activity-travel task in general and the choice for time of grocery shopping and its alternatives (during lunch break, after work, in the evening) in specific. A map of the fictive city with images for home and work place gave visual support. On the second page the shopping locations were introduced (week market, corner shop, a supermarket) and if necessary additional information on the product availability provided. Again, visual images of the shopping locations on the map were given for a better orientation. Finally, the available transport modes (represented by images for car, bicycle, and bus) and information on situational circumstances like traffic conditions were introduced on the third page. Situational relevant information and the images of the choice alternatives were repeated later in the interview during the elicitation of attributes and benefits. Anyhow, the variation of situational circumstances and choice alternatives led to the setup of five experimental scenarios which served to test the techniques' sensitivity on measuring mental representations.

Basic scenario

This scenario is the basic activity-travel task all other scenarios are based on. Owing to its neutral situational background it serves mainly as benchmark. On the three introduction pages respondents were provided with the following information (translated from the Dutch original):

Page1: *Imagine that you got a new job in another town and that you therefore moved to that town. On the map beside you can see your new house and working place. You work eight hours with a flexible start time and you can take a lunchbreak of one hour at maximum. In order to do the daily shoppings you have thus three possibilities:*

- *during lunchbreak*
- *directly after work*
- *later in the evening*

Page 2: *There are three shopping locations for daily shopping in your town:*

- *a little shop close to your house*
- *a big supermarket at the fringe of the town*
- *a week market in the city centre*

The products on your shopping list are at any time available at all locations.

Page 3: *Assume that you have the availability of*

- *a car and*
- *a bicycle*

Furthermore, all locations are accessible by

- *frequently operating buses*

You can travel on a direct route without long detours and a travel time between 10 and 15 min by all means of transport.

Summarized, respondents were asked to imagine to have moved to the city shown on a map for a new job position. They were working eight hours with flexible begin time. Travelling between the locations of interest would be possible on direct routes with a travel time from 10 to 15 minutes. Furthermore, respondents should assume that their desired groceries are available at all shopping locations.

<u>*Uncertainty scenario*</u>

Deviating from the basic scenario some fuzzy information about the situational aspects was given in this scenario. In detail, the chance for congestion with a travel time delay of 30 minutes was reported to be 25 %. Furthermore, respondents were informed that some products which they needed (e.g. bread) were possibly sold out. In detail, respondents got the following information:

Page 1: *Imagine that you got a new job in another town and that you therefore moved to that town. On the map beside you can see your new house and working place. You work eight hours with a flexible start time and you can take a lunchbreak of one hour at maximum. In order to do the daily shoppings you have thus three possibilities:*

- *during lunchbreak*
- *directly after work*
- *later in the evening*

Page 2: *There are three shopping locations for daily shopping in your town:*

- *a little shop close to your house*
- *a big supermarket at the fringe of the town*
- *a week market in the city centre*

Some products that you need are possibly sold out (e.g. bread).

Page 3: *Assume that you have the availability of*

- *a car and*
- *a bicycle*

Furthermore, all locations are accessible by

- *frequently operating buses*

You can travel on a direct route without long detours and a travel time between 10 and 15 min by all means of transport. The chance of traffic jams with a delay of 30 minutes amounts to 25%.

The idea behind the development of this scenario was to test whether mental representations become less complex, i.e. consist of fewer variables and links, when compared to mental representations for the basic activity-travel task. It is namely believed that the implied uncertainty of the decision situation increases the mental effort for the decision maker. Due to limited mental capacity less situation-relevant attributes and benefits are unlikely to be considered.

Distant scenario

In a third scenario some sort of psychological distance between the respondent and the situation was generated by presenting the basic activity-travel task for a decision situation over five years from now without support of a geographical map.

Page 1: *We assume a hypothetical situation over 5 years from now. Imagine that you have moved to another town by then. You have a fulltime job in the same town where you are going to live. In order to do the daily shoppings you will have three possibilities:*

- *during lunchbreak*
- *directly after work*
- *later in the evening*

Page 2: *There are three shopping locations for daily shopping in the town where you will live over five years from now:*

- *a little shop close to your house*
- *a big supermarket at the fringe of the town*
- *a week market in the city centre*

The products on your shopping list are at any time available at all locations.

Page 3: *Assume that you will have the availability of*

- *a car and*
- *a bicycle*

Furthermore, all locations are accessible by

- *frequently operating buses*

You can travel on a direct route without long detours and a travel time between 10 and 15 min by all means of transport.

Besides the already existing psychological distance between respondents' real life and the experimental situation the implied time shift was expected to increase that distance even more. According to Temporal Construal Theory (Trope and Liberman, 2003) people tend to think in rather abstract concepts when the temporal distance between the time of consideration and the time the considered situation is embedded increases. For the activity-travel task of this scenario we expect hence mental representations to be more benefit-oriented than the mental representations for the basic task where we expect attributes to be most central.

E-commerce scenario

The introduction of this scenario follows the wording of the basic scenario.

Page 1: *Imagine that you got a new job in another town and that you therefore moved to that town. On the map beside you can see your new house and working place. You work eight hours with a flexible start time and you can take a lunchbreak of one hour at maximum. In order to do the daily shoppings you have thus three possibilities:*

- *during lunchbreak*
- *directly after work*
- *later in the evening*

Page 2: *There are three shopping locations for daily shopping in your town:*

- *a little shop close to your house*
- *a big supermarket at the fringe of the town*
- *a week market in the city centre*

Furthermore, there is the possibility

- *to order the shoppings online from home or work and get them delivered later on.*

The products on your shopping list are at any time available at all locations.

Page 3: *Assume that you have the availability of*

- *a car and*
- *a bicycle*

Furthermore, all locations are accessible by

- *frequently operating buses*

You can travel on a direct route without long detours and a travel time between 10 and 15 min by all means of transport.

The only difference to the basic scenario occurs when the choice alternatives for the shopping locations are presented. In contrast to all other scenarios respondents have an additional option to do their grocery shopping online. This e-commerce option includes also a home delivery service. The other alternatives and situational specifications remain unchanged. The e-commerce option differs characteristically from the other three shopping alternatives; an assumption which is believed to result in a shift in the comparative consideration process. On the one hand, additional needs might become activated resulting in a higher number of benefits. Owing to this shift in the benefits also the consideration of attributes will differ. This shift might however not necessarily have a quantitative effect. Rather, it is expected that the nature of considered attributes will differ.

Risky scenario

The introduction to this scenario was more comprehensive than for the others.

Page 1: *Imagine that you got a new job in another town and that you therefore moved to that town. On the map beside you can see your new house and working place. You work eight hours with a flexible start time and you can take a lunchbreak of one hour at maximum.*

*Tonight you invited your **new boss for dinner** at your house. For the dish that you want to prepare for this special event you need very **special ingredients** which you **do not have in house.** Hence you need to buy them today. You can choose the time of doing the shoppings:*

- *during lunchbreak*
- *directly after work*
- *later in the evening*

Page 2: *There are three shopping locations for daily shopping in your town:*

- *a little shop close to your house*
- *a big supermarket at the fringe of the town*
- *a week market in the city centre*

Page 3: *Assume that you have the availability of*

- *a car and*
- *a bicycle*

Furthermore, all locations are accessible by

- *frequently operating buses*

You can travel on a direct route without long detours and a travel time between 10 and 15 min by all means of transport.

Besides the information from the basic activity-travel task respondents were asked to imagine their new boss would come for dinner tonight for which they want to prepare his favourite dish. Respondents were furthermore instructed that they would not have the special ingredients at home but needed to buy them only on that certain day. The key information was printed in bold.

This *risky* activity-travel task is expected to activate stronger needs than the task of all other scenarios. An anticipated failure of the planned activities is most likely connected with negative consequences for the decision maker. Hence, he might consider on his possible actions of choice by focussing on avoiding negative consequences or satisfying his activated needs, respectively. An increased complexity and a stronger focus on the implied risky aspects are esteemed as indicators for the shift in the mental representation.

4.4 Data collection and sample

The optimal application of the experimental scenarios to the measuring instruments would be a five (scenario) by two (technique) research design. Nonetheless, for reasons of sample recruitment it was decided to split the whole study into two waves. A first wave of experiments was conducted in May 2010. It comprehended the basic, the uncertain and the distant scenario applied to both CNET and HL. The second round of experiments took place in October 2010 and consisted merely of the e-commerce and risky scenario as CNET applications. The reasons for omitting HL in the second wave are twofold. First, HL is a proven technique which served merely to benchmark CNET. As will become clear further below, CNET proved to be a valid technique for measuring mental representations already in the first wave. Hence, the need for collecting data with HL and comparing them to CNET data was not given any longer. Second, the recruitment of respondents among panel members set limitations to the sample size as the next paragraph will outline.

In the conclusions of the pilot study (section 3.4.5) it has been stated that an anonymous recruitment of respondents through systematic distribution of invitations led to a non-representative sample. In order to overcome this problem the sample recruitment for the main study was taken over by CentERdata, a research institute attached to Tilburg University and supported by the Dutch Organization for Scientific Research (NWO), after the proposal of the author had been accepted. This organization keeps a nationwide panel of 5000 Dutch households, the so-called LISS panel. This panel is open for scientific online surveys and provides advantageous conditions for testing innovative ways of data collection. The management of socio-demographic background data of the panel members facilitates a representative sample according to the Dutch population. Thus, also difficult-to-reach groups are accessible. For instance, elder people are equipped with laptops and internet access at home in order to be able to participate. Furthermore, helpdesks provide phone assistance when respondents get in trouble. An internal incentive and rewarding system raises the attractiveness of survey participation for panel members. However, CentERdata ensures also that panel members do not participate too often in surveys or reject participation too frequently, respectively. In order to guarantee consistency and readability for respondents CentERdata required the adaptation of the CNET- and HL-applications according to their internal layout (see Appendices B and C) and the inclusion of a post-experimental questionnaire. This adaptation did however not regard technical or methodological changes.

In an agreement between CentERdata and the author it was decided to split the study into two waves of data collection as also other researchers were interested in using the LISS panel for their studies by that time. Furthermore, it was aimed at collecting mental representations of about 200 respondents for each experimental group. The selection of respondents was however restricted to three criteria: possession of a driving licence, aged between 18 and 60 years and having Dutch language skills. The former two characteristics were set up to ensure a real world reference for the experimental situations. The latter condition resulted from the interview language. According to these agreements CentERdata invited a selection of its panel members by email to participate in the survey. The potential respondents had about two weeks time to follow the link to the survey. The assignment of respondents to scenario and technique happened randomly but equally distributed over the experimental groups.

4.4.1 Sample characteristics

After the data collection had been finished CentERdata handed over the data of the elicited MRs together with the socio-demographic characteristics of the invited respondents. During a first cleaning step data of respondents who dropped out untimely or performed the interview several times needed to be removed from the data table *subjects* (compare section 3.2). More about the dropouts can be read in section 4.6.2.

In the following sample characteristics are presented from all respondents who finished the online interview successfully.

a) Gender

The composition of respondents according to gender as shown in Table 4-1 shows a slightly larger share of female respondents for all scenarios. Additional Chi-Square tests on the distribution between techniques and scenarios did not yield significant differences.

Table 4-1. Gender distribution of the sample.

interview technique			experimental scenario				
			basic	uncertainty	distance	e-commerce	risky
HL	Male	absolute	98	85	82		
		relative	46.0%	45.0%	42.5%		
	Female	absolute	115	104	111		
		relative	54.0%	55.0%	57.5%		
	Total		**213**	**189**	**193**		
CNET	Male	absolute	81	77	92	137	126
		relative	43.8%	46.1%	47.4%	47.2%	40.1%
	Female	absolute	104	90	102	153	188
		relative	56.2%	53.9%	52.6%	52.8%	59.9%
	Total		**185**	**167**	**194**	**290**	**314**

b) Age

Table 4-2 reports the age characteristics for the sample which however cannot be considered as representative for the Dutch population as only respondents between 18 and 60 years were selected. An ANOVA between the experimental groups did not yield significant differences (F=.461, df=7, p=.863).

Table 4-2. Age characteristics of the sample.

interview technique		experimental scenario				
		basic	uncertainty	distance	e-commerce	risky
HL	Mean	43.3	42.8	43.1		
	SD	11.1	11.4	11.2		
CNET	Mean	42.8	43.2	42.5	43.5	44.1
	SD	11.4	10.5	11.5	10.9	10.9

c) Marital status

Respondents were categorized according to their marital status into one of five groups: single, childless couple, couple with child, single parent and other. Table 4-3 reports the distribution per scenario and technique whereas Figure 4-1 shows a graph for the whole sample. More than half of the respondents live in traditional families.

Table 4-3. Marital status of respondents.

interview technique			experimental scenario				
			basic	uncertainty	distance	e-commerce	risky
HL	Single	absolute	28	23	26		
		relative	13.1%	12.2%	13.5%		
	Childless couple	absolute	54	46	52		
		relative	25.4%	24.3%	26.9%		
	Couple with child	absolute	118	110	105		
		relative	55.4%	58.2%	54.4%		
	Single parent	absolute	9	7	8		
		relative	4.2%	3.7%	4.1%		
	Other	absolute	4	3	2		
		relative	1.9%	1.6%	1.0%		
CNET	Single	absolute	25	28	24	38	44
		relative	13.5%	16.8%	12.4%	13.1%	14.0%
	Childless couple	absolute	58	45	55	79	94
		relative	31.4%	26.9%	28.4%	27.2%	29.9%
	Couple with child	absolute	92	81	97	156	157
		relative	49.7%	48.5%	50.0%	53.8%	50.0%
	Single parent	absolute	8	10	15	16	16
		relative	4.3%	6.0%	7.7%	5.5%	5.1%
	Other	absolute	2	3	3	1	3
		relative	1.1%	1.8%	1.5%	0.3%	1.0%

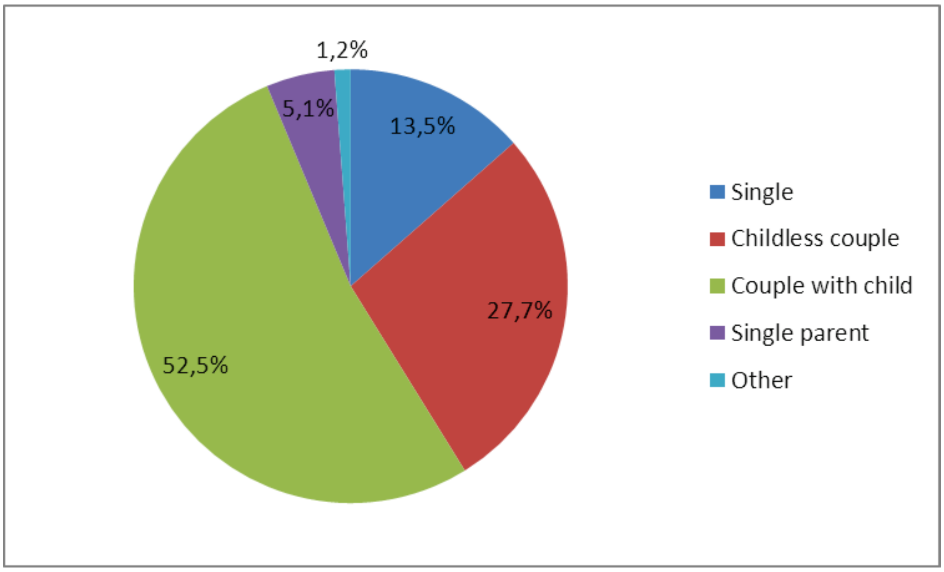

Figure 4-1. Sample distribution according to marital status.

d) Education

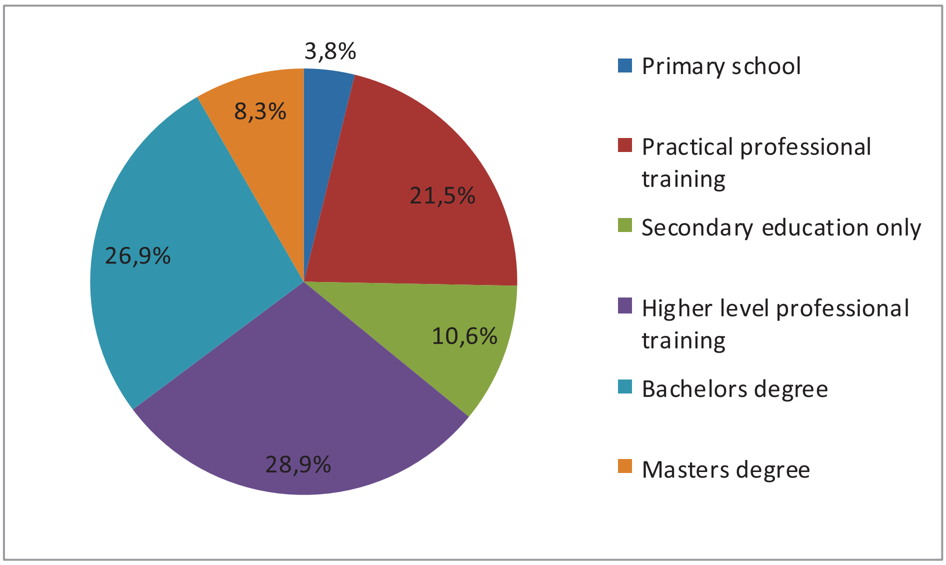

Figure 4-2. Sample distribution according to education level.

Figure 4-2 represents the education level for the whole sample as any statistical differences between HL and CNET or among the scenarios were not discovered. Remarkable is the relative decline of higher educated respondents (35.2%) compared to the pilot study (between 65.6% and 78.1%). Thanks to the selection of panel members the new numbers are much more representative for the Dutch population (www.cbs.nl).

Table 4-4. Education level of respondents.

interview technique			experimental scenario				
			basic	uncertain	distant	e-com.	risky
HL	Primary school	absolute	10	9	9		
		relative	4.7%	4.8%	4.7%		
	Practical professional training	absolute	52	38	36		
		relative	24.4%	20.2%	18.7%		
	Secondary education only	absolute	20	18	24		
		relative	9.4%	9.6%	12.4%		
	Higher level professional training	absolute	63	56	49		
		relative	29.6%	29.8%	25.4%		
	Bachelors degree	absolute	53	44	60		
		relative	24.9%	23.4%	31.1%		
	Masters degree	absolute	15	23	15		
		relative	7.0%	12.2%	7.8%		
CNET	Primary school	absolute	5	11	6	10	7
		relative	2.7%	6.6%	3.1%	3.5%	2.2%
	Practical professional training	absolute	39	36	43	58	72
		relative	21.1%	21.6%	22.2%	20.1%	23.0%
	Secondary education only	absolute	22	18	19	35	29
		relative	11.9%	10.8%	9.8%	12.1%	9.3%
	Higher level professional training	absolute	61	48	55	79	92
		relative	33.0%	28.7%	28.4%	27.3%	29.4%
	Bachelors degree	absolute	42	48	49	80	92
		relative	22.7%	28.7%	25.3%	27.7%	29.4%
	Masters degree	absolute	16	6	22	27	21
		relative	8.6%	3.6%	11.3%	9.3%	6.7%

4.5 Analysis of mental representations

4.5.1 Preparations

As mentioned in the previous section the raw data from CentERdata needed to be cleaned before the mental representations could be analysed. Besides removing entries of respondents who dropped out untimely all entries without assigned variable ID in the data tables *elicited attributes, elicited benefits, chosen attributes* and *chosen benefits* still needed to be interpreted. Missing a variable ID could have basically three reasons:

1) The consideration was added to the variable list in HL or in the summary step in CNET.
2) The consideration could not be interpreted by the string recognition tool or the respondent refused all suggested interpretations (CNET).
3) The respondent typed nonsense strings to finish the interview (CNET).

While the latter type of non-interpreted entries has been excluded from further analysis, the first two types of entries were coded manually by the researcher. With help of the list of variables he interpreted them as one of the pre-defined attributes and benefits or established a new variable ID whenever respondents' considerations did not match one of them. Despite of their undoubted reasonability some data entries could however not be interpreted as they were for instance too abstract or incomplete. Under such circumstances they were excluded from further analysis, too. The same applies to all data entries which were in fact statements about preferred choice alternatives, e.g. *I take the car, shopping after work,* or *supermarket.*

Table 4-5 gives an overview of the frequency and nature of non-interpreted data entries and how they were categorized by the researcher. The column *supposed attributes* represents considerations which were either added to the list of revealed attributes in HL (interview step 3), typed during the open elicitation in CNET (interview step 3) or added in the summary part in CNET (step 6). Although they in fact could be benefits as well they were previously treated as attributes in order to keep the interview algorithm on going. Correspondingly, the column *supposed benefits* represent considerations which were added to the list of revealed benefits (step 5 in CNET, step 4 in HL). In the column *% of all attributes/benefits*, the ratio of all unidentified entries to the overall number of elicited attributes or benefits is presented, respectively.

Table 4-5. Frequency and nature of non-interpreted data entries.

	Supposed attribute	% of all attributes	Post-experimentally categorized as:				
			attribute	*benefit*	*choice*	*nonsense*	*unclear*
HL	**47**	0.9	31	3	3	7	3
CNET (I)	**1484**	41.2	864	56	324	127	113
CNET (II)	**1646**	45.4	1061	125	223	155	82
	Supposed benefit	% of all benefits	Post-experimentally categorized as:				
			attribute	*benefit*	*choice*	*nonsense*	*unclear*
HL	**186**	3.7	43	106	24	3	10
CNET (I)	**239**	6.9	64	119	24	9	23
CNET (II)	**323**	6.9	73	196	22	32	0

When looking at the supposed attributes and benefits in Table 4-5 it becomes clear that a great extent could be categorized post-experimentally as meaningful variables. The majority of the supposed category was also the same as the final category. Still, coding a supposed benefit as attribute resulted in a cognitive subset of the form *decision variable – attribute –attribute* which did not match the definition of mental representations for this work as it does not terminate with a benefit. Hence, these variables were excluded from further analysis. A lot of CNET respondents used the open edit fields in interview step 3 to state their preferred choices for the decision variable at hand (547 observations). Probably this was caused by a misconception of the task. The many nonsense inputs in CNET (between 8 and 9% of the unidentified supposed attribute entries) could be an indicator that the survey was too demanding and therefore dismissed from respondents.

Before the actual analysis of the clean data could be performed another preparatory step needed to be done. Owing to the repetitive character of the elicitation process separately for each decision variable and owing to the generalization of considerations in CNET it is not uncommon that some attributes are elicited twice or even three times from one and the same respondent. Consequently, also the links to the underlying benefits might be measured several times. Thus, the data set of each respondent has been aggregated so that all double elicited variables and links were removed from the database. The remaining data represent in fact the basis for the analysis which has been done separately for the complexity and the content components of the mental representations as outlined in the next two sections.

4.5.2 The complexity of respondents' mental representations

This section describes the analysis of the measured mental representations in terms of number of attributes, number of benefits, number of benefits per attribute and number of cognitive subsets.

4.5.2.1 Number of attributes

The attributes (and situational variables) being part of the MR have been counted for each respondent. The means per scenario are presented in Table 4-6.

Table 4-6. Means for number of attributes.

	N	Mean	SD	Std. Error	95% Confidence Interval for Mean		Min	Max
					Lower Bound	Upper Bound		
HL basic	213	8.70	4.03	.28	8.16	9.24	0	24
HL uncertain	189	8.91	4.19	.31	8.32	9.51	2	22
HL distant	193	8.83	3.86	.28	8.29	9.38	2	22
CNET basic	185	3.77	2.20	.16	3.45	4.09	0	11
CNET uncertain	167	3.69	2.18	.17	3.36	4.02	0	13
CNET distant	194	3.89	2.04	.15	3.60	4.18	0	10
CNET e-commerce	290	4.25	2.45	.14	3.97	4.53	0	17
CNET risky	314	4.04	2.08	.12	3.81	4.27	0	14

When looking at the means for number of attributes it is obvious that HL yields more than twice as much attributes as CNET. A one-way ANOVA (Table 4-7) confirmed this significant difference. Additional post hoc tests did not find significant differences between scenarios (Table E-1 in Appendix E). Interesting is also a look into the columns *Min* and *Max.* The finding that *Min* equals 0 is partly caused by the fact that some respondents considered benefits without linking them to attributes and partly by the fact that some considerations were excluded from further analysis (see previous section). Even more striking is the *Max* value for HL*.* As only 24 attributes were shown during the interview some respondents must have indicated (almost) all of them.

Table 4-7. Results of an ANOVA on number of attributes between scenarios.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	9221.4	7	1317.3	150.992	<.001
Within Groups	15154.5	1737	8.7		
Total	24375.9	1744			

4.5.2.2 Number of benefits

The means for number of benefits are presented in Table 4-8. As for number of attributes HL yields significantly higher values than CNET. While HL respondents indicated about eight benefits, CNET respondents considered between six and seven benefits only. Minimum values of 0 are in fact not possible and are caused by the exclusion of non-interpretable inputs. The revealed benefit lists were tailored to the attribute at hand. Therefore, it is difficult to say how many benefits were presented to respondents. The max values in Table 4-8 come however very close to the number of all benefits in the database which was between 21 and 23 depending on the scenario.

Table 4-8. Means for number of benefits.

	N	Mean	SD	Std. Error	95% Confidence Interval for Mean		Min	Max
					Lower Bound	Upper Bound		
HL basic	213	8.10	3.71	.25	7.60	8.60	0	19
HL uncertain	189	8.29	4.11	.30	7.70	8.88	2	19
HL distant	193	8.51	4.01	.29	7.94	9.08	1	20
CNET basic	185	5.78	3.52	.26	5.27	6.29	1	18
CNET uncertain	167	6.31	3.54	.27	5.76	6.85	1	18
CNET distant	194	6.06	3.15	.23	5.61	6.50	1	18
CNET e-commerce	290	6.99	3.59	.21	6.57	7.40	1	17
CNET risky	314	6.23	3.45	.20	5.85	6.62	0	18

A one-way analysis of variance (ANOVA) has been performed to check for the significance of differences between scenarios. As expected number of benefits differ significantly between experimental groups (Table 4-9). Additional post hoc tests have been performed which can be found in Appendix E (Table E-2). Besides differences between HL and CNET, on the 0.05 level of significance the comparison between CNET basic (5.78) and CNET e-commerce (6.99) turned also out to be significant with p=.012.

Table 4-9. Results of an ANOVA on number of benefits between scenarios.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1728.2	7	246.9	18.710	<.001
Within Groups	22919.8	1737	13.2		
Total	24648.0	1744			

Besides analyzing the total number of benefits being part of the mental representations it was also investigated how many benefits respondents could recall in (the first phase of) CNET. Therefore, considerations from interview step 3 which were classified as benefits were counted for each scenario. Table 4-10 presents the means. Surprisingly, respondents recalled merely between 0.54 and 0.60 benefits on average. According to the analysis of variance shown in Table 4-11 there is no significant difference between scenarios.

Table 4-10. Means for number of recalled benefits.

	N	Mean	SD	Std. Error	95% Confidence Interval for Mean Lower Bound	Upper Bound	Min	Max
CNET basic	185	0.54	.73	.05	0.43	0.64	0	4
CNET uncertain	167	0.57	.71	.06	0.46	0.68	0	3
CNET distant	194	0.55	.88	.06	0.42	0.67	0	4
CNET e-commerce	290	0.58	.78	.05	0.49	0.67	0	3
CNET risky	314	0.60	.85	.05	0.50	0.69	0	4

Table 4-11. Results of an ANOVA on recalled benefits between scenarios.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.6	4	.1	.222	.926
Within Groups	727.4	1145	.6		
Total	727.9	1149			

4.5.2.3 Benefits per attribute

As a measure of compactness of MRs the ratio of benefits per attribute has been computed for each respondent. The scientific interpretation of this rather computational description is the question of how many needs (represented by benefits) a decision maker wants to satisfy by the consideration of a characteristic of the choice alternatives (conceptualized as attribute). Table 4-12 shows means and other statistical values for benefits per attribute.

Table 4-12. Means for benefits per attribute.

	N	Mean	SD	Std. Error	95% Confidence Interval for Mean Lower Bound	Upper Bound	Min	Max
HL basic	212	.96	.24	0.02	0.93	0.99	0.44	1.67
HL uncertain	189	.94	.25	0.02	0.91	0.98	0.33	1.67
HL distant	193	.98	.29	0.02	0.94	1.02	0.43	2
CNET basic	182	1.79	1.36	0.10	1.59	1.99	0.50	10
CNET uncertain	163	2.06	1.75	0.14	1.78	2.33	0.33	14
CNET distant	189	1.68	.87	0.06	1.56	1.81	0.33	5.50
CNET e-commerce	285	1.67	1.33	0.08	1.51	1.82	0	9
CNET risky	310	1.40	1.13	0.06	1.27	1.52	0	7

Taking a look into column *Mean* in Table 4-12 it is striking to see that the ratio of benefits per attribute is slightly smaller than 1 for all HL scenarios, i.e. HL respondents consider more attributes than benefits. The CNET scenarios show the opposite effect. They all yield ratios around 1.4 or greater because number of attributes is smaller than number of benefits. Consequently, the ANOVA (Table 4-13) indicates significant differences. Post hoc testing (Table E-3 in Appendix E) proves the significance of scenarios between HL and CNET with $p<.001$. Still, CNET measured also some differences between scenarios. Especially the uncertain scenario with 2.06 benefits per attribute differs significantly from the distant ($p=.027$), the e-commerce ($p=.005$) and the risky ($p<.001$) scenario. Furthermore, the basic scenario (1.79) yielded significantly ($p=.002$) higher values than the risky scenario (1.40).

Table 4-13. Results of an ANOVA on benefits per attribute between scenarios.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	246.0	7	35.1	31.487	<.001
Within Groups	1914.0	1715	1.1		
Total	2160.0	1722			

4.5.2.4 Number of cognitive subsets

The fourth and final measure to describe and compare MRs is *number of cognitive subsets*. It is referred to them as the chainlike series of linked variables. In other works the terms *(cognitive) subsets* (Kusumastuti 2011), *hiesets* (Farsari 2006) or even *ladders* (Reynolds and Gutman 1988) are used to describe the same or similar constructs. In this thesis cognitive subsets can have two forms, namely *decision variable – attribute – benefit* or *decision variable – benefit*. As situational variables are treated like attributes, cognitive subsets with situational variables fall within the first case. However, the link between decision variables and situational variables is not of causal nature. Rather, it stands for a mental association respondents have between these two. That explains the choice for the name of this measure. Its means are presented in Table 4-14.

Roughly spoken, HL elicits twice as much cognitive subsets as CNET. While HL respondents indicated on average between 18.77 and 21.32 cognitive subsets, CNET elicited only between 9.79 and 11.87 cognitive subsets per respondent on average. Minimum values of 0 are again a result of excluding non-usable inputs. In fact, all respondents indicated at least three cognitive subsets. Even more surprising are the maximum values. Especially some HL respondents who indicated most of the revealed attributes and benefits caused this high numbers. A one-way analysis of variance has been performed to check for differences between experimental groups. Its outcomes are shown in Table 4-15.

Table 4-14. Means for number of cognitive subsets.

	N	Mean	SD	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Min	Max
HL basic	213	18.77	17.00	1.17	16.48	21.07	0	171
HL uncertain	189	20.93	18.73	1.36	18.24	23.62	3	124
HL distant	193	21.32	18.74	1.35	18.66	23.98	3	105
CNET basic	185	10.05	9.80	.72	8.63	11.47	0	46
CNET uncertain	167	9.79	9.37	.73	8.36	11.22	0	75
CNET distant	194	9.99	9.73	.70	8.62	11.37	0	95
CNET e-commerce	290	11.74	10.46	.61	10.53	12.95	0	68
CNET risky	314	11.87	10.84	.61	10.67	13.08	0	75

Table 4-15. Results of an ANOVA on cognitive subsets between scenarios.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	36121.3	7	5160.2	28.588	<.001
Within Groups	313527.6	1737	180.5		
Total	349648.9	1744			

As the analysis of variance on number of cognitive subsets delivered significant results (*F*=28.588, *df*=7, *p*<.001) post hoc tests have been performed to see which experimental groups differ from each other (see Table E-4 in Appendix E). Except for highly significant (*p*<.001) results between techniques no differences between scenarios have been found.

4.5.2.5 Conclusions on the complexity of respondents' MRs

Taken together the results for the descriptors of the complexity of mental representations it can be concluded that HL yields larger and more complex MRs than CNET. This effect is very likely being caused by the revealed format of variables in HL. Kusumastuti *et al.* (2009) reports the same effect for techniques that work with revealed variables. The comparison of number of recalled benefits in CNET (interview step 3) and number of benefits that were selected from the list in CNET (interview step 5) confirms this effect. While respondents recalled merely between 0.54 and 0.60 benefits spontaneously the total number of benefits increased to the range between 5.78 and 6.99 after the lists of benefits were presented.

While the inter-technical comparison delivered significant results for all descriptors of MRs' complexity, the analysis of shifts between scenarios yielded a differentiated picture. For HL significant differences between scenarios have not been found. Among the CNET groups some findings were however significant. Firstly, number of benefits was significantly higher in the e-commerce than in the basic scenario and, secondly, benefits per attribute was significantly higher in the uncertain scenario than in the distant, the e-commerce and the risky scenario. The latter scenario differed also significantly from the basic scenario with regard to benefits per attribute.

The first finding confirms indeed the expectation that the introduction of additional choice alternatives which was the e-commerce option in that scenario leads to an activation of additional needs. Except for number of benefits no significant differences between the e-commerce and the basic scenario were found. Hence, respondents of both scenarios do not differ in the quantitative consideration of attributes which their mental capacity might be causal for. Whether the considered attributes between these scenarios differ with regard to their nature will be investigated in the content analysis.

The second finding shows that the complexity of MRs is lowest in the uncertain scenario and strongest in the risky scenario. In the former case the *negative situation* was expressed very concrete in terms of uncertainty about some attributes. Hence, respondents' focus stayed on these attributes and the limited mental capacity might have prevented an extensive evaluation of choice alternatives. Although number of attributes scored lowest for the uncertain scenario no statistical difference to other scenarios has been found. Nonetheless, in relation to underlying benefits number of attributes is low and this ratio proved to be significantly greater than for the distant, the e-commerce and the risky scenario. Any significant difference to the basic scenario could however not be determined for one of the four measures.

The risky scenario however showed the opposite effect. Here, the negative or risky situation was merely expressed by a situational state without referring to certain attributes. It led on the one hand to stronger need activation and on the other hand to a stronger evaluative consideration of the possible actions of choices. The ratio between attributes and benefits in the mental representation is thus more outbalanced than in the basic and the uncertain scenario.

The distant scenario did not result in significantly higher number of benefits or higher number of benefits per attribute than other scenarios. Possibly, all scenarios imply already a psychological distance to respondents so that the additional distance in that scenario did not cause a shift in the mental representation.

4.5.3 The content of respondents' mental representations

After the structural characteristics of the measured MRs have been analysed in the previous section the focus of this section is on the content components of the MRs. Thus, the nature of attributes, benefits and cognitive subsets will be examined and accordingly substantial shifts between scenarios investigated. The first subsection will however report how respondents ranked the decision variables.

4.5.3.1 Ranking of decision variables

In interview step 2 in both CNET and HL respondents were asked to rank the in random order shown decision variables *time of shopping* (TS), *transport mode* (TM), and *shopping location* (SL) according to the preferred sequence of decisions. Table 4-16 reports mean values and standard deviation per scenario. As there is no methodological difference the ranking was not analysed separately for HL and CNET.

Table 4-16. Rank order scores of the decision variables per scenario.

scenario	TM choice	SL choice	TS choice
	Rank mean (SD)	Rank mean (SD)	Rank mean (SD)
basic scenario	2.42 (0.76)	1.96 (0.69)	1.61 (0.79)
uncertain scenario	2.28 (0.82)	1.98 (0.70)	1.74 (0.83)
distant scenario	2.41 (0.73)	1.95 (0.74)	1.65 (0.80)
e-commerce scenario	2.23 (0.81)	2.00 (0.73)	1.77 (0.84)
risky scenario	2.37 (0.78)	1.92 (0.70)	1.71 (0.79)

The ranking results in Table 4-16 show a clear pattern of decision making over all scenarios. A multiple analysis of variance (see Table 4-17) confirms the difference between decision variables as significant (F=24313.3, df=2, p<.001). Thus, respondents prefer to consider *time of shopping* before *shopping location* and *transport mode*. While Kusumastuti *et al.* (2009) report also a first order rank for time of leisure shopping their findings for location and mode choice are reversed. Yet, according to Davidson *et al.* (2007) many activity-based models assume that the location choice is made before the mode choice which is herewith supported. According to Table 4-17 the MANOVA found also a significant effect for scenario. However, after the Bonferroni correction in post hoc tests the significance of this effect disappears.

Table 4-17. Results of a MANOVA on the rank order scores of the decision variables.

Multivariate Tests						
Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.965	24313.288	2	1739	<.001
	Wilks' Lambda	.035	24313.288	2	1739	<.001
	Hotelling's Trace	27.962	24313.288	2	1739	<.001
	Roy's Largest Root	27.962	24313.288	2	1739	<.001
scenario	Pillai's Trace	.010	2.182	8	3480	.026
	Wilks' Lambda	.990	2.185	8	3478	.026
	Hotelling's Trace	.010	2.187	8	3476	.026
	Roy's Largest Root	.009	4.015	4	1740	.003

4.5.3.2 The frequency of elicited attributes

All attributes and situational variables that were found in the elicited mental representations are attached as Appendix (Figures F-1 to F-8) for each experimental group. Figure 4-3 shows the results summarized for the HL scenarios for attributes being part of at least 10% of respondent's MRs. In fact these are all the 24 attributes which were revealed to respondents. Additional attributes which were typed by respondents did not exceed percentages of 1.5%. With a few exceptions Figure 4-3 shows a quite stable picture over the scenarios. *Available time to shop*, *number of bags to carry* and *opening hours* are considered by around 60% of the respondents in all three scenarios. Surprisingly, *travel costs* are considered by only 10% of the respondents whereas about 30% of respondents indicated to consider the more specific *parking costs* and about 14% *costs for petrol*. Correlations on the $p<.001$-level of significance were found between *travel costs* and *parking costs* ($r=.259$), *travel costs* and *costs for petrol* ($r=.388$) and *costs for petrol* and *parking costs* ($r=.305$) in the overall HL sample. There are however only a few salient differences between techniques. The most eye-catching one concerns *the durability of bought products* which is considered by 20% more respondents in the basic scenario than in the distant scenario. This could be an effect of the temporal distance as this attribute is a very specific aspect decision makers might rather consider due in time. A Chi-Square test for the distribution of attributes between the scenarios did however not find significant differences ($X^2=36.66$, $df=46$, $p=.836$).

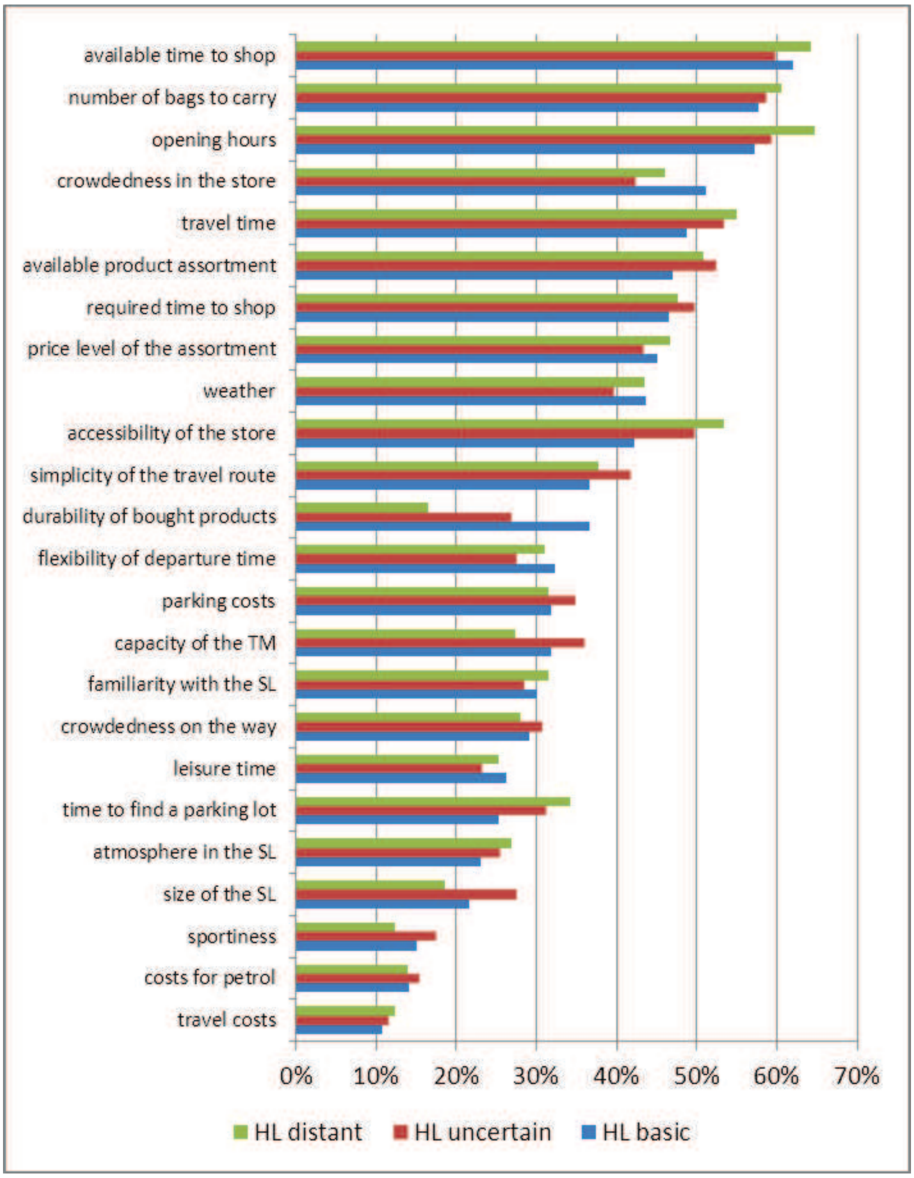

Figure 4-3. Frequency of elicited attributes in all HL scenarios.

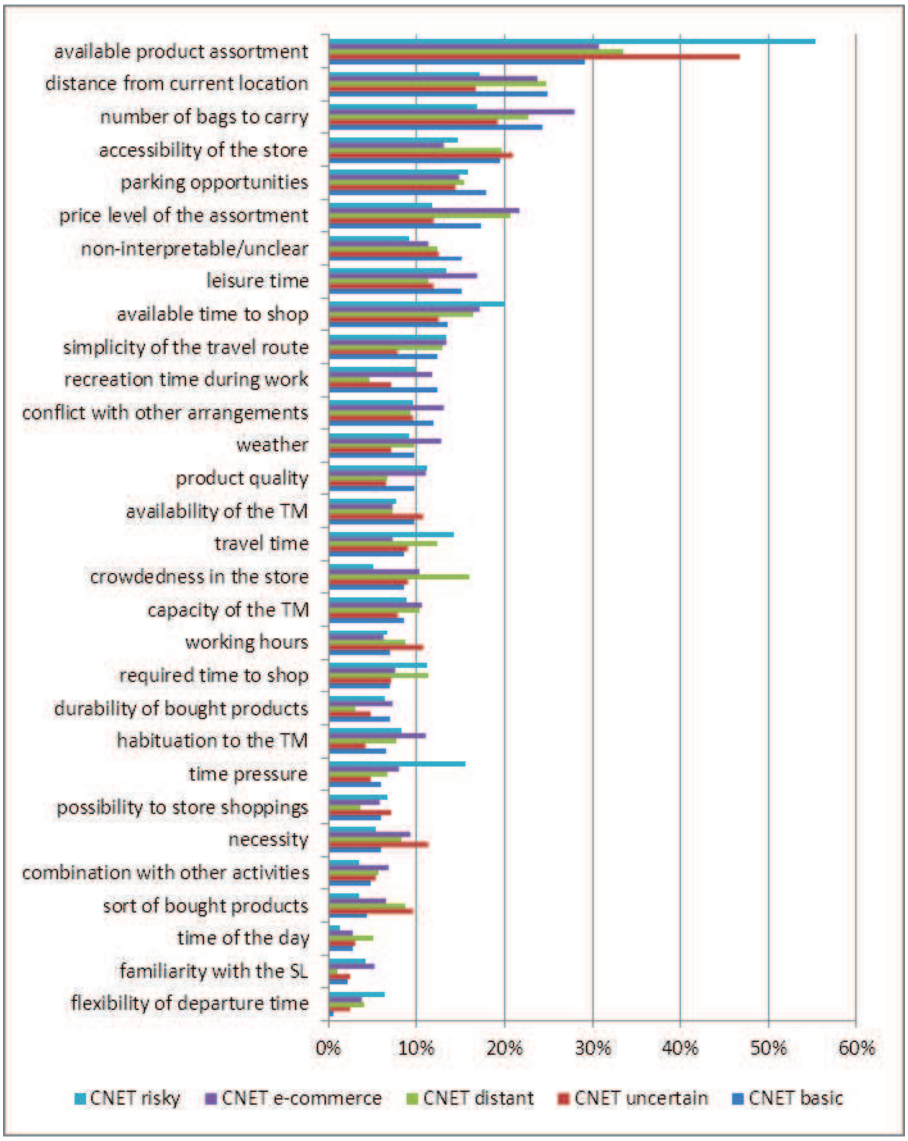

Figure 4-4. Frequency of elicited attributes in all CNET scenarios.

Figure 4-4 is the counterpart to Figure 4-3 for the five CNET scenarios and shows all attributes that were elicited from at least 5% of respondents in any scenario. This lower threshold compared to HL indicates already that there is less agreement about the considered attributes between CNET respondents. Still, as for HL *number of bags to carry* belongs to the most frequent considered attributes. Surprisingly, *opening* *hours* did not exceed the 5% threshold. Probably, CNET respondents took it for granted as the three choice alternatives for time of shopping fell within the usual opening hours. Yet, in CNET *distance from current location* is also among the most frequent variables although almost no one considered this attribute in HL. In contrast to HL there is no correlation between the cost attributes.

The variation between the experimental groups seems to be much greater for CNET than for HL. The risky and the uncertain scenario seem to capture the implied uncertainty or importance of the *available product assortment* as this variable is considered between 15 and 25% respondents more than in the other three scenarios. A Chi-Square test for the distribution of attributes between all five scenarios yields also significant differences (X^2=220.45, *df*=116, *p*<.001). Performing the Chi-Square test between the basic, uncertain and distant scenario only does however not result in significant outcomes (X^2=67.57, *df*=58, *p*<.183).

4.5.3.3 The frequency of elicited benefits

As for attributes the frequencies of elicited benefits are attached as appendices (Figures G-1 to G-8) for each experimental group.

Figure 4-5 gives an overview of all elicted benefits for the HL scenarios. It is obvious that *time savings*, *ease of shopping* and *ease of travelling* are the most frequent considered benefits as they appear in about 80% of MRs. *Financial savings* and *shopping success* are part of approximately 60% of MRs. Variation between scenarios is not significant (X^2=29.98, *df*=42, *p*=.918).

Figure 4-6 lists the frequencies of all elicited benefits for the five CNET scenarios. As for HL *time savings*, *ease of shopping* and *ease of travelling* are the most frequent considered benefits. Yet, their frequencies are about 10% below the HL-level. *Ease of shopping* yields only frequencies between 50 and 60% of MRs. This general drop in frequencies reflects the lower number of benefits in CNET compared to HL (see section 4.5.2). Still, the variation between scenarios is salient for some benefits. *Relaxation/recreation*, for instance, appears in about 10% more MRs in the e-commerce scenario than in all other scenarios. The influence of the uncertain and risky scenario on *shopping success* is also eye-catching. A Chi-Square test between all CNET scenarios resulted therefore in a significant difference (X^2=145.52, *df*=84, *p*<.001). Comparing only the basic, the uncertain and the distant scenario does however not reflect this variation (X^2=33.81, *df*=42, *p*<.812).

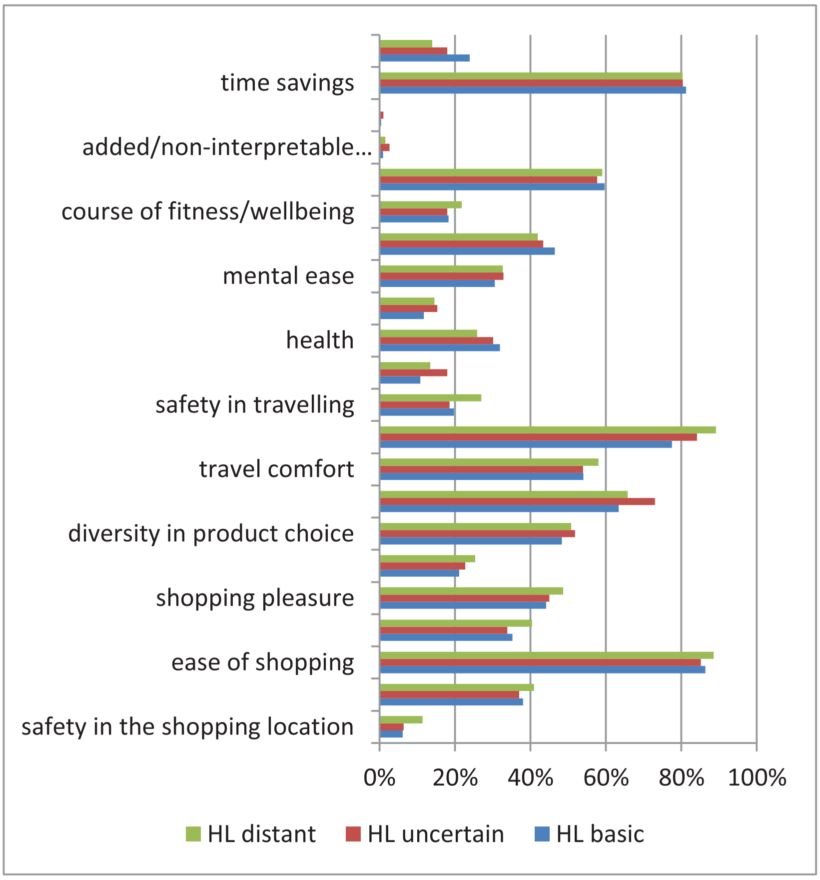

Figure 4-5. Frequency of elicited benefits in all HL scenarios.

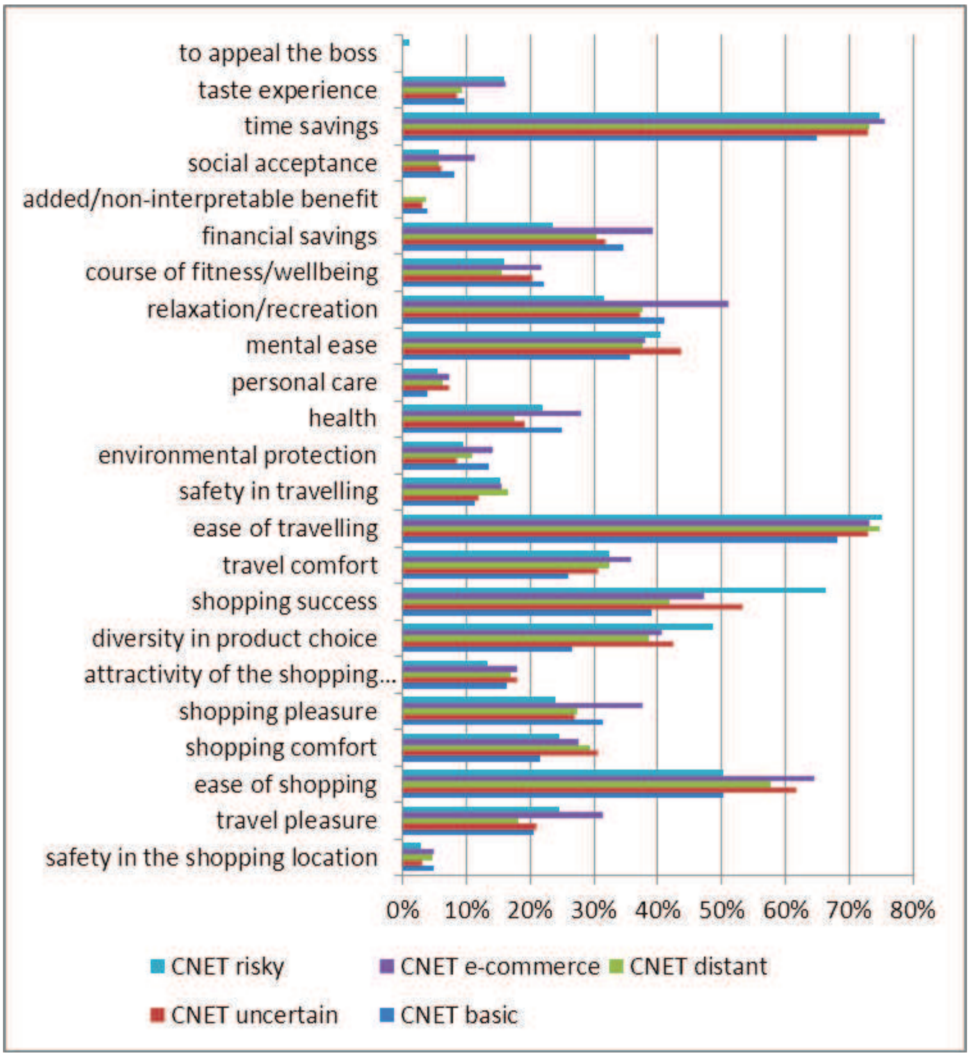

Figure 4-6. Frequency of elicited benefits in all CNET scenarios.

4.5.3.4 The frequency of elicited cognitive subsets

As for the pilot results, a frequent itemset analysis has been performed to investigate the cognitive subsets of the main study. The so-called support value represents the appearance of a certain cognitive subset over the amount of all elicited cognitive subsets as percentage value. As any cognitive subset can be elicited only once per respondent the support value represents at the same time the percentage of respondents who consider this subset. Figures 4-7 to 4-9 show cognitive subsets with support values greater than 25% for each HL scenario.

Figure 4-7. Most frequent cognitive subsets in HL basic (25% or higher).

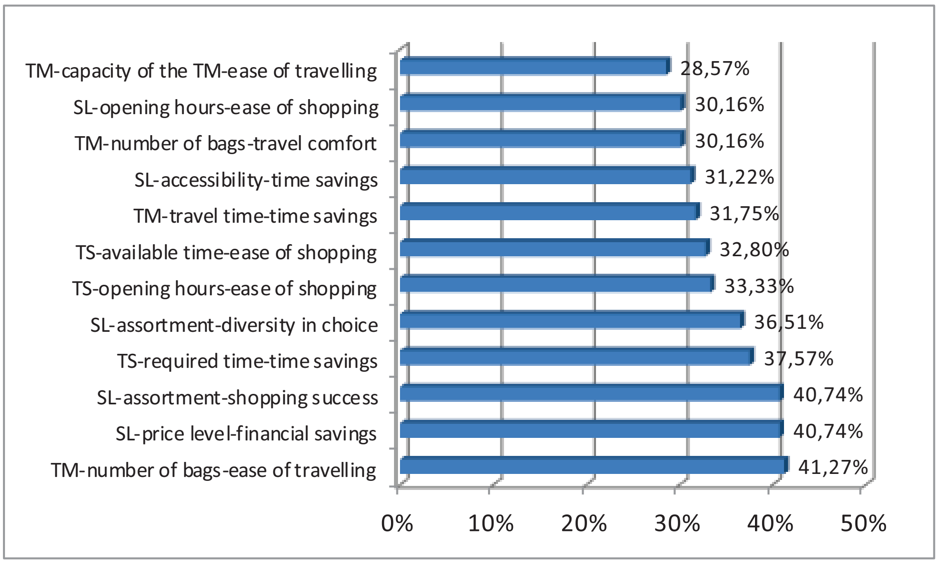

Figure 4-8. Most frequent cognitive subsets in HL uncertain (25% or higher).

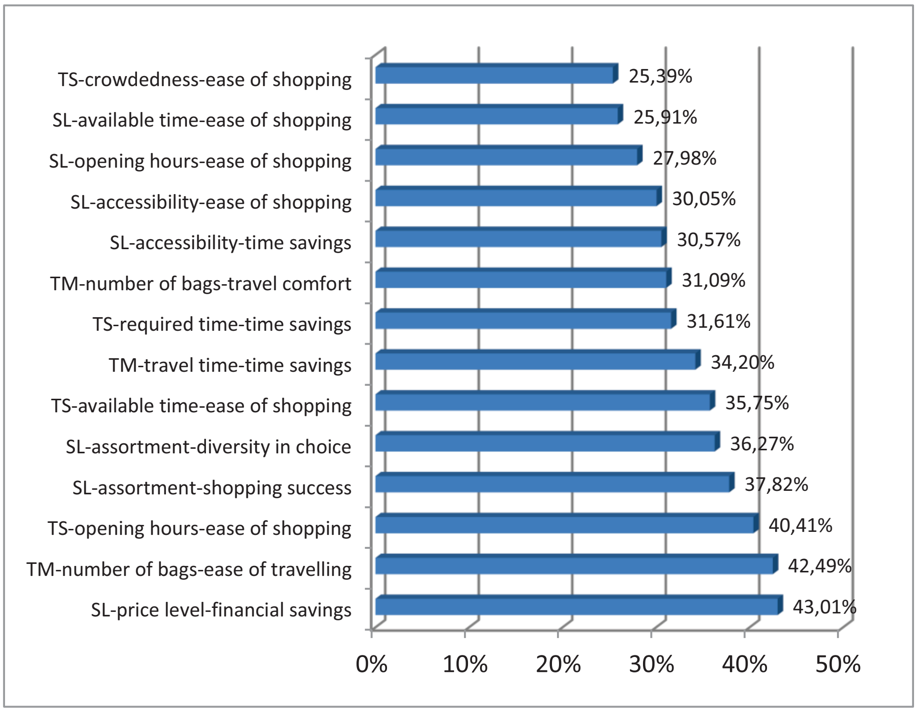

Figure 4-9. Most frequent cognitive subsets in HL distant (25% or higher).

According to Figures 4-7 to 4-9 the uncertain scenario (12) and the distant scenario (14) yield more cognitive subsets with a support value greater than 25% than the basic scenario (9). Interestingly, all frequent cognitive subsets from the basic scenario appear also among the frequent cognitive subsets of the uncertain and the distant scenario. The highest frequencies are attained in the distant scenario. However, the two most frequent considered subsets *SL – price level of assortment – financial savings* and *TM – number of bags to carry – ease of travelling* are stable over the three scenarios. A glance at Figure 4-10 reveals that there are almost no eye-catching differences between scenarios. Only the subset *SL - accessibility of the store – ease of shopping* differs considerably. A Chi-Square test for the 14 most frequent cognitive subsets did however not result in significant differences (X^2=15.70, *df*=26, *p*=.943) between scenarios.

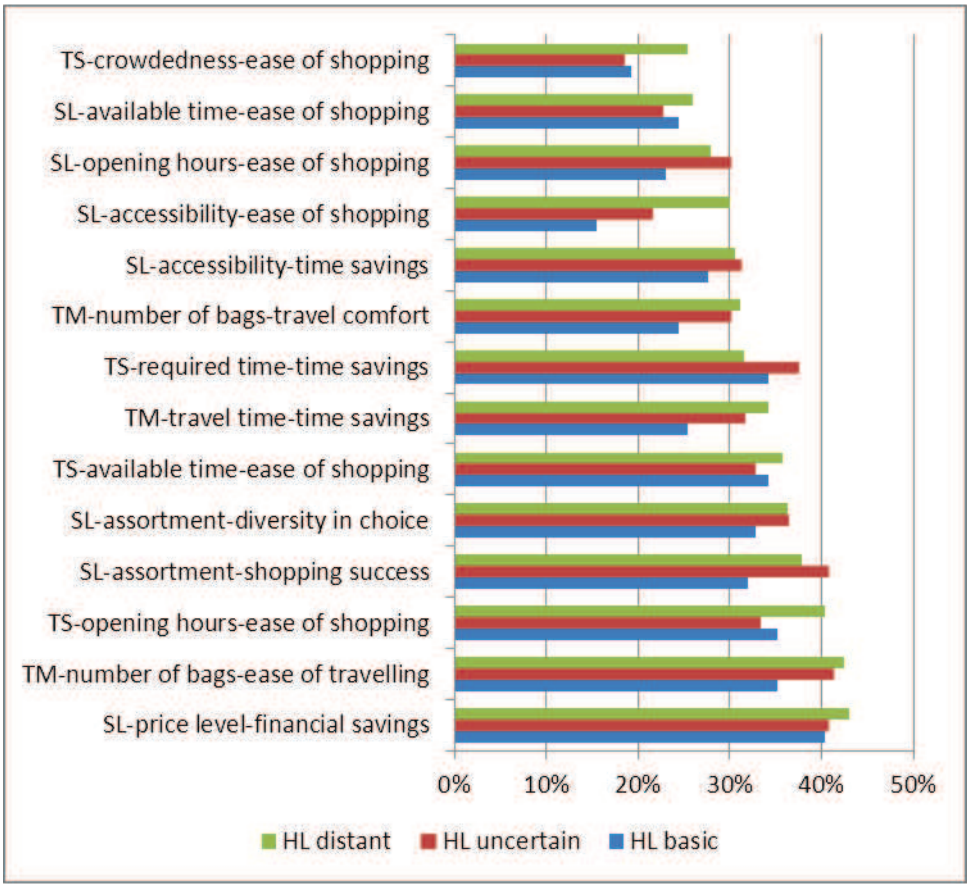

Figure 4-10. Cognitive subsets elicited from at least 25% of HL respondents.

Figures 4-11 to 4-15 show cognitive subsets with minimal support values of 10% for the five CNET scenarios. The support values are in general considerably lower than for HL. Only *SL - available product assortment – shopping success* and *SL - available product assortment – diversity in choice* reach support values greater than 25% for the two scenarios with an implied importance for *available product assortment*. The subsets *SL – price level of assortment – financial savings* and *TM – number of bags to carry – ease of travelling* appear also among the most frequent items in all CNET scenarios. They are however not as stable as in HL. Interestingly, the subset *TM – ease of travelling* without interlinked attribute exceeds the minimal support value in all CNET scenarios which evidences the importance of such direct links.

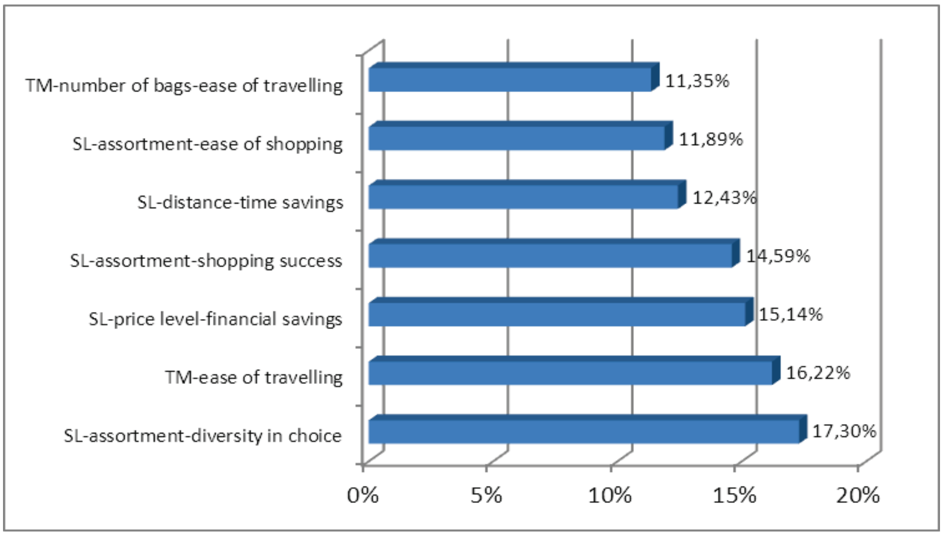

Figure 4-11. Most frequent cognitive subsets in CNET basic (10% or higher).

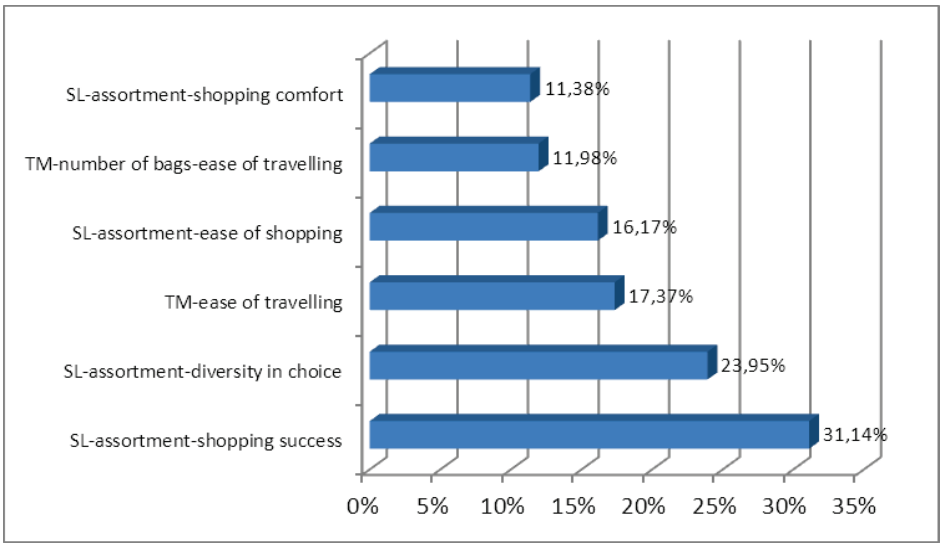

Figure 4-12. Most frequent cognitive subsets in CNET uncertain (10% or higher).

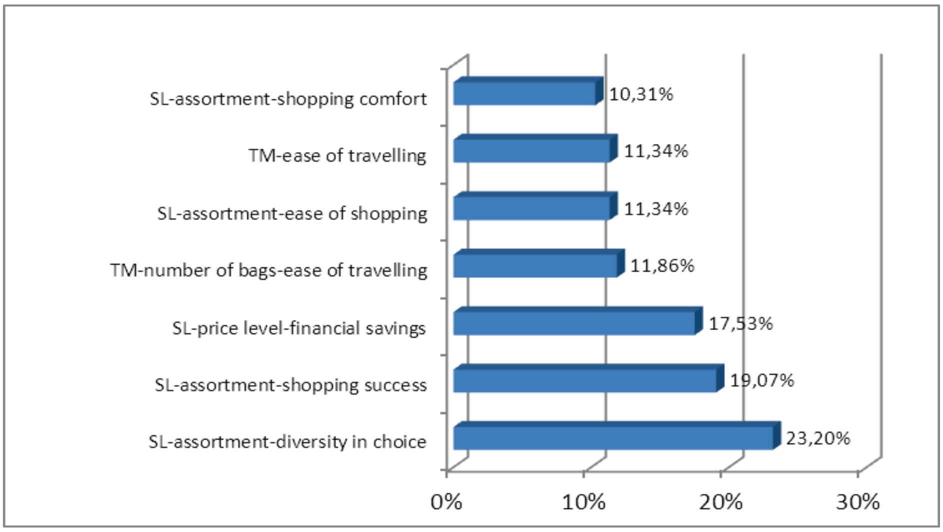

Figure 4-13. Most frequent cognitive subsets in CNET distant (10% or higher).

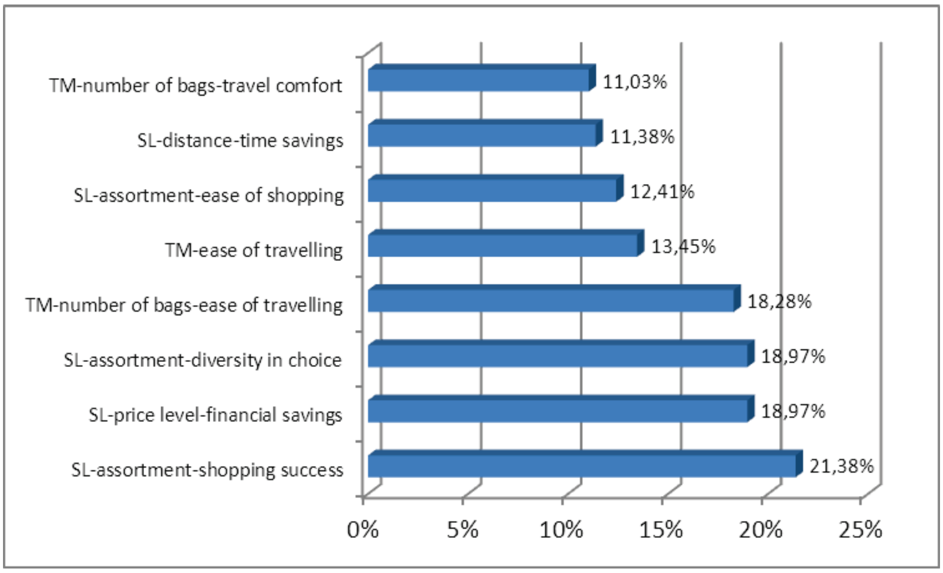

Figure 4-14. Most frequent cognitive subsets in CNET e-commerce (10% or higher).

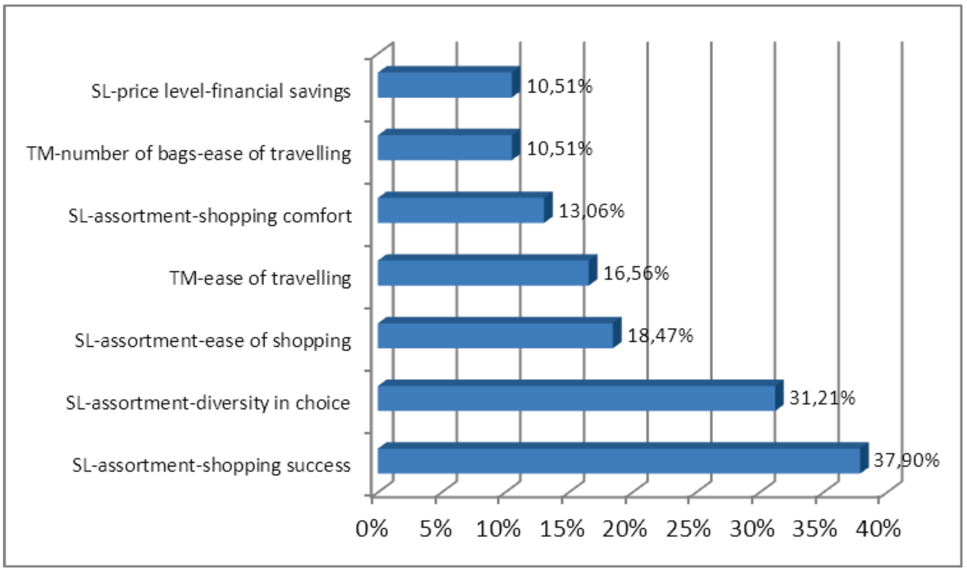

Figure 4-15. Most frequent cognitive subsets in CNET risky (10% or higher).

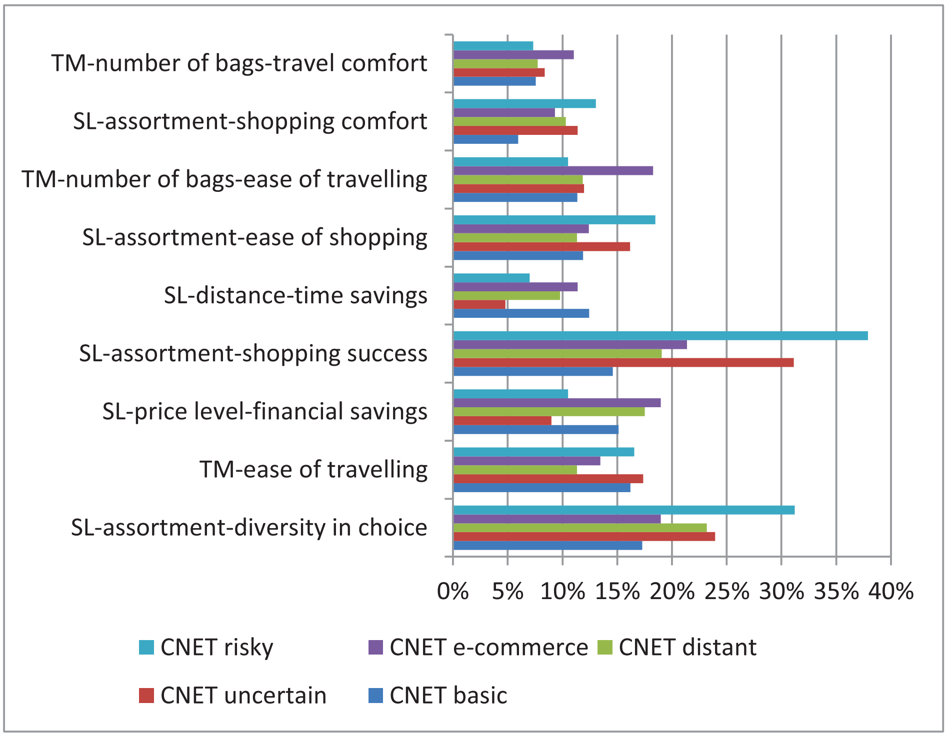

Figure 4-16. Cognitive subsets elicited from at least 10% of CNET respondents.

The five CNET scenarios yielded between six and eight cognitive subsets with a minimal support value of 10%. In total nine different cognitive subsets are hence considered as frequent which are depicted by Figure 4-16. The effect of scenario is clearly to see. While *SL - available product assortment – shopping success* and *SL - available product assortment – diversity in choice* are considered much more frequent in the risky (and the uncertain) scenario, both scenarios yield lower support values for the *SL – distance - time savings* subset. A shift can also be observed by looking at the higher support value for the subset *TM – number of bags to carry – ease of travelling* for the e-commerce option. Chi-Square tests for these nine cognitive subsets confirmed the significance of difference between all five scenarios (X^2=79.52, *df*=32, p<.001) and separately between the basic, the uncertain and the distant scenario only (X^2=28.66, *df*=16, *p*=.026).

4.5.3.5 Centrality of variables

The previous three sections analysed MRs in how far there is *agreement* among respondents in the considered attributes, benefits and cognitive subsets. While these three descriptors give insight in the salience of some components of MRs and how they differ between scenarios they say little about the role of these components within the causal network. For instance, it remains yet unclear whether the most frequent considered attribute is linked to one decision variable and benefit only or interlinked to several DVs and benefits. In the latter case, the attribute would have a central keyrole for the decision maker. Possibly, this central role of some attributes underlies shifts for different situational decision contexts.

In order to determine the *centrality* of variables an implication matrix has been set up for each respondent or MR, respectively. This comes in fact very close to the association pattern matrix where all variables which can be a parent node (DVs and attributes) are represented as rows and all variables which can serve as a child node (attributes and benefits) are represented as columns. All indicated causal links between them were coded as 1. All other cells were filled up with a 0. Adding then the row and column sum of a variable and dividing it by the matrix sum results in the centrality value of this variable which can take on values from the range between 0 and 1 (Knoke and Burt 1982). In other words, the centrality c of a variable V represents the sum of its k incoming (X, V) and l outgoing (V, Y) links over the sum of m occurring (X,Y) links in the MR of respondent j (Equation 4-1).

Table 4-18. Top ten central variables for each experimental group.

variable	HL basic	variable	HL uncertain	variable	HL distant
SL decision	0.103	SL decision	0.107	SL decision	0.106
TS decision	0.081	TS decision	0.076	TS decision	0.076
TM decision	0.067	TM decision	0.069	TM decision	0.069
crowdedness in store	0.043	Time savings	0.041	Ease of shopping	0.044
Time savings	0.043	Ease of shopping	0.040	Time savings	0.040
Ease of shopping	0.042	number of bags	0.039	travel time	0.038
available shopping time	0.039	travel time	0.036	crowdedness in store	0.036
number of bags	0.037	available assortment	0.036	number of bags	0.035
available assortment	0.030	Ease of travelling	0.036	opening hours	0.035
travel time	0.030	opening hours	0.034	avail. shopping time	0.034

variable	CNET basic	variable	CNET uncertain	variable	CNET distant
SL decision	0.084	SL decision	0.096	SL decision	.090
TM decision	0.080	available assortment	0.086	TM decision	.081
TS decision	0.070	TM decision	0.083	TS decision	.064
Ease of travelling	0.049	TS decision	0.064	available assortment	.061
available assortment	0.048	Ease of travelling	0.054	Time savings	.050
Time savings	0.042	Time savings	0.038	Ease of travelling	.050
distance	0.035	accessibility of store	0.030	distance	.034
accessibility of store	0.031	Shopping success	0.028	accessibility of store	.030
number of bags	0.030	Ease of shopping	0.027	Ease of shopping	.029
Ease of shopping	0.026	Mental ease	0.026	parking opportunities	.024

variable	CNET e-com	variable	CNET risky
SL decision	0.088	available assortment	0.091
TM decision	0.078	SL decision	0.084
TS decision	0.070	TM decision	0.075
available assortment	0.052	TS decision	0.073
Time savings	0.049	Time savings	0.051
Ease of travelling	0.042	Ease of travelling	0.048
distance	0.031	Shopping success	0.036
number of bags	0.029	Ease of shopping	0.023
Ease of shopping	0.029	accessibility of store	0.022
Relaxation	0.022	avail. shopping time	0.021

$$c_{Vj} = \frac{\sum_k (X,V)_k + \sum_l (V,Y)_l}{\sum_m (X,Y)_m} \qquad \text{(Equation 4-1)}$$

Table 4-18 lists means for the top ten central variables per scenario. DVs are highlighted in yellow and benefits in lightblue. Attributes are shown in normal style. Despite of the fact that DVs have (almost) no incoming links they score most central in almost all scenarios. This circumstance is not surprising when considering the fact that each cognitive subset has a DV as origin. Due to the limited number of decision variables their centrality values are this high. The more surprising it is that the attribute *available product assortment* breaks the centrality dominance of the DVs in the uncertain and risky scenario in CNET. This pattern is not measured with HL. In general, there is only little variation among the top ten central variables in the three HL scenarios. In almost all experimental groups the benefits *ease of shopping, time savings and ease of travelling* belong to the ten top central variables which speaks to the stability and general validity of these variables as underlying benefits. In the CNET uncertain and risky scenario, the implied risk of missing necessary products is reflected by the high centrality of the benefit *shopping success* which does not appear among the top ten variables in the other scenarios. But also the appearance of the benefit *relaxation* within the top ten in the e-commerce scenario reflects the increased need activation the e-commerce option entails.

In order to test the significance of differences in centrality between scenarios, a multivariate analysis of variance (MANOVA) was performed with the top central variables as dependent variables and scenario as factor (Table 4-19). The MANOVA was done separately for HL, CNET basic, uncertain and distant (CNET – wave I) and all CNET scenarios (CNET wave I+II).

Table 4-19. Results of the MANOVAs on the centrality of the top ten variables.

HL			**CNET – wave I**			**CNET – wave I+II**		
F	df	p	F	df	p	F	df	p
1.338	12	.192	0.885	13	.569	3.068	15	<.001

According to Table 4-19 the centrality of the twelve variables which are among the top ten in any of the HL scenarios does not differ significantly between scenarios (p=.192). Neither differs the centrality of the 13 top central variables between the basic, the uncertain and the distant scenario in CNET (p=.569). The comparison of the 15 top central variables from all five CNET scenarios results however in a significant difference (p<.001). According to the univariate tests (see Appendix H) for the corrected model the difference can be attributed to *available product assortment*, *time savings, accessibility of the store, shopping success and relaxation/recreation.*

4.5.4 The choice outcomes

Table 4-20. Chosen alternatives for the decision variables.

	TM choice			SL choice			TS choice		
	car	bicycle	bus	cornershop	market	supermarket	lunchbreak	after work	evening
HL									
basic	68.1%	31.5%	0.5%	34.7%	8.5%	56.8%	7.5%	71.4%	21.1%
uncertain	69.8%	28.6%	1.6%	29.1%	4.8%	66.1%	7.9%	67.7%	24.3%
distant	72.5%	24.9%	2.6%	37.3%	4.1%	58.5%	7.3%	61.1%	31.6%
CNET									
basic	64.3%	35.7%	0.0%	35.1%	9.2%	55.7%	10.8%	63.8%	25.4%
uncertain	67.7%	30.5%	1.8%	29.3%	6.0%	64.7%	10.8%	63.5%	25.7%
distant	70.1%	29.4%	0.5%	38.7%	5.2%	56.2%	7.7%	61.3%	30.9%
e-com.[1)]	59.0%	41.0%	0.0%	33.4%	7.9%	57.6%	11.7%	63.1%	25.2%
risky	63.1%	35.7%	1.3%	21.0%	11.5%	67.5%	24.2%	72.6%	3.2%
Chi-Square test[2)3)]									
	X^2	**df**	**p**	**X^2**	**df**	**p**	**X^2**	**df**	**p**
	14.84	7	.038	39.03	14	<.001	126.95	14	<.001

[1]*Outcomes of the online shopping option (1%) for the SL choice are not listed in the table*

[2]*For the Chi-Square test on TM choice bicycle and bus observations were grouped together to non car users*

[3]*The Chi-Square test on SL choice was performed without the observations for online shopping in CNET e-com.*

After the components of MRs had been elicited respondents were asked in interview step 5 (HL) or 7 (CNET) to indicate their preferred choice alternative for each of the three decision variables. Table 4-20 reports percentage of respondents per chosen alternative and the outcomes of Chi-Square tests between experimental groups. The latter found significant differences between scenarios. For the TM choice it is especially the e-commerce scenario where respondents deviated from the overall choice pattern. There, the relation of car choosers (59%) to bicycle choosers (41%) is almost 3:2 whereas this relation is much more in favour for the car in all other scenarios. For the SL decision it is the risky scenario which delivered a different choice pattern: It has the smallest percentage for cornershop choosers (21%) and the highest percentage for market (11.5%) and supermarket (67.5%) shoppers of all experimental groups. Also for the TS decision the risky scenario differs strongly from the other scenarios: It yielded much more lunchbreak shoppers (24.2%) and much less evening shoppers (3.2%).

One driving force of this work is the expectation to achieve insights into the principles of the construction of mental representations, their role for decision making and the link to choice behaviour. Among other interesting research questions in this regard it is for example of interest whether a given mental representation allows conclusions on an individual's choice. Although it is not the ambition of this thesis to find a scientific answer to this research task it is nonetheless of interest to investigate whether components of MRs differ between respondents with a different choice behaviour. Tables 4-21 and 4-22 show the results of Chi-Square tests on attributes and benefits between choice groups.

Table 4-21. Outcomes of Chi-Square tests on attributes for choice alternatives.

	TM choice			**SL choice**			**TS choice**		
	X^2	**df**	**p**	X^2	**df**	**p**	X^2	**df**	**p**
HL									
basic[1]	31.42	23	.113	39.51	46	.739	26.20	46	.992
uncertain[1,2]	41.06	23	.012	23.88	23	.422	28.39	46	.981
distant[1,2]	37.67	23	.028	29.47	23	.165	43.21	46	.590
CNET									
basic[1,2,3]	18.83	24	.761	43.06	24	.010	31.19	17	.019
uncertain[1,2,3]	20.07	21	.517	26.88	21	.175	26.88	6	.594
distant[1,2,3]	24.31	23	.387	42.31	23	.008	66.27	23	<.001
e-com.[1,2,3]	60.12	35	.005	75.84	35	<.001	42.44	27	.030
risky[1,2,4]	35.34	32	.313	39.33	32	.175	42.92	28	.035

[1] *For the TM choice bicycle and bus observations were grouped together to non car users*

[2] *For the SL choice cornershop and market observations were grouped together to non supermarket observations*

[3] *For the TS choice during lunchbreak and after work were grouped together*

[4] *For the TS choice after work and evening were grouped together*

According to Table 4-21, car choosers and non car choosers differ significantly in their considered attributes for HL uncertain, HL distant and CNET e-commerce. Furthermore, respondents who have chosen supermarket as preferred shopping location differ significantly in their considered attributes from respondents who indicated to shop elsewhere for CNET basic, distant and e-commerce. For time of shopping the choice groups differ significantly for all CNET scenarios except for CNET uncertain. It should however be noted that due to too little cell frequencies many attributes had to be skipped for CNET uncertain before the Chi-Square test could be performed. Regarding benefits only the choice groups for the transport mode and the shopping location differed significantly for CNET basic, distant, e-commerce and risky (see Table 4-22).

Table 4-22. Outcomes of Chi-Square tests on benefits for choice alternatives.

	TM choice			**SL choice**			**TS choice**		
	X^2	**df**	**p**	**X^2**	**df**	**p**	**X^2**	**df**	**p**
HL									
basic[1]	29.24	20	.083	28.60	40	.911	19.32	38	.995
uncertain[1,2]	29.15	20	.085	9.99	20	.968	14.44	38	1.000
distant[1,2]	10.62	19	.936	17.54	19	.554	27.78	38	.889
CNET									
basic[1,2,3]	38.81	20	.007	49.34	20	<.001	16.57	20	.681
uncertain[1,2,3]	20.43	20	.432	23.91	20	.246	20.37	20	.435
distant[1,2,3]	33.76	20	.028	66.36	20	<.001	26.40	20	.153
e-com.[1,2,3]	47.09	20	.001	66.59	20	<.001	15.49	20	.748
risky[1,2,4]	54.96	21	<.001	33.26	21	.043	30.02	21	.092

[1] *For the TM choice bicycle and bus observations were grouped together to non car users*

[2] *For the SL choice cornershop and market observations were grouped together to non supermarket observations*

[3] *For the TS choice during lunchbreak and after work were grouped together*

[4] *For the TS choice after work and evening were grouped together*

It would be beyond the scope of this research to list all attributes and benefits which differ somehow for any of the reported choice groups. The interested reader is referred to the cross-tables for attributes and benefits per decision variable and scenario in Appendix I and J. Nevertheless, the case of the shopping location choice for CNET basic illustrates representatively how MRs differ between respondents who chose different alternatives. As for almost all experimental groups corner shop and market choosers were grouped together due to too few observations. Hence, MRs of supermarket and non supermarket shoppers were compared. Between these two groups three attributes were found for which the difference in observation amounts more than ten percent. While 39% of non supermarket shoppers consider *distance from the current location* only 13.6% of the supermarket shoppers do so. Also the *simplicity of the travel route* is part of considerably more MRs of the non supermarket shoppers (19.5%) than of the supermarket shoppers (7.8%). In contrast, 40.8% of the super market shoppers think about *the available product assortment* whereas merely 14.6% of non supermarket shoppers consider this attribute. Among benefits there are even more differences. While the group of supermarket shoppers yields at least 10% more observations for *ease of shopping, shopping comfort, diversity in product choice* and *financial savings*, the group of market or grocery store shoppers considers *environmental protection, health, mental ease* and *time savings* about 10% more often.

This little digression on shifts in MRs between respondents with different choice outcomes delivered indeed interesting insights. HL measured only two significant differences between choice groups, namely for the TM choice in the uncertain and distant scenario. CNET in turn measured significant differences distributed over all choices and scenarios except for the uncertain scenario. The exemplified case illustrated plausibly which attributes and benefits differed quantitatively between choice groups. This information can be a good starting point for planners' and modellers' work.

4.6 Performance of HL and CNET

One purpose of the development of CNET (section 3.1) was the creation of an interview method which is attractive and accessible for (almost) all respondents. Therefore, this section will investigate how respondents interacted with the techniques and how they performed the interviews, respectively. The first section is still closely linked to the investigation of MRs' complexity as it sheds light on the question whether the education level has an influence on the elicitation of MRs' components. The second question deals with performance measures such as interview duration and dropouts. Finally, respondents' evaluation is analysed.

4.6.1 Impact of the education level on the elicitation of MRs

As it has been outlined further above a major difference between CNET and HL is the handling of variables. While they are hidden in the former technique, HL works with revealed variables. The elicitation of MR components requires therefore different cognitive processes and capacities. This fact leads to the question whether respondents with a different education background are equally able to cope with the elicitation of attributes, benefits and cognitive subsets.

4.6.1.1 Impact of the education level on the elicitation of attributes

Data for the education level have been collected on six categories as shown in Table 4.4. A Spearman rank-order correlation analysis has been performed between education level and number of elicited attributes, separately for each technique. A differentiation into scenarios has however not been taken into consideration. According to Table 4-23 there is a significant positive rank-order correlation for both techniques. For CNET it is, however, stronger and more significant (ρ=0.240, p<.001) than for HL (ρ=0.088, p=.032). Expressed in words, the higher the education of a respondent the more attributes are elicited.

Table 4-23. Rank-order correlations for number of attributes and education level.

interview technique			number of attributes	education level
HL	number of attributes	Correlation Coefficient	1	0.088
		Sig. (2-tailed)		0.032
		N	595	594
	education level	Correlation Coefficient	0.088	1
		Sig. (2-tailed)	0.032	
		N	594	594
CNET	number of attributes	Correlation Coefficient	1	.240
		Sig. (2-tailed)		<.001
		N	1151	1149
	education level	Correlation Coefficient	.240	1
		Sig. (2-tailed)	<.001	
		N	1149	1149

The descriptives for number of attributes per education level and technique are presented in Table 4-24. For HL the mean value varies between 8.04 (primary education) and 9.32 (bachelors degree). In CNET respondents having a practical professional training indicated least attributes (3.12) while respondents with a Masters degree indicated most attributes (4.75).

Table 4-24. Descriptives for number of attributes.

interview technique		N	Mean	SD	Std. Error	95% Confidence Interval for Mean	
						Lower Bound	Upper Bound
HL	Primary school	28	8.04	3.80	.72	6.56	9.51
	Practical professional training	126	8.50	4.27	.38	7.75	9.25
	Secondary education	62	9.05	3.67	.47	8.12	9.98
	Higher level professional training	168	8.50	4.14	.32	7.87	9.13
	Bachelors degree	157	9.32	3.95	.32	8.7	9.95
	Masters degree	53	9.08	3.71	.51	8.05	10.1
	Total	594	8.80	4.02	.17	8.48	9.13
CNET	Primary school	39	3.62	1.65	.26	3.08	4.15
	Practical professional training	248	3.12	1.78	.11	2.9	3.34
	Secondary education	123	4.35	2.26	.20	3.95	4.75
	Higher level professional training	335	3.66	2.08	.11	3.44	3.88
	Bachelors degree	311	4.68	2.35	.13	4.42	4.94
	Masters degree	92	4.75	2.28	.24	4.28	5.22
	Total	1148	3.98	2.21	.07	3.85	4.11

Analyses of Variance (ANOVAs) have been performed separately for both techniques. The outcomes are given in Table 4-25. Thus, number of attributes does not differ significantly between education levels in HL but does so in CNET (F=19.874, p<.001). A Bonferroni corrected posthoc test has been performed for CNET (see Appendix K) yielding that each education level differs at least from one other education level significantly. Respondents with practical professional training consider significantly less attributes than all other respondents except for the ones with primary education. Also the higher level professional training group differs significantly from all other respondents but the primary education group.

Table 4-25. Results of ANOVAs on number of attributes between education levels.

interview technique		Sum of Squares	df	Mean Square	F	Sig.
HL	Between Groups	93.9	5	18.8	1.163	0.326
	Within Groups	9491.5	588	16.1		
	Total	9585.4	593			
CNET	Between Groups	447.0	5	89.4	19.874	<.001
	Within Groups	5137.5	1142	4.5		
	Total	5584.5	1147			

4.6.1.2 *Impact of the education level on the elicitation of benefits*

As for attributes a Spearman rank-oder correlation analysis has been performed between the education level and number of elicited benefits. Table 4-26 presents the results which show again a highly significant positive correlation (ρ=0.145, p<.001) for CNET but not for HL.

Table 4-26. Rank-order correlations for number of benefits and education level.

interview technique			number of benefits	education level
HL	number of benefits	Correlation Coefficient	1	0.024
		Sig. (2-tailed)		0.561
		N	595	594
	education level	Correlation Coefficient	0.024	1
		Sig. (2-tailed)	0.561	
		N	594	594
CNET	number of benefits	Correlation Coefficient	1	.145
		Sig. (2-tailed)		<.001
		N	1151	1149
	education level	Correlation Coefficient	.145	1
		Sig. (2-tailed)	<.001	
		N	1149	1149

The descriptives for number of benefits per education level and technique are presented in Table 4-27. For HL the mean value varies between 7.7 (Masters degree) and 8.77 (secondary education). In CNET respondents having a practical professional training indicated least benefits (5.38) while respondents with a Bachelors degree indicated most benefits (7.17).

Table 4-27. Descriptives for number of benefits.

interview technique		N	Mean	SD	Std. Error	95% Confidence Interval for Mean	
						Lower Bound	Upper Bound
HL	Primary school	28	7.79	4.18	0.79	6.17	9.4
	Practical professional training	126	8.33	4.25	0.38	7.58	9.08
	Secondary education	62	8.77	3.8	0.48	7.81	9.74
	Higher level professional training	168	7.93	3.9	0.30	7.33	8.52
	Bachelors degree	157	8.75	3.81	0.30	8.15	9.35
	Masters degree	53	7.70	3.64	0.50	6.7	8.7
	Total	594	8.29	3.94	0.16	7.97	8.61
CNET	Primary school	39	6.31	2.97	0.48	5.35	7.27
	Practical professional training	248	5.38	3.16	0.20	4.98	5.77
	Secondary education	123	7.15	3.79	0.34	6.48	7.83
	Higher level professional training	335	5.91	3.4	0.19	5.55	6.28
	Bachelors degree	311	7.17	3.67	0.21	6.76	7.58
	Masters degree	92	6.58	2.87	0.30	5.98	7.17
	Total	1148	6.34	3.48	0.10	6.13	6.54

Table 4-28. Results of ANOVAs on number of benefits between education levels.

interview technique		Sum of Squares	df	Mean Square	F	Sig.
HL	Between Groups	95.8	5	19.2	1.24	0.3
	Within Groups	9100.8	588	15.5		
	Total	9196.6	593			
CNET	Between Groups	591.5	5	118.3	10.1	<.001
	Within Groups	13322.8	1142	11.7		
	Total	13914.2	1147			

Analyses of Variance (ANOVAs) have been performed for number of benefits between the education levels. According to the results in Table 4-28 there is no significant difference for number of benefits between education levels in HL. Yet, the ANOVA for CNET is significant (F=10.1, p<.001). The results of the Bonferroni corrected posthoc tests can be found in Table K-2 as appendix. Although less than for attributes there are still some significant differences between single education levels and this despite of the fact that benefits were revealed also in CNET (interview step 5). For example, respondents with a Bachelors degree considered significantly more benefits than respondents from the practical professional training and the higher level educational training group.

4.6.1.3 Impact of the education level on the elicitation of cognitive subsets

Finally, a Spearman rank-order correlation analysis has also been performed between the education level and number of cognitive subsets shown in Table 4-29. The correlation is only significant for CNET (ρ=0.202, p<.001).

Table 4-29. Correlations for number of cognitive subsets and education level.

interview technique			education level	number of cognitive subsets
HL	education level	Correlation Coefficient	1	0.060
		Sig. (2-tailed)		0.146
		N	594	594
	number of cognitive subsets	Correlation Coefficient	0.060	1
		Sig. (2-tailed)	0.146	
		N	594	595
CNET	education level	Correlation Coefficient	1	.202
		Sig. (2-tailed)		<.001
		N	1149	1149
	number of cognitive subsets	Correlation Coefficient	.202	1
		Sig. (2-tailed)	<.001	
		N	1149	1151

Table 4-30. Descriptives for number of cognitive subsets.

interview technique		N	Mean	SD	Std. Error	95% Confidence Interval for Mean	
						Lower Bound	Upper Bound
HL	Primary school	28	17.29	15.97	3.02	11.09	23.48
	Practical professional training	126	21.06	22.93	2.04	17.02	25.11
	Secondary education	62	20.03	14.58	1.85	16.33	23.74
	Higher level professional training	168	19.62	18.90	1.46	16.74	22.5
	Bachelors degree	157	21.59	15.98	1.28	19.07	24.11
	Masters degree	53	18.42	13.42	1.84	14.72	22.11
	Total	594	20.29	18.14	0.75	18.81	21.73
CNET	Primary school	39	10.56	8.00	1.28	7.97	13.16
	Practical professional training	248	7.63	6.85	0.44	6.77	8.48
	Secondary education	123	12.93	10.50	0.95	11.05	14.8
	Higher level professional training	335	9.74	9.90	0.54	8.68	10.8
	Bachelors degree	311	13.57	12.02	0.68	12.28	14.96
	Masters degree	92	12.73	9.66	1.01	10.73	14.73
	Total	1148	10.92	10.22	0.30	10.35	11.53

The descriptives for number of cognitive subsets per education level and technique are presented in Table 4-30. For HL the mean value varies between 17.3 (Primary school) and 21.6 (Bachelors degree). In CNET least cognitive subsets (7.63) were elicited from respondents having a practical professional training while respondents with a Bachelors degree indicated most cognitive subsets (13.6).

Table 4-31. Results of ANOVAs on cognitive subsets between education levels.

interview technique		Sum of Squares	df	Mean Square	F	Sig.
HL	Between Groups	857.6	5	171.5	0.519	0.762
	Within Groups	194471.7	588	330.7		
	Total	195329.4	593			
CNET	Between Groups	6222.1	5	1244.4	12.522	<.001
	Within Groups	113488.1	1142	99.4		
	Total	119710.2	1147			

As for number of attributes and benefits also for number of cognitive subsets analyses of Variance (ANOVAs) have been performed (Table 4-31). Again, a significant difference was merely found for CNET (F=12.522, p<.001). The results of the Bonferroni corrected posthoc tests are attached as Table K-3 in the appendix. It is especially the group of respondents with practical professional training who consider significantly less cognitive subsets than the higher educated respondents with a secondary education or Bachelors and Masters degree, respectively.

4.6.1.4 Discussion

As the previous three sections have shown there is a positive relationship between the education level and the elicitation of all MR components for CNET but almost not for HL. For the former technique the rank-order correlation and analyses of variance (ANOVAs) yielded significant results for number of attributes, benefits and cognitive subsets. Hard laddering in turn yielded only a significant rank-order correlation for number of attributes and educational level. It does, hence, not allow for a comprehensive discrimination of the complexity of MRs according to the education level of respondents. In CNET however better educated respondents indicate significantly more attributes, benefits and cognitive subsets than less educated respondents. Unclear is, however, where the difference between HL and CNET results from. Possibly, MRs of well educated people are indeed more complex than those of less educated people. This assumption would speak to CNET and against HL with regard to sensitiveness. On the other hand, one can also assume that the different outcomes for HL and CNET result from the higher demanding elicitation process in CNET. Lower educated CNET respondents might have had difficulties to render their complete MR conscious and express the single components in short and meaningful strings. Higher educated people might have a better articulateness and a clearer consciousness of their MR which might have resulted in a higher hit ratio of the string recognition and thus in a complexer MR. Both interpretations are conceivable and only respondents' evaluation of the techniques could shed some light on this question. The next sections will deal with that in more detail.

4.6.2 Interview duration and dropouts

As a measure of the techniques' readability and ease of interaction with the respondent the interview duration and the number of dropouts have been analysed. At first, Table 4-32 presents descriptives for interview duration per scenario. This measure was computed only from respondents who completed the interview successfully. It can be seen that the difference between the shortest (HL distant: 9 min 28s) and longest (CNET e-commerce: 13min 41s) mean interview duration amounts merely to 4 min 13s. In contrast, this difference amounted 6 min 22s in the pilot survey although the most extreme scenarios where not applied there. Nevertheless, an analysis of variance (ANOVA) reported in Table 4-33 still confirms a highly significant difference for interview duration between experimental groups (F=10.21, df=7, p<.001). Post hoc tests (see Table K-4 in the appendix) reveal that HL basic and HL distant have a significantly shorter interview duration than CNET uncertain, e-commerce, and risky. HL uncertain differs only from CNET e-commerce and CNET risky. Thus, there are no significant differences between experimental groups of the same technique or the same scenario.

Table 4-32. Descriptives for interview duration.

experimental group	**N**	**Minimum**	**Maximum**	**Mean**	**SD**
HL basic	213	0:01:18	0:53:07	0:09:44	0:06:52
HL uncertain	189	0:02:07	1:03:17	0:10:04	0:07:36
HL distant	193	0:01:43	0:28:03	0:09:28	0:04:58
CNET basic	185	0:01:59	1:16:39	0:11:32	0:07:57
CNET uncertain	166	0:02:15	0:47:17	0:12:25	0:07:53
CNET distant	193	0:02:16	0:46:39	0:11:28	0:07:09
CNET e-commerce	289	0:01:49	1:18:55	0:13:41	0:09:05
CNET risky	314	0:02:07	1:57:26	0:13:37	0:10:11

Table 4-33. Results of an ANOVA on interview duration between experimental groups.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	16846105	7	2406586	10.21	<.001
Within Groups	408854655	1734	235787		
Total	425700760	1741			

Next to the interview duration also number and stage of dropouts is an insightful indicator for respondents' willingness to perform and finish the interview techniques and respondents' struggling with certain interview stages. Table 4-34 shows frequencies for dropouts and completed interviews per experimental group. The column *starters* represents number of respondents who started the interview and the column *complete* represents number of respondents who finished successfully. The differences between these two values are reported in column *absolute dropouts* and their ratio to number of starters in column *relative dropouts*. Finally, column *dropouts before sorting DVs* reports number of respondents who did not come further than interview step 2 and their ratio to the total number of dropouts in brackets.

Table 4-34. Interview completion and dropouts per experimental group.

Experimental group		**starters**	**absolute dropouts**	**relative dropouts**	**dropout before sorting DVs**	**complete**
HL	basic	219	6	2.7%	3 (50.0%)	213
	uncertain	198	9	4.5%	4 (44.4%)	189
	distant	207	14	6.8%	11 (78.6%)	193
CNET	basic	202	17	8.4%	6 (35.3%)	185
	uncertain	178	11	6.2%	4 (36.4%)	167
	distant	213	19	8.9%	5 (26.3%)	194
	e-commerce	323	33	10.2%	11 (33.3%)	290
	risky	353	39	11.0%	22 (56.4%)	314

In total, 1893 respondents were surveyed of which finally 1745 completed an interview. This results in an overall finisher rate of 92.2%. This ratio differs however significantly between the experimental groups (X^2=1309.74, *df*=7, *p*<.001). While only 2.7% of respondents who were assigned to HL basic failed to complete the interview ultimately, CNET risky was not completed by 11% of the assigned respondents. It is also obvious that the sorting task was a big burden especially for HL respondents. The corresponding numbers for the early CNET dropouts are much lower for almost all scenarios. A Chi-Square test between experimental groups confirmed the difference (X^2=1617.88, *df*=7, *p*<.001).

4.6.2.1 Discussion

The interview duration between 9 and 14 minutes turned out to be short compared to the duration of conventional face-to-face interviews for measuring MRs. Dellaert *et al.* (2008) report a mean interview duration of about one hour. For the sake of completeness it has to be admitted that their interviews included an additional set of questions to reveal parameters of the causal network (i.e. conditional probabilities and utilities). Nevertheless, that alone cannot explain the four to five times longer interview duration. From a practical point of view, both online techniques can hence be considered as equally attractive for respondents as the difference between HL and CNET is negligibly small.

A more obvious difference is the higher number of dropouts in CNET. Owing to the fact that respondents were drawn from a panel their motivation to complete the interview might have been higher than under other circumstances. Once they dropped out many respondents started a second or third interview session at a later point in time. As CNET and HL did not differ methodologically up to the sorting of the decision variables in interview step 2 it is of interest to see how many of the dropouts happened thereafter. The results speak a clear language. In HL between 21.4% and 55.6% of the dropouts happened after the somewhat demanding drag-and-drop task making interview step 2 to the biggest burden. In CNET, however, the majority of dropouts failed during later interview steps, especially during the first time respondents encountered the string recognition tool. The dropouts declined however with repeated interaction. Nonetheless, CNET with its inherent string recognition tool seems to place a somewhat greater burden on respondents than HL.

4.6.3 Evaluation by respondents

Finally, besides these rather objective measures it is worthwhile to analyse respondents' evaluations. As usual for surveys performed among the LISS panel, respondents were asked to rate five statements on a scale from 1 (dissent) to 5 (consent) after completing the interview. Table 4-35 summarizes the means per technique and the outcomes of a t-test.

Table 4-35. Survey evaluation questions.

HL	CNET	t	df	p
1. Did you find it difficult to answer the questions?				
2.93	3.35	-6.05	1744	<.001
2. Were the questions clear to you?				
3.27	2.77	7.66	1261.27	<.001
3. Did the questionnaire trigger your thoughts?				
2.77	2.59	3.00	1744	.003
4. Did you have an interest in the research subject?				
3.10	2.97	2.14	1744	.033
5. Did you enjoy answering the questions?				
3.12	2.93	3.15	1286.28	.002

All results are significantly different between HL and CNET. Thereby, HL was favoured by respondents as it has been evaluated less difficult, clearer, more motivational, more interesting and more pleasant than CNET. Paradoxically, the clarity of the interview questions and the interest in the research subject were rated differently between techniques although neither the questions nor the research subject differed. The two additional CNET scenarios can however not be causal for the effect in question 4 as the difference becomes even more significant (t=2.26, df=1140, p=.024) when these two scenarios are left out. Surprising is also the low rating for the techniques' motivational effect on thinking about the choice problem. Especially striking is the higher value for the recognition-based HL whereas one would expect recall-based techniques evoke deliberation processes much stronger.

5

Modelling Component Activation in Mental Representations

5.1 Introduction

In section 2.3 of this thesis it has been outlined what a mental representation is, which components it consists of and how it is tailored to the specific task and contextual setting under concern. In section 4.5 data on MRs for an activity-travel task under different situational circumstances have been explored on their complexity and content. It has become clear that the components of MRs vary quantitatively and qualitatively with the decision context. This chapter presents a model-based analysis of the data by which several effects of context variables on the construction of MRs can be analysed. Therefore, a formal approach will be presented which has been worked out and proposed by Arentze, Dellaert, Horeni and Liberali (paper in progress) in order to describe and model the activation of MR components and their causal relationships for complex decision problems. This approach does not only allow for tests of differences in activation of MR components but also provide a formal explanation for the discovered differences. The next two sections will outline the formal model and its implications. Accordingly, the econometric model and two empirical applications to the data collected with CNET will be presented. Finally, this chapter closes with conclusions.

5.2 A formal model of MR component activation

Mental representations are temporary structures taken from (parts of) an individual's broader causal knowledge. The question of interest is what determines the activation of the relevant causal knowledge, i.e. the attributes, benefits and functional relationships in the mental representation. To model this process, the following sections describe the activation as the result of an implicit cognitive trade-off between the expected preference-information gain of an evaluation of a particular decision-attribute-benefit (DAB) chain and mental costs in greater detail. More specifically, this activation represents an implicit evaluation of the extent to which a choice of an alternative (D) influences the level of the benefit (B) that is achieved because of the fact that an attribute (A) is present and the model consists of gains and costs components to evaluate candidate DAB chains for inclusion in an MR.

5.2.1 Gains of including a DAB chain in the MR

Gains are tightly coupled to developing explicit preferences for choice alternatives. To develop a model for this component, it is helpful to first consider formation of preferences. Ignoring for the moment possible interactions between attributes, an evaluation of a choice alternative in a case where multiple decision variables are involved (e.g. location, time and travel mode choice) on a benefit-attribute relation can be written as:

$$r_{ij}(x_{jkg}) = \beta_{kg}^{ij} \qquad \text{(Equation 5-1)}$$

where x_{jkg} is an (expected) outcome of alternative *g* of decision variable *k* on attribute *j*. r_{ij} is an evaluation of the extent to which this outcome matches the most desired outcome given the need associated with benefit *i*. β_{kg}^{ij} is a corresponding systematic utility value. A perceived gain of a DAB chain evaluation is defined as the size of utility difference it reveals compared to the case where the chain is not inspected or, formally:

$$Z_{ijk} = SD(\beta_{k\bullet}^{ij}) \qquad \text{(Equation 5-2)}$$

where Z_{ijk} is the gain of evaluating DAB chain *ijk*, SD(•) is a measure of dispersion (e.g. standard deviation) reflecting the range of systematic utility values that the DAB can take on, and $\beta_{k\bullet}^{ij}$ is a vector of these utility values across alternatives of decision variable *k* with respect to benefit-attribute relation *ij*. This formulation is consistent with a general notion in discrete choice theory that a larger variance of utility values on an attribute corresponds to a larger weight of the attribute in an overall preference value.

Utility values $\beta_{k\bullet}^{ij}$ are not a-priori known to the individual. Therefore, their assessments are based on expectations that the individual derives from broader knowledge about the world and his or her own needs. A key distinction in this knowledge structure must be made between knowledge about relevant attributes and benefit components and the causal network connecting these components and how they relate to alternatives and the individual's own needs. Thus, equation 5-1 is extended as follows to reflect this underlying structure:

$$\alpha_i \cdot s^1_{ij} \cdot s^2_{jk} \cdot r^{'}_{ij}(x_{jkg}) = \beta^{ij}_{kg} \qquad \text{(Equation 5-3)}$$

where α_i is the activation of benefit *i*, s^1_{ij} is the (causal) influence of attribute *j* on benefit *i*, s^2_{ij} is the (causal) influence of decision variable *k* on attribute *j* and $r^{'}$ is a standardized (scale-less) preference value. By using a standardized value for *r*, the utility scale of the DAB chain is uniquely defined by the link strengths (s^1 and s^2) and benefit activation (α). The standardization is performed such that:

$$SD\left[r^{'}_{ij}(x_{jk\bullet})\right] \equiv 1 \qquad \text{(Equation 5-4)}$$

where *SD*(•), as before, is a measure of dispersion and $x_{jk\bullet}$ is an alternatives-vector of outcomes of decision variable *k* on attribute *j*. Combining Equations (5-2) – (5-4) gives a solution for the total gain *Z* as follows:

$$Z_{ijk} = SD[\alpha_i \cdot s^1_{ij} \cdot s^2_{jk} \cdot r^{'}_{ij}(x_{jkg})] \qquad \text{(Equation 5-5a)}$$

$$= \alpha_i \cdot s^1_{ij} \cdot s^2_{jk} \cdot SD[r^{'}_{ij}(x_{jkg})] \qquad \text{(Equation 5-5b)}$$

$$= \alpha_i \cdot s^1_{ij} \cdot s^2_{jk} \qquad \text{(Equation 5-5c)}$$

So, the gain of including a certain DAB in the MR is a multiplicative function of benefit activation and the strengths of the links in the DAB chain connecting the decision variable to the benefit variable. The gain is zero if the benefit has zero activation or if the decision has no consequences for attaining the benefit. Presumably, a subject has cognitive access to all these elements. Benefit activation is directly observable as a current state of internal needs (e.g. an individual feels like going out), whereas assessment of link strengths is based on a subject's causal knowledge of the domain (e.g. knowing that location choice for a shopping trip generally has a strong impact on travel time). In sum, by combining causal knowledge with an assessment of his own subjective state an individual is able to (consciously or subconsciously) make an assessment of the gain of including a given DAB chain in his MR for making decisions.

5.2.2 Costs of including a DAB chain in the MR

The cost component takes into account the mental effort involved in using the MR to determine likely outcomes of action alternatives (memory retrieval, inference, judgement, etc.). As is the case for gains, for the costs of evaluating a DAB chain an individual also has to rely on experience-based knowledge, as actual costs will be known only after an actual evaluation has been carried out. Moreover, a cost assessment requires a way of allocating total costs of using an MR to the individual DAB chains constituting the MR. These costs are modeled as follows:

$$C_{ijk} = c_{ij} + c_{jk} \qquad \text{(Equation 5-6)}$$

where C_{ijk} are the mental costs assigned to evaluating DAB chain *ijk*, c_{ij} are the assigned costs of deriving consequences of attribute *j* on benefit *i* and c_{jk} are the assigned costs of deriving consequences of decision variable *k* on attribute *j*. This model acknowledges the possibility that certain inferences are mentally more demanding than others. For example, deriving shopping destination travel time outcomes may be more demanding than deriving static attributes of travel mode choice alternatives as the former may require more complex mental simulations such as the consideration of a complex transport system.

5.2.3 Integration of gains and costs

Equations (5-5c) and (5-6) together determine the activation of DAB chains in the MR. The perceived net utility of activating a DAB is defined as:

$$U_{ijk} = Z_{ijk} - C_{ijk} \qquad \text{(Equation 5-7)}$$

We assume that a DAB is activated in an MR if the gain exceeds the costs, i.e. if the net utility *U* is bigger than zero. Thus, the probability that a particular DAB chain is activated in an MR for a given decision problem and individual is defined as:

$$P[(i,j,k) \in MR] = P(U_{ijk} > 0) \qquad \text{(Equation 5-8)}$$

Finally, to clarify interpretation and to remove redundancies in the gain model (Eq. 5-5c) it is helpful to introduce the following standardizations:

$$\sum_j s_{ij}^1 \equiv 1 \quad \forall i \qquad \text{(Equation 5-9a)}$$

$$\sum_k s_{jk}^2 \equiv 1 \quad \forall j$$ (Equation 5-9b)

Given these standardizations, we can derive a useful relationship between unobserved utility values and benefit activation as follows. Combining Equations 5.2 and 5.3 gives:

$$\alpha_i \cdot s_{ij}^1 \cdot s_{jk}^2 = SD(\beta_{k\bullet}^{ij})$$ (Equation 5-10a)

Solving for benefit activation yields:

$$\sum_{jk} \alpha_i \cdot s_{ij}^1 \cdot s_{jk}^2 = \sum_{jk} SD(\beta_{k\bullet}^{ij})$$ (Equation 5-10b)

$$\alpha_i \cdot \sum_{jk} s_{ij}^1 \cdot s_{jk}^2 = \sum_{jk} SD(\beta_{k\bullet}^{ij})$$ (Equation 5-10c)

$$\alpha_i = \sum_{jk} SD(\beta_{k\bullet}^{ij})$$ (Equation 5-10d)

Equation (5-10d) shows that, under standardization of link strengths, benefit activation determines a sum of dispersion sizes of utility values across attributes related to the benefit. We can derive a comparable relationship for chain strengths: Substituting Eq. 5-10d in Eq. 5-10a and rewriting gives:

$$s_{ij}^1 \cdot s_{jk}^2 \sum_{jk} SD(\beta_{k\bullet}^{ij}) = SD(\beta_{k\bullet}^{ij})$$ (Equation 5-11a)

Solving for link strengths results in:

$$s_{ij}^1 \cdot s_{jk}^2 = \frac{SD(\beta_{k\bullet}^{ij})}{\sum_{jk} SD(\beta_{k\bullet}^{ij})}$$ (Equation 5-11b)

As implied by Equation (5-11b), chain strength *ijk*, under standardization of link strengths, determines the proportion of dispersion in preference values *ijk* on total dispersion in preference values related to benefit *i*.

Although standardizations (5-9a and b) are not essential, they clarify the interpretation of the gain model given by Equation (5-5c). The first derivation (Eq. 5-10d) indicates that importance of a benefit always refers to the extent the benefit helps in discriminating choice alternatives – it does not give direct information on the size of the underlying need. For example, even if a current need is very important for the well-being of the individual, the corresponding benefit activation will be zero if the choice alternatives do not differ in terms of attainment of the need. The second derivation (Eq. 5-11b) shows that also link strengths relate to the purpose of making choices: even if a causal relationship between an attribute and benefit is strong, chain strength will still be small if choice alternatives do not differ (strongly) on the attribute.

5.3 Model Implications

The formal model allows us to make several predictions on how changes in variables of a situational setting or the need state of an individual are likely to influence size and composition of an MR. First, -all else equal- the size of an MR increases with greater impact of attributes on benefit values due to stronger causal relationships. With increased impact of attributes on benefit values preference differentiation between alternatives increases so that the information gains of DAB chain evaluations increases. Increases in mental effort have a comparable but opposite effect: with an increase in mental costs, the threshold for including DAB chains in the MR increases so that with an equal impact of attributes on benefit values the expected number of DAB chains decreases.

Second, MRs should vary qualitatively with different patterns of need activation. Need activation can vary across situations as it changes with physical and emotional states of an individual and with the situational factors (e.g. time pressure). Since causal relationships determine how a given pattern of need activation is distributed across DAB chains, a change of need activation will not only cause a shift in benefit activation but also in the selection of DAB chains. In behavioural terms, the model predicts that with a change in needs an individual evaluates choice alternatives differently because the same alternatives are evaluated in the light of different benefits.

Third and finally, the influence of situational variables deserves attention. Situational variables potentially have a moderating effect on causal relationships between attribute and benefit variables. For example, weather conditions often have an influence on consequences of locations and transport modes on comfort and convenience (e.g. indoor activities when it is raining). Thus, although causal knowledge may be stable over time, DAB chain strengths representing impacts of decisions on benefit outcomes may change as a function of context variables. This means that, even under the same need activation conditions, MRs predicted by the model are sensitive to situational variables. This holds for settings that are known to the individual at the moment of decision making.

5.4 Econometric model and estimation

Situation dependent benefit activation, link strengths and mental costs in the formal model are unknown to the researcher. Therefore, they need to be parametrized and estimated from a given sample of MRs. In line with the model, the assumed observations for each MR consist of a collection of DAB chains from the survey described earlier in this thesis. The specified model is based on random utility maximization theory and proposes a log-likelihood maximization framework for estimation.

The proposed utility function follows from the above theory and can be written as follows:

$$U_{ijk}^{n} = Z_{ijk}^{n} - C_{ijk}^{n} + \varepsilon_{ijk}^{n} \quad \forall (i,j,k) \in I \times J \times K \qquad \text{(Equation 5-12)}$$

where n is an index of observation (an MR), U is the utility of DAB chain *ijk*, Z and C, as before, are perceived gain and perceived costs of the DAB, I is an exhaustive set of benefit variables, J is an exhaustive set of attribute variables and K is an exhaustive set of decision variables for the choice task and setting considered, ε is an error term and $\times$ stands for Cartesian product. Assuming rational behaviour, as before, the probability of observing a DAB chain *ijk* is defined as:

$$P[(i,j,k) \in MR_{n}] = P(U_{ijk}^{n} > 0) \qquad \text{(Equation 5-13)}$$

The following parameterization for the gain component is applied. First, to make sure that link strength estimates are non-negative, the exponents of link strength parameters are estimated:

$$s_{ij}^{1} = \exp(\lambda_{ij}^{1}) \qquad \text{(Equation 5-14a)}$$

$$s_{jk}^{2} = \exp(\lambda_{jk}^{2}) \qquad \text{(Equation 5-14b)}$$

where λ are parameters to be estimated. Second, to account for possible impacts of context variables on all levels, the benefit activation and link strength parameters are defined by the following functions:

$$\alpha_{in} = \alpha_{i0} + \sum_{h} \alpha_{ih} \cdot X_{h}^{n} \qquad \text{(Equation 5-15)}$$

$$\lambda_{ij}^{1} = \lambda_{ij0}^{1} + \sum_{h} \lambda_{ijh}^{1} \cdot X_{h}^{n} \qquad \text{(Equation 5-16)}$$

$$\lambda_{jkn}^{2} = \lambda_{ij0}^{2} + \sum_{h} \lambda_{jkh}^{2} \cdot X_{h}^{n} \qquad \text{(Equation 5-17)}$$

where α's are parameters related to benefit activation, X_{h}^{n} is the value of the *h*-th context variable in case *n*. The functions take into account a base value (the first term on the right-hand-side of each equation) as well as effects of context conditions. Thus, the parameterization allows for systematic effects of context.

For the cost component a similar function of context variables is applied:

$$C_{ijk}^{n} = \theta_{0} + \sum_{h} \theta_{h} \cdot X_{h}^{n} \qquad \text{(Equation 5-18)}$$

where θ_0 is a base value and θ_h are context effects on the costs parameters. Note that this function does not represent a possible differentiation of costs depending on the DAB chain under concern. Rather, it represents an average value of (mental) costs of evaluating DAB chains (within context conditions). This average does not account for possible differences in mental effort between chains depending on the nature of the relationships involved. The reason of using an average here is that mental-effort effects of chains cannot be disentangled from strength effects of chains based on just chain-selection observations. Using this specification, variation in mental costs across chains will be captured by the error component in Equation (5-12) together with other non-systematic sources of variance.

Assuming that the error terms are independently and identically Gumbel distributed, the logit model can be used to determine the probabilities defined by Equation (5-8) of observing particular DAB chains in an MR as:

$$P_{ijk}^{n} = \frac{\exp[Z_{ijk}^{n} - C_{ijk}^{n}]}{1 + \exp[Z_{ijk}^{n} - C_{ijk}^{n}]} \qquad \text{(Equation 5-19)}$$

5.4.1 Required parameter restrictions

Equations (5-9a and b) imply that one AB link strength parameter per benefit variable cannot be estimated and one DA link strength parameter per attribute variable cannot be estimated but follow from the constraint that the sum of link strength parameters equals to one. Implementing the marginal constraint directly in a log-likelihood estimation hinders the search process. Therefore, an indirect method is chosen where for each benefit variable a base AB link and for each attribute variable a base DA link is determined. The link strength value for the base relationships is (arbitrarily) set to unity so that the strengths of all non-base relations are estimated against this value. In sum, rather than implementing the sum-is-one constraints given by equations 5-9a-b, we estimated link-strength parameters relative to link strengths assigned as base.

Finally, one last estimation issue deserves attention. Because the basic form of the chain-selection condition is given by $\alpha \cdot s^1 \cdot s^2 > \theta$, a strong correlation exists between benefit-activation parameters α and costs parameter θ. This correlation is due to the fact that for any given value of α_i and θ the likelihood of a given set of observations does not change when a constant Δ is introduced as $(\hat{\alpha}_i + \Delta)$ and $(\theta + \Delta)$. This is easy to see because $\hat{\alpha}_i$ represents the gain of the chain *i* of which both link strengths $\hat{s}^1$ and $\hat{s}^2$ are equal to one so that the form of the condition for a base chain reduces to $\alpha > \theta$ (adding a constant to both sides of the equation does not change the outcome of the equation). This means that rather than estimating a costs parameter θ directly a base value for this parameter can be pre-set and Δ in $(\theta + \Delta)$ and $(\hat{\alpha}_i + \Delta)$ estimated. This yields the same result, but has the beneficial property that it facilitates the search for parameters because it strongly reduces the correlations. This method is used in the application below. In sum, this means that the following equivalent forms for gain and costs functions (5-12) and (5-18) are used:

$$Z_{ijk}^{n} = (\alpha_{in} + \Delta) \cdot \exp(\lambda_{ijn}^{1}) \cdot \exp(\lambda_{jkn}^{2}) \qquad \text{(Equation 5-20)}$$

$$C_{ijk}^{n} = \theta_n + \Delta \qquad \text{(Equation 5-21)}$$

where θ is fixed to some arbitrary value and Δ is estimated instead and benefit activation, link strength and costs parameters are all a function of context variables (in the *n*-th case).

5.5 Results of the applications

When the experimental activity-travel task has been developed one expectation was that MRs of it would change slightly for different contextual settings. Hence, variations of the basic task were developed which were supposed to reflect a shift in individuals' need activation, causal relationships and mental costs. This section will now analyze these supposed shifts in light of the econometric model. Thereby, the analysis has been split up into two rounds. First, data from the uncertain and the risky scenario will be compared against data from the basic task. Owing to the conceptual similarity of the former two scenarios in terms of their implied uncertainty about important information and thus also in terms of the risk to fail the task, we expect a higher activation of needs which are essential for fulfilling these tasks (e.g. shopping success) in both scenarios. Besides failing to fulfill the task per se the risky scenario would imply even more negative consequences when the shopping activity cannot be performed. Thus, need activation there is expected to be even stronger and distributed over more benefits.

The second analysis regards data of the e-commerce scenario which are compared against merged data from the basic and the distant scenario. The introduction of a new choice alternative in the e-commerce scenario (online shopping) which is very distinct to the rest of the choice set is expected to result in additional considerations caused by a broader need activation. On one hand individuals might save mental effort to discriminate between choice alternatives. On the other hand online shopping might evoke new risks and chances. Data from the basic and the distant scenario were merged as they did not differ substantially in DAB-links or cognitive subsets, respectively (X^2=6.83, df=8, p=.555).

5.5.1 Descriptive analysis

Before the model could be estimated with the data from the CNET interviews the original classification of attributes, benefits and situational variables had to be revised as the observed frequencies were too little among some of them. Furthermore, too many attributes, situational variables and benefits would lead to a vast number of parameters to be estimated in the model. Therefore, variables that were similar in content have been merged to bigger categories. From the 57 original considered attributes 20 new were formed of which the new category *'other'* summarizes several rarely observed attributes. Likewise, the 25 situational variables were shrunk down to 19 and from the 22 original benefits just the half remained. Table 5-1 shows the observed frequencies of these newly categorised variables in decreasing order across the two analyses.

Table 5-1. Observed frequencies for decisions, attributes, situations and benefits.

Decision variable	*analysis 1*	*analysis 2*	*Merged from*
Transport mode	612	608	-
Shopping location	607	605	-
Timing of shopping	569	560	-
Attribute variable			
distance	128	163	-
familiarity	80	93	familiarity with TM and SL, type of shop, TM habituation
layout of the shopping location	34	44	canopy, layout, maintenance, restaurants, signage, size, possibilities to rest, atmosphere, diversity of branches, illumination
flexibility of the transport mode	32	27	departure time flexibility, route flexibility
accessibility of the store/public transport	129	121	accessibility store and public transport, handicapped people, TM use authorization
asssortment/special offers/service	325	239	service level, special offers, special events, assortment
product quality	63	62	-
reliability/safety	19	20	reliability and safety of the TM, reliability delivery service
waiting/preparation time	23	10	waiting time, expected delay, preparation and delivery time
capacity/privacy of the transport mode	60	76	capacity, privacy, chance of a seat in TM
costs for transport/parking/petrol	26	29	travel costs, costs for petrol, parking costs
possibility to store or receive shoppings	47	36	possibility to store products, possibility to receive an order
opening hours	27	26	-
simplicity of the travel route	81	88	-
travel/transport time	84	65	travel time, transport time
Leisure	93	101	-
sportiness/physical demand	42	42	sportiness, physical demand
parking options/infrastructure	108	107	bus shelter, parking options, available infrastructure
Other	14	14	amount of exhaust gases, paying options, cleanliness home, clothing, support middle class
price level of assortment	88	134	-
Situational variable			
available time to shop	108	106	-
time pressure	69	47	-
Internet access	0	11	-
weather	61	77	weather, outside temperature
baggage	128	168	-
durability/sort of products	71	76	durability of products, sort of products

Table 5-1 (continued).

Situational variable	analysis 1	analysis 2	Merged from
required time to shop	59	59	-
physical condition	14	16	-
working day	133	126	stress at work, recreation time at work, working hours
unexpected events	14	6	-
with or without company	7	14	-
crowdedness	56	87	crowdedness in the store, crowdedness on the way
availability of the transport mode	60	53	-
time to find a parking lot	27	24	-
necessity	46	54	-
time of the day	14	24	-
other activities/arrangements	91	113	conflict with other arrangements, combination with other activities,
opinion of friends	4	6	-
reason for boss visit	5	0	-
Benefit variable			
Safety	101	102	safety in the SL, safety in travelling
social - pleasure	285	318	travel pleasure, shopping pleasure, social acceptance, taste experience, to appeal the boss
shopping ease/comfort	356	387	ease of shopping, shopping comfort
attractivity of the shopping environment	93	97	-
shopping success/diversity	414	345	diversity in product choice, shopping success
travel ease/comfort	497	506	travel comfort, ease of travelling
good for health and/or environment	153	167	environmental protection, health
mental ease	237	216	-
personal care/fitness/relaxation	274	314	personal care, relaxation/recreation, course of fitness/wellbeing
financial savings	167	214	-
time savings	424	448	-

Although CNET uses the logic of DAB chains, possible responses are not strictly confined to this type of chains. Several deviations are possible. First, instead of attributes respondents occasionally mentioned situational variables as considerations for particular decisions such as for example *weather* or *necessity of shopping*. These chains were not omitted from the analysis, but rather treated like DAB chains. The only difference to real DAB chains is the interpretation of the DA link which is not of a causal nature but a cognitive association instead. Second, DB types are allowed to occur, i.e. direct links between decision variables and benefits. In the analysis a DB chain is coded as a DAB chain where A is a dummy attribute linked to D with strength of one, so that, effectively, the DA link is omitted from the equation and only the DB link persists.

In total, 3 decision variables, 23 attributes, 19 situational variables and 11 benefits occurred in either analysis. This defines a space of 3 × (23 + 19) × 11 = 1386 possible DAB chains. Many possible AB and DA links do however not occur or only with a very low frequency.

Estimating a link strength parameter is only meaningful for those links that occur in an MR with an above minimum probability; links with lower probability can be considered to have an approximately zero strength. Therefore, a minimum link probability has been defined and the set of candidate DAB chains was identified as those chains where both links in the chain exceed the minimum probability (note that the reduced set may still include chains that are never observed in MRs, because the minimum probability is defined for links, not chains). The choice of a minimum is somewhat arbitrary but not critical for the model. In the interpretation of results it should be kept in mind that a zero value of link strength does not mean zero probability but a probability below the used minimum value.

The minimal observed frequency of a link has been set to 30. The number of observed MRs equals 655 and 659 in the first and the second analysis, respectively. Hence, this minimum number corresponds to a probability of (30/655=) .046 for the first and (30/659=) .046 for the second analysis. 42 DA links, 45 AB links and 3 DB links meet this criterium in the first analysis and 54 DA links, 101 AB links and 2 DB links in the second analysis. This reduced the 1386 possible chains to 95 and 237 actual candidate chains, respectively. Thus, for each individual of the first analysis there are 95 observations of yes/no occurrence as the basis for the likelihood function in the logit model. In the second analysis, the number of observations amounts to 237. The number of link strength parameters to be estimated per group equals 20 (= 42 – 22) on the level of AD links and 38 (= 45 + 3 – 10) on the level of AB and DB links for the first analysis. Actually, there were 11 benefit variables, but one did not occur frequently enough in the chains in the first analysis. The number of parameters to be estimated per group for the second analysis amounts to 27 (= 54 – 27) on the level of DA links and 92 (= 101 + 2 – 11) on the level of AB and DB links. Arbitrarily, the link with the highest frequency was taken as base relation for AB links per benefit as well as for DA links per attribute. In relation to all parameters - benefit activation, link strength and costs thresholds - effects for context variables have been estimated. While in the first analysis data from the uncertain and the risky scenario have been compared separately with data from the basic scenario, in the second analysis data from the basic scenario have been merged with data from the distant scenario and compared against data from the e-commerce scenario. Although there were 11 benefit variables, one did not occur frequently enough in the chains in the first analysis. In total, the first model included 10 base values and 10 × 2 = 20 effect parameters and the second model 11 base values and 11 effect parameters for benefit activation.

Summarized for the first analysis 207 parameters were estimated: 20 for DA link strength, 38 for AB link strength, 10 for benefit activation and one threshold constant for each of the three experimental groups. During the second analysis 262 parameters were estimated: 27 for DA link strength, 92 for AB link strength, 11 for benefit activation and one threshold constant for each experimental group.

5.5.2 Model estimation results for the first analysis

The non-linear optimization model NLM in R was used to obtain the values of the parameters that maximize the log-likelihood function. The base value of the mental costs parameter was set to $\theta = 5$. This level roughly corresponds to the occurrence probability of chains that have zero frequency.

In total the estimation involves 207 parameters, 655 respondents and 95 (binary) observations per respondent. The null model is the model where all parameters are set to zero (zero activation and a threshold of 5). The final loglikelihood amounts -47765.8 with a loglikelihood of -55172 for the null model (threshold set to base value and all parameters set to zero). This means a rho-square of 0.134 based on this null model, which indicates a low goodness-of-fit (compared to a null model with appropriate threshold setting). After adjustment for number of parameters the rho-square value decreases only very modestly (0.130). Table 5-2 represents estimated values and *t*-values for parameters of benefit activation and mental costs.

Keeping the link strengths equal, *shopping success/product diversity* is the strongest activated benefit. *Shopping ease/comfort, financial savings, travel ease/comfort, time savings,* and *personal care/fitness/relaxation* are also important considerations in making the decisions. *Social-pleasure* related benefits, *health and environmental issues*, *the attractivity of the shopping environment* and *mental ease* have only little impact. In addition, there are some significant effects between scenarios. First, *shopping success/product diversity* becomes even more important when there is uncertainty about the product assortment or when importance of certain products is emphasized. Making a complex shopping trip under uncertainty (about the product assortment and the traffic situation) the importance of *time savings* decreases significantly. However, when the choice outcome (and its consequences) is perceived as risky there is no significant effect on *time savings*. Rather, *mental ease, shopping ease/comfort* and *social–pleasure* related considerations increase significantly in their importance. The latter effect captures also *taste experience* and *appeal* aspects (see Table 5-1). Mental costs are perceived as significantly stronger in the uncertain scenario and significantly weaker in the risky scenario when compared to the basic scenario.

Table 5-2. Estimation results: benefit activation and mental costs (analysis 1).

	Basic Scenario		**Effects of Uncertain Scenario**		**Effects of Risky Scenario**	
B	**value**	**t**	**value**	**t**	**value**	**t**
social - pleasure	2.468	9.924	0.424	1.3	**0.692**	2.43
shopping ease/comfort	3.497	19.805	0.38	1.604	**0.756**	3.671
attractivity of shopping environment	2.199	7.954	-0.132	-0.329	0.225	0.678
shopping success/product diversity	3.966	25.077	**0.629**	2.936	**0.966**	5.121
travel ease/comfort	3.25	16.219	-0.05	-0.167	-0.218	-0.828
good for health and/or environment	2.348	7.857	-0.812	-1.495	-0.07	-0.183
mental ease	1.898	6.045	0.622	1.566	**1.07**	3.084
personal care/fitness/relaxation	3.066	13.744	-0.369	-1.052	-0.584	-1.876
financial savings	3.336	16.472	-0.639	-1.889	-0.391	-1.443
time savings	3.241	17.579	**-0.835**	-2.659	-0.416	-1.677
mental costs	0.087	3.310	**0.187**	4.636	**-0.211**	-6.555

Numbers in bold are significant scenario effects.

Strengths of AB links are shown in Table 5-3. The t-values refer to a test of difference to strength of one. Overall, estimated strengths are in line with expectations. To give a few examples: the attribute *product quality* has an influence on the benefit *social-pleasure* in all three scenarios (0.786 versus 0.496 versus 0.835). Thus, the influence of *product quality* on *social-pleasure* is biggest in the risky scenario. As another example, in the basic scenario the attribute *accessibility* has an influence on benefits *social-pleasure* (0.607), *shopping comfort* (0.601), *shopping success/diversity* (0.553), *travel ease/comfort* (0.962), and *time-savings* (0.628). Thus, the influence on *travel ease/comfort* is much bigger than on the other benefits. All estimated values shown in the table can be interpreted in this way. A pattern that clearly emerges is that benefits considerably differ in the number of attributes they evoke for evaluating choice alternatives. *Travel ease/comfort* and *time savings* have by far the largest impact on MRs for the decision tasks of all scenarios. Apparently, there is a large number of attributes on which choice alternatives produce different outcomes in terms of these benefits.

Table 5-3. Link strength parameters for AB links (analysis 1).

AB links		**basic scenario**		**Effects of uncertain scenario**		**Effects of risky scenario**	
attribute	**benefit**	**value**	**t**	**value**	**t**	**value**	**t**
distance	travel ease/comfort	0.904	-1.17	-0.159	-1.325	-0.082	-0.758
distance	time savings	1	0				
familiarity	travel ease/comfort	0.639	-2.62	-0.184	-0.921	0.173	1.179
accessibility	social - pleasure	0.607	-1.96	0.168	0.858	-0.047	-0.274
accessibility	shopping ease/comfort	0.601	-3.63	-0.05	-0.426	-0.18	-1.857
accessibility	shopping success/diversity	0.553	-4.6	-0.076	-0.824	-0.267	-2.863
accessibility	travel ease/comfort	0.962	-0.44	0.006	0.048	-0.036	-0.31
accessibility	time savings	0.628	-3.11	**0.35**	2.2	0.076	0.585
assortment/service	social - pleasure	1	0				
assortment/service	shopping ease/comfort	1	0				
assortment/service	attractivity SL environment	1	0				
assortment/service	shopping success/diversity	1	0				
assortment/service	travel ease/comfort	0.564	-3.11	0.202	1.409	0.2	1.437
assortment/service	mental ease	1	0				
assortment/service	financial savings	0.633	-3.12	0.27	1.803	0.122	0.955
assortment/service	time savings	0.483	-3.07	**0.679**	3.323	**0.697**	3.603
product quality	social - pleasure	0.786	-1.18	-0.29	-1.177	0.049	0.269
TM capacity/privacy	travel ease/comfort	0.756	-2.17	-0.059	-0.401	0.022	0.164
simplicity of route	travel ease/comfort	0.757	-2.45	-0.052	-0.389	0.018	0.155
simplicity of route	time savings	0.73	-2.68	-0.028	-0.16	0.11	0.9
travel/transport time	travel ease/comfort	0.681	-2.92	-0.064	-0.481	0.184	1.497
travel/transport time	time savings	0.695	-2.84	0.259	1.606	**0.319**	2.443
leisure	personal care/relaxation	0.913	-0.82	0.035	0.212	-0.024	-0.143

Table 5-3 (continued).

AB links		**basic scenario**		**Effects of uncertain scenario**		**Effects of risky scenario**	
attribute	**benefit**	**value**	**t**	**value**	**t**	**value**	**t**
leisure	time savings	0.9	-1.09	0.003	0.019	0.007	0.054
parking/infrastructure	travel ease/comfort	0.841	-1.7	-0.034	-0.261	0.065	0.549
parking/infrastructure	time savings	0.759	-2.43	0.151	0.925	0.006	0.049
price level	financial savings	1	0				
available time to shop	shopping ease/comfort	0.752	-2.63	-0.13	-1.143	-0.136	-1.538
available time to shop	shopping success/diversity	0.352	-4.38	0.104	0.939	0.181	1.677
time pressure	time savings	0.298	-2.04	0.292	1.002	0.609	1.845
weather	social - pleasure	0.885	-0.76	-0.15	-0.801	**-0.327**	-1.99
weather	travel ease/comfort	0.728	-2.4	-0.039	-0.267	-0.011	-0.08
baggage	shopping ease/comfort	0.73	-3.28	-0.21	-1.76	**-0.294**	-3.32
baggage	travel ease/comfort	1	0				
required time to shop	shopping ease/comfort	0.474	-3.4	-0.09	-0.651	0.019	0.161
required time to shop	time savings	0.564	-2.95	0.241	1.298	0.235	1.54
working day	social - pleasure	0.953	-0.31	-0.19	-0.995	**-0.375**	-2.18
working day	mental ease	1.228	1.03	-0.164	-0.61	-0.382	-1.657
working day	personal care/relaxation	1	0				
crowdedness	shopping ease/comfort	0.647	-3.22	0.02	0.143	**-0.216**	-2.05
crowdedness	time savings	0.574	-3.21	**0.497**	2.883	0.035	0.25
availability of TM	travel ease/comfort	0.756	-2.17	-0.027	-0.186	-0.126	-0.886
availability of TM	time savings	0.704	-2.44	0.101	0.538	-0.086	-0.55
other activities	personal care/relaxation	0.711	-2.11	0.207	1.187	-0.18	-0.857
other activities	time savings	0.883	-1.26	0.168	1.015	0.055	0.43
transport mode	travel ease/comfort	1.062	0.74	0.012	0.094	0.127	1.042
transport mode	health/environment	1	0				
shopping location	shopping success/diversity	0.553	-3.94	-0.289	-1.546	-0.053	-0.571

Numbers in bold are significant scenario effects.

Three of the reported effects have been found as significant for the uncertain scenario; namely, the attributes' *accessibility* (+0.35), *assortment/service* (+0.679) and the situational variable's *availability of the transport mode* (+0.497) link to the benefit *time savings* is influenced stronger than in the basic scenario. These effects are plausible because prolonged travel times caused by traffic congestions were implied in the uncertain scenario. Therefore, respondents tried stronger to save time by considering the availability and accessibility of other travel modes. Also the accessibility of stores where respondents expected the assortment to be big enough for the necessary products is a reasonable consideration in order to save time.

In the risky scenario six effects were significant. *Time savings* is more strongly affected by assortment/service (+0.697) and travel/transport time (+0.319). This finding does not need much explanation as it is only logical that respondents aimed at saving time by minimizing travel time and choosing the store where the available assortment promises a short shopping time. Furthermore, the situational variables *weather* (-0.327) and *working day* (-0.375) influence the benefit *social-pleasure* less than in the basic scenario. This finding represents nicely the shift in MRs between the scenarios as suchlike non-utilitarian considerations fade into the background in risky situations. The same applies to the benefit *shopping ease/comfort* which is significantly less impacted by *number of baggage* (-0.294) and *crowdedness* (-0.216).

Table 5-4. Link strength parameters for DA links (analysis 1).

DA link	**basic scenario**		**Effects of uncertain scenario**		**Effects of risky scenario**	
	value	**t**	**value**	**t**	**value**	**t**
transport mode						
distance	0.933	-0.93	0.009	0.066	-0.029	-0.273
familiarity	1	0				
accessibility	1	0				
TM capacity/privacy	1	0				
simplicity of the travel route	0.884	-0.908	-0.102	-0.466	0.081	0.513
travel/transport time	1	0				
parking options/infrastructure	1	0				
available time to shop	0.821	-1.157	-0.072	-0.348	0.055	0.333
time pressure	0.602	-0.385	0.21	0.21	0.175	0.192
weather	1	0				
baggage	1	0				
crowdedness	0.716	-1.414	0.051	0.249	-0.067	-0.275
availability of the transport mode	1	0				

Table 5-4 (continued).

DA link	basic scenario		Effects of uncertain scenario		Effects of risky scenario	
	value	t	value	t	value	t
shopping location						
distance	1	0				
familiarity	0.606	-1.183	0.209	0.425	-0.2	-0.655
accessibility	0.834	-1.93	0.089	0.837	0.078	0.707
assortment/special offers/service	1	0				
product quality	1	0				
simplicity of the travel route	1	0				
travel/transport time	0.977	-0.162	-0.103	-0.5	-0.182	-1.198
parking options/infrastructure	0.929	-0.671	-0.206	-1.187	-0.027	-0.196
price level of assortment	1	0				
available time to shop	1	0				
baggage	0.846	-1.773	-0,33	-1.911	-0.104	-0.881
required time to shop	0.903	-0.414	0.097	0.308	0.066	0.259
crowdedness	0.836	-0.926	-0.097	-0.497	0.026	0.112
timing of shopping						
distance	0.922	-1.064	0.113	0.843	0.028	0.268
assortment/special offers/service	0.757	-4.645	0.08	1.409	0.079	1.524
product quality	0.498	-1.145	0.054	0.096	0.33	0.813
simplicity of the travel route	0.925	-0.603	-0.045	-0.214	0.097	0.614
travel/transport time	0.875	-0.832	-0.072	-0.345	-0.045	-0.286
leisure	1	0				
available time to shop	0.904	-0.667	0.012	0.061	0.141	0.859
time pressure	1	0				
weather	0.793	-1.332	-0.328	-1.163	-0.171	-0.821
baggage	0.818	-2.039	-0.284	-1.719	-0.024	-0.209
required time to shop	1	0				
working day	1	0				
crowdedness	1	0				
other activities/arrangements	1	0				

Table 5-4 showing the DA link strengths has to be interpreted in the same way. On this level, estimates concern perceived influences of decision variables (printed in bold) on attributes (shown in rows). Again, the values are largely in line with expectations. To give an example: in the basic scenario the decision *transport mode* has an influence on attributes *distance* (0.933), *familiarity* (1), *accessibility* (1), *capacity/privacy of the transport mode* (1), *simplicity of the travel route* (0.884), *travel/transport time* (1), and *parking options/infrastructure* (1). Furthermore, it influences the consideration of the situational variables *available time to shop* (0.821), *time pressure* (0.602), *weather* (1), *baggage* (1), *crowdedness* (0.716), and *availability of the transport mode* (1). Note that for each attribute the strongest DA link was set to 1 in the basic scenario.

Effects between scenarios were less strong than for the AB links. In the uncertain scenario, the strongest effect was obtained for *timing of shopping* on the consideration of *weather* (-0.328), and in the risky scenario, for *shopping location* on *travel/transport time* (-0.128). Those effects were however not significant.

These examples show that a wide range of considerations play a role in the decisions involved in the activity-travel task. Furthermore, the results indicate that almost all attributes are influenced by multiple decisions. Exceptions are *transport capacity/privacy, leisure, price level of assortment, working day, availability of the transport mode* and *other activities/arrangements*.

5.5.3 Model estimation results for the second analysis

As for the first analysis the base value of the mental costs parameter was set to $\theta = 5$. In total the estimation involved 262 parameters, 659 respondents and 237 (binary) observations per respondent. The final loglikelihood amounts to -46090.2 with a loglikelihood of -55289.2 for the null model. This means a rho-square of 0.166 based on this null model, which indicates a low goodness-of-fit (compared to a null model with appropriate threshold setting). After adjustment for number of parameters the rho-square value decreases only very modestly (0.162).

As equivalent to Table 5-2, Table 5-5 shows the estimated results for the benefit activation and mental costs. The results are very similar to the first analysis. Again with link strengths kept equal, *shopping success/product diversity* is the most important benefit in both scenarios. *Shopping ease/comfort, travel ease/comfort, financial savings, time savings, personal care/fitness/relaxation*, and *social-pleasure* are also important considerations in making the decisions. *Health and environmental issues, the attractivity of the shopping environment* and *mental ease* have only little impacts. *Safety* exceeded the minimum frequency in the second analysis but has only little importance. Only one significant effect has been found between scenarios. Namely, the activation of *travel ease/comfort* increases (+0.414) in the e-commerce scenario. This effect is not unexpected as the introduction of the additional e-shopping option comes along with facilitating amenities. The perception of mental costs for including an additional DAB chain does not differ significantly between the scenarios.

Table 5-5. Estimation results: benefit activation and mental costs (analysis 2).

	Basic + Distant Scenario		**Effects of E-commerce Scenario**	
B	**value**	**t**	**value**	**t**
safety	1.575	7.498	0.188	0.598
social - pleasure	2.713	17.216	-0.083	-0.351
shopping ease/comfort	3.49	28.648	0.318	1.837
attractivity of the shopping environment	2.174	11.147	0.057	0.2
shopping success/diversity	4.085	38.278	-0.016	-0.1
travel ease/comfort	3.294	24.991	**0.414**	2.21
good for health and/or environment	1.841	7.16	0.335	0.972
mental ease	1.519	7.824	-0.053	-0.166
personal care/fitness/relaxation	2.797	16.149	0.228	0.913
financial savings	3.41	24.672	0.217	1.074
time savings	3.2	25.828	0.075	0.411
mental costs	0.607	23.943	-0.243	-6.762

Numbers in bold are significant scenario effects.

Table 5-6. Link strength parameters for AB links (analysis 2).

AB links		**basic + distant scenario**		**Effects of e-commerce scenario**	
attribute	**benefit**	**value**	**t**	**value**	**t**
distance	safety	0.797	-1.37	-0.121	-0.61
distance	social-pleasure	0.707	-3.81	0.124	1.26
distance	shopping ease/comfort	0.572	-6.71	-0.044	-0.65
distance	shopping success/diversity	0.279	-5.86	0.11	1.29
distance	travel ease/comfort	0.932	-1.46	-0.109	-1.74

Table 5-6 (continued).

AB links		**basic + distant scenario**		**Effects of e-commerce scenario**	
attribute	**benefit**	**value**	**t**	**value**	**t**
distance	personal care/fitness/relaxation	0.565	-4.63	0.055	0.57
distance	time savings	1	0		
familiarity	social-pleasure	0.594	-3.54	0.16	1.24
familiarity	shopping ease/comfort	0.425	-4.94	0.134	1.35
familiarity	travel ease/comfort	0.624	-4.38	0.043	0.49
familiarity	mental ease	0.796	-1.12	0.442	1.64
familiarity	time savings	0.31	-3.58	0.243	1.63
layout of the SL	shopping ease/comfort	0.641	-4.59	-0.152	-1.44
flexibility of the TM	travel ease/comfort	0.489	-3.97	0.036	0.31
accessibility	social-pleasure	0.737	-3.16	0.031	0.28
accessibility	shopping ease/comfort	0.594	-5.83	-0.079	-0.98
accessibility	shopping success/diversity	0.521	-7.48	**-0.293**	-2.07
accessibility	travel ease/comfort	0.91	-1.77	**-0.202**	-2.73
accessibility	personal care/fitness/relaxation	0.719	-3.35	**-0.285**	**-**2.08
accessibility	time savings	0.711	-4.51	-0.016	-0.19
assortment/service	social-pleasure	1	0		
assortment/service	shopping ease/comfort	1	0		
assortment/service	attractivity of the shopping environment	1	0		
assortment/service	shopping success/diversity	1	0		
assortment/service	travel ease/comfort	0.651	-4.69	-0.09	-1.05
assortment/service	mental ease	1.245	1.83	0.064	0.25
assortment/service	personal care/fitness/relaxation	0.697	-3.27	-0.102	-0.89
assortment/service	financial savings	0.698	-4.66	0.067	0.89
assortment/service	time savings	0.789	-3.5	0.01	0.13
product quality	social-pleasure	0.689	-2.91	**0.277**	2.15
product quality	shopping success/diversity	0.409	-5.4	0.124	1.35
product quality	good for health and/or environment	1	0		
TM capacity/privacy	travel ease/comfort	0.813	-3	-0.052	-0.66
simplicity of route	social-pleasure	0.602	-4.55	-0.17	-1.23
simplicity of route	shopping ease/comfort	0.316	-5.6	0.079	0.84
simplicity of route	travel ease/comfort	0.698	-4.96	-0.06	-0.81

Table 5-6 (continued).

AB links		**basic + distant scenario**		**Effects of e-commerce scenario**	
attribute	**benefit**	**value**	**t**	**value**	**t**
simplicity of route	mental ease	1	0		
simplicity of route	personal care/fitness/relaxation	0.532	-4.9	-0.084	-0.74
simplicity of route	time savings	0.694	-4.94	0.034	0.42
travel/transport time	travel ease/comfort	0.741	-4.2	**-0.183**	-2.08
travel/transport time	time savings	0.814	-3.14	-0.076	-0.87
leisure	personal care/fitness/relaxation	0.963	-0.5	-0.014	-0.13
leisure	time savings	0.852	-2.44	0.021	0.25
sportiness	personal care/fitness/relaxation	0.754	-2.58	-0.184	-1.31
parking/infrastructure	shopping ease/comfort	0.59	-5.72	-0.124	-1.42
parking/infrastructure	travel ease/comfort	0.895	-2.03	**-0.15**	-2.06
parking/infrastructure	mental ease	1.034	0.24	-0.171	-0.66
parking/infrastructure	personal care/fitness/relaxation	0.675	-3.6	-0.237	-1.75
parking/infrastructure	time savings	0.735	-4.18	-0.099	-1.11
price level	shopping success/diversity	0.534	-6	0.103	1.32
price level	financial savings	1	0		
available time to shop	social-pleasure	0.578	-4.5	0.105	0.96
available time to shop	shopping ease/comfort	0.783	-4.27	-0.053	-0.83
available time to shop	shopping success/diversity	0.488	-8.39	0.06	0.96
available time to shop	travel ease/comfort	0.529	-6.15	-0.041	-0.51
available time to shop	mental ease	0.436	-2.28	0.516	1.89
available time to shop	personal care/fitness/relaxation	0.585	-4.62	0.071	0.73
available time to shop	time savings	0.614	-5.7	0.09	1.16
time pressure	social-pleasure	0.493	-3.23	0.268	1.71
time pressure	shopping ease/comfort	0.466	-4.56	0.045	0.44
time pressure	personal care/fitness/relaxation	0.533	-3.38	0.156	1.16
time pressure	time savings	0.335	-3.41	0.237	1.53
weather	social-pleasure	0.782	-2.68	0.091	0.8
weather	travel ease/comfort	0.793	-3.41	-0.05	-0.66
weather	good for health and/or environment	0.716	-1.75	0.034	0.18
weather	personal care/fitness/relaxation	0.669	-3.56	-0.054	-0.47
baggage	safety	1	0		

Table 5-6 (continued).

AB links		basic + distant scenario		Effects of e-commerce scenario	
attribute	**benefit**	**value**	**t**	**value**	**t**
baggage	social-pleasure	0.556	-4.25	0.205	1.77
baggage	shopping ease/comfort	0.731	-5.25	-0.011	-0.17
baggage	shopping success/diversity	0.253	-5.09	0.151	1.51
baggage	travel ease/comfort	1	0		
baggage	good for health and/or environment	0.484	-2.51	0.305	1.5
baggage	personal care/fitness/relaxation	0.718	-3.58	-0.126	-1.2
baggage	time savings	0.513	-5.47	0.096	1.05
sort of products	social-pleasure	0.593	-3.93	0.137	1.19
sort of products	shopping ease/comfort	0.616	-5.74	-0.018	-0.25
sort of products	shopping success/diversity	0.566	-7.52	-0.009	-0.14
sort of products	travel ease/comfort	0.494	-5.41	0.005	0.06
sort of products	good for health and/or environment	0.861	-0.98	-0.221	-1.26
sort of products	financial savings	0.302	-4.45	0.118	1.07
sort of products	time savings	0.51	-5.19	0.131	1.44
required time to shop	shopping ease/comfort	0.644	-5.34	**-0.258**	-2.33
required time to shop	personal care/fitness/relaxation	0.587	-3.94	-0.046	-0.38
required time to shop	time savings	0.716	-4.15	-0.061	-0.65
working day	social-pleasure	0.825	-2	0.063	0.51
working day	mental ease	1.313	2.24	0.141	0.5
working day	personal care/fitness/relaxation	1	0		
crowdedness	social-pleasure	0.627	-3.88	0.146	1.28
crowdedness	shopping ease/comfort	0.805	-3.9	**-0.148**	-2.13
crowdedness	shopping success/diversity	0.421	-7.01	-0.047	-0.58
crowdedness	travel ease/comfort	0.499	-5.42	-0.144	-1.41
crowdedness	personal care/fitness/relaxation	0.8	-2.67	-0.175	-1.69
crowdedness	time savings	0.775	-3.85	-0.084	-1.03
availability of the TM	travel ease/comfort	0.702	-3.91	-0.114	-1.19
availability of the TM	time savings	0.705	-3.73	-0.207	-1.57
time to find parking lot	travel ease/comfort	0.336	-3.16	0.037	0.23
necessity	time savings	0.53	-3.91	0.083	0.69
other activities	travel ease/comfort	0.565	-4.15	-0.017	-0.16

Table 5-6 (continued).

AB links		**basic + distant scenario**		**Effects of e-commerce scenario**	
attribute	**benefit**	**value**	**t**	**value**	**t**
other activities	mental ease	1.178	1.2	0.17	0.61
other activities	personal care/fitness/relaxation	0.736	-2.69	0.031	0.26
other activities	time savings	0.945	-1.02	0.02	0.26
transport mode	travel ease/comfort	0.999	-0.02	-0.095	-1.34
transport mode	good for health and/or environment	1.198	1.42	-0.107	-0.53

Numbers in bold are significant scenario effects.

Strengths of AB links are shown in Table 5-6 in the same manner as for the first analysis. Again it becomes evident that benefits differ in the number of attributes they evoke for evaluating choice alternatives. *Travel ease/comfort, time savings*, and *personal care/fitness/relaxation* have by far the largest impact on MRs in this estimation, i.e. there are many attributes on which choice alternatives produce different outcomes with respect to these benefits.

Eight of the estimated effects are significant. Originating from the attribute *accessibility* the links to benefits *shopping success/diversity* (-0.293), *travel ease/comfort* (-0.202), and *personal care/fitness/relaxation* (-0.285) are significantly less strong in the e-commerce scenario. This effect might be a consequence of the decreased importance of the accessibility of stores and public transport when the option of online shopping is provided. The same explanation holds for the weaker link strengths between *transport/travel time* and *travel ease/comfort* (-0.183) and *(parking) infrastructure* and *travel ease/comfort* (-0.15) as travelling (and parking) becomes obsolete for online shopping. The link strength between *product quality* and *social – pleasure* becomes however stronger (+0.277). Perhaps respondents doubted about the quality of online products or considered to find qualitatively higher products online which both could impact their perceived *shopping pleasure* and *taste experience* as partial contributors to the benefit *social-pleasure*. Finally, the links from *required time to shop* (-0.258) and *crowdedness* (-0.148) towards the benefit *shopping ease/comfort* become significantly weaker in the e-commerce scenario. Also this finding might be contributed to the online shopping option for which suchlike considerations become redundant due to its characteristics.

The DA link strengths are shown in Table 5-7. Again, the values are largely in line with expectations. Each decision variable has links to 18 attributes or situational variables, respectively, above the minimum frequency criterion. This finding evidences the importance of a wide-spread variety of attributes for the consideration of suchlike complex activity-travel tasks. Furthermore, the results showed that almost all attributes are influenced by multiple decisions. Exceptions are *layout of the shopping location*, *transport capacity/privacy, leisure, sportiness/physical demand, price level of assortment, working day, availability of the transport mode* and *other activities/arrangements*.

Effects between scenarios were not significant and less strong than for the AB links. The strongest effect that was obtained was for *timing of shopping* on the consideration of *product quality* (+0.242).

Table 5-7. Link strength parameters for DA links (analysis 2).

DA link	**basic + distant scenario**		**Effects of e-commerce scenario**	
	value	**t**	**value**	**t**
transport mode				
distance	0.926	-1.846	0.033	0.558
familiarity	1	0		
flexibility of the TM	1	0		
accessibility	1	0		
capacity/privacy of the TM	1	0		
simplicity of the travel route	0.983	-0.238	-0.136	-1.196
travel/transport time	1	0		
sportiness	1	0		
parking/infrastructure	1	0		
available time to shop	0.925	-1.182	-0.079	-0.901
time pressure	0.687	-1.606	0.085	0.435
weather	1	0		
baggage	1	0		
sort of products	0.832	-2.037	0.101	0.959
crowdedness	0.8	-3.281	0.057	0.62
availability of the TM	1	0		
time to find parking lot	1	0		

Table 5-7 (continued).

DA link	basic + distant scenario		Effects of e-commerce scenario	
	value	t	value	t
shopping location				
distance	1	0		
familiarity	0.851	-1.232	-0.012	-0.088
layout of the SL	1	0		
accessibility	0.933	-1.387	0.009	0.102
assortment/service	1	0		
product quality	1	0		
simplicity of travel route	1.047	0.657	-0.143	-1.268
travel/transport time	0.876	-1.637	-0.174	-1.202
parking/infrastructure	0.919	-1.525	0.007	0.073
price level of assortment	1	0		
available time to shop	1.002	0.038	-0.065	-0.763
weather	0.721	-3.123	-0.043	-0.385
baggage	0.869	-2.813	-0.083	-1.359
sort of products	0.855	-1.792	0.114	1.081
required time to shop	0.969	-0.367	-0.069	-0.436
crowdedness	0.846	-2.671	0.012	0.133
time to find parking lot	0.828	-0.327	0.172	0.272
necessity	1	0		
timing of shopping				
distance	0.925	-1.862	0.028	0.484
flexibility of the TM	0.687	-0.974	0.022	0.063
assortment/service	0.784	-7.456	0.066	1.775
product quality	0.575	-2.556	0.242	1.478
simplicity of travel route	1	0		
travel/transport time	0.8	-2.407	-0.048	-0.352
leisure	1	0		
available time to shop	1	0		
time pressure	1	0		
weather	0.782	-2.654	-0.071	-0.65
baggage	0.852	-3.114	-0.048	-0.786

Table 5-7 (continued).

DA link	basic + distant scenario		Effects of e-commerce scenario	
	value	t	value	t
sort of products	1	0		
required time to shop	1	0		
working day	1	0		
crowdedness	1	0		
time to find parking lot	0.827	-0.328	0.051	0.082
necessity	0.887	-0.471	0.073	0.245
other activities/arrangements	1	0		

5.6 Conclusions

The results indicate that utilitarian considerations, such as travel comfort/ease and time savings, are most important in location, timing and travel decisions for activity-travel tasks, at least, for the shopping related choice tasks considered in both analyses. These benefits were not only among the highly activated benefits but showed also the strongest link strength to most attributes. This finding suggests that choices are primarily based on outcomes of a utilitarian nature at least for the first analysis. In the second analysis, the influence of non-utilitarian personal care/fitness/relaxation considerations on many attributes evidences once again the context dependency of MRs. Hence, it can be concluded that there is a shift from utilitarian to non-utilitarian considerations when one choice alternative is superior to the rest of the choice set. The significant decreasing link strength of many utilitarian AB-links in the e-commerce scenario supports this interpretation.

To conclude, the model application illustrated how parameters of situation- and task dependent benefit activation, strengths of causal relationships and mental costs of evaluation can be estimated based on observations of MRs. The analyses reveal that significant differences in MRs occur that result from situation-dependent need activation and link strenghts despite the fact that all respondents faced the same spatial setting and that the task-relevant information variation was only limited. The attributes on which choice alternatives are evaluated and the underlying benefits appear to be sensitive to (un)certainty of task-relevant information, the severeness of anticipated choice consequences and the set of choice alternatives. The estimated model can be used to predict MRs depending on context variables for the choice task and setting considered.

The proposed formal approach has very likely more potential than just simply modelling the activation of MR components. Like measuring mental representations also the modelling part is a cornerstone for a better understanding of human decision making and a refined prediction of choice behaviour. Arentze *et al.* (2011), for instance, proposed an integrated RUM framework for modelling the influence of an individual's mental representation on their choice behaviour as a result of situational and individual need activation and cognitive selectivity. The underlying decision tasks of suchlike investigations are not limited to travel behaviour but can also be applied from other domains such as consumer decision making.

6

Conclusions

6.1 Introduction

This thesis contributes to the literature on measuring mental representations. More specifically, the focus was on the development of an electronic instrument for automatic data collection on mental representations. For this purpose two online interview techniques (Hard Laddering and the Causal Network Elicitation Technique) have been developed and tested among members of a Dutch household panel for variations of a complex activity-travel task. The collected data have been analysed in complexity and content and the performance of the interviews has been compared. Furthermore, a modelling approach has been presented that describes and models the activation of MR components and their causal relationships for complex decision problems. The proposition was that the technique with open questions (CNET) would be able to measure mental representations more accurately or equally accurately than HL which worked with revealed variables. Consecutively, it was argued that CNET would be more sensitive for measuring shifts in MRs which are caused by situational factors of the decision context. Finally, CNET was expected to deliver more interesting insights in the underlying driving forces of decision making and choice behaviour which might be of valuable importance for policy making and the refinement of activity-based modelling.

In the next section, all chapters of this thesis will be briefly summarized and the most important findings highlighted. Accordingly, a discussion of the findings and the limitations of online data collection will follow. The thesis closes with an outlook for future research and applications of the gained experiences.

6.2 Summary

The issue of heterogeneity in the description of urban transport demand was the opener to this thesis. It has been worked out in the very beginning how the different generations of transport models and streams of modelling approaches deal with the individual trip maker and how they cope with the incorporation of individual variability. It has become clear that a satisfying consideration of heterogeneity has barely been attained in any of the known models. Yet, the necessity and desirability of this concern, not only for the sake of activity-based modelling but also for the derivation of powerful transport policy measures, is undoubtable.

In order to be able to model individual variability, one first needs to understand how individuals make their decisions. A short intercourse into the different kinds of choices has been given. Thereby, it was learned that decision making can be of impulsive, habitual, script-based or rational nature. The last one is performed for infrequent deliberate decisions when individuals still need to explore and oversee their choice alternatives and the likely consequences of their behaviour. They conceptualize these causal interdependencies between the choice alternatives, the decision context, their inner needs and the task by means of simplified images of reality. These so-called mental representations became the core subject of this thesis as they represent the individual and situation specific information being necessary for the development of heterogeneous activity-based models.

Accordingly, different ways of measuring mental representations have been presented. It turned out that only techniques that work on a verbal level would be appropriate for activity-travel decision tasks. According to the memory retrieval process they stress, one can group them into recall and recognition-based techniques, respectively. For both categories a number of more or less sophisticated techniques exists among which laddering, face-to-face CNET and APT are the most prominent ones. Although all of them were applied successfully in small surveys for measuring mental representations, each of the techniques had specific drawbacks which prevented a large-based application on the investigation of individual variability in decision making. While the structured recognition-based techniques are held insensitive for measuring individual and contextual shifts, the unstructured recall-based techniques were too time consuming and their collected data difficult to analyse. Therefore, the need for the development of an electronic interview instrument was derived which is supposed to guarantee a successful measurement of mental representations for large surveys under circumvention of (most of) the shortcomings of the conventional techniques. Besides that the interview instrument was aimed at being user friendly for respondents and researchers alike.

Chapter 3 described the development process of the new online interview tool and the changes to the original CNET protocol which had been necessary before the application. As such the elicitation had to be restricted to cognitive subsets in the form *decision variable (– attribute/situational variables) – benefit*. Furthermore, a string recognition algorithm had to be applied in order to guarantee the automatic processing of the responses. In line with that a complex data base had been set up and partly pre-defined with possible response variables tailored to the experimental activity-travel task at hand. These variables were linguistically linked in a simple thesaurus. Next to the online CNET application, also hard laddering had been applied to the interview tool. The performance of the pilot study among 276 households in Eindhoven was then described and the collected mental representations were analysed and discussed. It could be concluded from the experiences of the pilot study that both CNET and HL can be brought online for large-scale surveys albeit with some concessions to the original interview protocols and some drawbacks like the low response (7%) and the high dropout rate (50%). It had also been experienced that the invitation to the online interview appealed mainly higher educated people. All these restrictions are however not uncommon for surveys that use this way of respondent recruitment.

The insights gained from the pilot study caused some minor changes for the main survey outlined in chapter 4. First of all, respondent recruitment was carried out by CentERdata; an organization which maintains a representative Dutch household panel. In order to be able to measure the contextual sensitivity of CNET and HL five contextual variations of a complex activity-travel problem have been developed. While the *basic*, the *uncertain* and the *distant* scenario were applied to both techniques during a first round of interviews, the second round of experiments with the *e-commerce* and the *risky* scenario was conducted with CNET only. In total, 1839 respondents were surveyed of which finally 1745 mental representations could be measured successfully.

The analytical part in chapter 4 has been split up for the structural complexity and the content of mental representations. With respect to the structural characteristics *number of attributes, number of benefits* and *number of cognitive subsets* HL yields significantly higher values than CNET which indicates an effect of the revealed handling of variables in HL. MRs elicited by HL are much bigger and the relation between benefits and attributes is quite outbalanced while CNET yields a significantly bigger benefit-attribute ratio. Significant differences between scenarios were only measured with CNET but not with HL which supports the idea of CNET's higher sensitivity. Yet, for the sake of completeness it has to be admitted that the measured differences were almost only found between scenarios applied to the first and the second round of interviews. Whether there is an effect of the round of interviews or whether the measured differences can completely be contributed to the scenarios remains unclear. In fact, it was aimed at avoiding a round effect by interpreting the unidentified entries by the same researcher in both rounds. However, between them a time of about six months elapsed and the database for the string recognition tool had been extended by a few additional variables tailored to the specific conditions of the new scenarios and by frequently used wordings of uninterpreted responses from the first round. On the other hand, the measured differences are justified by the experimental expectations.

The content analysis in chapter 4 revealed interesting insights into respondents' considerations for the applied activity-travel tasks. For instance, there is a standard pattern of decision making in the order *time of shopping*, *shopping location* and *transport mode*. Concerning the frequency of elicited variables and cognitive subsets it turned out that HL is not able to find differences between scenarios. CNET however is able to measure contextual shifts between scenarios as most saliently the variation for *available product assortment* indicated. Interestingly, both techniques showed agreement with respect to the most frequent benefits (*time savings*, *ease of shopping* and *ease of travelling)* and also among some of the most frequent attributes (e.g. *number of bags to carry*). Another evidence for CNET's higher sensitivity was given by the significant variation for the most frequent cognitive subsets which HL was not able to capture. Furthermore, the centrality of elicited variables has been computed in chapter 4. As expected there was variation among the top ten central variables between the five CNET scenarios but not among HL. Stability between almost all experimental groups was however found for *ease of travelling, ease of shopping* and *time savings*.

Additionally, the performance of the developed interview tool in the interaction with HL and CNET respondents were analysed. First, it was shown that there is an influence of respondents' educational level on the elicitation of MR components in CNET but not in HL. This relationship is not clearly linearly, but as a rule of thumb it can be generalized that the number of elicited components increases with the educational level. This finding is not unimportant as it raises questions about the reason for the apparently more extended mental representations of higher educated respondents and the appropriateness of the elicitation techniques. Therefore, the next section will discuss this finding in more detail.

Next, the interview duration and the dropout rate were compared between techniques. It turned out that the duration of suchlike MR elicitation interviews can be decreased with the online instrument to a forth or even a fifth of comparable face-to-face sessions. Although HL resulted in significantly shorter (9-10 minutes) interview sessions than CNET (11-14 minutes), these differences are rather negligible from a practical point of view. The dropout rate reveals more of the problems respondents faced during the interaction with the interview tool. In the HL scenarios only between 2.7% and 6.8% of respondents were finally not able to finish an interview successfully. These numbers are higher for CNET (6.2% and 11.0%, respectively). Thereby, the sorting of decision variables in interview step 2 and the (mis)interpretation of responses by the string recognition algorithm in CNET caused most of the dropouts.

Respondents' post-experimental evaluation of the techniques showed that HL was favoured as significantly less difficult, clearer, more motivational, more interesting and more pleasant in comparison to CNET. Some of these ratings were yet paradoxal as, for instance, the questioning or the research subject did not differ between techniques. A general discussion of techniques' user friendliness follows in the next section.

Finally, a formal approach has been presented in chapter 5 in order to describe and model the activation of MR components and their causal relationships for complex decision problems. This model application illustrated how parameters of situation- and task dependent benefit activation, strengths of causal relationships and mental costs of evaluation can be estimated based on observations of MRs in an econometric framework. The analysis revealed that significant differences in MRs occur that result from situation-dependent need activation despite the fact that all respondents faced the same spatial setting and that the task-relevant information variation was only limited. The attributes on which choice alternatives are evaluated and the underlying benefits appear to be sensitive to (un)certainty of task-relevant information, the severeness of anticipated choice consequences and the set of choice alternatives. The earlier findings from the content analysis were supported in that the utilitarian considerations *ease of travelling, ease of shopping* and *time savings* were among the highly activated benefits and showed the strongest link strengths to most attributes.

6.3 Discussion and conclusions

The objective of this project was the development of an online method for measuring MRs for large-scale applications in a flexible and open-ended elicitation process that maintains the scalability of the known approaches but possesses the sensitivity to measure shifts in MRs caused by contextual effects on the decision situation. As method the Causal Network Elicitation Technique (CNET) has been adapted and applied for data collection. Additionally, Hard Laddering (HL) was brought online in order to facilitate a methodological comparison and thus qualitative statements about CNET's performance.

First of all, the study showed that online CNET is able to collect data on MRs. This is an important result as such an open-ended elicitation interview was not brought online before. Still, it has to be admitted that concessions had to be made to the original interview protocol in order to guarantee a successful elicitation process. As such, attribute – attribute links were excluded and benefits were revealed fittingly if a response was interpreted as attribute. These adaptations were necessary as either pilot testing suggested them or the implementation of the original protocol would have complicated the steering algorithm of the interview drastically. Nonetheless, these changes seem acceptable as the elicited MRs represent the considered choice problem reasonably. Furthermore, also online applications of other proven techniques such as APT and previous HL variants have restrictions in linking variables which are even bigger.

An expectation of the new instrument was that it is able to measure mental representations more accurately or equally accurately than comparable proven techniques that work with revealed lists of variables and more restrictions in linking them. The structural and substantial comparison of MRs collected with HL and MRs collected with CNET showed that the latter are indeed smaller and more focussing on the task-relevant variables than MRs elicited with HL. Nevertheless, there was agreement among both techniques about the most frequent and most central variables. It seems hence indeed that the upper mentioned expectation has been fulfilled.

One cornerstore for this success was certainly the ambition to impact the respondents as little as possible in the elicitation process. Still, despite of all efforts in keeping the response freedom in CNET high, all respondents are still affected to some extent. Next to subtle impacts caused by the layout of the webpages and the presentation of the activity-travel task in terms of language and illustrations it is especially the string recognition and the limited amount of predefined wordings for variables which possibly influences the results. As it has been outlined in chapter 3, the generalization of responses is however necessary to guarantee the comparability of MRs between respondents. While this unavoidable impact is still somehow objective as all respondents are set out to it, the post-experimental interpretation of uninterpreted or misinterpreted responses by the analyst is even more undesired and was not expected to this extent.

When speaking about measuring mental representations the question of the validity is of course justified. Did not all these limitations and simplifications, the structuring of the interview protocol and the pre- and postexperimental researcher impacts bias the responses? Unfortunately, the scientific demand of this question prohibits a satisfying and clear answer. It has been worked out in the theoretical part of this thesis that MRs are latent constructs held in working memory which the decision maker is not explicitly conscious of. There is no objective way of evaluating a MR as right or wrong or complete or incomplete like it can be done for mental models of technical devices etc. Due to the activation of needs, differences in cognitive capabilities, experiences, knowledge, cultural background and context dependencies individuals differ in the construction of mental representations. Hence, only the decision maker himself would in fact be able to judge about the completeness and correctness of his elicited mental representation if he were completely conscious of it. Yet, the fact that many MRs, or at least components of the more abstract levels, need to be rendered conscious before they can be elicited makes that part very difficult. In the online CNET application it was attempted to account for that circumstance by the inclusion of the summary step at the end of the interview. There, respondents got an overview of the elicited attributes per benefit and the chance to indicate forgotten aspects. This problem is however not a shortcoming of CNET. It is inherent to any approach for measuring mental representations.

Another burden related with the validity of measuring MRs in general and with CNET in specific is the necessity of expressing considerations linguistically. While this is characteristical for all verbal techniques which base on recall, the threshold is indeed higher for CNET as respondents are asked to formulate their considerations succinctly so that the string recognition tool is able to understand it. The encountered differences between respondents with different education levels might be attributed to this burden. It can further not be excluded that some respondents used common easily retrievable wordings when the formulation of their own consideration caused too much mental effort or whenever the string recognition algorithm could not interpret their original response. Technically, it has been attempted to control for that by storing also the original input string in the data base. Thus, the individual formulation of the respondents' consideration could better be pursued post-experimentally.

A second expectation related with the objective of this thesis was that online CNET would be more sensitive in measuring shifts in MRs which are caused by situational factors of the decision context. The substantial analysis of the MRs confirmed indeed that expectation in several ways: The frequent itemset analysis yielded significant differences for attributes, benefits and the 14 most frequent cognitive subsets between the five experimental scenarios applied to CNET. Also the centrality of the top ten variables varied significantly between the five CNET scenarios. These effects were not measured with HL. Most eye-catching in this regard are the attribute *available product assortment* and the benefit *shopping success* as well as the cognitive subset of them for the shopping location choice which were elicited significantly more frequent in the uncertain and risky scenario than in all other scenarios. Another evidence of CNET's higher sensitivity is given by the benefit *relaxation* which is only ranked among the top ten central variables in the e-commerce scenario. This contextual shift in MRs as a consequence of additional benefit activation caused by the introduction of new choice alternatives was however not supported by the analysis of the benefit activation parameters in the model estimation for the merged benefit *personal care/ fitness/ relaxation*. Nonetheless, for other benefits significant differences in the activation parameters were found between scenarios.

Third, CNET was expected to deliver more interesting insights in the underlying driving forces of decision making and choice behaviour than the structured interview techniques. Arguably, the wide response freedom left room for individual considerations and did not narrow down the elicitation process during the interview. Therefore, surprising insights into individuals' decision making could be attained. In general, it turned out that attributes and benefits which stand for utilitarian considerations in terms of physical and temporal effort are the most important driving forces for the investigated activity-travel task. Financial considerations occurred less than expected. Rather, some respondents indicated to be willingly to pay more in order to support the middle class. This finding might be of valuable importance for future model development as monetary costs are mostly treated as core determinant in many transport or shopping decision models. Yet, this finding has to be taken with caution as it was not measured in CNET how much weight respondents attach to each benefit. The activation parameters showed thus that *financial savings* is a strongly activated but compared to the number and strengths of attribute links it has not the strongest benefit.

Modellers might also be interested in the finding that MRs differ in the considered components for respondents who differ in their choice behaviour. While this observation was made for attributes of the transport mode choice in two HL scenarios only, benefits and attributes differed for almost all decisions in CNET except for the uncertain scenario. This finding suggests that it should be possible to conclude on the choice behaviour by knowing the attributes, benefits and contextual variables an individual considers. Reversely, knowing on which attributes and benefits choices are based marketing strategies can be developed tailored to the target group.

For policy makers and marketing experts it might be also of interest to see how the introduction of choice alternatives that are very distinct to the rest of the choice set activates additional benefits. For example, already nowadays new means of communication via internet and mobile applications facilitate activites and travelling to a great extent. When online services are able to substitute offline activities even the necessity of travelling to the location of the offline activity becomes obsolete. Hence, e-activities are a means to attain the political and societal goals in reducing the negative cosequences of traffic. In order to ensure the acceptance of suchlike e-activities it is necessary to understand which (new) needs people activate during their decision process. These needs should thus be regarded and promoted in marketing. CNET is able to support the experts with the necessary knowledge about MRs.

In sum it cannot generally be concluded that CNET is the better technique for measuring mental representations online. But that was neither the ambition of this work. The results support the expectation that CNET is more appropriate for measuring individual and contextual shifts in mental representations. If this is the purpose of a scientific large-scale investigation, CNET might indeed do better than completely structured techniques with revealed variables. If however the focus of a survey is on getting a rather rough idea of the causal knowledge of a population, HL or comparable techniques might suffice.

Next to the scientific expectations about the quality of the data also organizational considerations played a role for the development of the online interview. As such one requirement was that the new instrument is attractive and well accessible for all respondents. The post-experimental standard questions are not a good indicator for the attractivity as they did not target the technique per se. Rather attitudes about the survey and the clarity of questions were measured which showed that respondents favoured HL significantly. Respondents’ post-experimental statements were twofold. While some critisized the open character which costed so much deliberation others welcomed the new and creative way of collecting data. Both points of view reflect opinions of panel members who had a certain expectation about the type of survey. The standard questionnaire LISS panel members are used to is, namely, multiple choice. The confrontation with CNET (and HL) must hence have come very unexpectedly to these respondents.

The decision to collect MRs with the panel had however to do with accessibility considerations. The pilot survey showed that merely higher educated people feel appealed to participate in the study when the invitation is printed anonymously on paper cards. People without internet access can neither be approached. The offer to collect data among the LISS panel promised indeed to be a good solution for the survey. Not only it was ensured that the sample is representative, but also all members were equipped with internet and IT. Thus, CNET and HL were accessible 24 hours every day for all invited respondents regardless where these people were, how long they needed to complete the interview or whether other respondents were busy at the same time. These circumstances mean a significant improvement in the accessibility and attractiveness for respondents compared to conventional interview techniques.

Nonetheless, one instance connected with the application to a panel should not remain unmentioned. The downside of the actual desirable maintenance of a representative household panel is that even groups of the population are equipped with IT and internet who otherwise are not interested in this medium. Hence, their experiences and computer skills are only little developed and struggles with special computer practices are not uncommon. The drag-and-drop task for ranking the decision variables with the mouse turned out as such a technical threshold where many respondents dropped out or called the help desk for clarification. Even the inclusion of an animation of this knack in the second wave of data collection could not remedy the problem completely. Therefore, it has to be concluded that online techniques can facilitate the spatial and temporal accessibility to a survey but they make participation harder for other groups of the population.

Finally, the electronic way of data collection was also supposed to come along with ease of work for researchers. Namely, as no interviewers are necessary any longer and the collected data exist already in electronic format much less time, personnel effort and thus costs would be necessary compared to face-to-face techniques. In general this assumption still holds. Yet, the pre-experimental data collection on possible attributes, benefits, situational variables and the enormous amount of synonymous expressions as well as the post-experimental data processing in order to code uninterpreted responses put this statement into perspective. Thereby, the amount of work for CNET is considerably larger than for HL. It should however not be forgotten that this survey had a pioneer character with lots of test rounds and pre-experimental data collection. Repeated surveys will hence require much less preparation time. Considering the amount of approached respondents online CNET means doubtlessly also for the researcher an economic improvement in measuring mental representations.

6.4 Future research

Having reported the long way from the first attempts of scientific transport models up to the technical problems respondents encountered during a CNET interview it remains to say which scientific steps should be done in the future.

There is no doubt that the exploration of MRs is only about to start. The enormous amount of choice situations from all societal domains would provide many interesting approaches for deeper investigation of MRs. Inter-individual differences in benefit activation and its effect on decision making might be a very interesting topic to study. Thus, do individuals from different age groups, education levels, cultures, man and woman, etc. differ in the way they image a decision problem? Besides these rather snapshot like recordings of individuals' MRs also the investigation of more dynamic effects due to learning and updating, effects of priming, habitualisation effects, etc. seems to be worth to be put high on the research agenda. Cross-technical comparisons might furthermore be of interest in order to solve the question which technique delivers the more genuine image respondents bear in mind.

From a formal point of view, results of suchlike investigations could thus help to incorporate more heterogeneity in (transport) choice models. Another future project is the extension of discrete choice models to account for need activation and cognitive selectivity in choice processes. As such Arentze *et al.* (2011) showed how both cognitive selectivity and choice of an alternative can be modelled in an integrated RUM framework and how the integrated model can be parameterized and estimated by loglikelihood methods based on observations of both MRs and choice outcomes. In this regard it is only a logical consequence to shed also light on the relevance of MRs for the prediction of choice behaviour.

From a practictal point of view, progress in measuring mental representations could also simply improve our knowledge about how individuals face a certain decision problem. These insights could be very worthwhile for policy makers, transport planners and marketing experts in order to tailor travel demand measures, transport options, and consumer products according to the needs of (groups of) individuals.

Yet, although CNET as it has been developed and tested worked in a reliable and satisfying manner some improvements are still desirable which could further facilitate the elicitation process. In order to overcome the need to collect synonyms and hypernyms for the predefined variables the implementation of an existing thesaurus like *WordNet* is recommended. Furthermore, the advancement of the string recognition algorithm would probably increase the match rate during the interpretation of responses. This would not only save a lot of post-experimental effort for the researcher (and thus diminish the bias) but would probably also lead to less frustration and thus a decrease in dropouts among the respondents. The fast development in the area of pattern and string recognition should provide fitting solutions.

There are, however, also other ideas which could further increase the attractivity of CNET for researchers. For instance, it would be desirable to implement a graphical tool which displays the elicited MRs as causal network. At the same time the interview could be extended so that the elicitation of causal probability and utility values as it was part in the original semi-structured CNET interview protocol is integrated. That would in fact allow researchers to simulate individual decision processes.

As a final note it can be announced that CNET is available also for other researchers. Recently, the CNET code has been professionally programmed by LaQuSo, Eindhoven. On their website scientists can download the source code and an installation program which guides the interested researcher through the construction of the database, the definition of variables and the set up of a survey. This makes CNET hopefully to a valuable tool for the investigation of mental representations.

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Appendix

A. String Recognition Algorithm applied in online CNET

```
$matchcheck = $db->extended->getOne("SELECT id FROM synsets WHERE name = '$entry'");
if ($matchcheck == "") {
  $trimmed = rtrim($entry, " .,?!:;'");
  $strings = explode(' ', strtolower($trimmed));
$omit=array('aan','af','afhankelijk','als','ben','bij','dat','de','deze','die','dit','door','dus','een','één','en','
er','geen','haar','hangt','heb','hebben','heeft','het','hoe','ik','in','is','je',
'kan','Laura','me','met','naar','niet','nog','of','om','op','over','per','\'s','samen','te','toe','tot','van','vanw
ege','voor','waar','wat','wel','welk','welke','wil','ze','zij','zijn','zo','','?');
  $words = array_values(array_diff($strings, $omit));
      for($i = 0; $i < count($words); $i++) {
        $matches = $db->extended->getAll("SELECT word, synset FROM variables WHERE soundex
= ?", null, SOUNDEX($words[$i]), null, MDB2_FETCHMODE_ASSOC, false, false);
          if (MDB2::isError($matches)) {
            die('Failed to issue query, error message : ' . $matches->toString());
          }
          for($j = 0; $j < count($matches); $j++) {
            $lev = levenshtein($words[$i], $matches[$j]["word"]);
            if (!isset($new[$i][$matches[$j]["synset"]]) || $lev < $new[$i][$matches[$j]["synset"]]) {
              $new[$i][$matches[$j]["synset"]] = $lev;
            }
          }
      }

      $matching_synsets = null;
      for($i = 0; $i < count($new); $i++) {
        if($matching_synsets == null) $matching_synsets = array_keys($new[$i]);
          else $matching_synsets = array_intersect($matching_synsets, array_keys($new[$i]));
        }
 if($matching_synsets == null) {
   $prompt = "Helaas kan uw input niet verwerkt worden. U kunt op WIJZIGEN klikken en uw input
herschrijven of met deze onbekende input DOORGAAN.";
   $hint = "";
   $unknown_save = $db->extended->autoExecute(
    'unknown_inputs', array(
     'subject_id' => $subject,
     'child_of' => $mother_id,
     'unknown' => $entry,
     'rejections' => false,
    ), MDB2_AUTOQUERY_INSERT
   );
 }
 else {
   for($i = 0; $i < count($new); $i++) {
     $new[$i] = array_intersect_key_with_value($new[$i], $matching_synsets);
   }

   $weighted_matching_synsets = array();

   foreach($new as $row) {
```

```
    foreach ($row as $synset => $lev) {
      if(!array_key_exists($synset, $weighted_matching_synsets)) {
        $weighted_matching_synsets[$synset] = 0;
      }
      $weighted_matching_synsets[$synset] = $lev++;
    }
  }

  asort($weighted_matching_synsets);

  foreach ($weighted_matching_synsets as $key => $value) {
    $suggestion[]=$db->extended->getRow("SELECT name, id FROM synsets WHERE id = ?", null,
$key, null, MDB2_FETCHMODE_ASSOC, false, false);
  }
  $other_attribute = $db->extended->getAll("SELECT name, id FROM synsets WHERE category =
?", null, 'o', null, MDB2_FETCHMODE_ASSOC, false, false);
  if (MDB2::isError($other_attribute)) {
    die('Failed to issue query, error message : ' . $other_attribute->toString());
  }
  $variable_options = array_merge($suggestion, $other_attribute);
 }
 if(isset($_POST['adjust'])) {
  $_SESSION['anchor'] = 30;
  header('Location: director.php');
  exit;
 }

 if(isset($_POST['forward'])) {
  if(!isset($_POST['match'])) {
    if($matching_synsets == null){
      $store_unknown = $db->extended->autoExecute(
       'elicited_attributes', array(
        'subject_id' => $subject,
        'synset_id' => 99,
        'child_of' => $mother_id,
        'unknown_text' => $entry,
       ), MDB2_AUTOQUERY_INSERT
      );
      if(MDB2::isError($store_unknown)) {
        die('Failed to store the attributes, error message : '. $store_unknown->toString());
      }
      $upd_rc = $db->extended->autoExecute(
       'recalled_considerations', array(
        'synset_id' => 99,
       ), MDB2_AUTOQUERY_UPDATE,
       "id = $id"
      );
      if(MDB2::isError($upd_rc)) {
        die('Failed to store the attributes, error message : '. $upd_rc->toString());
      }
      $_SESSION['anchor'] = 5;
      header('Location: director.php');
      exit;
    }
    else{
      $error = "U heeft geen suggestie gekozen.";
```

```
    }
  }
  else{
    $syn = $_POST['match'];
    $category = $db->extended->getOne("SELECT category FROM synsets WHERE id = $syn");
    if($category == a){
      $ais_already_stored = $db->extended->getOne("SELECT synset_id FROM elicited_attributes
WHERE subject_id = $subject AND synset_id = $syn AND child_of = $decision_id");
      if(MDB2::isError($ais_already_stored)) {
        die('Failed to check whether the attribute already had been saved, error message : '.
$ais_already_stored->toString());
      }
      if($ais_already_stored == ""){
          $store_syn = $db->extended->autoExecute(
           'elicited_attributes', array(
            'subject_id' => $subject,
            'synset_id' => $syn,
            'child_of' => $mother_id,
           ), MDB2_AUTOQUERY_INSERT
          );
          if(MDB2::isError($store_syn)) {
            die('Failed to store the attribute, error message : '. $store_syn->toString());
          }
          $upd_rc = $db->extended->autoExecute(
           'recalled_considerations', array(
            'synset_id' => $syn,
           ), MDB2_AUTOQUERY_UPDATE,
           "id = $id"
          );
          if(MDB2::isError($upd_rc)) {
            die('Failed to update the synset_id in recalled_considerations, error message : '. $upd_rc-
>toString());
          }
          $_SESSION['anchor'] = 5;
          header('Location: director.php');
          exit;
        }
        else{
          $_SESSION['syn'] = $syn;
          $_SESSION['anchor'] = 40;
          header('Location: director.php');
          exit;
        }
    }
    if($category == b){
      $bis_already_stored = $db->extended->getOne("SELECT synset_id FROM elicited_benefits
WHERE subject_id = $subject AND decision_id = $decision_id AND synset_id = $syn");
      if(MDB2::isError($bis_already_stored)) {
        die('Failed to check whether the benefit already had been saved, error message : '.
$bis_already_stored->toString());
      }
        if($bis_already_stored == ""){
            $store_syn = $db->extended->autoExecute(
             'elicited_benefits', array(
              'decision_id' => $decision_id,
              'subject_id' => $subject,
```

```
              'synset_id' => $syn,
             ), MDB2_AUTOQUERY_INSERT
            );
            if(MDB2::isError($store_syn)) {
              die('Failed to store the benefit, error message : '. $store_syn->toString());
            }
            $upd_rc = $db->extended->autoExecute(
             'recalled_considerations', array(
              'synset_id' => $syn,
             ), MDB2_AUTOQUERY_UPDATE,
             "id = $id"
            );
            if(MDB2::isError($upd_rc)) {
              die('Failed to update the synset_id in recalled_considerations, error message : '.
$upd_rc->toString());
            }
            $_SESSION['anchor'] = 5;
            header('Location: director.php');
            exit;
        }
        else{
          $_SESSION['syn'] = $syn;
          $_SESSION['anchor'] = 40;
          header('Location: director.php');
          exit;
        }
    }
    if($category == o){
      $store_syn = $db->extended->autoExecute(
       'elicited_attributes', array(
        'subject_id' => $subject,
        'synset_id' => 99,
        'child_of' => $mother_id,
        'unknown_text' => $entry,
       ), MDB2_AUTOQUERY_INSERT
      );
      if(MDB2::isError($store_syn)) {
        die('Failed to store the attribute, error message : '. $store_syn->toString());
      }
      $upd_rc = $db->extended->autoExecute(
       'recalled_considerations', array(
        'synset_id' => 99,
       ), MDB2_AUTOQUERY_UPDATE,
       "id = $id"
      );
      if(MDB2::isError($upd_rc)) {
        die('Failed to update the synset_id in recalled_considerations, error message : '. $upd_rc-
>toString());
      }
      $_SESSION['anchor'] = 5;
      header('Location: director.php');
      exit;
    }
  }
 }
}
```

B. Screenshots of online CNET (CentERdata layout)

Figure B-1. Introduction to the experiment (interview step 1a).

Figure B-2. Introduction to the experiment (interview step 1b).

Figure B-3. Introduction to the experiment (interview step 1c).

Figure B-4. Ranking of decision variables (interview step 2).

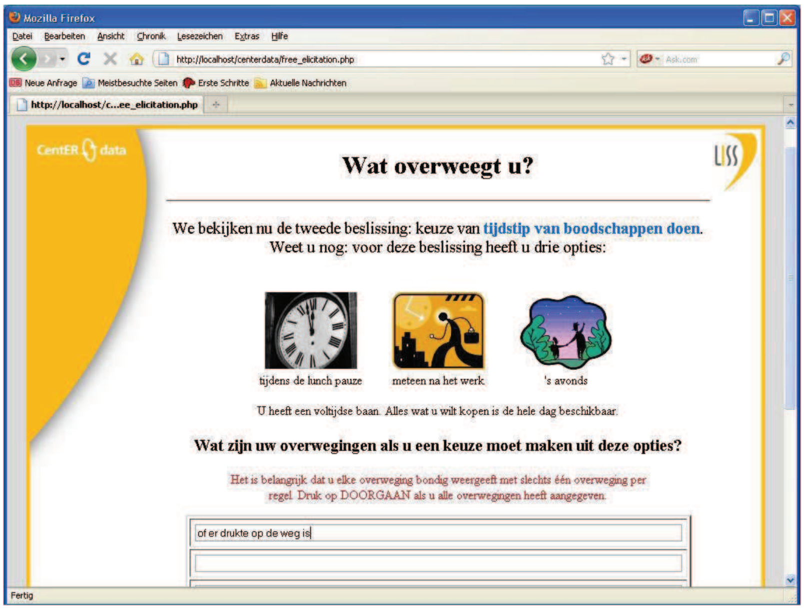

Figure B-5. Input of considerations (interview step 3).

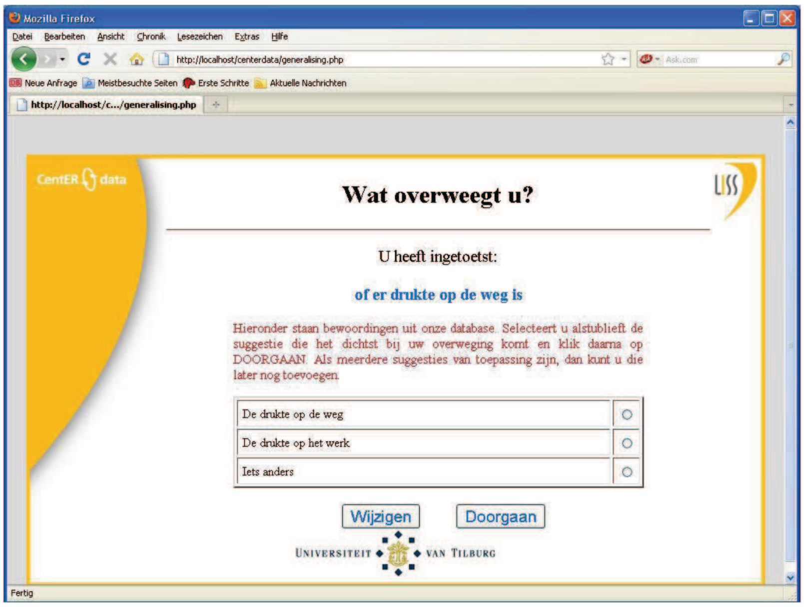

Figure B-6. Interpretation of a typed consideration (interview step 4).

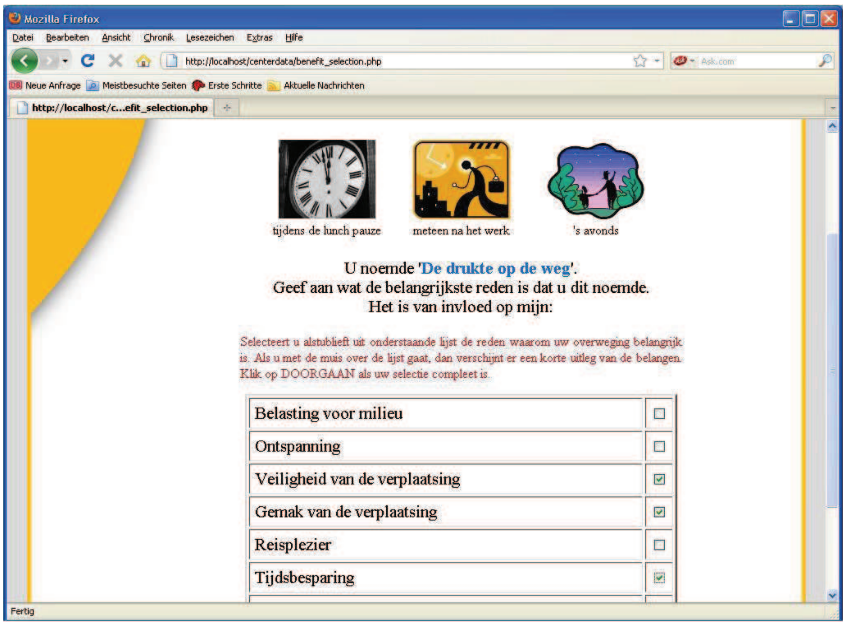

Figure B-7. Indication of underlying benefits (interview step 5).

Figure B-8. Indication of missing links during summary (interview step 6).

C. Screenshots of online HL (CentERdata layout)

Figure C-1. Ranking of decision variables (interview step 2).

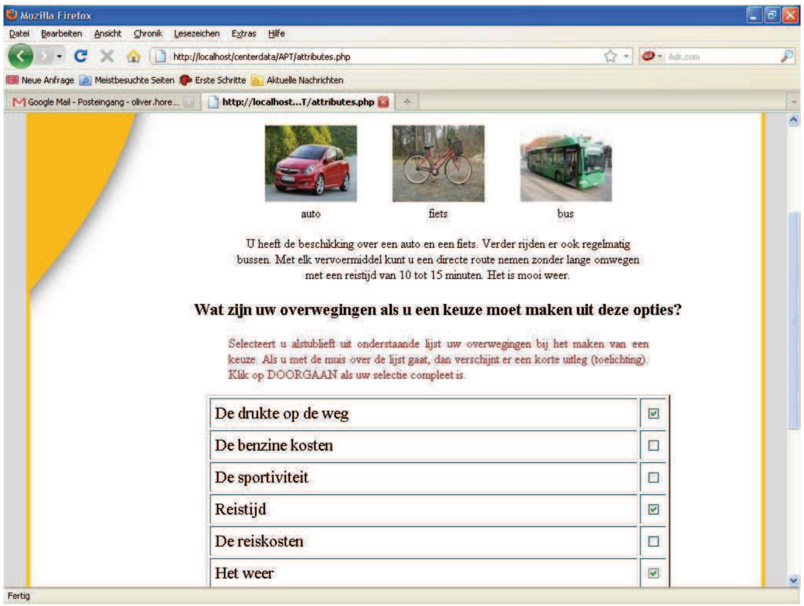

Figure C-2. Indication of considered attributes (interview step 3).

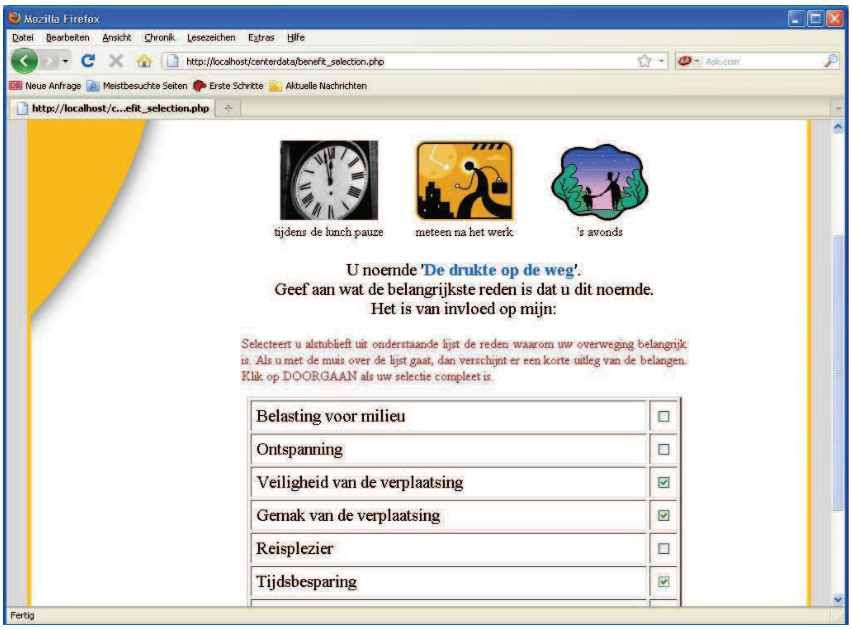

Figure C-3. Indication of underlying benefits (interview step 4).

D. Predefined variables in the database

Table D-1. Attributes and situational variables presented in HL.

Dutch attribute label	**English translation**	**TM***	**SL***	**TS***
gemakkelijkheid van de route	simplicity of the route	x	x	
reistijd	travel time	x	x	x
hoeveelheid aan tassen	number of bags to carry	x	x	x
openingstijden	opening hours		x	x
weer	weather	x	x	x
parkeerkosten	parking costs	x	x	x
beschikbare productkeuze	available product assortment		x	
drukte in de winkel	crowdedness in the store		x	x
zoektijd voor het parkeren	time to find a parking lot		x	x
flexibiliteit van de vertrektijd vervoermiddel	flexibility of departure time	x		x
grootte van de winkellocatie	size of the shopping location		x	
beschikbare tijd voor het boodschappen doen	available time to shop		x	x
drukte op de weg	crowdedness on the road	x	x	x
prijsniveau van het assortiment	price level of the assortment		x	
bereikbaarheid van de winkel	accessibility of the store		x	
houdbaarheid van de boodschappen	durability of products			x
capaciteit van het vervoermiddel	capacity of the transport mode	x		
sportiviteit	sportiness	x		
sfeer in de winkellocatie	atmosphere in the shopping location		x	x
benzine kosten	costs for petrol	x		
reiskosten	travel costs	x		
bekendheid met de winkellocatie	familiarity with the shopping location		x	
vrijetijd	leisure time			x
benodigde tijd voor het boodschappen doen	required time to shop			x
iets anders	something else	x	x	x

**The columns TM (Transport mode), SL (Shopping Location), and TS (Time of Shopping) indicate for which decision variables the listed attributes were presented.*

Table D-2. Hidden attributes and situational variables understood by CNET.

Dutch attribute label	**English translation**
afstand van de actuele locatie	distance from current location
beschikbare tijd voor het boodschappen doen	available time to shop
tijdsdruk	time pressure
beschikbaarheid internet*	internet access*
weer	weather
buitentemperatuur	outside temperature
hoeveelheid aan tassen	number of bags to carry
houdbaarheid van de boodschappen	durability of products
benodigde tijd voor het boodschappen doen	required time to shop
bekendheid met het vervoermiddel	familiarity with the TM
lichamelijke gesteldheid	physical condition
drukte op het werk	stress at work
kans op onverwachte gebeurtenissen	chance of unexpected events
serviceniveau van de winkel	service level of the store
overdektheid van de winkellocatie	canopy at the SL
wel of niet gezelschap	with or without company
hoeveelheid van groenvoorzieningen	amount of greenspace
layout van de winkellocatie	layout of the SL
staat van het onderhoud van de winkellocatie	state of maintenance of the SL
flexibiliteit van de vertrektijd vervoermiddel	flexibility of departure time
bereikbaarheid van de winkel	accessibility of the store
aanwezigheid van horeca op de winkellocatie	presence of gastronomy in the SL
toegankelijkheid voor gehandicapten	accessibility for the disabled
bewegwijzering binnen de winkellocatie	signage in the SL
uitrustmogelijkheden	possibilities to rest
sfeer in de winkellocatie	atmosphere in the SL
drukte in de winkel	crowdedness in the store
grootte van de winkellocatie	size of the SL
beschikbaarheid vervoermiddel	availability of the TM
speciale aanbiedingen	special offers
aanwezigheid van speciale evenementen	presence of special events
bekendheid met de winkellocatie	familiarity with the SL

Table D-2 (continued).

Dutch attribute label	**English translation**
kwaliteit van producten	quality of products
prijsniveau van het assortiment	price level of assortment
beschikbare productkeuze	available product assortment
winkeltype	type of shop (chain)
zoektijd voor het parkeren	time to find a parking lot
betrouwbaarheid vervoermiddel	reliability of the TM
wachttijd	waiting time
verwachte vertragingstijd	expected delay
voorbereidingstijd	preparation time
capaciteit van het vervoermiddel	capacity of the TM
privacy in het vervoermiddel	privacy in the TM
kans op zitplaatsen in vervoermiddel	chance of a seat in the TM
aanwezigheid van een wachthokje	presence of a bus shelter
gewenning aan het vervoermiddel	habituation to the TM
reiskosten	travel costs
benzine kosten	costs for petrol
parkeerkosten	parking costs
mogelijkheid boodschappen op te slaan	possibility to store shoppings
flexibiliteit van het vervoermiddel in de routebepaling	route flexibility of the TM
veiligheid van het vervoermiddel	safety of the TM
diversiteit branches	diversity of branches
openingstijden	opening hours
bereikbaarheid openbaar vervoer	accessibility of public transport
geluidsoverlast	noise pollution
bestedingsbevoegdheid van het vervoermiddel	authorisation to use the TM
gemakkelijkheid van de route	simplicity of the travel route
transporttijd van boodschappen	time to transport shoppings
ontspanningtijd tijdens werk	recreation time at work
noodzaak	necessity
vrijetijd	leisure time
sportiviteit	sportiness
reistijd	travel time

Table D-2 (continued).

Dutch attribute label	**English translation**
parkeermogelijkheden (auto/fiets)	parking possibilities (car/bicycle)
tijd van de dag	time of the day
mogelijk conflict met geplande afspraken	conflict with planned agreements
combinatie met andere activiteiten	combination with other activities
fysieke belasting	physical effort
drukte op de weg	crowdedness on the road
verlichting	illumination
werktijd	working hours
soort boodschappen	type of shoppings
mening van vrienden	opinion of friends
hoeveelheid uitlaatgassen	amount of exhaust gases
levertijd van de bestelling*	delivery time of the order*
leveringskosten*	delivery costs*
betrouwbaarheid bestelservice*	reliability of the delivery service*
afleveringsmogelijkheid*	possibility to receive a delivery*
betaalmogelijkheden*	pay options*
tijdstip van het bezoek van baas*	time of boss' visit*
verhouding tot baas*	relation with boss*
verwachtingspatroon van de baas*	expectation of the boss*
netheid van mijn huishouden*	cleanliness at home*
steun middenstand	support middle class

**only in CNET e-commerce and CNET risky*

Table D-3. Benefits presented in HL and CNET.

Dutch benefit label	**English translation**
tijdsbesparing	time savings
gemak van het winkelen	ease of shopping
winkelcomfort	shopping comfort
plezier tijdens winkelen	shopping pleasure
reisplezier	travel pleasure
diversiteit in productkeuze	diversity in product choice
slagingskans boodschappenproduct	shopping success
comfort verplaatsing	travel comfort
gemak van de verplaatsing	ease of travelling
veiligheid van de verplaatsing	safety of travelling
gezondheid	health
mentaal gemak	mental ease
ontspanning	relaxation/recreation
financiële besparing	financial savings
veiligheid in de winkellocatie	safety in the shopping location
aantrekkelijkheid van de winkelomgeving	attractivity of the shopping location
hoeveel u van het eten kunt genieten	culinary pleasure
sociale acceptatie	social acceptance
belasting voor milieu	environmental pollution
persoonlijke verzorging	personal care
verloop fitheid door de dag	course of fitness/wellbeing
iets anders	something else
goede indruk maken bij de baas*	give a good impression to the boss*
loopbaankansen*	career chances*

**only in CNET risky*

E. Statistical tests on MR's complexity

Table E-1. Post hoc test for number of attributes between experimental groups.

Multiple Comparisons

Bonferroni

Dependent Variable	(I) exp_group	(J) exp_group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
number of attributes	HL basic	HL uncertain	-.211	.295	1.000	-1.13	.71
		HL distant	-.135	.294	1.000	-1.05	.78
		CNET basic	4.927*	.297	.000	4.00	5.86
		CNET uncertain	5.011*	.305	.000	4.06	5.97
		CNET distant	4.808*	.293	.000	3.89	5.72
		CNET e-commerce	4.451*	.267	.000	3.62	5.29
		CNET risky	4.658*	.262	.000	3.84	5.48
	HL uncertain	HL basic	.211	.295	1.000	-.71	1.13
		HL distant	.076	.302	1.000	-.87	1.02
		CNET basic	5.137*	.305	.000	4.18	6.09
		CNET uncertain	5.221*	.314	.000	4.24	6.20
		CNET distant	5.018*	.302	.000	4.07	5.96
		CNET e-commerce	4.662*	.276	.000	3.80	5.53
		CNET risky	4.869*	.272	.000	4.02	5.72
	HL distant	HL basic	.135	.294	1.000	-.78	1.05
		HL uncertain	-.076	.302	1.000	-1.02	.87
		CNET basic	5.061*	.304	.000	4.11	6.01
		CNET uncertain	5.146*	.312	.000	4.17	6.12
		CNET distant	4.942*	.300	.000	4.00	5.88
		CNET e-commerce	4.586*	.274	.000	3.73	5.44
		CNET risky	4.793*	.270	.000	3.95	5.64
	CNET basic	HL basic	-4.927*	.297	.000	-5.86	-4.00
		HL uncertain	-5.137*	.305	.000	-6.09	-4.18
		HL distant	-5.061*	.304	.000	-6.01	-4.11
		CNET uncertain	.084	.315	1.000	-.90	1.07
		CNET distant	-.119	.304	1.000	-1.07	.83
		CNET e-commerce	-.475	.278	1.000	-1.34	.39
		CNET risky	-.268	.274	1.000	-1.12	.59
	CNET uncertain	HL basic	-5.011*	.305	.000	-5.97	-4.06
		HL uncertain	-5.221*	.314	.000	-6.20	-4.24
		HL distant	-5.146*	.312	.000	-6.12	-4.17
		CNET basic	-.084	.315	1.000	-1.07	.90
		CNET distant	-.203	.312	1.000	-1.18	.77
		CNET e-commerce	-.560	.287	1.000	-1.46	.34
		CNET risky	-.353	.283	1.000	-1.24	.53
	CNET distant	HL basic	-4.808*	.293	.000	-5.72	-3.89
		HL uncertain	-5.018*	.302	.000	-5.96	-4.07
		HL distant	-4.942*	.300	.000	-5.88	-4.00
		CNET basic	.119	.304	1.000	-.83	1.07
		CNET uncertain	.203	.312	1.000	-.77	1.18
		CNET e-commerce	-.357	.274	1.000	-1.21	.50
		CNET risky	-.150	.270	1.000	-.99	.69
	CNET e-commerce	HL basic	-4.451*	.267	.000	-5.29	-3.62
		HL uncertain	-4.662*	.276	.000	-5.53	-3.80
		HL distant	-4.586*	.274	.000	-5.44	-3.73
		CNET basic	.475	.278	1.000	-.39	1.34
		CNET uncertain	.560	.287	1.000	-.34	1.46
		CNET distant	.357	.274	1.000	-.50	1.21
		CNET risky	.207	.241	1.000	-.55	.96
	CNET risky	HL basic	-4.658*	.262	.000	-5.48	-3.84
		HL uncertain	-4.869*	.272	.000	-5.72	-4.02
		HL distant	-4.793*	.270	.000	-5.64	-3.95
		CNET basic	.268	.274	1.000	-.59	1.12
		CNET uncertain	.353	.283	1.000	-.53	1.24
		CNET distant	.150	.270	1.000	-.69	.99
		CNET e-commerce	-.207	.241	1.000	-.96	.55

*. The mean difference is significant at the 0.05 level.

Table E-2. Post hoc test for number of benefits between experimental groups.

Multiple Comparisons

Bonferroni

Dependent Variable	(I) exp_group	(J) exp_group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
number of benefits after review	HL basic	HL uncertain	-.192	.363	1.000	-1.33	.94
		HL distant	-.414	.361	1.000	-1.54	.72
		CNET basic	2.320*	.365	.000	1.18	3.46
		CNET uncertain	1.793*	.375	.000	.62	2.97
		CNET distant	2.042*	.361	.000	.91	3.17
		CNET e-commerce	1.112*	.328	.020	.09	2.14
		CNET risky	1.866*	.322	.000	.86	2.87
	HL uncertain	HL basic	.192	.363	1.000	-.94	1.33
		HL distant	-.222	.372	1.000	-1.38	.94
		CNET basic	2.513*	.376	.000	1.34	3.69
		CNET uncertain	1.986*	.386	.000	.78	3.19
		CNET distant	2.234*	.371	.000	1.07	3.40
		CNET e-commerce	1.305*	.340	.004	.24	2.37
		CNET risky	2.059*	.334	.000	1.01	3.10
	HL distant	HL basic	.414	.361	1.000	-.72	1.54
		HL uncertain	.222	.372	1.000	-.94	1.38
		CNET basic	2.735*	.374	.000	1.57	3.90
		CNET uncertain	2.208*	.384	.000	1.01	3.41
		CNET distant	2.456*	.369	.000	1.30	3.61
		CNET e-commerce	1.527*	.337	.000	.47	2.58
		CNET risky	2.280*	.332	.000	1.24	3.32
	CNET basic	HL basic	-2.320*	.365	.000	-3.46	-1.18
		HL uncertain	-2.513*	.376	.000	-3.69	-1.34
		HL distant	-2.735*	.374	.000	-3.90	-1.57
		CNET uncertain	-.527	.388	1.000	-1.74	.69
		CNET distant	-.278	.373	1.000	-1.45	.89
		CNET e-commerce	-1.208*	.342	.012	-2.28	-.14
		CNET risky	-.454	.337	1.000	-1.51	.60
	CNET uncertain	HL basic	-1.793*	.375	.000	-2.97	-.62
		HL uncertain	-1.986*	.386	.000	-3.19	-.78
		HL distant	-2.208*	.384	.000	-3.41	-1.01
		CNET basic	.527	.388	1.000	-.69	1.74
		CNET distant	.249	.383	1.000	-.95	1.45
		CNET e-commerce	-.681	.353	1.000	-1.78	.42
		CNET risky	.073	.348	1.000	-1.02	1.16
	CNET distant	HL basic	-2.042*	.361	.000	-3.17	-.91
		HL uncertain	-2.234*	.371	.000	-3.40	-1.07
		HL distant	-2.456*	.369	.000	-3.61	-1.30
		CNET basic	.278	.373	1.000	-.89	1.45
		CNET uncertain	-.249	.383	1.000	-1.45	.95
		CNET e-commerce	-.930	.337	.164	-1.98	.12
		CNET risky	-.176	.332	1.000	-1.21	.86
	CNET e-commerce	HL basic	-1.112*	.328	.020	-2.14	-.09
		HL uncertain	-1.305*	.340	.004	-2.37	-.24
		HL distant	-1.527*	.337	.000	-2.58	-.47
		CNET basic	1.208*	.342	.012	.14	2.28
		CNET uncertain	.681	.353	1.000	-.42	1.78
		CNET distant	.930	.337	.164	-.12	1.98
		CNET risky	.754	.296	.306	-.17	1.68
	CNET risky	HL basic	-1.866*	.322	.000	-2.87	-.86
		HL uncertain	-2.059*	.334	.000	-3.10	-1.01
		HL distant	-2.280*	.332	.000	-3.32	-1.24
		CNET basic	.454	.337	1.000	-.60	1.51
		CNET uncertain	-.073	.348	1.000	-1.16	1.02
		CNET distant	.176	.332	1.000	-.86	1.21
		CNET e-commerce	-.754	.296	.306	-1.68	.17

*. The mean difference is significant at the 0.05 level.

Table E-3. Post hoc test for benefits per attribute between experimental groups.

Multiple Comparisons

Bonferroni

(I) experimental group	(J) experimental group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
HL basic	HL uncertain	.01395	.10568	1.000	-.3167	.3446
	HL distant	-.02472	.10510	1.000	-.3535	.3041
	CNET basic	-.83400*	.10675	.000	-1.1680	-.5000
	CNET uncertain	-1.09667*	.11005	.000	-1.4410	-.7524
	CNET distant	-.72356*	.10568	.000	-1.0542	-.3929
	CNET e-commerce	-.70728*	.09581	.000	-1.0070	-.4075
	CNET risky	-,43894*	,09415	,000	-.7335	-.1444
HL uncertain	HL basic	-.01395	.10568	1.000	-.3446	.3167
	HL distant	-.03866	.10811	1.000	-.3769	.2996
	CNET basic	-.84795*	.10971	.000	-1.1912	-.5047
	CNET uncertain	-1.11062*	.11292	.000	-1.4639	-.7573
	CNET distant	-.73750*	.10867	.000	-1.0775	-.3975
	CNET e-commerce	-.72122*	.09910	.000	-1.0313	-.4112
	CNET risky	-.45289*	.09749	.000	-.7579	-.1479
HL distant	HL basic	.02472	.10510	1.000	-.3041	.3535
	HL uncertain	.03866	.10811	1.000	-.2996	.3769
	CNET basic	-.80929*	.10915	.000	-1.1508	-.4678
	CNET uncertain	-1.07195*	.11238	.000	-1.4235	-.7204
	CNET distant	-.69884*	.10811	.000	-1.0371	-.3606
	CNET e-commerce	-.68256*	.09848	.000	-.9907	-.3744
	CNET risky	-.41423*	.09686	.001	-.7173	-.1112
CNET basic	HL basic	.83400*	.10675	.000	.5000	1.1680
	HL uncertain	.84795*	.10971	.000	.5047	1.1912
	HL distant	.80929*	.10915	.000	.4678	1.1508
	CNET uncertain	-.26267	.11392	.595	-.6191	.0938
	CNET distant	.11044	.10971	1.000	-.2328	.4537
	CNET e-commerce	-.12673	.10024	1.000	-.1869	.4403
	CNET risky	.39506*	.09865	.002	-.0864	.7037
CNET uncertain	HL basic	1.09667*	.11005	.000	.7524	1.4410
	HL uncertain	1.11062*	.11292	.000	.7573	1.4639
	HL distant	1.07195*	.11238	.000	.7204	1.4235
	CNET basic	.26267	.11392	.595	-.0938	.6191
	CNET distant	.37311*	.11292	.027	.0198	.7264
	CNET e-commerce	.38939*	.10374	.005	.0648	.7140
	CNET risky	.65773*	.10221	.000	.3379	.9775
CNET distant	HL basic	.72356*	.10568	.000	.3929	1.0542
	HL uncertain	.73750*	.10867	.000	.3975	1.0775
	HL distant	.69884*	.10811	.000	.3606	1.0371
	CNET basic	-.11044	.10971	1.000	-.4537	.2328
	CNET uncertain	-.37311*	.11292	.027	-.7264	-.0198
	CNET e-commerce	-.01628	.09910	1.000	-.2938	.3263
	CNET risky	-.28462	.09749	.100	-.0204	.5896
CNET e-commerce	HL basic	.70728*	.09581	.000	.4075	1.0070
	HL uncertain	.72122*	.09910	.000	.4112	1.0313
	HL distant	.68256*	.09848	.000	.3744	.9907
	CNET basic	-.12673	.10024	1.000	-.4403	.1869
	CNET uncertain	-.38939*	.10374	.005	-.7140	-.0648
	CNET distant	-.01628	.09910	1.000	-.3263	.2938
	CNET risky	.26833	.08669	.056	-.0029	.5396
CNET risky	HL basic	.43894*	.09415	.000	.1444	.7335
	HL uncertain	.45289*	.09749	.000	.1479	.7579
	HL distant	.41423*	.09686	.001	.1112	.7173
	CNET basic	-.39506*	.09865	.002	-.7037	-.0864
	CNET uncertain	-.65773*	.10221	.000	-.9775	-.3379
	CNET distant	-.28462	.09749	.100	-.5896	.0204
	CNET e-commerce	-.26833	.08669	.056	-.5396	.0029

*. The mean difference is significant at the 0.05 level.

Table E-4. Post hoc test for number of associations between experimental groups.

Multiple Comparisons

Bonferroni

(I) experimental group	(J) experimental group	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
HL basic	HL uncertain	-2.157	1.343	1.000	-6.36	2.04
	HL distant	-2.547	1.335	1.000	-6.72	1.63
	CNET basic	8.726*	1.350	.000	4.50	12.95
	CNET uncertain	8.984*	1.389	.000	4.64	13.33
	CNET distant	8.780*	1.333	.000	4.61	12.95
	CNET e-commerce	7.037*	1.212	.000	3.24	10.83
	CNET risky	6.902*	1.193	.000	3.17	10.63
HL uncertain	HL basic	2.157	1.343	1.000	-2.04	6.36
	HL distant	-.390	1.375	1.000	-4.69	3.91
	CNET basic	10.883*	1.389	.000	6.54	15.23
	CNET uncertain	11.141*	1.427	.000	6.68	15.60
	CNET distant	10.936*	1.373	.000	6.64	15.23
	CNET e-commerce	9.193*	1.256	.000	5.26	13.12
	CNET risky	9.059*	1.237	.000	5.19	12.93
HL distant	HL basic	2.547	1.335	1.000	-1.63	6.72
	HL uncertain	.390	1.375	1.000	-3.91	4.69
	CNET basic	11.273*	1.382	.000	6.95	15.60
	CNET uncertain	11.531*	1.420	.000	7.09	15.97
	CNET distant	11.326*	1.366	.000	7.05	15.60
	CNET e-commerce	9.583*	1.248	.000	5.68	13.49
	CNET risky	9.449*	1.229	.000	5.60	13.29
CNET basic	HL basic	-8.726*	1.350	.000	-12.95	-4.50
	HL uncertain	-10.883*	1.389	.000	-15.23	-6.54
	HL distant	-11.273*	1.382	.000	-15.60	-6.95
	CNET uncertain	.258	1.434	1.000	-4.23	4.74
	CNET distant	.054	1.381	1.000	-4.27	4.37
	CNET e-commerce	-1.689	1.264	1.000	-5.64	2.27
	CNET risky	-1.824	1.245	1.000	-5.72	2.07
CNET uncertain	HL basic	-8.984*	1.389	.000	-13.33	-4.64
	HL uncertain	-11.141*	1.427	.000	-15.60	-6.68
	HL distant	-11.531*	1.420	.000	-15.97	-7.09
	CNET basic	-.258	1.434	1.000	-4.74	4.23
	CNET distant	-.204	1.418	1.000	-4.64	4.23
	CNET e-commerce	-1.948	1.305	1.000	-6.03	2.14
	CNET risky	-2.082	1.287	1.000	-6.11	1.94
CNET distant	HL basic	-8.780*	1.333	.000	-12.95	-4.61
	HL uncertain	-10.936*	1.373	.000	-15.23	-6.64
	HL distant	-11.326*	1.366	.000	-15.60	-7.05
	CNET basic	-.054	1.381	1.000	-4.37	4.27
	CNET uncertain	.204	1.418	1.000	-4.23	4.64
	CNET e-commerce	-1.743	1.246	1.000	-5.64	2.16
	CNET risky	-1.878	1.227	1.000	-5.72	1.96
CNET e-commerce	HL basic	-7.037*	1.212	.000	-10.83	-3.24
	HL uncertain	-9.193*	1.256	.000	-13.12	-5.26
	HL distant	-9.583*	1.248	.000	-13.49	-5.68
	CNET basic	1.689	1.264	1.000	-2.27	5.64
	CNET uncertain	1.948	1.305	1.000	-2.14	6.03
	CNET distant	1.743	1.246	1.000	-2.16	5.64
	CNET risky	-.135	1.094	1.000	-3.56	3.29
CNET risky	HL basic	-6.902*	1.193	.000	-10.63	-3.17
	HL uncertain	-9.059*	1.237	.000	-12.93	-5.19
	HL distant	-9.449*	1.229	.000	-13.29	-5.60
	CNET basic	1.824	1.245	1.000	-2.07	5.72
	CNET uncertain	2.082	1.287	1.000	-1.94	6.11
	CNET distant	1.878	1.227	1.000	-1.96	5.72
	CNET e-commerce	.135	1.094	1.000	-3.29	3.56

*. The mean difference is significant at the 0.05 level.

F. Elicited attributes

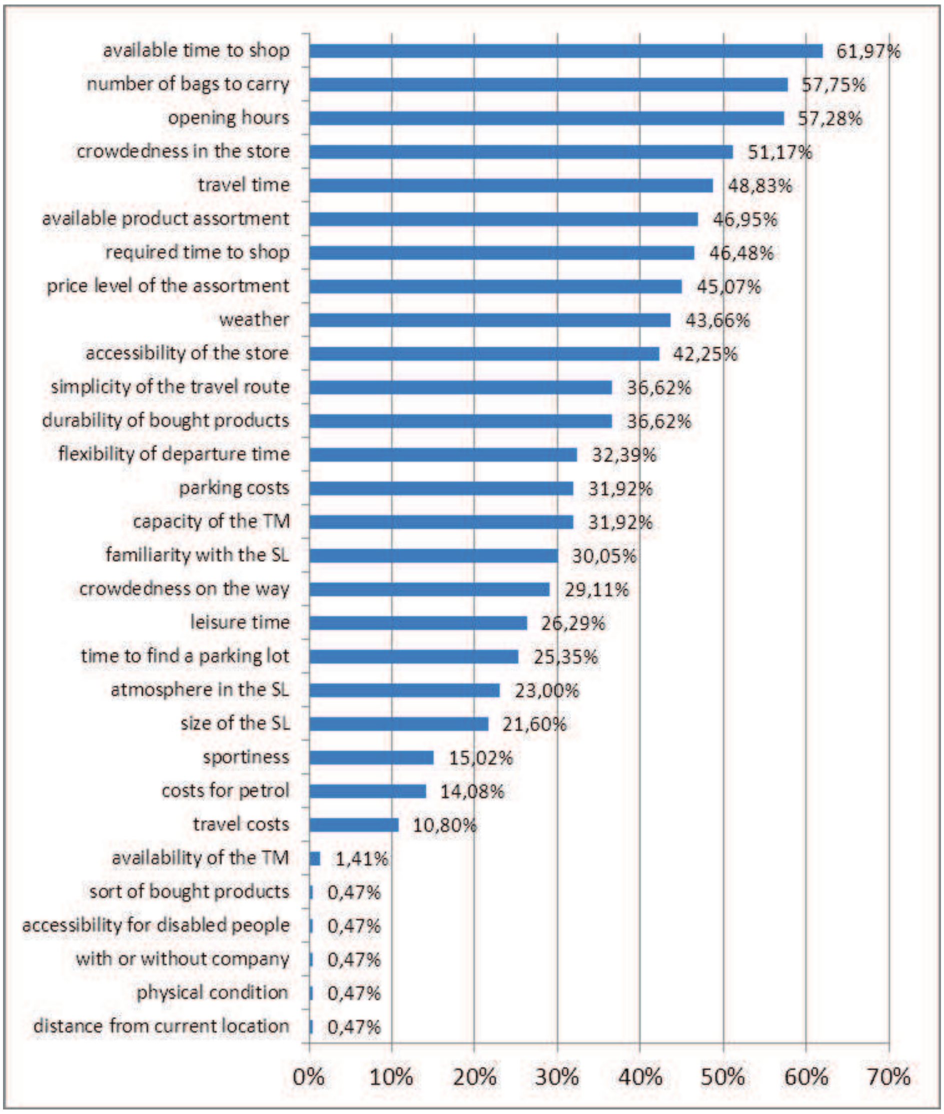

Figure F-1. Frequency of attributes in MRs of the HL basic scenario.

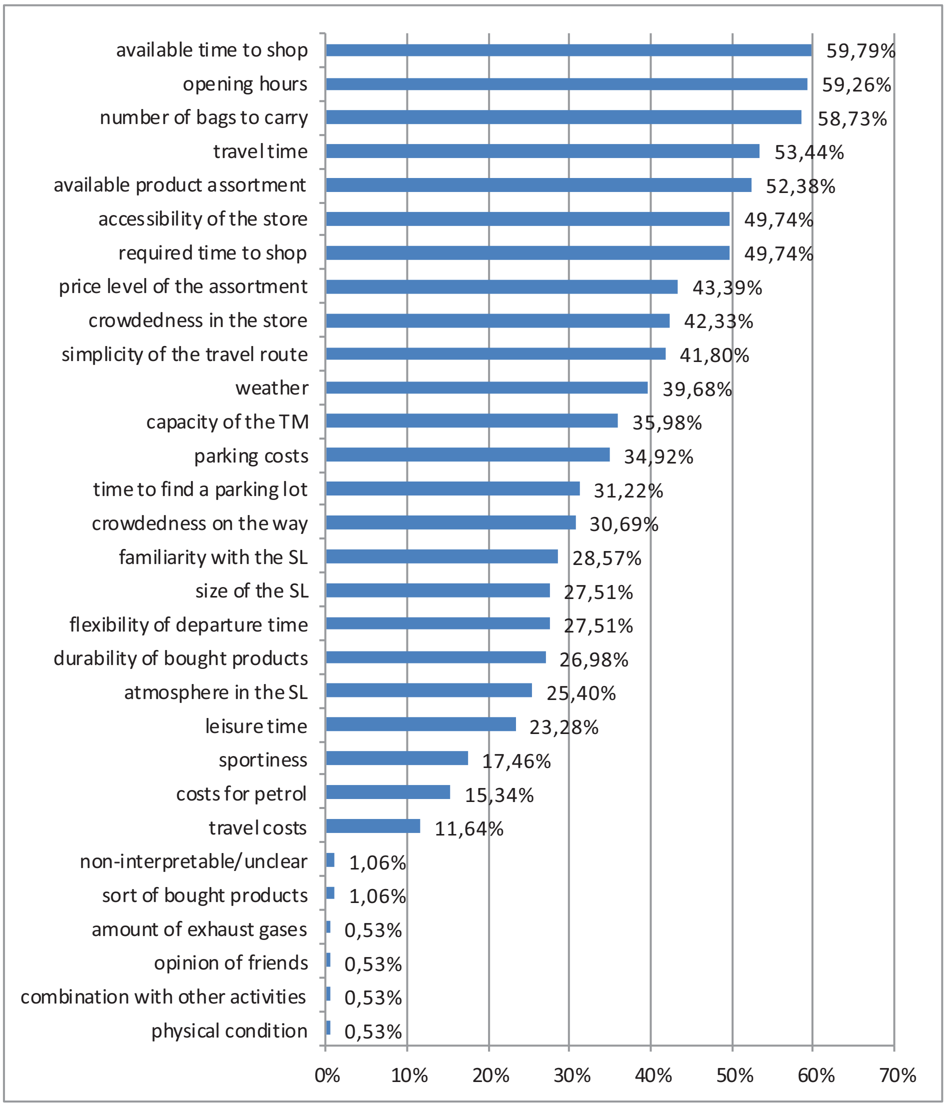

Figure F-2. Frequency of attributes in MRs of the HL uncertain scenario.

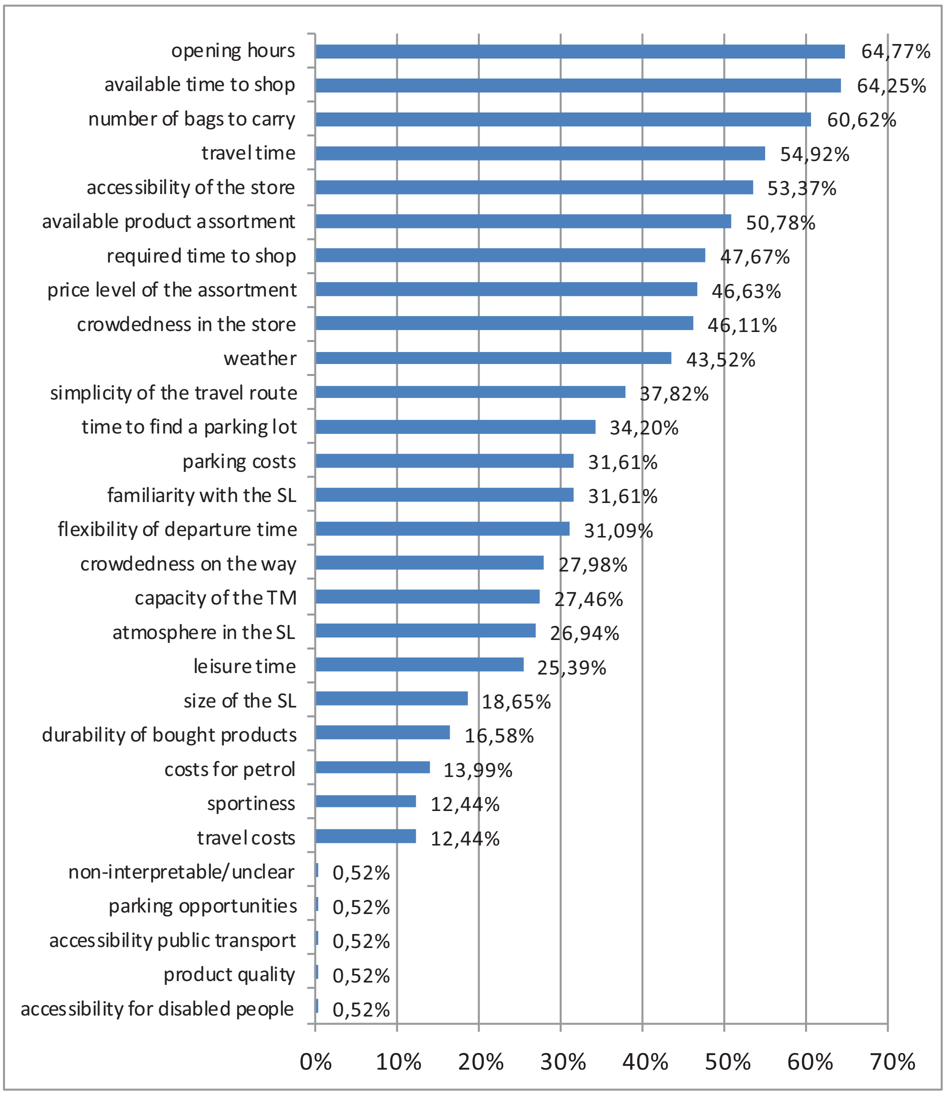

Figure F-3. Frequency of attributes in MRs of the HL distant scenario.

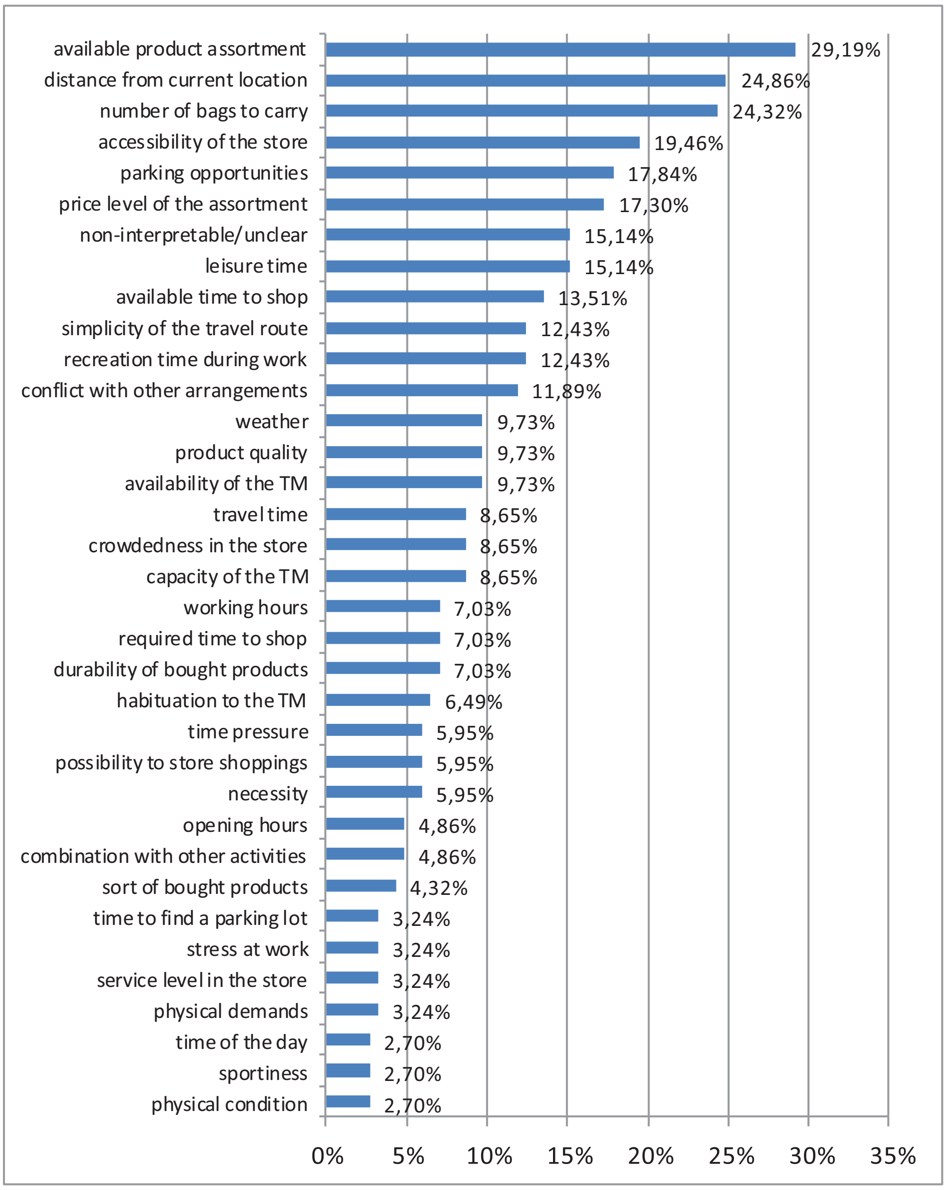

Figure F-4. Frequency of attributes in MRs of the CNET basic scenario

(only attributes with more than 4 observations).

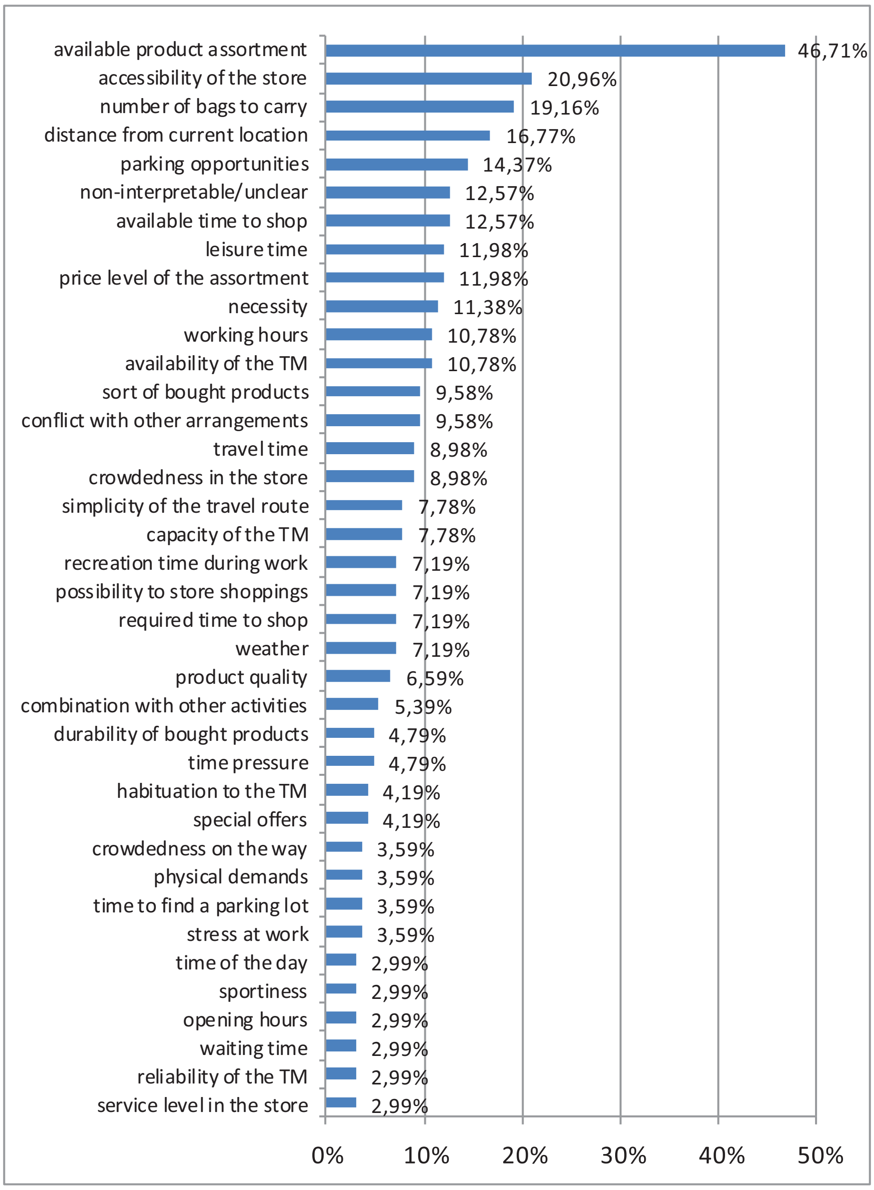

Figure F-5. Frequency of attributes in MRs of the CNET uncertain scenario (only attributes with more than 4 observations).

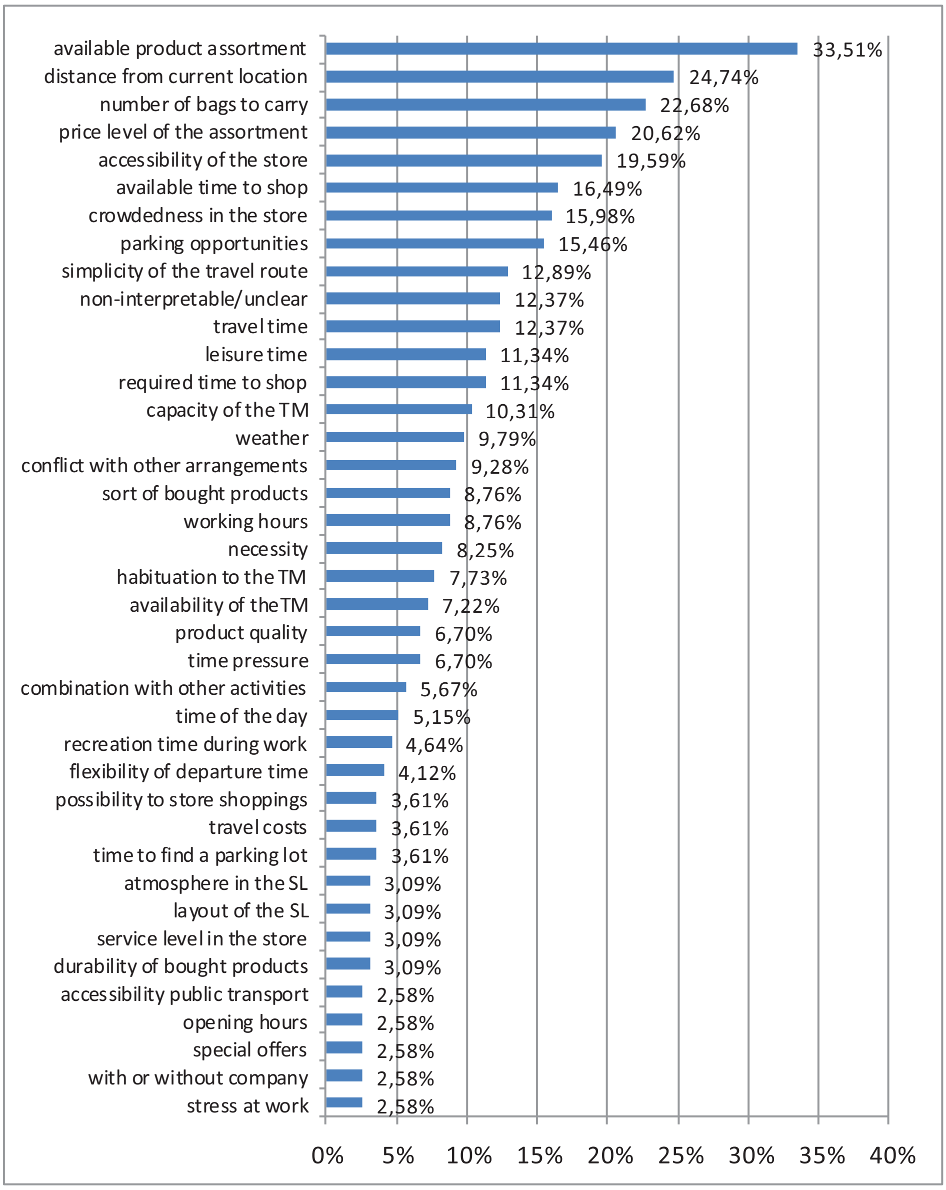

Figure F-6. Frequency of attributes in MRs of the CNET distant scenario (only attributes with more than 4 observations).

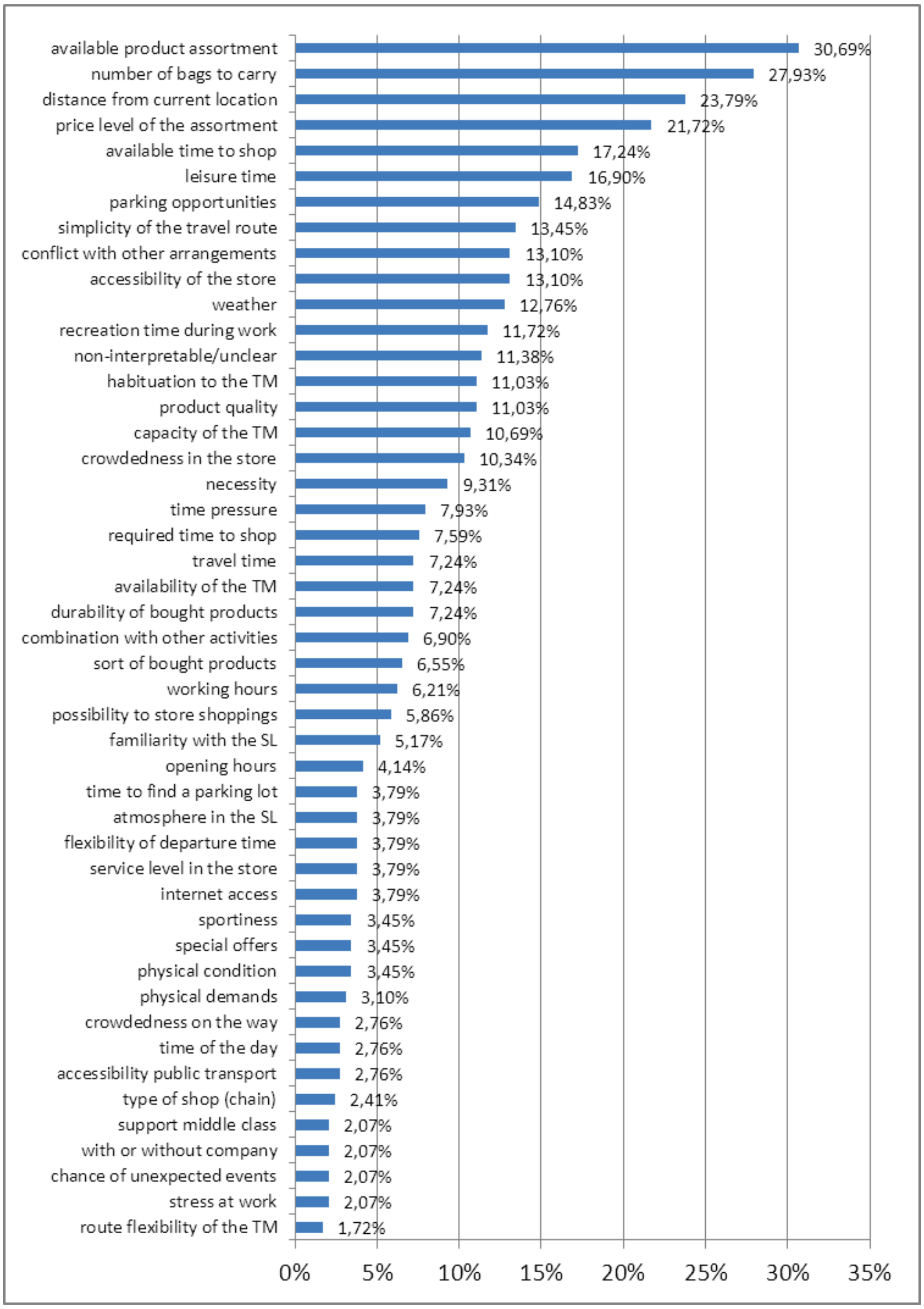

Figure F-7. Frequency of attributes in MRs of the CNET e-commerce scenario

(only attributes with more than 4 observations).

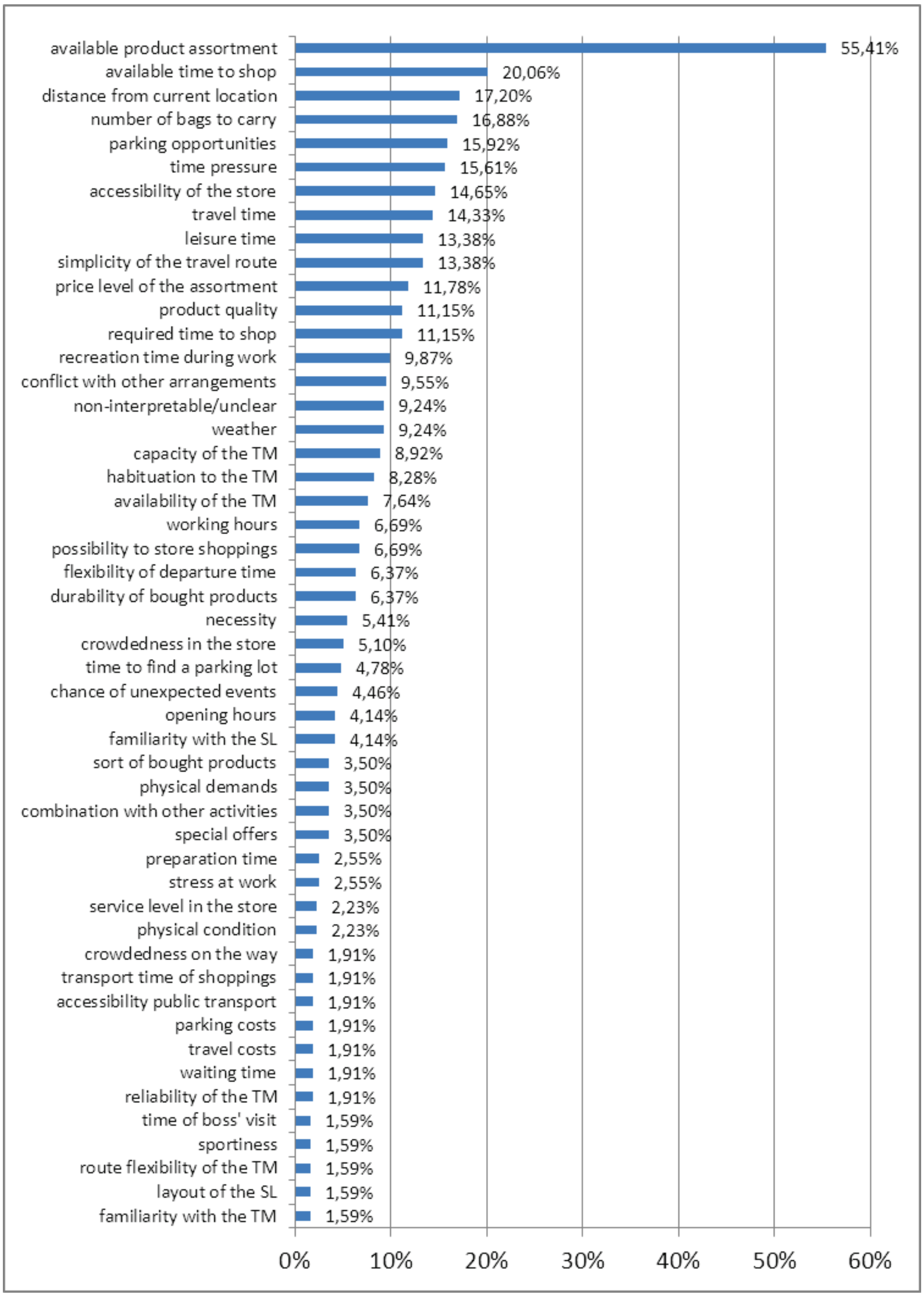

Figure F-8. Frequency of attributes in MRs of the CNET risky scenario (only attributes with more than 4 observations).

G. Elicited benefits

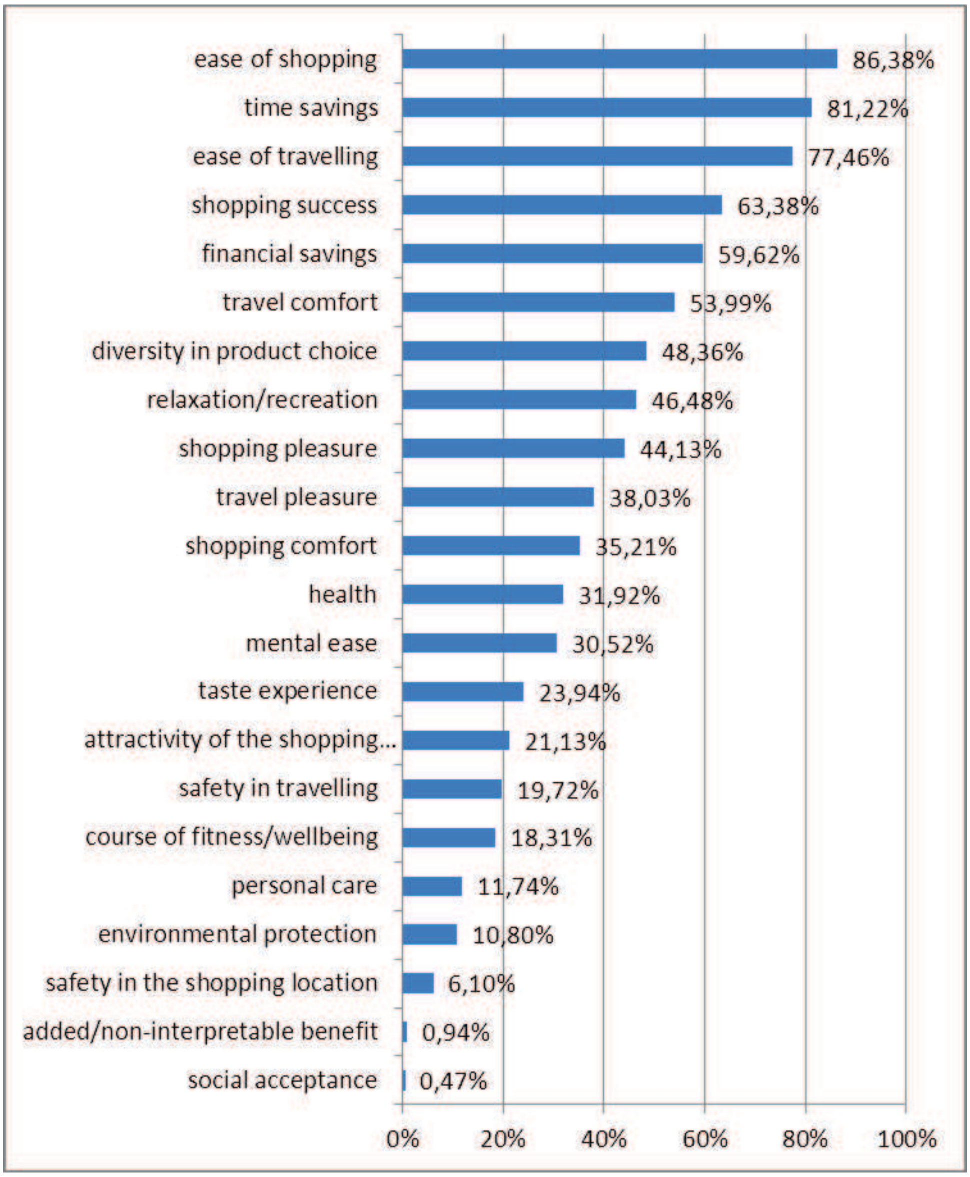

Figure G-1. Frequency of benefits in MRs of the HL basic scenario.

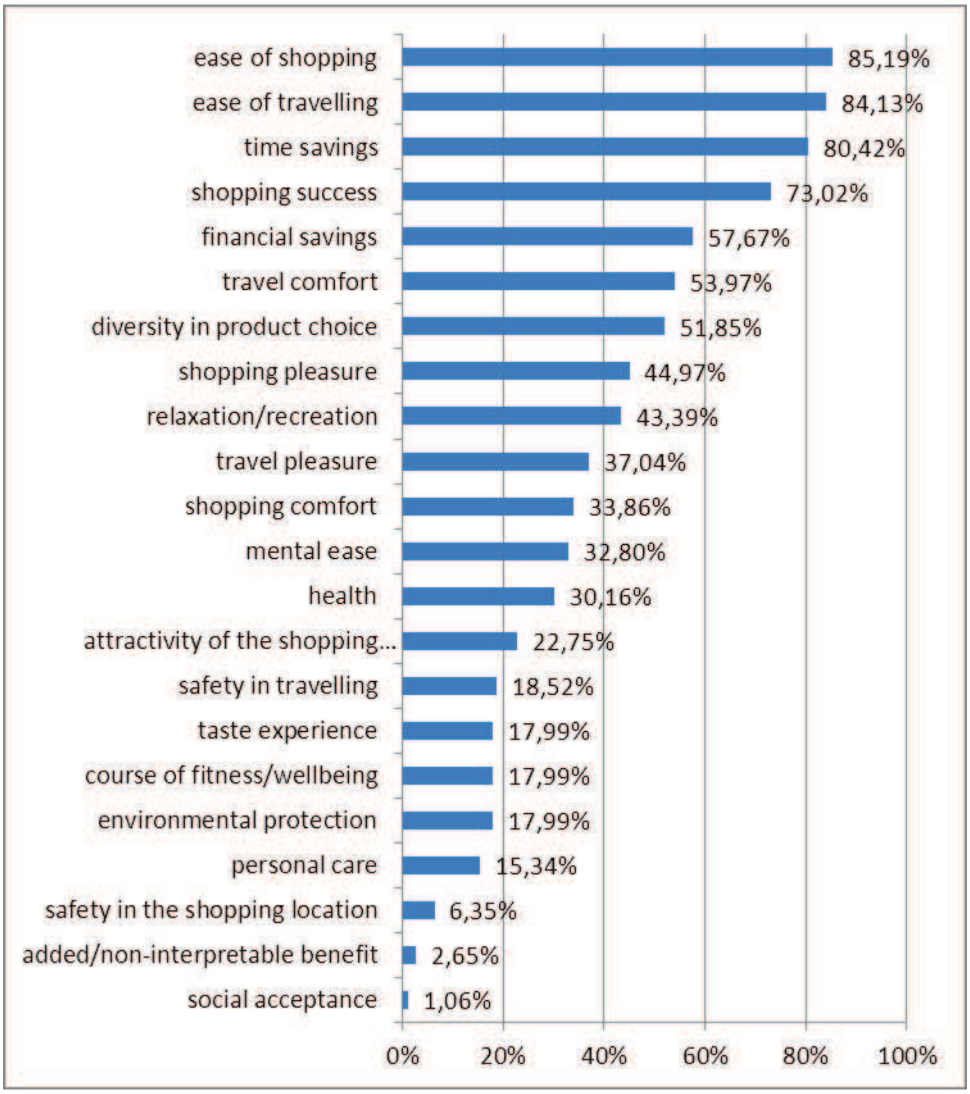

Figure G-2. Frequency of benefits in MRs of the HL uncertain scenario.

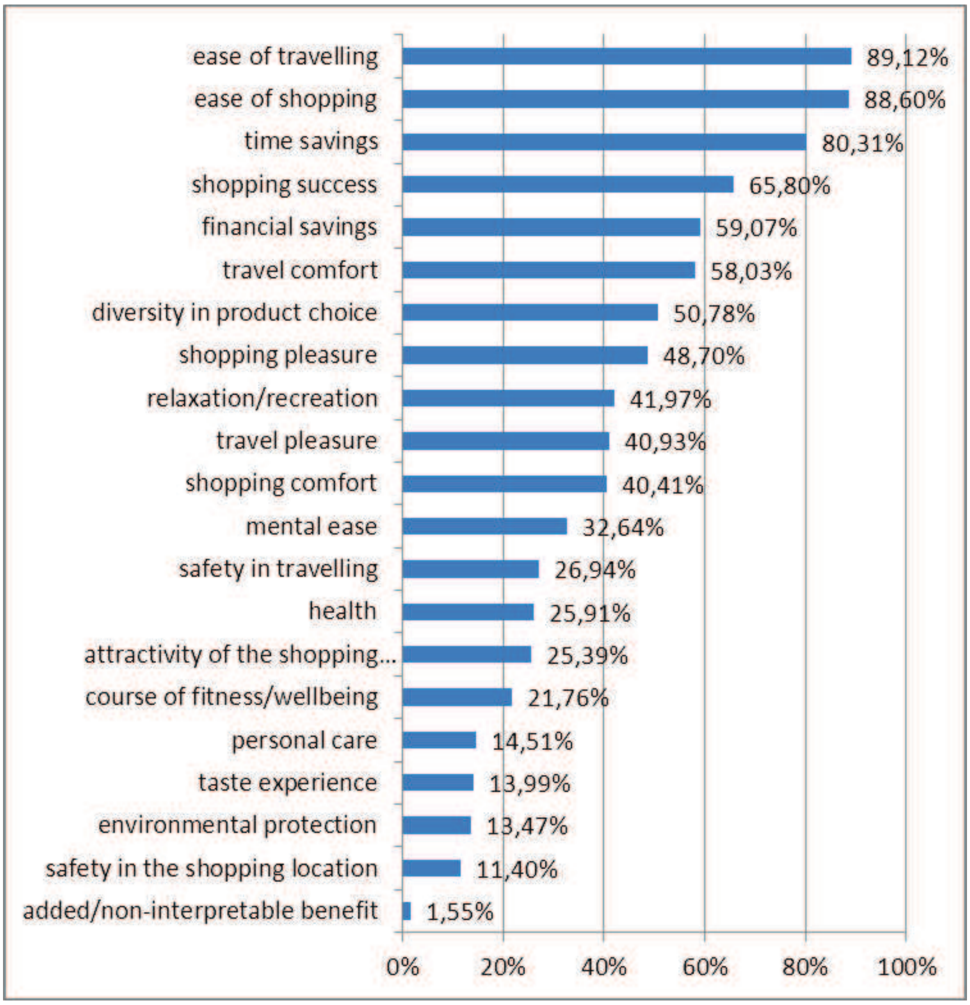

Figure G-3. Frequency of benefits in MRs of the HL distant scenario.

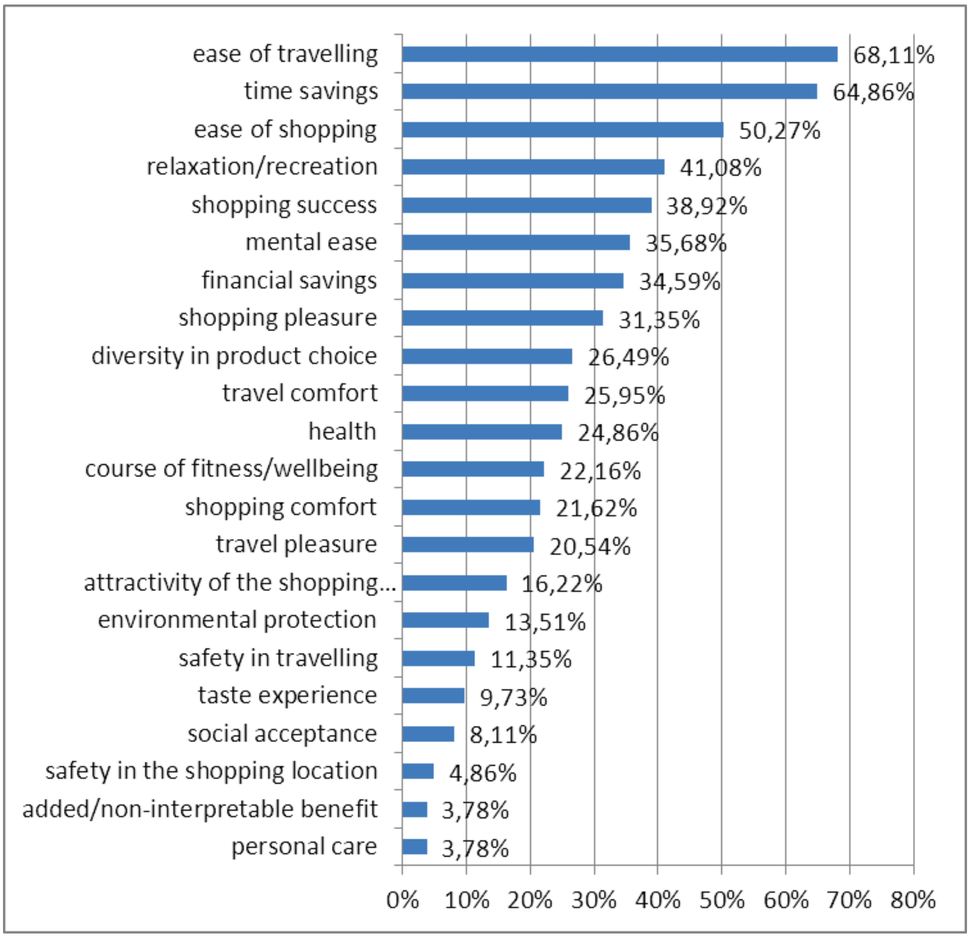

Figure G-4. Frequency of benefits in MRs of the CNET basic scenario.

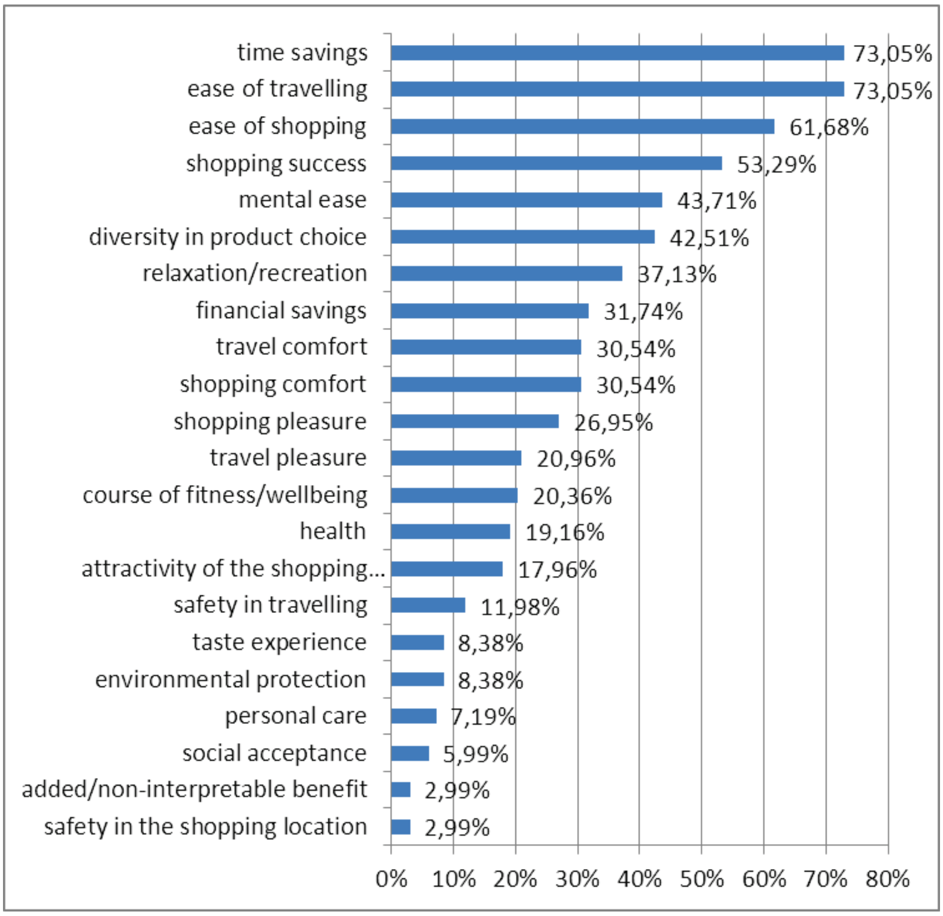

Figure G-5. Frequency of benefits in MRs of the CNET uncertain scenario.

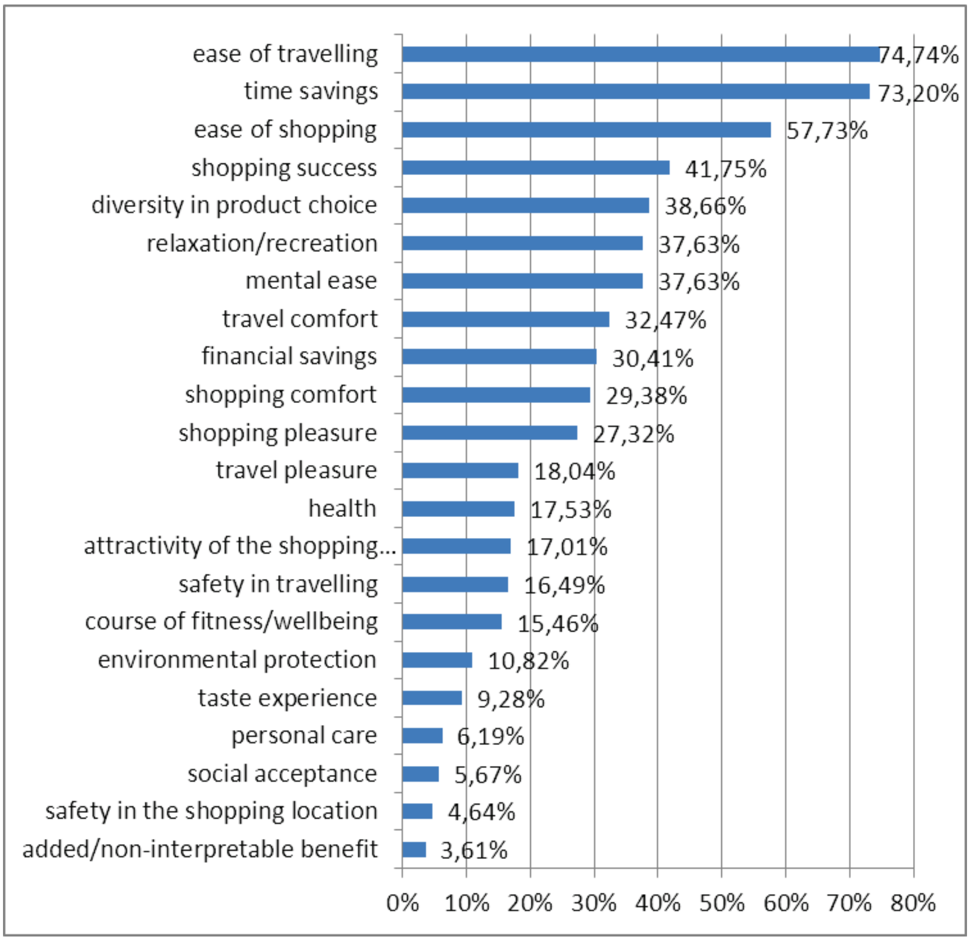

Figure G-6. Frequency of benefits in MRs of the CNET distant scenario.

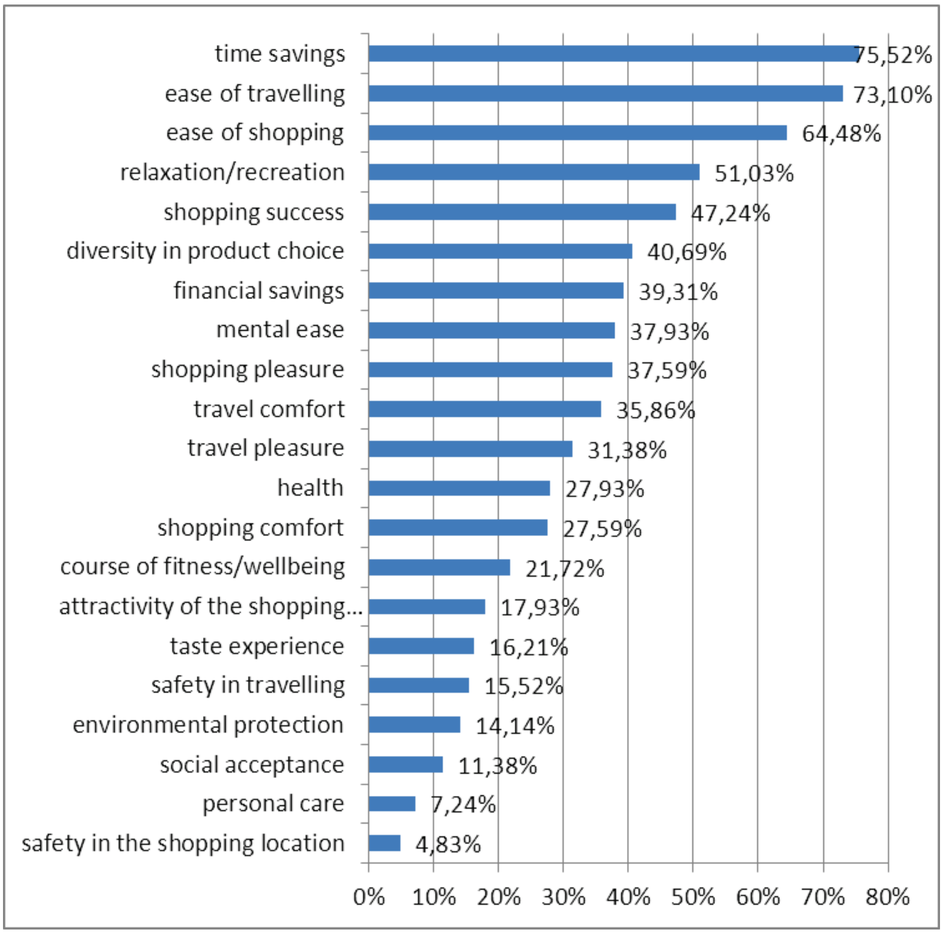

Figure G-7. Frequency of benefits in MRs of the CNET e-commerce scenario.

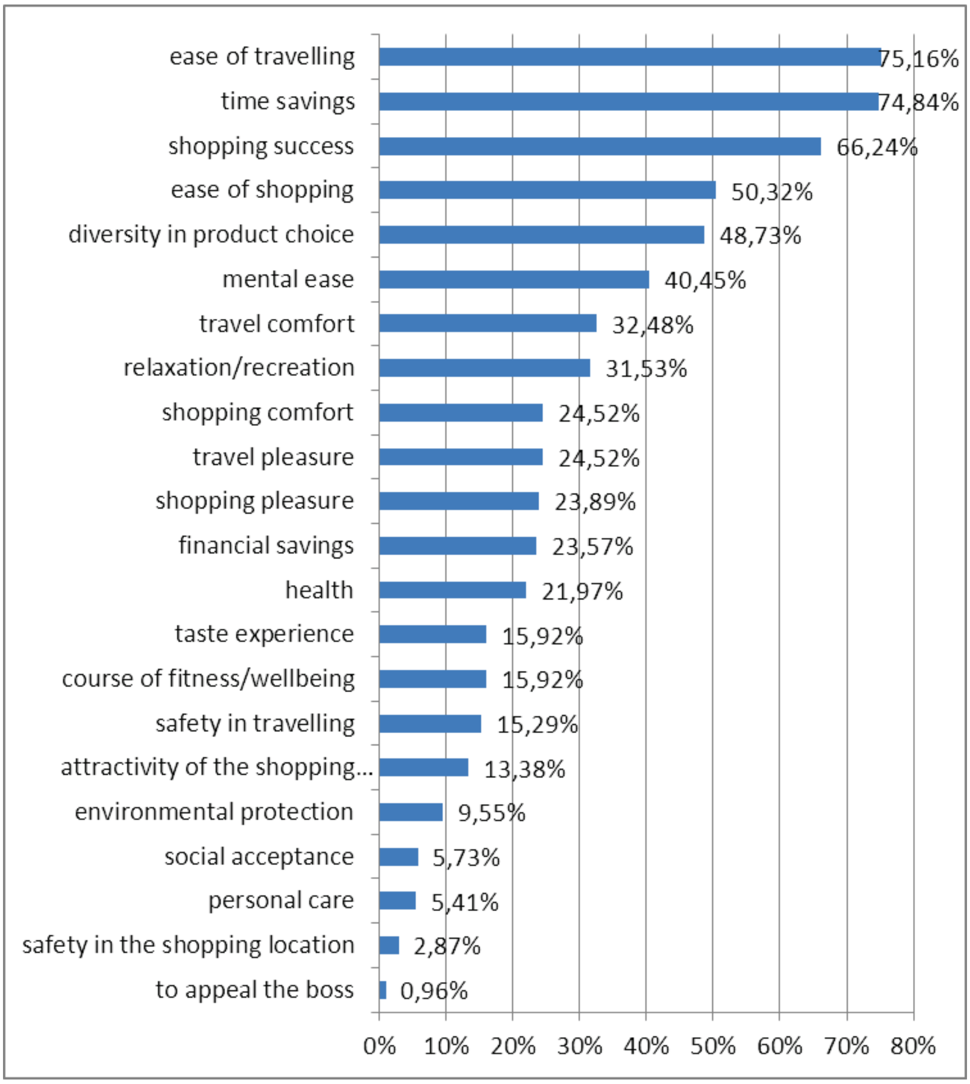

Figure G-8. Frequency of benefits in MRs of the CNET risky scenario.

H. Statistical tests on the centrality of variables.

Table H-1. Tests of Between-Subjects Effects for the top central variables of CNET – wave I+II (corresponding to Table 4-18).

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	TM	.005	1	.005	2.068	.151
	SL	.003	1	.003	.924	.337
	TS	.004	1	.004	1.782	.182
	ease of travelling	.003	1	.003	1.423	.233
	available assortment	.087	1	.087	8.392	.004
	time savings	.018	1	.018	6.773	.009
	distance	.012	1	.012	2.775	.096
	accessibility of store	.019	1	.019	4.337	.038
	number of bags	.008	1	.008	2.782	.096
	ease of shopping	.001	1	.001	.566	.452
	shopping success	.010	1	.010	6.631	.010
	mental ease	.000	1	.000	.334	.563
	parking opportunities	.002	1	.002	.864	.353
	relaxation	.004	1	.004	3.907	.048
	available time to shop	.006	1	.006	2.275	.132
Intercept	TM	.425	1	.425	165.819	.000
	SL	.485	1	.485	174.077	.000
	TS	.196	1	.196	79.616	.000
	ease of travelling	.169	1	.169	68.594	.000
	available assortment	.047	1	.047	4.557	.033
	time savings	.046	1	.046	17.222	.000
	distance	.100	1	.100	23.137	.000
	accessibility of store	.103	1	.103	22.948	.000
	number of bags	.069	1	.069	23.360	.000
	ease of shopping	.049	1	.049	42.871	.000
	shopping success	.007	1	.007	4.977	.026
	mental ease	.028	1	.028	19.699	.000
	parking opportunities	.035	1	.035	12.982	.000
	relaxation	.041	1	.041	36.742	.000
	available time to shop	.004	1	.004	1.561	.212
Exp_group	TM	.005	1	.005	2.068	.151
	SL	.003	1	.003	.924	.337
	TS	.004	1	.004	1.782	.182
	ease of travelling	.003	1	.003	1.423	.233
	available assortment	.087	1	.087	8.392	.004
	time savings	.018	1	.018	6.773	.009
	distance	.012	1	.012	2.775	.096
	accessibility of store	.019	1	.019	4.337	.038
	number of bags	.008	1	.008	2.782	.096
	ease of shopping	.001	1	.001	.566	.452
	shopping success	.010	1	.010	6.631	.010
	mental ease	.000	1	.000	.334	.563
	parking opportunities	.002	1	.002	.864	.353
	relaxation	.004	1	.004	3.907	.048
	available time to shop	.006	1	.006	2.275	.132

Table H-1 (continued).

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Error	TM	2.896	1129	.003		
	SL	3.147	1129	.003		
	TS	2.778	1129	.002		
	ease of travelling	2.776	1129	.002		
	available assortment	11.710	1129	.010		
	time savings	3.006	1129	.003		
	distance	4.871	1129	.004		
	accessibility of store	5.070	1129	.004		
	number of bags	3.336	1129	.003		
	ease of shopping	1.281	1129	.001		
	shopping success	1.643	1129	.001		
	mental ease	1.587	1129	.001		
	parking opportunities	3.048	1129	.003		
	relaxation	1.264	1129	.001		
	available time to shop	2.958	1129	.003		
Total	TM	9.926	1131			
	SL	11.860	1131			
	TS	8.136	1131			
	ease of travelling	5.372	1131			
	available assortment	17.109	1131			
	time savings	5.503	1131			
	distance	5.794	1131			
	accessibility of store	5.801	1131			
	number of bags	3.976	1131			
	ease of shopping	2.079	1131			
	shopping success	2.333	1131			
	mental ease	2.027	1131			
	parking opportunities	3.459	1131			
	relaxation	1.666	1131			
	available time to shop	3.368	1131			
Corrected Total	TM	2.901	1130			
	SL	3.149	1130			
	TS	2.783	1130			
	ease of travelling	2.779	1130			
	available assortment	11.797	1130			
	time savings	3.024	1130			
	distance	4.883	1130			
	accessibility of store	5.090	1130			
	number of bags	3.344	1130			
	ease of shopping	1.281	1130			
	shopping success	1.652	1130			
	mental ease	1.588	1130			
	parking opportunities	3.051	1130			
	relaxation	1.269	1130			
	available time to shop	2.964	1130			

I. Cross-tables for attributes and choice outcomes.

Table I-1. Cross-Table for attributes and the TM choice in HL basic.

attributes	car		non car		Total
	absolute	relative	absolute	relative	
available time to shop	91	62.8%	41	60.2%	132
weather	60	41.4%	33	48.4%	93
number of bags to carry	88	60.8%	35	51.3%	123
durability of bought products	56	38.7%	22	32.3%	78
required time to shop	68	46.9%	31	45.5%	99
departure time flexibility of the TM	47	32.4%	22	32.3%	69
accessibility of the store	62	42.8%	28	41.1%	90
atmosphere in the SL	31	21.4%	18	26.4%	49
crowdedness in the store	77	53.2%	32	46.9%	109
size of the SL	34	23.5%	12	17.6%	46
familiarity with the SL	43	29.7%	21	30.8%	64
price level of the assortment	70	48.3%	26	38.1%	96
available product assortment	76	52.5%	24	35.2%	100
time to find a parking lot	42	29.0%	12	17.6%	54
capacity of the TM	45	31.1%	23	33.7%	68
travel costs	15	10.4%	8	11.7%	23
costs for petrol	18	12.4%	12	17.6%	30
parking costs	50	34.5%	18	26.4%	68
opening hours	86	59.4%	36	52.8%	122
simplicity of the travel route	52	35.9%	26	38.1%	78
leisure time	33	22.8%	23	33.7%	56
sportiness	11	7.6%	21	30.8%	32
travel time	72	49.7%	32	46.9%	104
crowdedness on the way	40	27.6%	22	32.3%	62

Table I-2. Cross-Table for attributes and the SL choice in HL basic.

attributes	cornershop		weekmarkt		supermarkt	
	absolute	relative	absolute	relative	absolute	relative
available time to shop	47	63.6%	13	71.8%	72	59.5%
weather	36	48.7%	8	44.2%	49	40.5%
number of bags to carry	43	58.2%	11	60.8%	69	57.0%
durability of bought products	27	36.5%	8	44.2%	43	35.5%
required time to shop	33	44.6%	11	60.8%	55	45.5%
departure time flexibility	25	33.8%	8	44.2%	36	29.8%
accessibility of the store	29	39.2%	6	33.1%	55	45.5%
atmosphere in the SL	18	24.4%	3	16.6%	28	23.1%
crowdedness in the store	36	48.7%	6	33.1%	67	55.4%
size of the SL	10	13.5%	1	5.5%	35	28.9%
familiarity with the SL	22	29.8%	5	27.6%	37	30.6%
price level of the assortment	25	33.8%	12	66.3%	59	48.8%
available product assortment	25	33.8%	12	66.3%	63	52.1%
time to find a parking lot	18	24.4%	6	33.1%	30	24.8%
capacity of the TM	26	35.2%	8	44.2%	34	28.1%
travel costs	9	12.2%	4	22.1%	10	8.3%

Table I-2 (continued).

attributes	cornershop		weekmarkt		supermarkt	
	absolute	relative	absolute	relative	absolute	relative
costs for petrol	9	12.2%	5	27.6%	16	13.2%
parking costs	20	27.1%	10	55.2%	38	31.4%
opening hours	42	56.8%	14	77.3%	66	54.6%
simplicity of the travel route	36	48.7%	7	38.7%	35	28.9%
leisure time	20	27.1%	7	38.7%	29	24.0%
sportiness	12	16.2%	5	27.6%	15	12.4%
travel time	42	56.8%	10	55.2%	52	43.0%
crowdedness on the way	22	29.8%	9	49.7%	31	25.6%

Table I-3. Cross-Table for attributes and the TS choice in HL basic.

attributes	lunchbreak		after work		evening	
	absolute	relative	absolute	relative	absolute	relative
available time to shop	12	75.1%	90	59.2%	30	66.8%
weather	5	31.3%	73	48.0%	15	33.4%
number of bags to carry	7	43.8%	90	59.2%	26	57.9%
durability of bought products	5	31.3%	57	37.5%	16	35.6%
required time to shop	11	68.9%	72	47.3%	16	35.6%
departure time flexibility of TM	5	31.3%	52	34.2%	12	26.7%
accessibility of the store	8	50.1%	61	40.1%	21	46.7%
atmosphere in the SL	2	12.5%	36	23.7%	11	24.5%
crowdedness in the store	8	50.1%	75	49.3%	26	57.9%
size of the SL	4	25.0%	32	21.0%	10	22.3%
familiarity with the SL	3	18.8%	44	28.9%	17	37.8%
price level of the assortment	6	37.6%	69	45.4%	21	46.7%
available product assortment	6	37.6%	69	45.4%	25	55.6%
time to find a parking lot	2	12.5%	41	27.0%	11	24.5%
capacity of the TM	2	12.5%	50	32.9%	16	35.6%
travel costs	1	6.3%	17	11.2%	5	11.1%
costs for petrol	2	12.5%	22	14.5%	6	13.4%
parking costs	8	50.1%	44	28.9%	16	35.6%
opening hours	7	43.8%	83	54.6%	32	71.2%
simplicity of the travel route	6	37.6%	53	34.8%	19	42.3%
leisure time	6	37.6%	38	25.0%	12	26.7%
sportiness	4	25.0%	23	15.1%	5	11.1%
travel time	8	50.1%	75	49.3%	21	46.7%
crowdedness on the way	6	37.6%	48	31.6%	8	17.8%

Table I-4. Cross-Table for attributes and the TM choice in HL uncertain.

attributes	car		non car		Total
	absolute	relative	absolute	relative	
available time to shop	80	60.6%	33	57.8%	113
weather	45	34.1%	30	52.6%	75
number of bags to carry	86	65.2%	25	43.8%	111
durability of bought products	35	26.5%	16	28.0%	51
required time to shop	66	50.0%	28	49.1%	94
departure time flexibility of the TM	37	28.0%	15	26.3%	52
accessibility of the store	63	47.8%	31	54.3%	94
atmosphere in the SL	31	23.5%	17	29.8%	48
crowdedness in the store	58	44.0%	22	38.5%	80
size of the SL	37	28.0%	15	26.3%	52
familiarity with the SL	34	25.8%	20	35.0%	54
price level of the assortment	57	43.2%	25	43.8%	82
available product assortment	70	53.1%	29	50.8%	99
time to find a parking lot	44	33.4%	15	26.3%	59
capacity of the TM	51	38.7%	17	29.8%	68
travel costs	12	9.1%	10	17.5%	22
costs for petrol	14	10.6%	15	26.3%	29
parking costs	43	32.6%	23	40.3%	66
opening hours	79	59.9%	33	57.8%	112
simplicity of the travel route	58	44.0%	21	36.8%	79
leisure time	27	20.5%	17	29.8%	44
sportiness	11	8.3%	22	38.5%	33
travel time	68	51.5%	33	57.8%	101
crowdedness on the way	37	28.0%	21	36.8%	58

Table I-5. Cross-Table for attributes and the SL choice in HL uncertain.

attributes	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
available time to shop	36	56.2%	77	61.6%	113
weather	29	45.3%	46	36.8%	75
number of bags to carry	35	54.6%	76	60.8%	111
durability of bought products	19	29.7%	32	25.6%	51
required time to shop	33	51.5%	61	48.8%	94
departure time flexibility of the TM	15	23.4%	37	29.6%	52
accessibility of the store	32	49.9%	62	49.6%	94
atmosphere in the SL	15	23.4%	33	26.4%	48
crowdedness in the store	33	51.5%	47	37.6%	80
size of the SL	10	15.6%	42	33.6%	52
familiarity with the SL	22	34.3%	32	25.6%	54
price level of the assortment	24	37.5%	58	46.4%	82
available product assortment	28	43.7%	71	56.8%	99
time to find a parking lot	19	29.7%	40	32.0%	59
capacity of the TM	21	32.8%	47	37.6%	68
travel costs	8	12.5%	14	11.2%	22

Table I-5 (continued).

attributes	**non supermarket** absolute	relative	**supermarket** absolute	relative	**Total**
costs for petrol	14	21.9%	15	12.0%	29
parking costs	27	42.1%	39	31.2%	66
opening hours	33	51.5%	79	63.2%	112
simplicity of the travel route	27	42.1%	52	41.6%	79
leisure time	19	29.7%	25	20.0%	44
sportiness	16	25.0%	17	13.6%	33
travel time	36	56.2%	65	52.0%	101
crowdedness on the way	23	35.9%	35	28.0%	58

Table I-6. Cross-Table for attributes and the TS choice in HL uncertain.

	lunchbreak		**after work**		**evening**	
attributes	absolute	relative	absolute	relative	absolute	relative
available time to shop	9	60.3%	77	60.2%	27	58.8%
weather	7	46.9%	55	43.0%	13	28.3%
number of bags to carry	8	53.6%	80	62.5%	23	50.1%
durability of bought products	6	40.2%	36	28.1%	9	19.6%
required time to shop	5	33.5%	70	54.7%	19	41.4%
departure time flexibility	7	46.9%	36	28.1%	9	19.6%
accessibility of the store	6	40.2%	66	51.6%	22	47.9%
atmosphere in the SL	5	33.5%	33	25.8%	10	21.8%
crowdedness in the store	5	33.5%	58	45.3%	17	37.0%
size of the SL	3	20.1%	35	27.4%	14	30.5%
familiarity with the SL	5	33.5%	40	31.3%	9	19.6%
price level of the assortment	5	33.5%	60	46.9%	17	37.0%
available product assortment	7	46.9%	68	53.1%	24	52.3%
time to find a parking lot	2	13.4%	45	35.2%	12	26.1%
capacity of the TM	4	26.8%	49	38.3%	15	32.7%
travel costs	1	6.7%	18	14.1%	3	6.5%
costs for petrol	1	6.7%	24	18.8%	4	8.7%
parking costs	5	33.5%	49	38.3%	12	26.1%
opening hours	7	46.9%	72	56.3%	33	71.9%
simplicity of the travel route	6	40.2%	54	42.2%	19	41.4%
leisure time	1	6.7%	37	28.9%	6	13.1%
sportiness	2	13.4%	23	18.0%	8	17.4%
travel time	3	20.1%	74	57.8%	24	52.3%
crowdedness on the way	3	20.1%	43	33.6%	12	26.1%

Table I-7. Cross-Table for attributes and the TM choice in HL distant.

attributes	car		non car		Total
	absolute	relative	absolute	relative	
available time to shop	87	62.2%	37	69.7%	124
weather	53	37.9%	31	58.4%	84
number of bags to carry	88	62.9%	29	54.6%	117
durability of bought products	23	16.4%	9	17.0%	32
required time to shop	71	50.7%	21	39.6%	92
departure time flexibility of the TM	43	30.7%	17	32.0%	60
accessibility of the store	76	54.3%	27	50.9%	103
atmosphere in the SL	36	25.7%	16	30.1%	52
crowdedness in the store	72	51.5%	17	32.0%	89
size of the SL	28	20.0%	8	15.1%	36
familiarity with the SL	45	32.2%	16	30.1%	61
price level of the assortment	64	45.7%	26	49.0%	90
available product assortment	71	50.7%	27	50.9%	98
time to find a parking lot	54	38.6%	12	22.6%	66
capacity of the TM	45	32.2%	8	15.1%	53
travel costs	14	10.0%	10	18.8%	24
costs for petrol	14	10.0%	13	24.5%	27
parking costs	43	30.7%	18	33.9%	61
opening hours	92	65.7%	33	62.2%	125
simplicity of the travel route	49	35.0%	24	45.2%	73
leisure time	36	25.7%	13	24.5%	49
sportiness	10	7.1%	14	26.4%	24
travel time	76	54.3%	30	56.5%	106
crowdedness on the way	37	26.4%	17	32.0%	54

Table I-8. Cross-Table for attributes and the SL choice in HL distant.

attributes	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
available time to shop	48	60.1%	76	67.3%	124
weather	38	47.6%	46	40.7%	84
number of bags to carry	46	57.6%	71	62.9%	117
durability of bought products	15	18.8%	17	15.1%	32
required time to shop	34	42.6%	58	51.4%	92
departure time flexibility of the TM	23	28.8%	37	32.8%	60
accessibility of the store	49	61.3%	54	47.8%	103
atmosphere in the SL	23	28.8%	29	25.7%	52
crowdedness in the store	31	38.8%	58	51.4%	89
size of the SL	9	11.3%	27	23.9%	36
familiarity with the SL	28	35.0%	33	29.2%	61
price level of the assortment	31	38.8%	59	52.3%	90
available product assortment	33	41.3%	65	57.6%	98
time to find a parking lot	26	32.5%	40	35.4%	66
capacity of the TM	16	20.0%	37	32.8%	53
travel costs	13	16.3%	11	9.7%	24
costs for petrol	15	18.8%	12	10.6%	27

Table I-8 (continued).

attributes	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
parking costs	24	30.0%	37	32.8%	61
opening hours	49	61.3%	76	67.3%	125
simplicity of the travel route	38	47.6%	35	31.0%	73
leisure time	22	27.5%	27	23.9%	49
sportiness	13	16.3%	11	9.7%	24
travel time	52	65.1%	54	47.8%	106
crowdedness on the way	23	28.8%	31	27.5%	54

Table I-9. Cross-Table for attributes and the TS choice in HL distant.

attributes	lunchbreak		after work		evening	
	absolute	relative	absolute	relative	absolute	relative
available time to shop	9	63.9%	76	64.4%	39	64.0%
weather	9	63.9%	55	46.6%	20	32.8%
number of bags to carry	10	71.0%	75	63.6%	32	52.5%
durability of bought products	3	21.3%	24	20.4%	5	8.2%
required time to shop	6	42.6%	51	43.2%	35	57.4%
departure time flexibility of the TM	3	21.3%	35	29.7%	22	36.1%
accessibility of the store	4	28.4%	67	56.8%	32	52.5%
atmosphere in the SL	5	35.5%	33	28.0%	14	23.0%
crowdedness in the store	5	35.5%	49	41.6%	35	57.4%
size of the SL	3	21.3%	18	15.3%	15	24.6%
familiarity with the SL	3	21.3%	42	35.6%	16	26.3%
price level of the assortment	5	35.5%	58	49.2%	27	44.3%
available product assortment	6	42.6%	63	53.4%	29	47.6%
time to find a parking lot	4	28.4%	41	34.8%	21	34.5%
capacity of the TM	4	28.4%	29	24.6%	20	32.8%
travel costs	2	14.2%	16	13.6%	6	9.8%
costs for petrol	1	7.1%	16	13.6%	10	16.4%
parking costs	2	14.2%	37	31.4%	22	36.1%
opening hours	4	28.4%	77	65.3%	44	72.2%
simplicity of the travel route	3	21.3%	53	44.9%	17	27.9%
leisure time	1	7.1%	37	31.4%	11	18.1%
sportiness	2	14.2%	17	14.4%	5	8.2%
travel time	3	21.3%	67	56.8%	36	59.1%
crowdedness on the way	7	49.7%	31	26.3%	16	26.3%

Table I-10. Cross-Table for attributes and the TM choice in CNET basic.

attributes	car		non car		Total
	absolute	relative	absolute	relative	
distance from current location	25	21.0%	21	31.8%	46
available time to shop	19	16.0%	5	7.6%	24
time pressure	7	5.9%	4	6.1%	11
weather	10	8.4%	8	12.1%	18
number of bags to carry	23	19.3%	21	31.8%	44
durability of bought products	6	5.0%	8	12.1%	14
required time to shop	8	6.7%	5	7.6%	13
accessibility of the store	21	17.7%	15	22.7%	36
crowdedness in the store	10	8.4%	7	10.6%	17
availability of the TM	13	10.9%	5	7.6%	18
product quality	9	7.6%	8	12.1%	17
price level of the assortment	21	17.7%	11	16.7%	32
available product assortment	37	31.1%	17	25.7%	54
capacity of the TM	12	10.1%	5	7.6%	17
habituation to the TM	8	6.7%	4	6.1%	12
possibility to store shoppings	7	5.9%	4	6.1%	11
simplicity of the travel route	16	13.5%	8	12.1%	24
recreation time during work	13	10.9%	10	15.1%	23
necessity	4	3.4%	7	10.6%	11
leisure time	21	17.7%	9	13.6%	30
travel time	8	6.7%	9	13.6%	17
parking opportunities	19	16.0%	14	21.2%	33
conflict with other agreements	11	9.2%	9	13.6%	20
combination with other activities	5	4.2%	6	9.1%	11
working hours	8	6.7%	5	7.6%	13

Table I-11. Cross-Table for attributes and the SL choice in CNET basic.

attributes	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
distance from current location	32	39.0%	14	13.6%	46
available time to shop	8	9.8%	16	15.5%	24
time pressure	3	3.7%	8	7.8%	11
weather	8	9.8%	10	9.7%	18
number of bags to carry	21	25.6%	23	22.3%	44
durability of bought products	8	9.8%	6	5.8%	14
required time to shop	6	7.3%	7	6.8%	13
accessibility of the store	18	22.0%	18	17.5%	36
crowdedness in the store	6	7.3%	11	10.7%	17
availability of the TM	7	8.5%	11	10.7%	18
product quality	8	9.8%	9	8.7%	17
price level of the assortment	11	13.4%	21	20.4%	32
available product assortment	12	14.6%	42	40.8%	54
capacity of the TM	8	9.8%	9	8.7%	17
habituation to the TM	3	3.7%	9	8.7%	12
possibility to store shoppings	6	7.3%	5	4.9%	11

Table I-11 (continued).

attributes	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
simplicity of the travel route	16	19.5%	8	7.8%	24
recreation time during work	13	15.9%	10	9.7%	23
necessity	7	8.5%	4	3.9%	11
leisure time	10	12.2%	20	19.4%	30
travel time	11	13.4%	6	5.8%	17
parking opportunities	15	18.3%	18	17.5%	33
conflict with other agreements	10	12.2%	10	9.7%	20
combination with other activities	5	6.1%	6	5.8%	11
working hours	6	7.3%	7	6.8%	13

Table I-12. Cross-Table for attributes and the TS choice in CNET basic.

attributes	during/after work		evening		Total
	absolute	relative	absolute	relative	
distance from current location	37	26.8%	9	19.2%	46
available time to shop	16	11.6%	8	17.0%	24
weather	12	8.7%	6	12.8%	18
number of bags to carry	30	21.7%	14	29.8%	44
durability of bought products	12	8.7%	2	4.3%	14
accessibility of the store	27	19.6%	9	19.2%	36
crowdedness in the store	6	4.3%	11	23.4%	17
availability of the TM	15	10.9%	3	6.4%	18
product quality	14	10.1%	3	6.4%	17
price level of the assortment	24	17.4%	8	17.0%	32
available product assortment	39	28.3%	15	31.9%	54
capacity of the TM	10	7.2%	7	14.9%	17
simplicity of the travel route	23	16.7%	1	2.1%	24
recreation time during work	18	13.0%	5	10.6%	23
leisure time	26	18.8%	4	8.5%	30
travel time	12	8.7%	5	10.6%	17
parking opportunities	21	15.2%	12	25.5%	33
conflict with other agreements	15	10.9%	5	10.6%	20

Table I-13. Cross-Table for attributes and the TM choice in CNET uncertain.

attributes	**car**		**non car**		**Total**
	absolute	relative	absolute	relative	
distance from current location	20	17.7%	8	14.8%	28
available time to shop	10	8.8%	11	20.4%	21
weather	7	6.2%	6	11.1%	13
number of bags to carry	19	16.8%	12	22.2%	31
required time to shop	8	7.1%	3	5.6%	11
accessibility of the store	24	21.2%	11	20.4%	35
crowdedness in the store	10	8.8%	5	9.3%	15
availability of the TM	10	8.8%	8	14.8%	18
product quality	8	7.1%	3	5.6%	11
price level of the assortment	9	8.0%	10	18.5%	19
available product assortment	57	50.4%	20	37.1%	77
capacity of the TM	8	7.1%	4	7.4%	12
possibility to store shoppings	8	7.1%	4	7.4%	12
simplicity of the travel route	9	8.0%	6	11.1%	15
recreation time during work	10	8.8%	2	3.7%	12
necessity	12	10.6%	6	11.1%	18
leisure time	14	12.4%	7	13.0%	21
travel time	7	6.2%	8	14.8%	15
parking opportunities	16	14.2%	8	14.8%	24
conflict with other agreements	12	10.6%	5	9.3%	17
working hours	16	14.2%	2	3.7%	18
sort of bought products	10	8.8%	5	9.3%	15

Table I-14. Cross-Table for attributes and the SL choice in CNET uncertain.

attributes	**non supermarket**		**supermarket**		**Total**
	absolute	relative	absolute	relative	
distance from current location	13	22.1%	15	13.9%	28
available time to shop	7	11.9%	14	13.0%	21
weather	7	11.9%	6	5.6%	13
number of bags to carry	10	17.0%	21	19.4%	31
required time to shop	2	3.4%	9	8.3%	11
accessibility of the store	13	22.1%	22	20.4%	35
crowdedness in the store	5	8.5%	10	9.3%	15
availability of the TM	10	17.0%	8	7.4%	18
product quality	1	1.7%	10	9.3%	11
price level of the assortment	7	11.9%	12	11.1%	19
available product assortment	15	25.4%	62	57.4%	77
capacity of the TM	6	10.2%	6	5.6%	12
possibility to store shoppings	7	11.9%	5	4.6%	12
simplicity of the travel route	3	5.1%	12	11.1%	15
recreation time during work	4	6.8%	8	7.4%	12
necessity	6	10.2%	12	11.1%	18
leisure time	7	11.9%	14	13.0%	21
travel time	6	10.2%	9	8.3%	15
parking opportunities	6	10.2%	18	16.7%	24
conflict with other agreements	6	10.2%	11	10.2%	17
working hours	6	10.2%	12	11.1%	18
sort of bought products	5	8.5%	10	9.3%	15

Table I-15. Cross-Table for attributes and the TS choice in CNET uncertain.

attributes	**during/after work**		**evening**		**Total**
	absolute	relative	absolute	relative	
distance from current location	22	17.7%	6	14.0%	28
available time to shop	17	13.7%	4	9.3%	21
number of bags to carry	24	19.3%	7	16.3%	31
accessibility of the store	27	21.8%	8	18.6%	35
available product assortment	59	47.5%	18	41.9%	77
leisure time	20	16.1%	1	2.3%	21
parking opportunities	17	13.7%	7	16.3%	24

Table I-16. Cross-Table for attributes and the TM choice in CNET distant.

attributes	car		non car		Total
	absolute	relative	absolute	relative	
distance from current location	29	21.3%	19	32.8%	48
available time to shop	18	13.2%	14	24.1%	32
time pressure	9	6.6%	4	6.9%	13
weather	11	8.1%	8	13.8%	19
number of bags to carry	31	22.8%	12	20.7%	43
required time to shop	19	14.0%	5	8.6%	24
accessibility of the store	25	18.4%	13	22.4%	38
crowdedness in the store	22	16.2%	9	15.5%	31
availability of the TM	9	6.6%	5	8.6%	14
product quality	7	5.1%	6	10.3%	13
price level of the assortment	30	22.1%	9	15.5%	39
available product assortment	58	42.6%	9	15.5%	67
capacity of the TM	17	12.5%	4	6.9%	21
habituation to the TM	9	6.6%	6	10.3%	15
simplicity of the travel route	16	11.8%	9	15.5%	25
necessity	12	8.8%	4	6.9%	16
leisure time	14	10.3%	8	13.8%	22
travel time	16	11.8%	8	13.8%	24
parking opportunities	19	14.0%	11	19.0%	30
time of the day	8	5.9%	3	5.2%	11
conflict with other agreements	11	8.1%	7	12.1%	18
combination with other activities	7	5.1%	5	8.6%	12
working hours	13	9.6%	5	8.6%	18
sort of bought products	9	6.6%	6	10.3%	15

Table I-17. Cross-Table for attributes and the SL choice in CNET distant.

attributes	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
distance from current location	27	31.7%	21	19.3%	48
available time to shop	13	15.3%	19	17.4%	32
time pressure	5	5.9%	8	7.3%	13
weather	7	8.2%	12	11.0%	19
number of bags to carry	16	18.8%	27	24.8%	43
required time to shop	12	14.1%	12	11.0%	24
accessibility of the store	16	18.8%	22	20.2%	38
crowdedness in the store	10	11.7%	21	19.3%	31
availability of the TM	6	7.0%	8	7.3%	14
product quality	5	5.9%	8	7.3%	13
price level of the assortment	14	16.4%	25	22.9%	39
available product assortment	13	15.3%	54	49.5%	67
capacity of the TM	7	8.2%	14	12.8%	21
habituation to the TM	8	9.4%	7	6.4%	15
simplicity of the travel route	18	21.1%	7	6.4%	25
necessity	7	8.2%	9	8.3%	16
leisure time	12	14.1%	10	9.2%	22
travel time	13	15.3%	11	10.1%	24

Table I-17 (continued).

attributes	non supermarket absolute	non supermarket relative	supermarket absolute	supermarket relative	Total
parking opportunities	11	12.9%	19	17.4%	30
time of the day	5	5.9%	6	5.5%	11
conflict with other agreements	10	11.7%	8	7.3%	18
combination with other activities	7	8.2%	5	4.6%	12
working hours	4	4.7%	14	12.8%	18
sort of bought products	4	4.7%	11	10.1%	15

Table I-18. Cross-Table for attributes and the TS choice in CNET distant.

attributes	during/after work absolute	during/after work relative	evening absolute	evening relative	Total
distance from current location	39	29.1%	9	15.0%	48
available time to shop	23	17.2%	9	15.0%	32
time pressure	6	4.5%	7	11.7%	13
weather	15	11.2%	4	6.7%	19
number of bags to carry	31	23.2%	12	20.0%	43
required time to shop	16	12.0%	8	13.3%	24
accessibility of the store	27	20.2%	11	18.3%	38
crowdedness in the store	13	9.7%	18	30.0%	31
availability of the TM	13	9.7%	1	1.7%	14
product quality	9	6.7%	4	6.7%	13
price level of the assortment	25	18.7%	14	23.4%	39
available product assortment	40	29.9%	27	45.0%	67
capacity of the TM	5	3.7%	16	26.7%	21
habituation to the TM	11	8.2%	4	6.7%	15
simplicity of the travel route	21	15.7%	4	6.7%	25
necessity	14	10.5%	2	3.3%	16
leisure time	19	14.2%	3	5.0%	22
travel time	19	14.2%	5	8.3%	24
parking opportunities	17	12.7%	13	21.7%	30
time of the day	7	5.2%	4	6.7%	11
conflict with other agreements	15	11.2%	3	5.0%	18
combination with other activities	9	6.7%	3	5.0%	12
working hours	17	12.7%	1	1.7%	18
sort of bought products	8	6.0%	7	11.7%	15

Table I-19. Cross-Table for attributes and the TM choice in CNET e-commerce.

attributes	car		non car		Total
	absolute	relative	absolute	relative	
distance from current location	34	19.9%	35	29.4%	69
available time to shop	30	17.5%	20	16.8%	50
time pressure	15	8.8%	8	6.7%	23
internet access	7	4.1%	4	3.4%	11
weather	16	9.4%	21	17.7%	37
number of bags to carry	42	24.5%	39	32.8%	81
durability of bought products	15	8.8%	6	5.0%	21
required time to shop	15	8.8%	7	5.9%	22
physical condition	4	2.3%	6	5.0%	10
service level in the store	3	1.8%	8	6.7%	11
departure time flexibility of the TM	9	5.3%	2	1.7%	11
accessibility of the store	16	9.4%	22	18.5%	38
atmosphere in the SL	3	1.8%	8	6.7%	11
crowdedness in the store	18	10.5%	12	10.1%	30
availability of the TM	17	9.9%	4	3.4%	21
special offers	4	2.3%	6	5.0%	10
familiarity with the SL	10	5.8%	5	4.2%	15
product quality	16	9.4%	16	13.5%	32
price level of the assortment	36	21.0%	27	22.7%	63
available product assortment	63	36.8%	26	21.9%	89
time to find a parking lot	7	4.1%	4	3.4%	11
capacity of the TM	20	11.7%	11	9.3%	31
habituation to the TM	19	11.1%	13	10.9%	32
possibility to store shoppings	11	6.4%	6	5.0%	17
opening hours	9	5.3%	3	2.5%	12
simplicity of the travel route	20	11.7%	19	16.0%	39
recreation time during work	19	11.1%	15	12.6%	34
necessity	16	9.4%	11	9.3%	27
leisure time	30	17.5%	19	16.0%	49
sportiness	0	0.0%	10	8.4%	10
travel time	13	7.6%	8	6.7%	21
parking opportunities	27	15.8%	16	13.5%	43
conflict with other agreements	24	14.0%	14	11.8%	38
combination with other activities	8	4.7%	12	10.1%	20
working hours	10	5.8%	8	6.7%	18
sort of bought products	10	5.8%	9	7.6%	19

Table I-20. Cross-Table for attributes and the SL choice in CNET e-commerce.

attributes	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
distance from current location	42	34.2%	27	16.2%	69
available time to shop	26	21.2%	24	14.4%	50
time pressure	10	8.2%	13	7.8%	23
internet access	6	4.9%	5	3.0%	11
weather	17	13.9%	20	12.0%	37
number of bags to carry	32	26.1%	49	29.3%	81
durability of bought products	7	5.7%	14	8.4%	21
required time to shop	4	3.3%	18	10.8%	22
physical condition	4	3.3%	6	3.6%	10
service level in the store	7	5.7%	4	2.4%	11
departure time flexibility of the TM	4	3.3%	7	4.2%	11
accessibility of the store	18	14.7%	20	12.0%	38
atmosphere in the SL	7	5.7%	4	2.4%	11
crowdedness in the store	9	7.3%	21	12.6%	30
availability of the TM	8	6.5%	13	7.8%	21
special offers	3	2.4%	7	4.2%	10
familiarity with the SL	10	8.2%	5	3.0%	15
product quality	17	13.9%	15	9.0%	32
price level of the assortment	22	17.9%	41	24.5%	63
available product assortment	16	13.0%	73	43.7%	89
time to find a parking lot	5	4.1%	6	3.6%	11
capacity of the TM	10	8.2%	21	12.6%	31
habituation to the TM	16	13.0%	16	9.6%	32
possibility to store shoppings	6	4.9%	11	6.6%	17
opening hours	4	3.3%	8	4.8%	12
simplicity of the travel route	18	14.7%	21	12.6%	39
recreation time during work	21	17.1%	13	7.8%	34
necessity	13	10.6%	14	8.4%	27
leisure time	19	15.5%	30	18.0%	49
sportiness	8	6.5%	2	1.2%	10
travel time	9	7.3%	12	7.2%	21
parking opportunities	13	10.6%	30	18.0%	43
conflict with other agreements	15	12.2%	23	13.8%	38
combination with other activities	12	9.8%	8	4.8%	20
working hours	10	8.2%	8	4.8%	18
sort of bought products	7	5.7%	12	7.2%	19

Table I-21. Cross-Table for attributes and the TS choice in CNET e-commerce.

attributes	during/after work		evening		Total
	absolute	relative	absolute	relative	
distance from current location	56	25.8%	13	17.8%	69
available time to shop	42	19.4%	8	10.9%	50
time pressure	21	9.7%	2	2.7%	23
weather	27	12.4%	10	13.7%	37
number of bags to carry	67	30.9%	14	19.2%	81
durability of bought products	15	6.9%	6	8.2%	21
required time to shop	15	6.9%	7	9.6%	22
accessibility of the store	30	13.8%	8	10.9%	38
crowdedness in the store	18	8.3%	12	16.4%	30
availability of the TM	18	8.3%	3	4.1%	21
familiarity with the SL	10	4.6%	5	6.8%	15
product quality	26	12.0%	6	8.2%	32
price level of the assortment	49	22.6%	14	19.2%	63
available product assortment	69	31.8%	20	27.4%	89
capacity of the TM	18	8.3%	13	17.8%	31
habituation to the TM	22	10.1%	10	13.7%	32
possibility to store shoppings	15	6.9%	2	2.7%	17
opening hours	9	4.1%	3	4.1%	12
simplicity of the travel route	35	16.1%	4	5.5%	39
recreation time during work	25	11.5%	9	12.3%	34
necessity	20	9.2%	7	9.6%	27
leisure time	44	20.3%	5	6.8%	49
travel time	18	8.3%	3	4.1%	21
parking opportunities	36	16.6%	7	9.6%	43
conflict with other agreements	31	14.3%	7	9.6%	38
combination with other activities	15	6.9%	5	6.8%	20
working hours	17	7.8%	1	1.4%	18
sort of bought products	11	5.1%	8	10.9%	19

Table I-22. Cross-Table for attributes and the TM choice in CNET risky.

attributes	car		non car		Total
	absolute	relative	absolute	relative	
distance from current location	33	16.7%	21	18.1%	54
available time to shop	46	23.2%	17	14.6%	63
time pressure	28	14.1%	21	18.1%	49
weather	13	6.6%	16	13.8%	29
number of bags to carry	39	19.7%	14	12.1%	53
durability of bought products	10	5.0%	10	8.6%	20
required time to shop	20	10.1%	15	12.9%	35
chance of unexpected events	9	4.5%	5	4.3%	14
departure time flexibility of the TM	11	5.6%	9	7.7%	20
accessibility of the store	32	16.2%	14	12.1%	46
crowdedness in the store	7	3.5%	9	7.7%	16
availability of the TM	16	8.1%	8	6.9%	24
special offers	8	4.0%	3	2.6%	11
familiarity with the SL	8	4.0%	5	4.3%	13
product quality	20	10.1%	15	12.9%	35
price level of the assortment	23	11.6%	14	12.1%	37
available product assortment	105	53.0%	69	59.4%	174
time to find a parking lot	9	4.5%	6	5.2%	15
capacity of the TM	23	11.6%	5	4.3%	28
habituation to the TM	16	8.1%	10	8.6%	26
possibility to store shoppings	16	8.1%	5	4.3%	21
opening hours	5	2.5%	8	6.9%	13
simplicity of the travel route	25	12.6%	17	14.6%	42
recreation time during work	19	9.6%	12	10.3%	31
necessity	9	4.5%	8	6.9%	17
leisure time	25	12.6%	17	14.6%	42
travel time	28	14.1%	17	14.6%	45
parking opportunities	23	11.6%	27	23.2%	50
conflict with other agreements	21	10.6%	9	7.7%	30
combination with other activities	8	4.0%	3	2.6%	11
physical demands	6	3.0%	5	4.3%	11
working hours	15	7.6%	6	5.2%	21
sort of bought products	7	3.5%	4	3.4%	11

Table I-23. Cross-Table for attributes and the SL choice in CNET risky.

attributes	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
distance from current location	24	23.5%	30	14.2%	54
available time to shop	19	18.6%	44	20.8%	63
time pressure	16	15.7%	33	15.6%	49
weather	11	10.8%	18	8.5%	29
number of bags to carry	15	14.7%	38	17.9%	53
durability of bought products	5	4.9%	15	7.1%	20
required time to shop	13	12.7%	22	10.4%	35
chance of unexpected events	9	8.8%	5	2.4%	14
departure time flexibility of the TM	8	7.8%	12	5.7%	20
accessibility of the store	16	15.7%	30	14.2%	46
crowdedness in the store	5	4.9%	11	5.2%	16
availability of the TM	7	6.9%	17	8.0%	24
special offers	4	3.9%	7	3.3%	11
familiarity with the SL	6	5.9%	7	3.3%	13
product quality	16	15.7%	19	9.0%	35
price level of the assortment	9	8.8%	28	13.2%	37
available product assortment	37	36.3%	137	64.6%	174
time to find a parking lot	5	4.9%	10	4.7%	15
capacity of the TM	6	5.9%	22	10.4%	28
habituation to the TM	12	11.8%	14	6.6%	26
possibility to store shoppings	4	3.9%	17	8.0%	21
opening hours	5	4.9%	8	3.8%	13
simplicity of the travel route	16	15.7%	26	12.3%	42
recreation time during work	12	11.8%	19	9.0%	31
necessity	7	6.9%	10	4.7%	17
leisure time	12	11.8%	30	14.2%	42
travel time	17	16.7%	28	13.2%	45
parking opportunities	15	14.7%	35	16.5%	50
conflict with other agreements	10	9.8%	20	9.4%	30
combination with other activities	1	1.0%	10	4.7%	11
physical demands	3	2.9%	8	3.8%	11
working hours	7	6.9%	14	6.6%	21
sort of bought products	3	2.9%	8	3.8%	11

Table I-24. Cross-Table for attributes and the TS choice in CNET risky.

attributes	lunchbreak		after work/evening		Total
	absolute	relative	absolute	relative	
distance from current location	8	10.5%	46	19.3%	54
available time to shop	13	17.1%	50	21.0%	63
time pressure	15	19.7%	34	14.3%	49
weather	5	6.6%	24	10.1%	29
number of bags to carry	14	18.4%	39	16.4%	53
durability of bought products	3	3.9%	17	7.1%	20
required time to shop	5	6.6%	30	12.6%	35
chance of unexpected events	8	10.5%	6	2.5%	14
departure time flexibility of the TM	6	7.9%	14	5.9%	20
accessibility of the store	12	15.8%	34	14.3%	46
crowdedness in the store	4	5.3%	12	5.0%	16
availability of the TM	8	10.5%	16	6.7%	24
familiarity with the SL	2	2.6%	11	4.6%	13
product quality	9	11.8%	26	10.9%	35
price level of the assortment	6	7.9%	31	13.0%	37
available product assortment	44	57.9%	130	54.6%	174
time to find a parking lot	3	3.9%	12	5.0%	15
capacity of the TM	3	3.9%	25	10.5%	28
habituation to the TM	1	1.3%	25	10.5%	26
possibility to store shoppings	6	7.9%	15	6.3%	21
opening hours	2	2.6%	11	4.6%	13
simplicity of the travel route	8	10.5%	34	14.3%	42
recreation time during work	13	17.1%	18	7.6%	31
necessity	3	3.9%	14	5.9%	17
leisure time	4	5.3%	38	16.0%	42
travel time	10	13.2%	35	14.7%	45
parking opportunities	13	17.1%	37	15.5%	50
conflict with other agreements	10	13.2%	20	8.4%	30
working hours	4	5.3%	17	7.1%	21

J. Cross-tables for benefits and choice outcomes.

Table J-1. Cross-Table for benefits and the TM choice in HL basic.

benefits	car		non car		Total
	absolute	relative	absolute	relative	
safety in the SL	8	5.5%	5	7.3%	13
travel pleasure	47	32.4%	34	49.9%	81
ease of shopping	129	88.9%	55	80.7%	184
shopping comfort	52	35.8%	23	33.7%	75
shopping pleasure	61	42.1%	33	48.4%	94
attractivity of the SL environment	28	19.3%	17	24.9%	45
diversity in product choice	77	53.1%	26	38.1%	103
shopping success	90	62.0%	45	66.0%	135
travel comfort	82	56.5%	33	48.4%	115
ease of travelling	112	77.2%	53	77.8%	165
safety in travelling	29	20.0%	13	19.1%	42
environmental protection	11	7.6%	11	16.1%	22
health	39	26.9%	29	42.5%	68
personal care	13	9.0%	12	17.6%	25
mental ease	44	30.3%	21	30.8%	65
relaxation/recreation	62	42.7%	37	54.3%	99
course of fitness/wellbeing	18	12.4%	21	30.8%	39
financial savings	92	63.4%	35	51.3%	127
social acceptance	0	0.0%	1	1.5%	1
time savings	118	81.3%	54	79.2%	172
taste experience	35	24.1%	16	23.5%	51

Table J-2. Cross-Table for benefits and the SL choice in HL basic.

benefits	cornershop		weekmarket		supermarket	
	absolute	relative	absolute	relative	absolute	relative
safety in the SL	5	6.8%	1	5.5%	7	5.8%
travel pleasure	30	40.6%	9	49.7%	42	34.7%
ease of shopping	65	87.9%	15	82.9%	104	86.0%
shopping comfort	23	31.1%	5	27.6%	47	38.8%
shopping pleasure	30	40.6%	8	44.2%	56	46.3%
attractivity of SL environment	14	18.9%	5	27.6%	26	21.5%
diversity in product choice	26	35.2%	10	55.2%	67	55.4%
shopping success	43	58.2%	14	77.3%	78	64.5%
travel comfort	40	54.1%	11	60.8%	64	52.9%
ease of travelling	57	77.1%	15	82.9%	93	76.9%
safety in travelling	15	20.3%	7	38.7%	20	16.5%
environmental protection	9	12.2%	3	16.6%	10	8.3%
health	26	35.2%	6	33.1%	36	29.8%
personal care	11	14.9%	5	27.6%	9	7.4%
mental ease	27	36.5%	7	38.7%	31	25.6%
relaxation/recreation	31	41.9%	10	55.2%	58	47.9%
course of fitness/wellbeing	18	24.4%	4	22.1%	17	14.1%
financial savings	35	47.4%	15	82.9%	77	63.6%
social acceptance	0	0.0%	0	0.0%	1	0.8%
time savings	62	83.9%	14	77.3%	96	79.3%
taste experience	14	18.9%	8	44.2%	29	24.0%

Table J-3. Cross-Table for benefits and the TS choice in HL basic.

benefits	lunchbreak		after work		evening	
	absolute	relative	absolute	relative	absolute	relative
safety in the SL	1	6.3%	7	4.6%	5	11.1%
travel pleasure	6	37.6%	58	38.1%	17	37.8%
ease of shopping	15	93.9%	128	84.2%	41	91.2%
shopping comfort	5	31.3%	54	35.5%	16	35.6%
shopping pleasure	6	37.6%	61	40.1%	27	60.1%
attractivity of SL environment	2	12.5%	35	23.0%	8	17.8%
diversity in product choice	8	50.1%	71	46.7%	24	53.4%
shopping success	10	62.6%	90	59.2%	35	77.9%
travel comfort	7	43.8%	86	56.5%	22	49.0%
ease of travelling	12	75.1%	120	78.9%	33	73.4%
safety in travelling	2	12.5%	28	18.4%	12	26.7%
environmental protection	0	0.0%	18	11.8%	4	8.9%
health	5	31.3%	50	32.9%	13	28.9%
personal care	2	12.5%	15	9.9%	8	17.8%
mental ease	3	18.8%	46	30.2%	16	35.6%
relaxation/recreation	11	68.9%	68	44.7%	20	44.5%
course of fitness/wellbeing	4	25.0%	28	18.4%	7	15.6%
financial savings	10	62.6%	86	56.5%	31	69.0%
time savings	14	87.6%	124	81.5%	34	75.7%
taste experience	3	18.8%	38	25.0%	10	22.3%

Table J-4. Cross-Table for benefits and the TM choice in HL uncertain.

benefits	car		non car		Total
	absolute	relative	absolute	relative	
safety in the SL	7	5.3%	5	8.8%	12
travel pleasure	44	33.4%	24	42.0%	68
ease of shopping	109	82.6%	52	91.1%	161
shopping comfort	43	32.6%	21	36.8%	64
shopping pleasure	59	44.7%	25	43.8%	84
attractivity of the SL environment	30	22.7%	13	22.8%	43
diversity in product choice	67	50.8%	31	54.3%	98
shopping success	100	75.8%	38	66.6%	138
travel comfort	75	56.9%	26	45.6%	101
ease of travelling	112	84.9%	46	80.6%	158
safety in travelling	25	19.0%	10	17.5%	35
environmental protection	14	10.6%	19	33.3%	33
health	30	22.7%	27	47.3%	57
personal care	20	15.2%	9	15.8%	29
mental ease	46	34.9%	15	26.3%	61
relaxation/recreation	50	37.9%	32	56.1%	82
course of fitness/wellbeing	19	14.4%	15	26.3%	34
financial savings	75	56.9%	34	59.6%	109
social acceptance	1	0.8%	1	1.8%	2
time savings	105	79.6%	47	82.3%	152
taste experience	19	14.4%	15	26.3%	34

Table J-5. Cross-Table for benefits and the SL choice in HL uncertain.

benefits	non supermarket		supermarkt		Total
	absolute	relative	absolute	relative	
safety in the SL	3	4.7%	9	7.2%	12
travel pleasure	26	40.6%	42	33.6%	68
ease of shopping	50	78.0%	111	88.9%	161
shopping comfort	22	34.3%	42	33.6%	64
shopping pleasure	30	46.8%	54	43.2%	84
attractivity of the SL environment	12	18.7%	31	24.8%	43
diversity in product choice	29	45.3%	69	55.2%	98
shopping success	44	68.7%	94	75.2%	138
travel comfort	35	54.6%	66	52.8%	101
ease of travelling	52	81.2%	106	84.8%	158
safety in travelling	17	26.5%	18	14.4%	35
environmental protection	14	21.9%	19	15.2%	33
health	22	34.3%	35	28.0%	57
personal care	8	12.5%	21	16.8%	29
mental ease	21	32.8%	40	32.0%	61
relaxation/recreation	30	46.8%	52	41.6%	82
course of fitness/wellbeing	12	18.7%	22	17.6%	34
financial savings	34	53.1%	75	60.0%	109
social acceptance	1	1.6%	1	0.8%	2
time savings	52	81.2%	100	80.0%	152
taste experience	12	18.7%	22	17.6%	34

Table J-6. Cross-Table for benefits and the TS choice in HL uncertain.

benefits	lunchbreak		after work		evening	
	absolute	relative	absolute	relative	absolute	relative
safety in the SL	0	0.0%	8	6.3%	4	8.7%
travel pleasure	4	26.8%	51	39.9%	13	28.3%
ease of shopping	12	80.4%	112	87.5%	37	80.6%
shopping comfort	4	26.8%	46	36.0%	14	30.5%
shopping pleasure	8	53.6%	58	45.3%	18	39.2%
attractivity of SL environment	2	13.4%	31	24.2%	10	21.8%
diversity in product choice	7	46.9%	68	53.1%	23	50.1%
shopping success	10	67.0%	94	73.5%	34	74.0%
travel comfort	9	60.3%	72	56.3%	20	43.5%
ease of travelling	13	87.1%	107	83.6%	38	82.7%
safety in travelling	3	20.1%	26	20.3%	6	13.1%
environmental protection	3	20.1%	26	20.3%	4	8.7%
health	3	20.1%	42	32.8%	12	26.1%
personal care	2	13.4%	21	16.4%	6	13.1%
mental ease	5	33.5%	46	36.0%	10	21.8%
relaxation/recreation	6	40.2%	60	46.9%	16	34.8%
course of fitness/wellbeing	2	13.4%	27	21.1%	5	10.9%
financial savings	5	33.5%	81	63.3%	23	50.1%
time savings	9	60.3%	110	86.0%	33	71.9%
taste experience	4	26.8%	25	19.5%	5	10.9%

Table J-7. Cross-Table for benefits and the TM choice in HL distant.

benefits	car		non car		Total
	absolute	relative	absolute	relative	
safety in the SL	18	12.9%	4	7.5%	22
travel pleasure	54	38.6%	25	47.1%	79
ease of shopping	127	90.8%	44	82.9%	171
shopping comfort	56	40.0%	21	39.6%	77
shopping pleasure	65	46.5%	29	54.6%	94
attractivity of the SL environment	38	27.2%	11	20.7%	49
diversity in product choice	71	50.7%	27	50.9%	98
shopping success	91	65.0%	36	67.8%	127
travel comfort	84	60.0%	28	52.8%	112
ease of travelling	123	87.9%	49	92.3%	172
safety in travelling	38	27.2%	14	26.4%	52
environmental protection	15	10.7%	11	20.7%	26
health	31	22.2%	18	33.9%	49
personal care	19	13.6%	9	17.0%	28
mental ease	46	32.9%	17	32.0%	63
relaxation/recreation	53	37.9%	28	52.8%	81
course of fitness/wellbeing	31	22.2%	11	20.7%	42
financial savings	79	56.5%	35	65.9%	114
time savings	112	80.0%	43	81.0%	155
taste experience	18	12.9%	9	17.0%	27

Table J-8. Cross-Table for benefits and the SL choice in HL distant.

benefits	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
safety in the SL	8	10.0%	14	12.4%	22
travel pleasure	30	37.5%	49	43.4%	79
ease of shopping	66	82.6%	105	93.0%	171
shopping comfort	31	38.8%	46	40.7%	77
shopping pleasure	34	42.6%	60	53.1%	94
attractivity of the SL environment	18	22.5%	31	27.5%	49
diversity in product choice	31	38.8%	67	59.3%	98
shopping success	50	62.6%	77	68.2%	127
travel comfort	41	51.3%	71	62.9%	112
ease of travelling	71	88.9%	101	89.5%	172
safety in travelling	21	26.3%	31	27.5%	52
environmental protection	13	16.3%	13	11.5%	26
health	25	31.3%	24	21.3%	49
personal care	15	18.8%	13	11.5%	28
mental ease	33	41.3%	30	26.6%	63
relaxation/recreation	39	48.8%	42	37.2%	81
course of fitness/wellbeing	17	21.3%	25	22.1%	42
financial savings	44	55.1%	70	62.0%	114
time savings	68	85.1%	87	77.1%	155
taste experience	12	15.0%	15	13.3%	27

Table J-9. Cross-Table for benefits and the TS choice in HL distant.

benefits	lunchbreak		after work		evening	
	absolute	relative	absolute	relative	absolute	relative
safety in the SL	2	14.2%	15	12.7%	5	8.2%
travel pleasure	9	63.9%	46	39.0%	24	39.4%
ease of shopping	9	63.9%	105	89.0%	57	93.5%
shopping comfort	4	28.4%	45	38.2%	28	45.9%
shopping pleasure	6	42.6%	62	52.6%	26	42.6%
attractivity of SL environment	2	14.2%	32	27.1%	15	24.6%
diversity in product choice	6	42.6%	59	50.0%	33	54.1%
shopping success	9	63.9%	82	69.5%	36	59.0%
travel comfort	6	42.6%	71	60.2%	35	57.4%
ease of travelling	12	85.2%	106	89.9%	54	88.5%
safety in travelling	5	35.5%	39	33.1%	8	13.1%
environmental protection	3	21.3%	18	15.3%	5	8.2%
health	4	28.4%	36	30.5%	9	14.8%
personal care	1	7.1%	21	17.8%	6	9.8%
mental ease	6	42.6%	37	31.4%	20	32.8%
relaxation/recreation	6	42.6%	53	44.9%	22	36.1%
course of fitness/wellbeing	5	35.5%	21	17.8%	16	26.2%
financial savings	9	63.9%	69	58.5%	36	59.0%
time savings	10	71.0%	96	81.4%	49	80.3%
taste experience	2	14.2%	20	17.0%	5	8.2%

Table J-10. Cross-Table for benefits and the TM choice in CNET basic.

benefits	car		non car		Total
	absolute	relative	absolute	relative	
safety in the SL	3	2.5%	6	3.2%	9
travel pleasure	15	12.6%	20	10.8%	35
ease of shopping	54	45.4%	28	15.1%	82
shopping comfort	23	19.3%	10	5.4%	33
shopping pleasure	31	26.1%	16	8.6%	47
attractivity of the SL environment	19	16.0%	8	4.3%	27
diversity in product choice	30	25.2%	14	7.6%	44
shopping success	41	34.5%	27	14.6%	68
travel comfort	29	24.4%	14	7.6%	43
ease of travelling	79	66.4%	41	22.2%	120
safety in travelling	13	10.9%	5	2.7%	18
environmental protection	5	4.2%	14	7.6%	19
health	16	13.5%	26	14.1%	42
personal care	4	3.4%	3	1.6%	7
mental ease	38	31.9%	17	9.2%	55
relaxation/recreation	39	32.8%	29	15.7%	68
course of fitness/wellbeing	21	17.7%	18	9.7%	39
financial savings	37	31.1%	21	11.4%	58
social acceptance	6	5.0%	4	2.2%	10
time savings	65	54.6%	40	21.6%	105
taste experience	8	6.7%	10	5.4%	18

Table J-11. Cross-Table for benefits and the SL choice in CNET basic.

benefits	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
safety in the SL	6	7.3%	3	2.9%	9
travel pleasure	20	24.4%	15	14.6%	35
ease of shopping	31	37.8%	51	49.5%	82
shopping comfort	8	9.8%	25	24.3%	33
shopping pleasure	19	23.2%	28	27.2%	47
attractivity of the SL environment	10	12.2%	17	16.5%	27
diversity in product choice	12	14.6%	32	31.1%	44
shopping success	27	32.9%	41	39.8%	68
travel comfort	19	23.2%	24	23.3%	43
ease of travelling	53	64.7%	67	65.0%	120
safety in travelling	5	6.1%	13	12.6%	18
environmental protection	15	18.3%	4	3.9%	19
health	28	34.2%	14	13.6%	42
personal care	4	4.9%	3	2.9%	7
mental ease	29	35.4%	26	25.2%	55
relaxation/recreation	31	37.8%	37	35.9%	68
course of fitness/wellbeing	19	23.2%	20	19.4%	39
financial savings	17	20.7%	41	39.8%	58
social acceptance	6	7.3%	4	3.9%	10
time savings	56	68.3%	49	47.6%	105
taste experience	8	9.8%	10	9.7%	18

Table J-12. Cross-Table for benefits and the TS choice in CNET basic.

benefits	lunchbreak/after work		evening		Total
	absolute	relative	absolute	relative	
safety in the SL	7	5.1%	2	4.3%	9
travel pleasure	26	18.8%	9	19.2%	35
ease of shopping	59	42.8%	23	48.9%	82
shopping comfort	24	17.4%	9	19.2%	33
shopping pleasure	33	23.9%	14	29.8%	47
attractivity of the SL environment	20	14.5%	7	14.9%	27
diversity in product choice	28	20.3%	16	34.0%	44
shopping success	53	38.4%	15	31.9%	68
travel comfort	29	21.0%	14	29.8%	43
ease of travelling	89	64.5%	31	66.0%	120
safety in travelling	10	7.2%	8	17.0%	18
environmental protection	12	8.7%	7	14.9%	19
health	33	23.9%	9	19.2%	42
personal care	5	3.6%	2	4.3%	7
mental ease	43	31.2%	12	25.5%	55
relaxation/recreation	50	36.2%	18	38.3%	68
course of fitness/wellbeing	30	21.7%	9	19.2%	39
financial savings	41	29.7%	17	36.2%	58
social acceptance	4	2.9%	6	12.8%	10
time savings	80	58.0%	25	53.2%	105
taste experience	15	10.9%	3	6.4%	18

Table J-13. Cross-Table for benefits and the TM choice in CNET uncertain.

benefits	car		non car		Total
	absolute	relative	absolute	relative	
safety in the SL	4	3.5%	1	1.9%	5
travel pleasure	19	16.8%	12	22.2%	31
ease of shopping	59	52.2%	29	53.8%	88
shopping comfort	31	27.4%	10	18.5%	41
shopping pleasure	24	21.2%	18	33.4%	42
attractivity of the SL environment	17	15.0%	9	16.7%	26
diversity in product choice	40	35.4%	24	44.5%	64
shopping success	60	53.1%	24	44.5%	84
travel comfort	28	24.8%	11	20.4%	39
ease of travelling	78	69.0%	37	68.6%	115
safety in travelling	8	7.1%	9	16.7%	17
environmental protection	5	4.4%	6	11.1%	11
health	15	13.3%	10	18.5%	25
personal care	4	3.5%	5	9.3%	9
mental ease	41	36.3%	20	37.1%	61
relaxation/recreation	37	32.7%	19	35.2%	56
course of fitness/wellbeing	16	14.2%	12	22.2%	28
financial savings	24	21.2%	18	33.4%	42
social acceptance	2	1.8%	5	9.3%	7
time savings	60	53.1%	35	64.9%	95
taste experience	7	6.2%	7	13.0%	14

Table J-14. Cross-Table for benefits and the SL choice in CNET uncertain.

benefits	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
safety in the SL	2	3.4%	3	2.8%	5
travel pleasure	14	23.7%	17	15.7%	31
ease of shopping	27	45.8%	61	56.5%	88
shopping comfort	7	11.9%	34	31.5%	41
shopping pleasure	14	23.7%	28	25.9%	42
attractivity of the SL environment	10	17.0%	16	14.8%	26
diversity in product choice	16	27.1%	48	44.4%	64
shopping success	19	32.2%	65	60.2%	84
travel comfort	12	20.4%	27	25.0%	39
ease of travelling	43	72.9%	72	66.6%	115
safety in travelling	8	13.6%	9	8.3%	17
environmental protection	3	5.1%	8	7.4%	11
health	9	15.3%	16	14.8%	25
personal care	3	5.1%	6	5.6%	9
mental ease	26	44.1%	35	32.4%	61
relaxation/recreation	20	33.9%	36	33.3%	56
course of fitness/wellbeing	9	15.3%	19	17.6%	28
financial savings	13	22.1%	29	26.8%	42
social acceptance	5	8.5%	2	1.9%	7
time savings	33	56.0%	62	57.4%	95
taste experience	5	8.5%	9	8.3%	14

Table J-15. Cross-Table for benefits and the TS choice in CNET uncertain.

benefits	lunchbreak/after work		evening		Total
	absolute	relative	absolute	relative	
safety in the SL	4	3.2%	1	2.3%	5
travel pleasure	25	20.1%	6	14.0%	31
ease of shopping	67	54.0%	21	48.9%	88
shopping comfort	27	21.8%	14	32.6%	41
shopping pleasure	32	25.8%	10	23.3%	42
attractivity of the SL environment	14	11.3%	12	28.0%	26
diversity in product choice	48	38.7%	16	37.3%	64
shopping success	66	53.2%	18	41.9%	84
travel comfort	29	23.4%	10	23.3%	39
ease of travelling	90	72.5%	25	58.2%	115
safety in travelling	12	9.7%	5	11.6%	17
environmental protection	6	4.8%	5	11.6%	11
health	18	14.5%	7	16.3%	25
personal care	8	6.4%	1	2.3%	9
mental ease	53	42.7%	8	18.6%	61
relaxation/recreation	41	33.0%	15	34.9%	56
course of fitness/wellbeing	22	17.7%	6	14.0%	28
financial savings	32	25.8%	10	23.3%	42
social acceptance	4	3.2%	3	7.0%	7
time savings	74	59.6%	21	48.9%	95
taste experience	11	8.9%	3	7.0%	14

Table J-16. Cross-Table for benefits and the TM choice in CNET distant.

benefits	car		non car		Total
	absolute	relative	absolute	relative	
safety in the SL	5	3.7%	3	5.2%	8
travel pleasure	21	15.4%	10	17.2%	31
ease of shopping	78	57.4%	27	46.5%	105
shopping comfort	41	30.1%	10	17.2%	51
shopping pleasure	29	21.3%	17	29.3%	46
attractivity of the SL environment	17	12.5%	7	12.1%	24
diversity in product choice	58	42.6%	9	15.5%	67
shopping success	58	42.6%	18	31.0%	76
travel comfort	46	33.8%	12	20.7%	58
ease of travelling	98	72.1%	40	69.0%	138
safety in travelling	19	14.0%	8	13.8%	27
environmental protection	9	6.6%	10	17.2%	19
health	15	11.0%	13	22.4%	28
personal care	4	2.9%	4	6.9%	8
mental ease	45	33.1%	21	36.2%	66
relaxation/recreation	39	28.7%	24	41.4%	63
course of fitness/wellbeing	15	11.0%	10	17.2%	25
financial savings	37	27.2%	16	27.6%	53
social acceptance	3	2.2%	4	6.9%	7
time savings	95	69.9%	40	69.0%	135
taste experience	14	10.3%	4	6.9%	18

Table J-17. Cross-Table for benefits and the SL choice in CNET distant.

benefits	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
safety in the SL	5	5.9%	3	2.8%	8
travel pleasure	15	17.6%	16	14.7%	31
ease of shopping	40	47.0%	65	59.6%	105
shopping comfort	13	15.3%	38	34.9%	51
shopping pleasure	21	24.7%	25	22.9%	46
attractivity of the SL environment	9	10.6%	15	13.8%	24
diversity in product choice	11	12.9%	56	51.4%	67
shopping success	19	22.3%	57	52.3%	76
travel comfort	20	23.5%	38	34.9%	58
ease of travelling	62	72.8%	76	69.7%	138
safety in travelling	13	15.3%	14	12.8%	27
environmental protection	13	15.3%	6	5.5%	19
health	13	15.3%	15	13.8%	28
personal care	7	8.2%	1	0.9%	8
mental ease	30	35.2%	36	33.0%	66
relaxation/recreation	29	34.1%	34	31.2%	63
course of fitness/wellbeing	11	12.9%	14	12.8%	25
financial savings	18	21.1%	35	32.1%	53
social acceptance	7	8.2%	0	0.0%	7
time savings	64	75.1%	71	65.1%	135
taste experience	4	4.7%	14	12.8%	18

Table J-18. Cross-Table for benefits and the TS choice in CNET distant.

benefits	lunchbreak/after work		evening		Total
	absolute	relative	absolute	relative	
safety in the SL	7	5.2%	1	1.7%	8
travel pleasure	22	16.4%	9	15.0%	31
ease of shopping	64	47.7%	41	68.4%	105
shopping comfort	28	20.9%	23	38.4%	51
shopping pleasure	31	23.1%	15	25.0%	46
attractivity of the SL environment	17	12.7%	7	11.7%	24
diversity in product choice	41	30.6%	26	43.4%	67
shopping success	50	37.3%	26	43.4%	76
travel comfort	44	32.8%	14	23.4%	58
ease of travelling	92	68.6%	46	76.7%	138
safety in travelling	16	11.9%	11	18.3%	27
environmental protection	15	11.2%	4	6.7%	19
health	24	17.9%	4	6.7%	28
personal care	6	4.5%	2	3.3%	8
mental ease	46	34.3%	20	33.4%	66
relaxation/recreation	42	31.3%	21	35.0%	63
course of fitness/wellbeing	21	15.7%	4	6.7%	25
financial savings	32	23.9%	21	35.0%	53
social acceptance	6	4.5%	1	1.7%	7
time savings	98	73.1%	37	61.7%	135
taste experience	15	11.2%	3	5.0%	18

Table J-19. Cross-Table for benefits and the TM choice in CNET e-commerce.

benefits	car		non car		Total
	absolute	relative	absolute	relative	
safety in the SL	6	3.5%	4	3.4%	10
travel pleasure	40	23.4%	38	32.0%	78
ease of shopping	108	63.1%	64	53.8%	172
shopping comfort	47	27.5%	24	20.2%	71
shopping pleasure	46	26.9%	48	40.4%	94
attractivity of the SL environment	20	11.7%	26	21.9%	46
diversity in product choice	67	39.2%	37	31.1%	104
shopping success	81	47.3%	46	38.7%	127
travel comfort	59	34.5%	35	29.4%	94
ease of travelling	115	67.2%	88	74.0%	203
safety in travelling	26	15.2%	11	9.3%	37
environmental protection	9	5.3%	21	17.7%	30
health	24	14.0%	39	32.8%	63
personal care	11	6.4%	7	5.9%	18
mental ease	58	33.9%	37	31.1%	95
relaxation/recreation	67	39.2%	57	47.9%	124
course of fitness/wellbeing	23	13.4%	27	22.7%	50
financial savings	64	37.4%	39	32.8%	103
social acceptance	11	6.4%	17	14.3%	28
time savings	121	70.7%	87	73.2%	208
taste experience	25	14.6%	19	16.0%	44

Table J-20. Cross-Table for benefits and the SL choice in CNET e-commerce.

benefits	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
safety in the SL	7	5.7%	3	1.8%	10
travel pleasure	38	30.9%	39	23.3%	77
ease of shopping	63	51.2%	107	64.1%	170
shopping comfort	20	16.3%	50	29.9%	70
shopping pleasure	40	32.5%	53	31.7%	93
attractivity of the SL environment	21	17.1%	25	15.0%	46
diversity in product choice	24	19.5%	80	47.9%	104
shopping success	37	30.1%	89	53.3%	126
travel comfort	30	24.4%	63	37.7%	93
ease of travelling	82	66.7%	119	71.2%	201
safety in travelling	10	8.1%	26	15.6%	36
environmental protection	21	17.1%	9	5.4%	30
health	33	26.8%	28	16.8%	61
personal care	7	5.7%	10	6.0%	17
mental ease	37	30.1%	55	32.9%	92
relaxation/recreation	57	46.4%	64	38.3%	121
course of fitness/wellbeing	28	22.8%	21	12.6%	49
financial savings	35	28.5%	68	40.7%	103
social acceptance	16	13.0%	12	7.2%	28
time savings	89	72.4%	116	69.4%	205
taste experience	21	17.1%	23	13.8%	44

Table J-21. Cross-Table for benefits and the TS choice in CNET e-commerce.

benefits	lunchbreak/after work		evening		Total
	absolute	relative	absolute	relative	
safety in the SL	7	3.2%	3	4.1%	10
travel pleasure	54	24.9%	24	32.8%	78
ease of shopping	123	56.7%	49	67.0%	172
shopping comfort	50	23.0%	21	28.7%	71
shopping pleasure	70	32.3%	24	32.8%	94
attractivity of the SL environment	38	17.5%	8	10.9%	46
diversity in product choice	76	35.0%	28	38.3%	104
shopping success	93	42.9%	34	46.5%	127
travel comfort	72	33.2%	22	30.1%	94
ease of travelling	159	73.3%	44	60.2%	203
safety in travelling	26	12.0%	11	15.1%	37
environmental protection	23	10.6%	7	9.6%	30
health	46	21.2%	17	23.3%	63
personal care	10	4.6%	8	10.9%	18
mental ease	70	32.3%	25	34.2%	95
relaxation/recreation	92	42.4%	32	43.8%	124
course of fitness/wellbeing	42	19.4%	8	10.9%	50
financial savings	73	33.7%	30	41.1%	103
social acceptance	21	9.7%	7	9.6%	28
time savings	161	74.2%	47	64.3%	208
taste experience	36	16.6%	8	10.9%	44

Table J-22. Cross-Table for benefits and the TM choice in CNET risky.

benefits	car		non car		Total
	absolute	relative	absolute	relative	
safety in the SL	7	3.5%	2	1.7%	9
travel pleasure	33	16.7%	35	30.1%	68
ease of shopping	100	50.6%	48	41.3%	148
shopping comfort	52	26.3%	17	14.6%	69
shopping pleasure	46	23.3%	24	20.7%	70
attractivity of the SL environment	21	10.6%	19	16.4%	40
diversity in product choice	96	48.5%	49	42.2%	145
shopping success	128	64.7%	75	64.6%	203
travel comfort	60	30.3%	29	25.0%	89
ease of travelling	147	74.3%	83	71.4%	230
safety in travelling	28	14.2%	19	16.4%	47
environmental protection	7	3.5%	20	17.2%	27
health	27	13.6%	38	32.7%	65
personal care	13	6.6%	3	2.6%	16
mental ease	79	39.9%	42	36.2%	121
relaxation/recreation	54	27.3%	41	35.3%	95
course of fitness/wellbeing	26	13.1%	22	18.9%	48
financial savings	38	19.2%	29	25.0%	67
social acceptance	8	4.0%	8	6.9%	16
time savings	147	74.3%	77	66.3%	224
taste experience	30	15.2%	17	14.6%	47
to appeal the boss	3	1.5%	0	0.0%	3

Table J-23. Cross-Table for benefits and the SL choice in CNET risky.

benefits	non supermarket		supermarket		Total
	absolute	relative	absolute	relative	
safety in the SL	1	1.0%	8	3.8%	9
travel pleasure	24	23.5%	44	20.8%	68
ease of shopping	42	41.2%	106	50.0%	148
shopping comfort	12	11.8%	57	26.9%	69
shopping pleasure	21	20.6%	49	23.1%	70
attractivity of the SL environment	18	17.6%	22	10.4%	40
diversity in product choice	28	27.4%	117	55.2%	145
shopping success	51	50.0%	152	71.7%	203
travel comfort	25	24.5%	64	30.2%	89
ease of travelling	68	66.6%	162	76.4%	230
safety in travelling	12	11.8%	35	16.5%	47
environmental protection	12	11.8%	15	7.1%	27
health	23	22.5%	42	19.8%	65
personal care	4	3.9%	12	5.7%	16
mental ease	39	38.2%	82	38.7%	121
relaxation/recreation	37	36.3%	58	27.4%	95
course of fitness/wellbeing	16	15.7%	32	15.1%	48
financial savings	17	16.7%	50	23.6%	67
social acceptance	6	5.9%	10	4.7%	16
time savings	71	69.6%	153	72.2%	224
taste experience	17	16.7%	30	14.2%	47
to appeal the boss	1	1.0%	2	0.9%	3

Table J-24. Cross-Table for benefits and the TS choice in CNET risky.

benefits	lunchbreak		after work/evening		Total
	absolute	relative	absolute	relative	
safety in the SL	5	6.6%	4	1.7%	9
travel pleasure	12	15.8%	56	23.5%	68
ease of shopping	35	46.1%	113	47.5%	148
shopping comfort	18	23.7%	51	21.4%	69
shopping pleasure	22	29.0%	48	20.2%	70
attractivity of the SL environment	10	13.2%	30	12.6%	40
diversity in product choice	33	43.4%	112	47.1%	145
shopping success	50	65.8%	153	64.3%	203
travel comfort	26	34.2%	63	26.5%	89
ease of travelling	50	65.8%	180	75.6%	230
safety in travelling	14	18.4%	33	13.9%	47
environmental protection	11	14.5%	16	6.7%	27
health	15	19.7%	50	21.0%	65
personal care	0	0.0%	16	6.7%	16
mental ease	30	39.5%	91	38.2%	121
relaxation/recreation	19	25.0%	76	31.9%	95
course of fitness/wellbeing	16	21.1%	32	13.4%	48
financial savings	15	19.7%	52	21.8%	67
social acceptance	0	0.0%	16	6.7%	16
time savings	50	65.8%	174	73.1%	224
taste experience	10	13.2%	37	15.5%	47
to appeal the boss	1	1.3%	2	0.8%	3

K. Statistical tests on respondents' performance

Table K-1. Post hoc test for number of attributes between education levels.

Multiple Comparisons					
Bonferroni					
interview technique	(I) education level	(J) education level	Mean Difference (I-J)	Std. Error	Sig.
CNET	primary school	practical professional training	0.494	0.365	1
		secondary education only	-0.734	0.39	0.898
		higher level professional training	-0.044	0.359	1
		Bachelors degree	-1.066*	0.36	0.047
		Masters degree	-1.135	0.405	0.078
	practical professional training	primary school	-0.494	0.365	1
		secondary education only	-1.229*	0.234	<.001
		higher level professional training	-.539*	0.178	0.037
		Bachelors degree	-1.561*	0.181	<.001
		Masters degree	-1.629*	0.259	<.001
	secondary education only	primary school	0.734	0.39	0.898
		practical professional training	1.229*	0.234	<.001
		higher level professional training	.690*	0.224	0.031
		Bachelors degree	-0.332	0.226	1
		Masters degree	-0.4	0.292	1
	higher level professional training	primary school	0.044	0.359	1
		practical professional training	.539*	0.178	0.037
		secondary education only	-.690*	0.224	0.031
		Bachelors degree	-1.022*	0.167	<.001
		Masters degree	-1.090*	0.25	<.001
	Bachelors degree	primary school	1.066*	0.36	0.047
		practical professional training	1.561*	0.181	<.001
		secondary education only	0.332	0.226	1
		higher level professional training	1.022*	0.167	<.001
		Masters degree	-0.068	0.252	1
	Masters degree	primary school	1.135	0.405	0.078
		practical professional training	1.629*	0.259	<.001
		secondary education only	0.4	0.292	1
		higher level professional training	1.090*	0.25	<.001
		Bachelors degree	0.068	0.252	1

*. The mean difference is significant at the 0.05 level.

Table K-2. Post hoc test for number of benefits between education levels.

Multiple Comparisons					
Bonferroni					
interview technique	(I) education level	(J) education level	Mean Difference (I-J)	Std. Error	Sig.
CNET	primary school	practical professional training	0.933	0.588	1
		secondary education only	-0.847	0,628	1
		higher level professional training	0.394	0.578	1
		Bachelors degree	-0.86	0.58	1
		Masters degree	-0.268	0.653	1
	practical professional training	primary school	-0.933	0.588	1
		secondary education only	-1.779*	0.377	<.001
		higher level professional training	-0.538	0.286	0.902
		Bachelors degree	-1.792*	0.291	<.001
		Masters degree	-1.201	0.417	0.061
	secondary education only	primary school	0.847	0.628	1
		practical professional training	1.779*	0.377	<.001
		higher level professional training	1.241*	0.36	0.009
		Bachelors degree	-0.013	0.364	1
		Masters degree	0.578	0.471	1
	higher level professional training	primary school	-0.394	0.578	1
		practical professional training	0.538	0.286	0.902
		secondary education only	-1.241*	0.36	0.009
		Bachelors degree	-1.254*	0.269	<.001
		Masters degree	-0.663	0.402	1
	Bachelors degree	primary school	0.86	0.58	1
		practical professional training	1.792*	0.291	<.001
		secondary education only	0.013	0.364	1
		higher level professional training	1.254*	0.269	<.001
		Masters degree	0.591	0.405	1
	Masters degree	primary school	0.268	0.653	1
		practical professional training	1.201	0.417	0.061
		secondary education only	-0.578	0.471	1
		higher level professional training	0.663	0.402	1
		Bachelors degree	-0.591	0.405	1

*. The mean difference is significant at the 0.05 level.

Table K-3. Post hoc test for number of cognitive subsets between education levels.

Multiple Comparisons					
Bonferroni					
interview technique	(I) education level	(J) education level	Mean Difference (I-J)	Std. Error	Sig.
CNET	primary school	practical professional training	2.939	1.717	1
		secondary education only	-2.363	1.832	1
		higher level professional training	0.824	1.687	1
		Bachelors degree	-3.053	1.693	1
		Masters degree	-2.164	1.905	1
	practical professional training	primary school	-2.939	1.717	1
		secondary education only	-5.302*	1.099	<.001
		higher level professional training	-2.115	0.835	0.172
		Bachelors degree	-5.992*	0.849	<.001
		Masters degree	-5.103*	1.217	<.001
	secondary education only	primary school	2.363	1.832	1
		practical professional training	5.302*	1.099	<.001
		higher level professional training	3.187*	1.051	0.037
		Bachelors degree	-0.691	1.062	1
		Masters degree	0.199	1.374	1
	higher level professional training	primary school	-0.824	1.687	1
		practical professional training	2.115	0.835	0.172
		secondary education only	-3.187*	1.051	0.037
		Bachelors degree	-3.877*	0.785	<.001
		Masters degree	-2.988	1.173	0.165
	Bachelors degree	primary school	3.053	1.693	1
		practical professional training	5.992*	0.849	<.001
		secondary education only	0.691	1.062	1
		higher level professional training	3.877*	0.785	<.001
		Masters degree	0.889	1.183	1
	Masters degree	primary school	2.164	1.905	1
		practical professional training	5.103*	1.217	<.001
		secondary education only	-0.199	1.374	1
		higher level professional training	2.988	1.173	0.165
		Bachelors degree	-0.889	1.183	1

*. The mean difference is significant at the 0.05 level.

Table K-4. Post hoc test for interview duration between experimental groups.

Multiple Comparisons				
Bonferroni				
(I) experimental group	(J) experimental group	Mean Difference (I-J)	Std. Error	Sig.
HL basic	HL uncertain	-0:00:20.551	0:00:48.524	1.000
	HL distant	0:00:15.992	0:00:48.256	1.000
	CNET basic	-0:01:48.009	0:00:48.801	.756
	CNET uncertain	-0:02:41.044*	0:00:50.273	.039
	CNET distant	-0:01:43.811	0:00:48.256	.885
	CNET e-commerce	-0:03:56.638*	0:00:43.850	<.001
	CNET risky	-0:03:53.597*	0:00:43.103	<.001
HL uncertain	HL basic	0:00:20.551	0:00:48.524	1.000
	HL distant	0:00:36.543	0:00:49.691	1.000
	CNET basic	-0:01:27.458	0:00:50.220	1.000
	CNET uncertain	-0:02:20.493	0:00:51.652	.185
	CNET distant	-0:01:23.261	0:00:49.691	1.000
	CNET e-commerce	-0:03:36.087*	0:00:45.425	<.001
	CNET risky	-0:03:33.046*	0:00:44.704	<.001
HL distant	HL basic	-0:00:15.992	0:00:48.256	1.000
	HL uncertain	-0:00:36.543	0:00:49.691	1.000
	CNET basic	-0:02:04.000	0:00:49.962	.369
	CNET uncertain	-0:02:57.036*	0:00:51.401	.016
	CNET distant	-0:01:59.803	0:00:49.431	.433
	CNET e-commerce	-0:04:12.630*	0:00:45.139	<.001
	CNET risky	-0:04:09.589*	0:00:44.414	<.001
CNET basic	HL basic	0:01:48.009	0:00:48.801	.756
	HL uncertain	0:01:27.458	0:00:50.220	1.000
	HL distant	0:02:04.000	0:00:49.962	.369
	CNET uncertain	-0:00:53.035	0:00:51.913	1.000
	CNET distant	0:00:04.197	0:00:49.962	1.000
	CNET e-commerce	-0:02:08.629	0:00:45.721	.139
	CNET risky	-0:02:05.588	0:00:45.005	.149
CNET uncertain	HL basic	0:02:41.044*	0:00:50.273	.039
	HL uncertain	0:02:20.493	0:00:51.652	.185
	HL distant	0:02:57.036*	0:00:51.401	.016
	CNET basic	0:00:53.035	0:00:51.913	1.000
	CNET distant	0:00:57.233	0:00:51.401	1.000
	CNET e-commerce	-0:01:15.594	0:00:47.289	1.000
	CNET risky	-0:01:12.553	0:00:46.597	1.000
CNET distant	HL basic	0:01:43.811	0:00:48.256	.885
	HL uncertain	0:01:23.261	0:00:49.691	1.000
	HL distant	0:01:59.803	0:00:49.431	.433
	CNET basic	-0:00:04.197	0:00:49.962	1.000
	CNET uncertain	-0:00:57.233	0:00:51.401	1.000
	CNET e-commerce	-0:02:12.826	0:00:45.139	.092
	CNET risky	-0:02:09.785	0:00:44.414	.099
CNET e-commerce	HL basic	0:03:56.638*	0:00:43.850	<.001
	HL uncertain	0:03:36.087*	0:00:45.425	<.001
	HL distant	0:04:12.630*	0:00:45.139	<.001
	CNET basic	0:02:08.629	0:00:45.721	.139
	CNET uncertain	0:01:15.594	0:00:47.289	1.000
	CNET distant	0:02:12.826	0:00:45.139	.092
	CNET risky	0:00:03.041	0:00:39.583	1.000
CNET risky	HL basic	0:03:53.597*	0:00:43.103	<.001
	HL uncertain	0:03:33.046*	0:00:44.704	<.001
	HL distant	0:04:09.589*	0:00:44.414	<.001
	CNET basic	0:02:05.588	0:00:45.005	.149
	CNET uncertain	0:01:12.553	0:00:46.597	1.000
	CNET distant	0:02:09.785	0:00:44.414	.099
	CNET e-commerce	-0:00:03.041	0:00:39.583	1.000

Summary

The technological and societal challenges connected with the direct and indirect consequences of the still increasing traffic volume are keeping many people in research and practice busy. While some try to develop alternatives and travel demand measures to keep the traffic volume low others work on the improvement of travel demand prediction. Both have in common that they target human choice behaviour with their work. An essential condition for the success of travel demand measures and transport models is therefore to understand how individuals make their (travel) decisions and which needs they want to fulfill with their choices.

The investigation of mental representations seems to be the key to understand human decision making. Mental representations are in fact images individuals bear in mind to oversee the consequences of their choices. They are tailored to the specific task and contextual setting under concern and show a significant simplification of reality. Next to the nature of the considered choice alternatives, the temporal construal of the task, the severeness of consequences and the (un)certainty of necessary information are held among others as determinants of mental representations. Shifts in the composition of mental representations are thus expectable when these contextual settings are changing.

A drawback connected with the investigation of MRs is that so far only a few techniques exist by which these latent constructs can be elicited from individuals. Yet, all these methods are limited in the sense that they either influence or restrict respondents in their statements or are inappropriate for large-scale applications. This thesis introduced therefore a new online instrument for measuring mental representations which is able to collect data fully automatically. The first application of that instrument has its origin in the semi-structured CNET interview protocol from Arentze *et al.* (2008) and Dellaert *et al.* (2008). While online CNET is due to its open format still able to elicit an unbiased picture of respondents' spontaneous recalls, adaptations to the original interview protocol had to be made to ensure the elicitation of benefits. In order to allow for a methodological comparison to online CNET an alternative application (online HL) has been developed that works only with revealed response options.

As experimental subject a fictive trivial activity-travel choice task was chosen that consisted of scheduling working and grocery shopping activities for a normal working day in a fictive urban environment. In sum, decisions for the shopping location,

the transport mode and the time of the shopping activity had to be considered. Side information was given for situational settings depending on the scenario. Next to the basic task four scenarios were developed of which one implied uncertainty about the side information, one implied a temporal distance of five years between the moment of decision making and the fictive moment of action, one introduced an additional online shopping alternative, and one implied negative consequences when the activity-travel task could not be fulfilled successfully.

Data on these scenarios were collected among households subscribed to the nationwide Dutch LISS panel. The survey took place in two waves in spring and autumn 2010. While the first survey collected data on the basic, the uncertain and the distant scenario with both online CNET and HL, the second wave of experiments for the e-commerce and risky task was conducted with CNET only. In total, 1745 mental representations could be measured successfully which were subsequently analysed in an explorative and model-based approach.

The analysis of the collected data showed a significant smaller structure of mental representations elicited with CNET compared to mental representations elicited with HL as the former consisted of significantly fewer components than the latter. This finding suggests an influence of the revealed handling of variables in HL which is supported by the fact that no shifts between scenarios could be measured with this technique. CNET however turned out to be sensitive for shifts caused by contextual manipulations. The substantial analysis of the uncertain, e-commerce and risky scenarios showed thus increased frequency and centrality values for attributes which were targeted by the experimental situations. For instance, the *available product assortment* nearly doubled its centrality value in the risky and uncertain scenario compared to the basic setting. Disappointing was however the distant scenario. An expected shift towards benefits could not be measured. A stable finding that was made with both techniques and in all scenarios was the high importance of the benefits *time savings*, *ease of shopping* and *ease of travelling.* These are in fact the driving forces of people's choices for the investigated activity-travel task.

These findings were supported by means of a formal model application which estimated parameters for MR component activation and strength of causal relationships in light of varying contexts. The analysis revealed that significant differences in MRs occur that result from situation-dependent need activation. The attributes on which choice alternatives are evaluated and the underlying benefits appear to be sensitive to (un)certainty of task-relevant information, the severeness of anticipated choice consequences and the set of choice alternatives.

In conclusion, this thesis confirms the ability of online CNET to measure mental representations in a more sensitive and less influencing manner than online HL. Besides this scientific advantage CNET provides still all amenities of automatic online surveys for both respondents and researchers. These circumstances speak to the appropriateness of online CNET as a tool to elicit mental representations from decision makers of any choice task and perhaps also to a better understanding of human travel behaviour.

Curriculum Vitae

Oliver Horeni was born on the 10th of March, 1982 in Stollberg, Germany. He studied transport and traffic engineering at Dresden University of Technology, Germany. There he came into contact with transport psychology and transport modelling and the need for an integration of either approach. Still during his studies Oliver did a six months internship at the Department of Psychology at Gothenburg University, Sweden, where he worked together with Tommy Gärling on a project of car users' adaptation to increased travel costs. The good cooperation with Tommy Gärling led to his graduation project on travellers' attitudes towards transport modes for long distance travel between Gothenburg and Stockholm. After receiving his master degree in March 2007, Oliver joined the Design and Decision Support Systems unit at the Department of Architecture, Building and Planning, Eindhoven University of Technology, The Netherlands as a PhD candidate. Next to data collection methods his research interests concern travel behaviour and the link to decision making in an activity-based frame.