DOCTORAATSPROEFSCHRIFT

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Scrutinizing fun-shopping travel decisions: Modelling individuals' mental representations

Proefschrift voorgelegd tot het behalen van de graad van
Doctor in de Verkeerskunde, te verdedigen door:

Diana KUSUMASTUTI

Promotor: prof. dr. Geert Wets (UHasselt)
Copromotor: prof. dr. Benedict G.C. Dellaert
(Erasmus University Rotterdam)

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Faith—When you walk to the edge of all the light you have
and take that first step into the darkness of the unknown,
you must believe that one of two things will happen:
There will be something solid for you to stand upon,
or, you will be taught how to fly
Patrick Overton

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Diana

Diepenbeek, 24 February 2011

SAMENVATTING

De toenemende hoeveelheid vrije tijd in ontwikkelde landen leidt tot een toename aan vrijetijdsactiviteiten. Een versnippering van locaties en een inefficiënt openbaar vervoersysteem voor vrijetijdsactiviteiten dragen bovendien bij tot een verhoogd autogebruik. Een van de meest voorkomende vrijetijdsactiviteiten is het vrijetijdswinkelen ('fun shoppen'). In een typische Europese stad, vinden fun shopping activiteiten gewoonlijk plaats in het stadscentrum. Dit leidt tot een verhoogde druk op stedelijke infrastructuren en problemen in de stad, veroorzaakt door congestie, vervuilende emissies, enz. De meeste mobiliteitsmaatregelen willen mensen ertoe aanzetten om gebruik te maken van duurzamere vervoersmethoden, zoals fiets en bus. Echter, in veel gevallen is de doeltreffendheid van dit beleid om het niet-duurzame autogebruik te ontraden niet optimaal. Onderzoek naar het menselijke gedrag kan dit fenomeen mee verklaren. Verkeers- en voersmaatregelen worden minder effectief en efficiënt geïmplementeerd wanneer zij niet behoren tot de doorslaggevende factoren die mensen overwegen bij het nemen van beslissingen in verband met hun vervoer.

Het nauwkeurig voorspellen van het verplaatsingsgedrag van individuen is een echte uitdaging geworden in het domein van de activiteitgebaseerde verplaatsingsmodellen. Bovendien gebruiken modellen die de vervoersvraag modelleren, zoals FEATHERS, enkele veronderstellingen die vaak bekritiseerd worden omdat ze niet steunen op reëel gedrag. Dit leidt tot minder nauwkeurige voorspellingen en benadrukt des te meer de nood aan fundamentele studies naar het verplaatsingsgedrag van mensen, in het bijzonder naar hun beslissingsproces bij het maken van hun vervoerskeuzen. .

Uiteindelijk kunnen we proberen om het verplaatsingsgedrag van individuen zo realistisch mogelijk modelleren door mentale modellen te genereren die gebruik maken van het beslissingsproces van mensen, samen met andere additionele inputparameters. Zulk een model maakt meestal gebruik van een techniek uit

het domein van de artificiële intelligentie, zoals een beslissingsnetwerk, beslissingsboom, enz. Bij de methode van een beslissingsnetwerk, kan het gedachteproces van elk individu afzonderlijk worden gemodelleerd om zijn/haar verplaatsingskeuzen te voorspellen, gebaseerd op factoren die zich voordoen en die geacht worden van belang te zijn in het beslissingsproces. Dergelijke studies komen echter nog niet veel voor, noch in het domein van de artificiële intelligentie, noch in het domein van verkeer en vervoer.

Uitgaande van de bovengenoemde onderzoekachtergrond, wil dit doctoraal onderzoekproject licht werpen op het beslissingsproces van individuen. Meer specifiek concentreert het doctoraal onderzoeksproject zich op het gebruik van gedragsgegevens om transportmaatregelen met een grote impact te analyseren, om feedback te geven op aannames m.b.t. gedrag in FEATHERS, en om mentale modellen te ontwikkelen die de wijziging van het verplaatsingsgedrag van mensen kunnen beoordelen, gebruik makend van het beslissingsnetwerk en beslissingsboomtechnieken. Deze studie steunt op de theorie van belissingsprocessen en mentale voorstellingen. In deze theorie stellen we dat individuen een tijdelijke mentale voorstelling maken bij het oplossen van een beslissingsprobleem. In deze mentale voorstelling weegt een individu de onderliggende *voordelen* die hij of zij wenst te bereiken af, alsook de *instrumenten* (of kenmerken) van de keuzealternatieven, evenals de *contexten* waarin deze voordelen belangrijk zijn. Een onderling verbonden set van context, instrument en voordeel wordt geregistreerd als een 'cognitieve subset'. Er zijn twee types van cognitieve subsets: subsets die geactiveerd worden door contexten (d.w.z. {context, instrument, voordeel}), en subsets die normaal aanwezig zijn, ongeacht de omstandigheden (d.w.z. {normaal, instrument, voordeel}). Één subset kan verbonden zijn met andere subsets, en zo samen een mentale voorstelling van een beslissingsprobleem creëren. Om deze mentale voorstelling te begrijpen, moet er eerst een methode ontwikkeld worden om deze informatie te achterhalen.

Om deze reden worden er twee experimenten uitgevoerd. In beide onderzoeken wordt het beslissingsproces onderzocht van mensen bij het maken van verplaatsingen voor fun shoppen naar het stadscentrum van Hasselt, België. In het eerste experiment, wordt de Causal Network Elicitation Technique (CNET), een semigestructureerde en face-to-face interviewmethode vergeleken met het CNET 'kaartspel'. Deze laatste techniek lijkt op een volledig gestructureerd interviewprotocol. Beide methodes onderzoeken *welke* aspecten belangrijk zijn in het beslissingsproces, *waarom* zij significant zijn, en *hoe* zij beslissingsresultaten beïnvloeden. In dit experiment gebruikt men een kleine steekproef van 26 jongvolwassenen. De resultaten, alsook de subjectieve techniekevaluaties van de deelnemers, worden gebruikt voor de ontwikkeling van een computergebaseerde (CB) elicitatietechniek, het zogeheten CB-CNET. In het tweede experiment, achterhalen we door middel van de CB-CNET interface de mentale voorstellingen van het beslissingsproces van 221 deelnemers. Bovendien genereert de interface automatisch vragen om de parameters te achterhalen, gebaseerd op de verkregen mentale voorstellingen. Zo kunnen deze gemodelleerd worden aan de hand van beslissingsnetwerken en beslissingsboomtechnieken.

Tijdens de experimenten worden de belangrijke aspecten van de mentale voorstellingen van mensen geïdentificeerd. Zo lijken *weersomstandigheden* een bepalende factor te zijn die een grote invloed heeft op de vervoerswijzekeuze van mensen. Nochtans wordt met dit aspect nog geen rekening gehouden in de huidige verplaatsingsdagboekjes die algemeen gebruikt worden als input voor modellen die de vervoersvraag modelleren, zoals FEATHERS. Bovendien verschijnt, in de data die verkregen wordt uit de CB-CNET interface, de cognitieve subset {normaal, gemak bij parkeren, efficiëntie} in de mentale voorstellingen van deelnemersgroepen die zich gewoonlijk per fiets of bus verplaatsen. Deze subset, of andere subsets met betrekking tot het *gemak van parkeren*, komen niet voor in de mentale voorstellingen van de deelnemers die gewoonlijk de auto gebruiken bij het vrijetijdswinkelen. Dit kan erop wijzen dat parkeer-gerelateerde maatregelen in Hasselt strenger gemaakt zouden moeten worden dan zij momenteel zijn, bijvoorbeeld door het aantal gratis parkeerplaatsen te reduceren, de parkeerkosten te verhogen, enz.

Met betrekking tot mentale modellen, wordt de nauwkeurigheid van beslissingsnetwerkmodellen bij het voorspellen van het gedrag van mensen vergeleken met de nauwkeurigheid van beslissingsboommodellen. De resultaten tonen aan dat hoewel de modellen van het beslissingsnetwerk redelijk goed zijn, de resultaten van de beslissingsboommodellen nog beter zijn. Omwille van de verschillende sterke punten van beide technieken, zou de selectie van de methode echter gebaseerd moeten worden op het specifieke onderzoeksdoel. Het beslissingsnetwerk is geschikt om kennis op te bouwen over het beslissingsvormingsproces van mensen en om de te verwachten invloed te onderzoeken van de verkregen contexten op de daadwerkelijke keuzen. Echter, deze modelleringstechniek maakt ook gebruik van inschattingen van de probabiliteit van verwachtte gebeurtenissen door de ondervraagden. Daarom is er nood aan een studie die onderzoek voert naar manieren waarop men fouten in de inputwaarden kan verminderen. Zo kan er bijvoorbeeld een model gegenereerd worden dat de gebundelde mentale voorstellingen clustert. De probabiliteitsdistributie van de inschattingen kan verkregen worden uit de verzamelde gegevens en deze kan vervolgens gebruikt worden als input voor het model.

SUMMARY

The growing amount of leisure time in developed countries leads to the increasing performance of leisure activities. Furthermore, sporadic leisure activity locations and inefficient public transport systems make this activity type contribute to the growth of car-use. An example of the most common leisure activities is fun-shopping. In a typical European city, fun-shopping activities are usually performed in the city centre, adding more pressures on urban infrastructures and problems in the city caused by traffic jams, pollutant emissions, etc. Many transport-related strategies aim at encouraging people to use more sustainable transport modalities, such as bike and bus. However, in many cases, the effectiveness of these policies in altering people's unsustainable car-use behaviour has not yet been optimal. Human behavioural research field offers a plausible explanation to this phenomenon. Transportation measures are implemented less effectively and efficiently because they are not in line with determinant aspects considered by people when making travel decisions.

Predicting individuals' travel behaviour with a great accuracy has also become a real challenge in the field of activity-based travel demand models. Furthermore, the computational process models of travel demand, such as FEATHERS, use some assumptions often criticized due to the lack of an actual behavioural foundation. This brings about less accurate predictive results and further highlights the need to carry out fundamental studies regarding people's travel behaviour, in particular concerning their travel decision making processes.

At last, modelling individuals' travel behaviour as realistic as possible can be done by generating mental-level models that use people's decision processes along with other additional parameters as input. Such a model commonly employs an artificial intelligence technique, such as influence diagram, decision tree, etc. Using the influence diagram method, every individual's thought process can be modelled separately to predict his travel choices based on occurring aspects considered important in his decision making. However, such

studies are still limited in both the artificial intelligence and transportation domains.

Based on the above research background, this PhD research project aims at shedding light on individuals' decision making processes. Moreover, it focuses on using behavioural data to analyse high impact transport policies, to give behavioural feedback on assumptions in FEATHERS, and to develop mental-level models that can assess the alteration of people's travel behaviours using the influence diagram and decision tree techniques. This study is grounded in the theory of decision making and mental representations. This theory argues that when solving a decision problem, an individual activates a temporarily mental representation in his mind. In this representation, the underlying *benefits* that someone wants to gain are assessed together with the *instruments* (or characteristics) of the choice options, and the *contexts* in which these benefits are important. An interlinking set of a context, an instrument and a benefit is registered as a cognitive subset. There are two types of cognitive subsets: subsets activated by contexts (i.e. {*context, instrument, benefit*}), and subsets normally present regardless of the circumstances (i.e. {*normally, instrument, benefit*}). One subset can be linked to other subsets, creating a mental representation of a decision problem. In order to understand this representation, an elicitation method should firstly be developed.

Hence, two experiments are carried out. Both of them investigate travel decision making of people when performing leisure-shopping in Hasselt city centre, Belgium. In the first experiment, the Causal Network Elicitation Technique (CNET), a semi-structured and face-to-face interview method is tested against the CNET card game. The latter technique resembles a fully structured interview protocol. Both methods probe *what* aspects are important in decision making, *why* they are significant, and *how* they influence decision outcomes. This experiment uses a small sample size of 26 young adults. The results, along with the participants' subjective evaluations of the techniques, are used to develop a computer-based (CB) elicitation protocol, called CB-CNET. In the second experiment, the CB-CNET interface elicits 221 participants' mental representations. Besides, the interface automatically generates parameter questions based on the elicited representations, allowing them to be modelled using the influence diagram and decision tree techniques.

During the experiments, important aspects in people's mental representations are identified. For instance, *weather conditions* appear as a determinant factor that strongly affects people's transport mode choices. However, this aspect has not yet been taken into account in current travel diaries, commonly used as input to computational process models such as FEATHERS. Furthermore, in the data derived from the CB-CNET interface, the cognitive subset of {*normally, easiness for parking, efficiency*} appears in the mental representations of groups of participants whose transport mode habit is bike-use or bus-use. However, this subset, or other subsets related to *the easiness for parking*, does not occur in the mental representation of the participants with a habit of car-use when shopping. This could indicate that parking-related measures should be made harder than what they currently are in Hasselt, for instance by reducing the number of free parking spaces, increasing parking cost, etc.

With regard to mental-level models, the accuracy of the influence diagram models in predicting people's behaviours is compared to the accuracy of the decision tree models. The results show that even though the influence diagram models perform quite reasonably well, the performance of the decision tree models is even better. However, due to different strengths of both techniques, a method selection should rest on the research goal. Influence diagram is suited to build understanding of people's decision making processes and to investigate the likely influence of the revealed contexts on the actual choices. However, this modelling technique also uses probability estimates of expected events directly from the respondents' account. Therefore, a future study is needed to investigate ways for diminishing any errors in the input values. For instance, a model for clustered mental representations can be generated and the probability distribution of the estimates can be learned from the gathered data and used as input for the model.

LIST OF ABBREVIATION

AB	Activity Based
AI	Artificial Intelligence
ALBATROSS	A Learning-BAsed TRansportation Oriented Simulation System
API	Application Programming Interface
AR	Association Rules
BRT	Bus Rapid Transit
CA	Cluster Analysis
CB-CNET	Computer-Based Causal Network Elicitation Technique
CG	CNET Card Game
CHAID	Chi-squared Automatic Interaction Detector
CI	Confidence Interval
CNET	Causal Network Elicitation Technique
CPM	Computational Process Model
CPT	Conditional Probability Table
DT	Decision Tree
EM	Expectation Maximization
EU	Expected Utility values
FCM	Fuzzy Cognitive Map
FEATHERS	Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS
FFD	Fractional Factorial Design
FI	Frequent Itemset
HOV	High Occupant Vehicle
ID	Influence Diagram
MINCON	MINimum CONfidence
MINSUP	MINimum SUPport
MR	Mental Representations
NTP	No Time Pressure scenario
PBS	Public Bike Systems
RUM	Random Utility Model

TDM	Travel Demand Management
TP	Time Pressure scenario
UT	Conditional Utility Table
VKT	Vehicle Kilometres Travelled
W1	Weighting method-1
W2	Weighting method-2

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1 Introduction

"Science may set limits to knowledge, but should not set limits to imagination."
Bertrand Russell

1.1 Problem statement

An increased amount of leisure time can be observed in the world today, especially in developed countries. For instance, weekly free-time in the USA increased from 35 hours in 1965 to 40 hours in 1985 (Robinson & Godbey, 1997), and has remained stable since then. A similar trend can also be observed in Germany (Chlond & Zumkeller, 1997), the UK (Anable, 2002), Sweden (Tillberg, 2002), and other Western industrialized countries. The reduction in weekly working hours and the larger amount of paid vacation time have resulted in longer leisure time, yielding growing numbers of leisure activities that could be fitted into that free-time.

Thus, leisure activities account for an apparent share of activities that people perform in time and space (Larsen, Urry, & Axhausen, 2006). This activity type includes going out and strolling around, outdoor recreations, entertainment, visiting friends and relatives, (non-grocery) shopping, sports, and other non-maintenance activities (Lanzendorf, 2002). It is commonly believed in the activity-based (AB) travel analysis that travel is a derived demand from the prerequisite to carry out different activities that spread in geographical spaces. Accordingly, the growing importance of leisure activities contributes to the steady increase in the number of yearly Vehicle Kilometres Travelled (VKT). For instance, leisure trips account for around 41% of VKT in Germany in 1997. This figure increases to 48% when combined with holiday trips (Schlich, Schonfelder, Hanson, & Axhausen, 2004). In the USA, leisure trips constitute 75% of all domestic trips in the country (LaMondia & Bhat, 2009). Furthermore, higher incomes, better standards of living, more advanced technology, faster information distribution, and bigger social network coverage may also explain the rising number of leisure trips (LaMondia & Bhat, 2009).

Unlike typical daily routines such as going to work, leisure activities are not (or less) mandatory. Therefore, they may not be conducted on a regular basis. Additionally, there are a large number of leisure activity locations and purposes, making them harder to study. These trips are mostly performed by using private cars due to the limited service coverage and inefficiency of public transport systems. Additionally, scattered leisure activity locations boost individuals' preferences over cars, making such activities contribute to the increase in car-use and its negative externalities (Schlich et al., 2004).

Transport Demand Management (TDM) is of crucial importance for reducing travel-related energy consumption and lowering high pressure on urban infrastructure. TDM, or also known as "*mobility management*", is a term for measures or strategies to make better use of transportation resources by reducing travel demand or distributing it in time and space (Victoria Transport Institute, 2010). Many attempts have been made to enforce TDM that would influence individuals' unsustainable travel behaviour towards more sustainable forms (Gärling et al., 2002; Loukopoulos & Scholz, 2004; Stauffacher, Schlich, Axhausen, & Scholz, 2005). However, TDM can be effectively and efficiently implemented if they are developed based on a deep understanding of the basic determinants of travel, such as people's *motives* and *preferences* (Schlich et al., 2004), and comprehensive knowledge of people's behaviours (LaMondia & Bhat, 2009; Bradley, 2006). Accordingly, to increase the behavioural impact of TDM, travel choices should be studied at the disaggregate level, as the outcome of every individual's decision making process (Dellaert, Arentze, & Timmermans, 2008; Stauffacher et al., 2005). With regard to individuals' leisure travels, behavioural studies may provide some insight into how to make people predominantly shift their transport mode choice from car to public transport for going to leisure locations.

Furthermore, over the past several decades, there has been an impressive development in the field of AB models of travel demand (Doherty, Miller, Axhausen, & Gärling, 2002). These approaches aim at modelling individuals' travel behaviours as realistic as possible, providing tools to understand and forecast travel demand to improve urban planning and policy. Moreover, the next generation of AB models is designed to address a variety of environmental issues (Beckx et al., 2009; Davidson et al., 2007), such as pollutant emissions and energy consumption. For this purpose, a number of studies and modelling approaches have been made. However, they are often criticized for their theoretical basis (Svenson, 1998) and their lack of behavioural foundation (Bradley, 2006), resulting in less accurate and realistic modelling results. From the behavioural perspective, this shortcoming happens because basic fundamental questions regarding people's travel behaviours remain unanswered, especially concerning *why* people travel the way that they do.

Hence, the descriptions above illustrate the necessity to conduct more fundamental studies regarding individuals' travel decisions, particularly about how people organize their activities in time and space and manage the consequent travels of those activities (Doherty & Ettema, 2006). Furthermore, the rising importance of leisure activities in generating travels and defining travel patterns also boosts the need to deeply study people's leisure travel decisions. Results of such studies can provide ways to analyse a number of high impact TDM measures. Furthermore, behavioural research can give feedback to AB models to strengthen their assumptions regarding people's travel behaviour.

Due to the multitude of leisure activities that people could perform, emphasis should be given to leisure-shopping activity by highlighting its travel-related decisions. Shopping as a pastime is one of the most common type of leisure activities (Timothy, 2003). For instance, it has been previously reported (i.e. Jansen, 1989) that shopping is one of the main leisure activities in the UK, at the same level as spending time on the beach. Shopping has been considered as one of the most culturally revealing activities performed by human and it shows individuals' motivations, values and lifestyles (Snepenger, Murphy, O'Connell, & Gregg, 2003). It is also considered as a significant economic, psychological and social pursuit (Gunn, 1988; MacCannel, 2002; McIntosh & Goeldner, 1990 in

Snepenger et al., 2003). Details regarding the meaning of fun-shopping can be found in Appendix A.

Considering the importance of shopping as a recreational activity and its impact on generating trips, a study should be conducted to address individuals' reasoning behind and complex relationships between various aspects in leisure-shopping travel decisions. Individuals' transport mode and destination choices in a city centre should be further studied in detail, especially in Europe. In a typical historical European city, most of shops are located in the city centre. Furthermore, the application of results derived from such a behavioural study should be demonstrated, for instance regarding how to evaluate a number of TDM based on people's thought aspects. An additional issue regarding how to use behavioural study results to ground assumptions in current AB models should be addressed as well.

From a methodological point of view, data concerning individuals' decision making processes can be used as input to generate *mental-level models.* Such models treat each individual as an agent with mental attributes, such as *beliefs*, *goals*, and *preferences* (Brafman & Tennenholtz, 1997). In order to generate a mental-level model, a number of artificial intelligence (AI) techniques can be employed, such as *influence diagram* (ID), *fuzzy cognitive map* (FCM), *neural network*, etc. They try to realistically mimic people's decision making processes. Accordingly, they can be used not only to understand people's travel behaviours at an individual level, but also to forecast the changes in their behaviours due to some factors in their decision environment. Regardless of these advantages, their application in the transportation field is still relatively scarce. Certainly, more studies should be conducted in order to find ways to better represent and model people's travel decision making and accordingly to investigate how well such mental-level models perform. For this purpose, the ID technique can be employed. ID takes into account *values* (or *benefits*) that people pursue (Arentze, Dellaert, & Timmermans, 2008a), making it suited to model the thought process. Additionally, *decision tree* (DT) model can also be used to learn rules in (behavioural) data, to predict people's travel behaviours.

Mental-level models could be alternatives to well-known AB travel demand models. The main distinction between the former and the latter approaches lays on their input data. AB models commonly use data derived from traditional travel surveys and/or travel diaries, whereas mental-level models require behavioural data as input. Travel surveys and other quantitative methods are considered insufficient to reveal aspects in decision making because they can only record decision outcomes. The underlying processes behind people's choices remain obscure. In general, quantitative methods can answer questions of *what*, *when*, *where*, *whose* (or *with whom*) activity-travel plans are executed, but they cannot sufficiently explain *why* people choose certain transport modes and *how* they come to certain decisions (Bradley, 2006; Weston, 2004). Therefore, they provide inadequate information to understand decision processes that ground people's travel behaviours (Pendyala & Bricka, 2006).

Qualitative methods, such as focus groups, in-depth interviews and participant-observer techniques, may shed light on the above problem. These techniques can provide information that cannot be obtained using quantitative methods (Clifton & Handy, 2003). They are crucial tools to extract beliefs and decision making underneath the behavioural phenomena from agents' perspective (Goulias, 2003). This way, qualitative methods can as well address *why* and *how* certain decisions are made (Bradley, 2006). However, qualitative research has its own downsides, such as small sample sizes making it hard to generalize research outcomes to specific population groups. Thus, when qualitative approaches are used in conjunction with quantitative methods, both techniques may become a robust tool to understand the complexity of individuals' travel behaviours. These combinations of techniques result in *behavioural process data*.

Bradley (2006 p. 491) defines process data as *"…a combination of quantitative and qualitative information, collected systematically to reveal individual travel choice processes over time."* Pendyala & Bricka (2006) state that process data intends to describe people's decision processes in terms of sequences and procedures by emphasizing information use to make choices, including information collection, absorption, assimilation, and interpretation. This idea is illustrated in Figure 1.1.

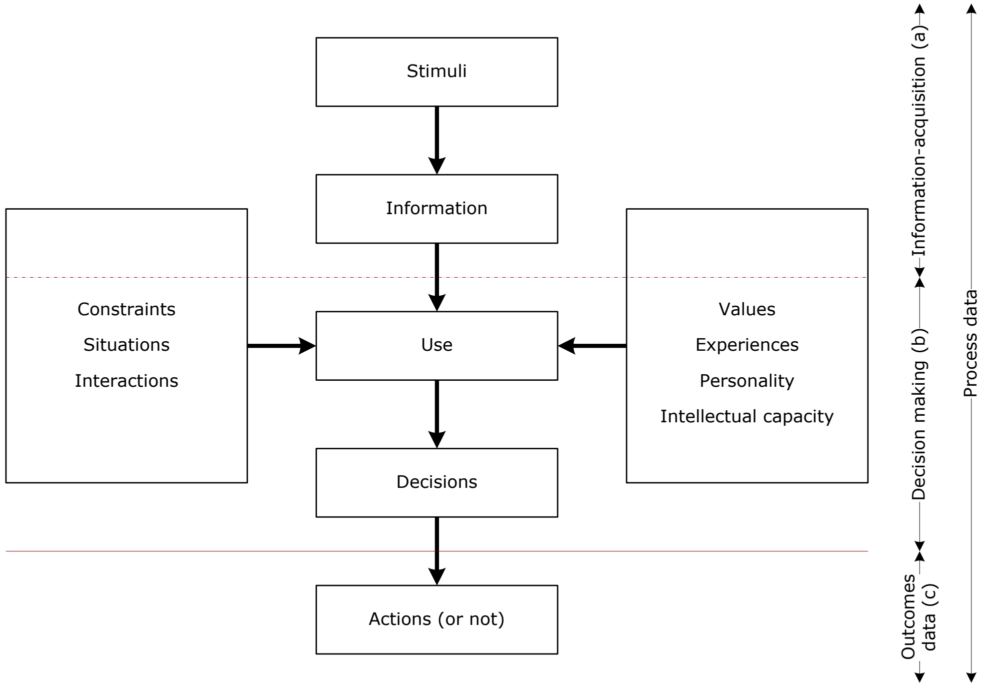


Figure 1.1 A framework of behavioural process data, including information acquisition (a); decision making (b); and outcomes data (c) (Pendyala & Bricka, 2006)

In the framework shown in Figure 1.1, information and stimuli acquired by decision makers in the initial stage (Figure 1.1a) are used as input in the decision making stage (Figure 1.1b). In this second stage, information is combined with external factors (such as constraints, situations, and interactions) and internal aspects (i.e. values, personal experiences, personality, and intellectual capacity) to make decisions. In the end, actions are (or are not) executed (Figure 1.1c). Travel behaviour process data comprise all stages of the framework, whereas conventional travel survey data usually cover only its last stage.

Despite the strength of behavioural process data in explaining people's behaviours, methods to obtain such data are still not well explored and only used scarcely in the transportation research (Bradley, 2006). Furthermore, qualitative methods to obtain that type of data are often regarded only as a complementary part to already known quantitative methods, such as stated preference surveys. An example of a travel demand study that uses a combination of qualitative and quantitative methods to explain people's travel behaviour is reported by Goulias, Brog, & Erl (1998), referred to as *situational survey approach*. It starts by describing the actual behaviour akin to traditional household travel surveys. This information is used later on as a base to ask in-depth questions regarding individuals' perceptions, preferences, and other subjective factors that driven their choice processes. Another example of a combined method is used by Clifton (2001). She uses semi-structured interviews to identify factors that hinder the mobility of low-income households. Results of that study are used to complement regional travel diary data, explaining the decision making process and the mobility needs of the targeted group of people. In short, methods to elicit behavioural process data are usually tailored to research objectives (Pendyala & Bricka, 2006).

A (pure) qualitative approach has been developed to elicit individuals' reasoning behind their complex travel-related decisions, named as the Causal Network Elicitation Technique (CNET) (Arentze et al., 2008a). The CNET protocol is designed as a qualitative semi-structured and face-to-face interview protocol. This technique is grounded in the decision making theory of mental models, in which a decision maker considers *different aspects of choice alternatives*, *his subjective values*, and *affecting contexts and constraints* prior to making choices. In this thought process, different factors are linked by causal relationships, creating a temporary mental representation or mental model of a certain decision problem. To enable the elicitation of individuals' mental representations (MR), the CNET interview evolves around *why* and *how* questions.

As a part of qualitative research methods, the CNET interview protocol offers a framework to elicit rational, careful, and conscious travel decision making. However, travel choices are not always made that way. Selections could also be based on *heuristics* or *scripts* (namely *script-based choices*) or come out of *habit*. Accordingly, the CNET method should be further enhanced to accommodate the differences in people's decision making styles. Despite being successfully applied in previous research (i.e. Den Hartog, 2004), the CNET interview protocol inherits some limitations of other qualitative approaches, such as being time consuming and accordingly costly. Because of these drawbacks, this method can only be applied to small sample sizes, making it difficult to conclude research outcomes for specific population groups. Small sample sizes may lead to some reliability issues when applying such results to ground behavioural assumptions in AB models and to assess high impact TDM. Moreover, results of such a qualitative study are also often questioned due to researchers' subjective interpretations of respondents' open answers during interviews (Clifton & Handy, 2003). Besides, in order to use behavioural process data as input to individuals' models that can explicate their travel behaviours, additional input of parameters based on people's elicited aspects should be gathered. For instance, ID and DT models can be developed from MR data when combined with additional required data, adding more demand to the whole data gathering procedure. These ground the need to develop an automated and computerized elicitation approach for large sample sizes.

One of the major issues in applying qualitative research methods is the assessment of research quality. It gives an indicator that simple errors (such as researchers' bias) are minimized (Taylor, Gibbs, & Lewins, 2005). The quality of quantitative research is often determined by *validity*, *reliability*, and *generalisability* of data, analyses, and research outcomes. In qualitative research, slightly different approaches are used to measure research quality, namely *credibility*, *dependability*, and *transferability* (Lincoln & Guba, 1985). In brief, *credibility (*or *validity)* defines if a study measures what it aims at, assuring the accuracy of analyses. *Dependability* (or *reliability*) signifies research trustworthiness. This means that repeated studies by the same or other observers should result in the same data. At last, *transferability* (or *generalisability*) is defined as the richness of research outcomes, particularly related to how they differ from other undertaken studies.

One of techniques that can be used to measure the quality of qualitative research is *intercoder* (or *inter-rater*) *reliability* (Lombard, Snyder-Duch, & Bracken, 2008). It measures the degree of agreement among different coders, interviewers, or observers. Therefore, it is commonly used in *content analysis* (Babbie, 2003), a qualitative research type that studies the content of communication. Content analysis focuses on meanings behind recorded transcripts of interviews. The CNET interview protocol aims at eliciting considered aspects in decision making. Thus, understanding real meanings behind people's answers and descriptions during the interviews become a crucial issue, making *content analysis* relevant. *Intercoder reliability* provides a way to ensure the reliability of research outcomes, as it shows the degree of interviewers' bias. This technique is often considered as a standard measure of research quality (Lombard, Snyder-Duch, & Bracken, 2002). Since the CNET interview protocol is a relatively new qualitative approach, a further study should also be done to investigate the quality of this technique (in general) and (specific) research that employs it. This can be done, for instance, by applying an intercoder reliability technique to the CNET interview recoded data.

1.2 Research objectives

In summary, Section 1.1 highlights the importance of a behavioural study to understand people's decision making processes when planning their trips. It also explains the necessity to investigate travel decisions related to leisure-shopping activities. The use of behavioural data for developing mental-level models using AI techniques is also stated in Section 1.1. Furthermore, the CNET interview method to elicit these data is briefly mentioned, highlighting the need to have an automated elicitation interface. Given the research background described in Section 1.1, the PhD research objectives are formulated, as detailed in the following paragraphs and illustrated in Figure 1.2.

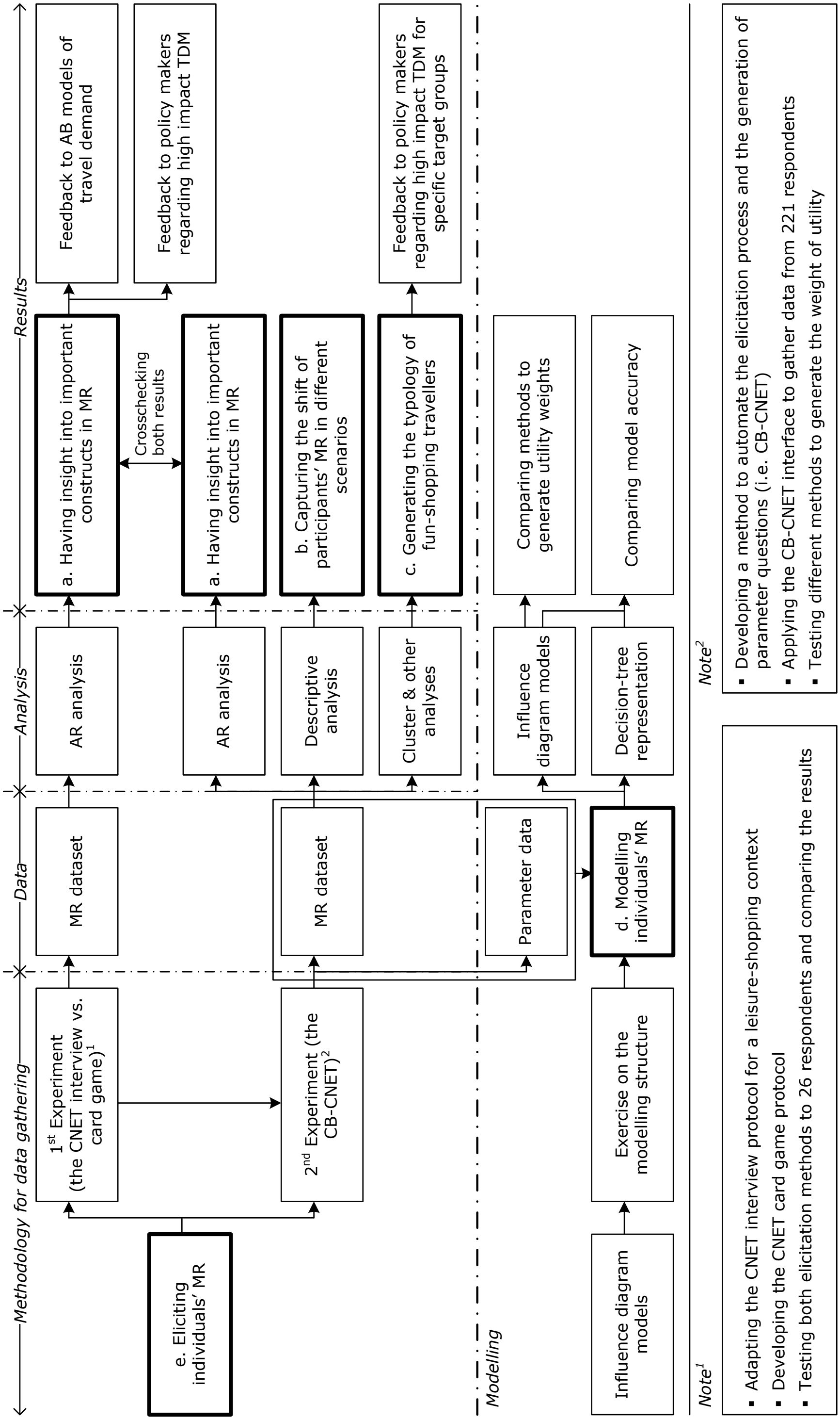


Figure 1.2 Research objectives

One of the main research goals is *to deepen the insight into fun-shopping travel decision making process*, especially regarding important constructs and beliefs in individuals' MR that lie beneath travel choices (Figure 1.2a). For this purpose, a case study of fun-shopping in Hasselt is selected. Hasselt is a typical European historical city located in the region of Flanders in Belgium. People's leisure-shopping travel decisions are studied, such as the *transport mode* and *shopping location* choices.

Additionally, this research aims at demonstrating the use of behavioural process data, in this case MR data, to inform policy makers about important aspects that best signify people's choice processes to identify high impact TDM policies. The application of MR data to discuss decisive factors in people's decision processes and aspects taken into account in an AB model is also shown. In this research, attention is especially paid to a Computational Process Model (CPM) of AB models, namely FEATHERS (Arentze, Timmermans, Janssens, & Wets, 2008b; Bellemans, Janssens, Wets, Arentze, & Timmermans, 2010) FEATHERS stands for "*Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS*". It is an activity-travel behaviour model of people in Flanders, Belgium. In order to find out about important factors in peoples' MR, association rules (AR) algorithm is used. This data mining technique is designed to learn rules in a dataset. Applying it on MR data brings about rules that appear people's decision making processes.

Within the research scope to gain a better understanding of individuals' travel decisions, this research also tries to *capture the changes of people's MR in distinct scenarios* (Figure 1.2b). In this research, attention is particularly given to the situational constraint of *time availability* and its impact on travel decisions. Based on many existing studies (e.g. Mattson, 1982; Maule, Hockey, & Bdzola, 2000), this aspect is considered as a significant factor which influences people's behaviour. Thus, two shopping scenarios are tested to investigate the differences in size and content of people's MR, namely *shopping with* and *without time pressures*.

The next objective focuses on *exploring different groups of individuals based on their MR* (Figure 1.2c). Special emphasis is given to study the relation between these groups and people's transport mode habits. It is a well known fact that car-use habitual behaviour has caused some major problems, such as traffic jams, accidents, car emissions, etc. Therefore, policy makers should identify TDM measures that can break car-use habit and steer people's travel behaviour towards more sustainable forms. This study intends to contribute to this effort, highlighting the typology of leisure-shopping travellers based on shopping travel decisions. *Cluster analysis* (CA), *frequent itemset* (FI) and *Fisher's test* are employed. The FI analysis is a part of AR, focusing on learning frequent items or combinations of items from a dataset. The results may provide tools to analyse effective TDM strategies to break car-use habit.

This research also aims at exploring the possibility to generate individuals' mental-level models based on people's elicited MR using the ID technique. MR data are further used as input to generate a DT model. *The accuracy of both modelling techniques in forecasting behavioural changes of people due to certain contexts and constraints* is examined next (Figure 1.2d). The results offer the possibility to understand people's travel behaviours and their variation based on numerous influential factors.

Concisely, this research focuses on fun-shopping travel-related decision making processes and their representations, highlighting people's travel behaviour from the standpoint of agents (or individuals) as the executors of their travel decisions. Furthermore, individuals' mental-level models that can best represent their thought processes are generated. However, in order to achieve these objectives, the method to elicit MR data should first of all be established.

The current CNET interview technique can be used to elicit people's thought processes, as previously addressed in Section 1.1. However, akin to other qualitative research methods, this technique consumes considerable time and effort for data collection. Consequently, it is limited to small sample sizes. Alas, to accomplish the mentioned objectives above, the data should be analysed quantitatively using statistical analyses (e.g. *clustering analysis*) and data mining techniques (e.g. *AR analysis*), implying that the number of participants should be sufficient for conducting those analyses. Additionally, generating individuals' mental-level models using ID and DT techniques requires subsequent parameters to be gathered for every individual separately, adding data collection effort. These issues emphasize the need to *develop an automated computer-based elicitation method to ease the overall data collection procedure* (Figure 1.2e).

In order to automate the elicitation interface, the CNET interview is firstly adapted to the leisure-shopping context. Another elicitation method is developed next, named as the CNET card game. The card game method is anchored to variable recognition, opposing to self-initiated recall in the CNET interview. *Both techniques are tested on a small sample group of 26 participants and used to assess the participants' activity-scheduling, transport mode, and location decisions when carrying out fun-shopping activities in Hasselt*. Each participant is interviewed using both elicitation techniques. These interviews are audio-recorded and used to study the reliability of the CNET interview protocol, emphasizing different researchers' assigned codes. For this purpose, *intercoder reliability* techniques are applied.

The experiences and evaluations of the CNET interview and card game are used to develop an automated protocol, to elicit people's MR and directly generate subsequent parameter questions for the modelling purposes. This technique is transferred into a computer-based (CB) application, named CB-CNET interface, and used to conduct another experiment on a large sample group of 221 participants. In this second testing, only two travel decisions are focused on; i.e. *the transport mode* and *location choices*. In addition to eliciting MR, two methods to generate the utility weights as part of parameter estimations are tested. The results are used to give feedback to the protocol.

1.3 Outline

In Chapter 1, the problem statement that sets up the research project is explained and the research objectives are formulated. Hence, the remainder of this book is explicated in the following paragraphs. The scheme that explains how this book is organized can be seen in Figure 1.3.

Chapter 2 focuses on the methodological discussions, emphasizing *methods to elicit individuals' MR* and *ID modelling technique to represent the elicited MR*. People's decision making processes are strongly highlighted in this section. Therefore, the theory of decision making is presented in the beginning. Following that, *soft*- and *hard-elicitation methods* are discussed. Next, the CNET interview and card game protocols are explained. Both methods are used to gather MR data from 26 participants, each of them is the subject of both techniques. The results are compared and discussed from the methodological point of view. This section is based on Kusumastuti et al. (2009a). Moreover, a study is performed to investigate the reliability of the CNET interview technique, employing intercoder reliability measures. This part is developed based on De Ceunynck, Kusumastuti, Hannes, Janssens, & Wets (2011). Modelling individuals' MR using ID technique is discussed next. The theoretical background of ID model is initially explained. Furthermore, different ways to structure a mental-level model using the ID technique are shown next. Eventually, conclusions are made regarding how to model people's elicited MR.

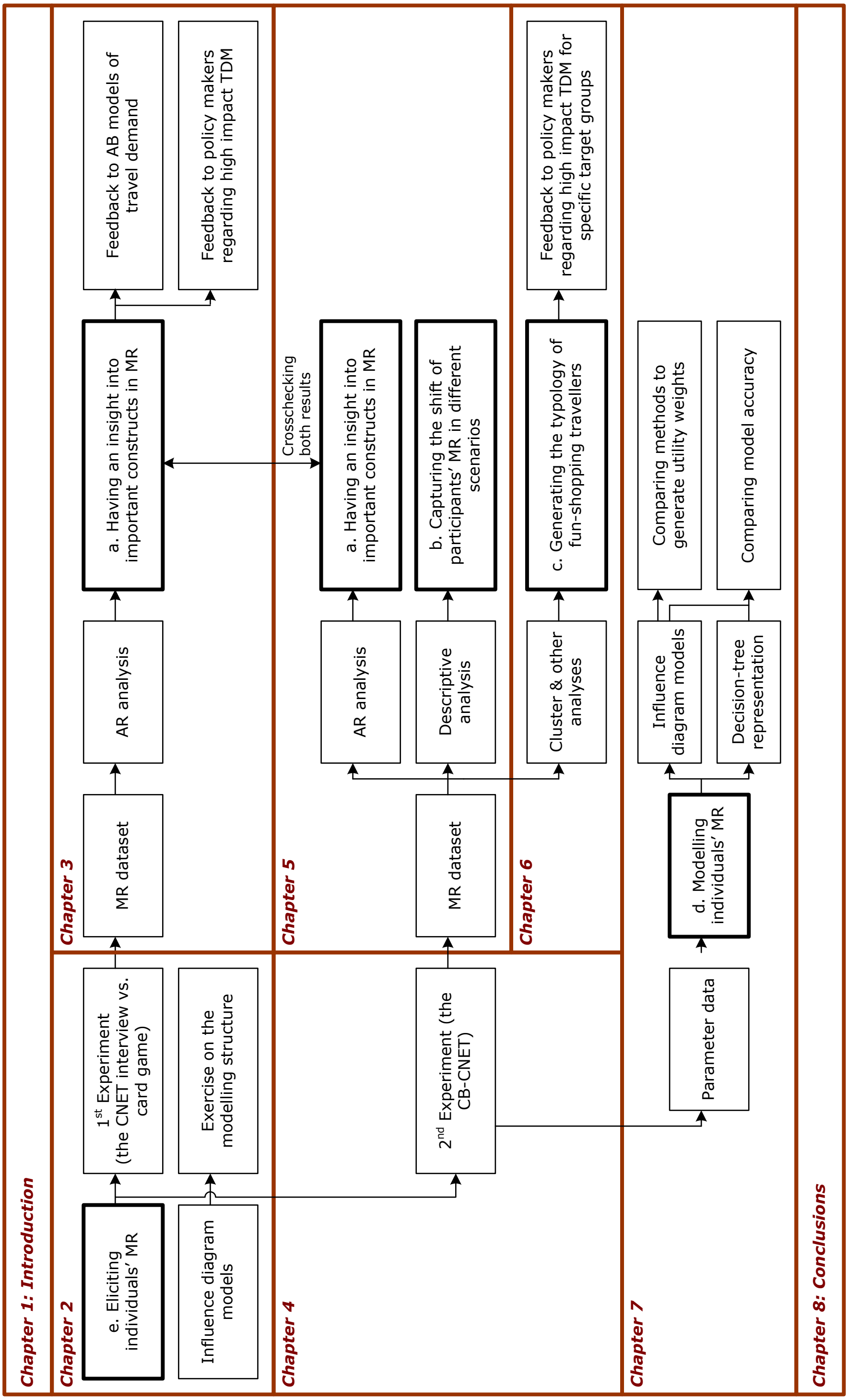


Figure 1.3 Outline of the PhD book

Chapter 3 emphasizes the analysis on the CNET interview and card game datasets, using the data derived from 26 respondents. To begin with, some descriptive analyses are used to study the frequency of elicitation of each aspect. However, based on the theory of decision making presented in Chapter 2, aspects are intertwined in people's MR and the descriptive analysis cannot capture this. Therefore, AR analysis is employed. The AR results of the CNET interview are used next to discuss the differences between aspects in people's MR and factors appear in FEATHERS. This section is built upon Kusumastuti, Hannes, Janssens, Wets, & Dellaert, (2010a). In addition to that, the AR results of the CNET card game are discussed to give feedback to policy makers regarding high-impact TDM in line with the way people make their travel decisions. The major part of this section is taken from Kusumastuti, Hannes, Janssens, Wets, & Dellaert (2009b).

Chapter 4 details the development of the CB-CNET protocol based on the CNET interview and card game results. Beforehand, the advantages of using computers in the survey are detailed. In this chapter, the application of the CB-CNET interface to survey 221 participants in Hasselt is pointed up. Similar to the first experiment using the CNET interview and card game, the CB-CNET interface is developed to assess people's leisure-shopping travel behaviour, highlighting two sequential decisions of *the transport mode* and *location choices*. Besides eliciting the participants' MR, the interface is also used to gather subsequent data for the modelling purposes. This chapter is based on Kusumastuti et al. (2011a)

In Chapter 5, the sample group of 221 respondents surveyed by using the CB-CNET interface is detailed, describing the participants' socio-demographic, travel behaviour, and shopping behaviour characteristics. FI analysis, as a part of AR, is applied next to learn interconnected aspects in the participants' MR. The results of this study are compared with the AR results of the CNET interview and card game. The impact of time constraints on the size and content of participants' MR is explored as well in this chapter.

Chapter 6 focuses on generating the typology of fun-shopping travellers based on 221 participants' MR data. Different groups of people are learned from the data. The participants in the same group share similar MR. In order to have a complete idea of these groups, their members' socio-demographic, travel behaviour and fun-shopping behaviour characteristics are examined. Particular emphasis is given to people's transport mode habits. The results are discussed from the environmental perspective, particularly related to TDM that can break car-use habit and encourage people to predominantly shit their transport mode choice from car to bus or bike, especially to go to the city centre for leisure-shopping. This chapter is based on a working paper by Kusumastuti et al. (2011b).

Chapter 7 concentrates on a number of modelling techniques to generate mental-level models, i.e. the DT representation and ID model. Furthermore, the performance of both methods in predicting people's travel choices is studied. This chapter is taken from Kusumastuti et al. (2010b). Besides, two ways to generate the utility weights as part of parameter estimation are also tested and presented in this chapter.

At last, Chapter 8 presents the general conclusions of this PhD research. The limitations of this study are discussed next, suggesting improvements for other studies along the lines of this research. At last, directions for future research are highlighted.

2 Eliciting and modelling individuals' fun-shopping travel decisions

"You may have heard the world is made up of atoms and molecules, but it's really made up of stories. When you sit with an individual that's been here, you can give quantitative data a qualitative overlay."
William Turner

2.1 Introduction

The main research objective addressed in Chapter 2 intends to unveil *how* people come to certain fun-shopping travel decisions and *why* particular choices are made. Consequently, methods to acquire this information are needed. It has been explained in Chapter 1 that quantitative research methods such as travel survey generally can only capture the observed travel outcomes, but cannot sufficiently explain the underlying aspects behind travel decisions. Qualitative research approaches such as *face-to-face interviews*, *focus groups* and *participant-observer methods* can provide answers to the questions above. These methods have been applied in the transportation field to address varieties of issues that are left unexplained by quantitative techniques.

Face-to-face interviews offer a unique opportunity to identify travel choice factors in cognitive processes and to assess their causal relationships directly from respondents' account (Bradley, 2006). Focus groups suggest an effective way to understand specific groups of people regarding their travel choices. For instance, Goodwin (1990) conducts a group interview to investigate the effect of altering public transit systems on the mobility of women. Participant-observer methods are another practice in qualitative research. This technique directly involves researchers in the daily-life of their participants to investigate the phenomenon under study (Clifton & Handy, 2003). Therefore, it is commonly used in the anthropological studies and in particular in the ethnographic research (Kawulich, 2005). Despite the strength of this method in directly studying individuals' behaviours, its application in the transportation research field is still scarce. This happens because of the intensity of data collection procedure. Researchers have to initially be accepted by their target group, consuming considerable time, effort, and emotion (Clifton & Handy, 2003).

Hence, face-to-face interviews are one of the best suited methods to understand each individual's thought and consideration in the decision process. They are generally less demanding than the participant-observer technique. An experiment can be conducted using face-to-face interviews in which the main questions revolve around *what, why* and *how* aspects are considered when making choices. These probing questions last until individuals' pursued benefits, or even more, personal values are elicited. Such a method has been widely applied in the marketing domain, in order to understand consumers' cognitive perceptions of current products and develop strategies to position new products (Reynolds & Gutman, 1988). This method is based on the *Means-End Theory* (Gutman, 1982) and it is often referred to as *laddering technique*.

Recently, a similar method is developed in the transportation research field, named as CNET (Arentze et al., 2008a). The CNET method is designed to elicit individuals' MR of travel decision problems. MR consists of a number of intertwining aspects temporarily activated when decision makers deduce about their problems. Thus, the CNET interview probes about *what* aspects come to people's mind when making travel decisions and *why* or *how* those considerations affect their choices, providing a framework to structurally extract people's pursued benefits based on a number of other influential factors. This method has been used to assess the differences in individuals' travel decision processes in a hypothetical setting (Arentze et al., 2008a).

Thus, in order to investigate individuals' fun-shopping trip decisions, the CNET interview method is used after adapting it to the leisure-shopping context, i.e. by developing an extensive predefined list of variables to code respondents' open answers. Additionally, another elicitation method is developed, named as CNET card game. It is a fully-structured face-to-face interview procedure using predefined variables printed on cards. Unlike the CNET interview that bases on individuals' self-revealed aspects, the CNET card game originates from variable recognition. Both the CNET methods are tested in the leisure-shopping context of the city centre of Hasselt, Belgium, to extract 26 participants' cognitions when making their travel decisions. The differences of both elicitation techniques are discussed based on the participants' evaluations, consisting of the *easiness*, *pleasantness*, *comprehensiveness*, and *representativeness* of these methods.

However, despite the strength of qualitative research in explaining people's behaviour, it is still often questioned for lack of scientific rigour (Clifton & Handy, 2003). Moreover, the reliability of such qualitative study results is often doubted due to researchers' subjective interpretations. When properly done, qualitative research requires a large amount of time and accordingly effort, making it limited to small sample sizes. The latter drawback can also be seen as the strength of qualitative methods. Indeed, such a qualitative study requires large investments in time and effort. However, the gathered behavioural information is rich and extensive, which cannot be obtained using its quantitative counterparts.

Furthermore, the CNET interview and other qualitative methods are alike and they tend to share the same limitations. Accordingly, elicited aspects using the CNET interview method could also be questioned. Since the CNET interview is still a relatively new method, its reliability should be investigated, especially concerning how different coders (researchers) interpret respondents' open answers in interviews. *Intercoder reliability* can be used for this purpose. This technique checks if data interpretations among a number of researchers (or coders) are valid (Lombard, Snyder-Duch, & Bracken, 2008). Accordingly, the audio-records of the interviews derived from the experiment using the CNET interview method are used to elucidate this issue.

Besides eliciting individuals' MR of their leisure-shopping travels, this PhD research also aims at using the elicited MR (along with additional data of parameters) as input to generate individuals' *mental-level models* at the disaggregate level by means of a formal modelling approach. AI techniques, such as ID and FCM, can be used for this purpose (Hannes et al., 2010). However, their properties to model individuals' mental states have not been studied extensively (Brafman & Tennenholtz, 1997). Individuals' mental-level models can be used not only to understand people's travel behaviour but also to forecast their behavioural changes.

ID takes into account *sequential decision making* and *interconnected aspects*, making it suitable to model MR. For instance, an individual's transport mode decision can be made after choosing a location to perform an activity. Moreover, modelling individuals' MR as ID gives benefits to understand important aspects in people's decision making that affect people's travel choices, reflecting on their actual travel behaviour. However, since this type of studies is still limited, further research still has to be done.

This chapter explores a number of possibilities to model MR using ID, highlighting issues about how to link aspects inside a cognitive subset, to connect a number of cognitive subsets, and to relate these subsets in decisions. All of them are included in the ID model structure. Hence, an existing model structure approach proposed by Arentze et al. (2008a) is used as a starting point. Another model structure is developed and presented.

Ultimately, if the purpose of the research is solely to gain insight into individuals' decision making processes, then using a qualitative research method for data collection could be sufficient. On the other hand, modelling individuals' MR highlights the need for quantitative data analyses. Because of that, the amount of behavioural data should be sufficient. This leads to the necessity to develop an automatic quantitative elicitation method that can ease the burden of the data collection procedure. This issue is elaborated in Chapter 4. It should be noted that the differences between qualitative and quantitative methods and their derived data are often unclear (Clifton & Handy, 2003). Many surveys include questions about qualitative aspects, such as people's attitudes and behaviour. And, in some (rare) cases, qualitative methods gather data that can be quantified. The results of the experiment using the CNET interview and card game (from the methodological point of view) can be used as an input to develop an automatic elicitation procedure using computers.

Concisely, Chapter 2 gives emphasis to the methodological discussions of *how to elicit* and *model* individuals' MR. Hence, what is left in this chapter is structured in Figure 2.1. Since people' MR is highlighted, the theory of decision making and MR is presented to start with (Section 2.2). The subsequent part (Section 2.3) emphasizes the elicitation methods to elicit individuals' MR. For this purpose, an experiment to test the CNET interview and card game is conducted, using fun-shopping in Hasselt city centre as the scenario. Both methods are detailed successively. The respondents' actual evaluations of both techniques and intercoder reliability of the CNET interview are presented next in sequence. Section 2.4 focuses on modelling individuals' MR using ID models. Therefore, the theory of ID is described to start with. The existing and alternative ways to structurally model an individual's MR using ID are explained successively. In the end, the researcher's experience in using the CNET interview and card game to gather the data for the modelling purpose is described. Section 2.5 presents the general conclusions of how to elicit individuals' MR and how to represent the elicited MR into ID models.

2.1 Introduction

2.2 The theory of decision making & mental representations

- 2.1.1 Rational decision making in travel decisions
- 2.1.2 Mental representation of a complex shopping-trip decision
- 2.1.3 Habitual and script-based travel mode choices

2.3 Eliciting individuals' fun-shopping travel decisions

- 2.3.1 Elicitation methods
  - 2.3.1.1 Laddering technique
  - 2.3.1.2 Soft- and hard-elicitation techniques
- 2.3.2 Research setting and sample
- 2.3.3 The CNET interview method
- 2.3.4 The CNET card game method
- 2.3.5 Methodological notes of the CNET interview and card game techniques
- 2.3.6 Measuring the reliability of the CNET interview method using the intercoder reliability techniques

2.4 Modelling individuals' fun-shopping travel decisions using the influence diagram technique

- 2.4.1 Influence diagram
- 2.4.2 The existing modelling approach
- 2.4.3 The alternative modelling approach
- 2.4.4 Evaluating the CNET protocols to gather data for the influence diagram technique

2.5 Conclusions

Figure 2.1 The structure of Chapter 2

2.2 The theory of decision making and mental representations

People have to make decisions in nearly every aspect of their lives. The complexity of such decisions varies from trivial choices (e.g. selecting a pair of shoes to wear) to crucial ones (e.g. choosing a career). Some choices are made in quick habitual processes while others need careful thought and deliberation among different choice alternatives (Verplanken & Svenson, 1997; Harte & Koele, 1997). When solving complex or novel decision problems, individuals create a temporary MR, herein detailing relevant attributes of alternatives and judging its subjective values, attractiveness or suitability (Dellaert et al., 2008). There are a number of ways to study individuals' judgement and decision making behaviour, but generally they are grouped into the *normative* and the *descriptive* approaches (Shafir, 2007). The first approach focuses on decisions that an individual should make to optimize his goals, while the second one studies how an individual processes available information when making a choice (Crozier & Ranyard, 1997; Harte & Koele, 1997; Selart, 1997). This research addresses the *descriptive approach*, emphasizing how people come to their fun-shopping travel decisions.

In this study, different decision making styles are detailed, focusing on rational and automatic behaviours. Fun-shopping travel decisions may involve rational thinking because of a multitude of different influencing situational factors that occur randomly during the decision process, making it difficult to have readymade solutions based on past experiences, especially when such activities are only performed occasionally. In these cases, a rational mental choice process is activated and different choice alternatives are evaluated (Arentze et al., 2008a). Additionally, performing out-of-home activities such as fun-shopping usually involves interactions between different decisions simultaneously attached to the trip (e.g. transport mode, location, activity-scheduling decisions, etc.), adding more complexity to the decision processes (Dellaert et al., 2008) and enabling many possible solutions (Timmermans, Arentze, & Joh, 2002).

However, when leisure-shopping activities are executed on a regular basis under stable environments, it is possible that some people simply use their ready-made heuristics or habits to solve the problems, for instance by always taking car as the transport mode choice (habit) or using a *"IF-THEN"* script-based choice (e.g. *IF* it is raining, *THEN* a car is chosen). Such automatic behaviours are developed over time, when an action has been executed repeatedly. In this case, decision makers feel that there is no need to re-evaluate the choice alternatives again since this process has been done before.

According to the above lines of thought, some theories about *rational*, *habitual*, and *script-based* decision making are described. They are fitted into the theory of MR. Furthermore, the applicability of these concepts for fun-shopping travel behaviours is examined in all parts.

2.2.1 Rational decision making in travel decisions

When facing novel or infrequent decision problems, a rational decision making setting is activated. This setting may entail complex and deliberate cognitive processes in which an individual decision maker evaluates different choice alternatives based on their attributes and dimensions to come up with the best possible solution (Payne, Bettman, & Johnson, 1993). Initially, an individual develops a repertoire of possible alternatives and courses of action for solving the occurring problems. Following that, advantages and disadvantages of each decision alternative regarding their instruments are assessed vis-à-vis individual's goals or pursued benefits, and occurring contexts and constraints in the decision environment. In the end, the most satisfying alternative to solve the problem is selected and a choice is made. This process is illustrated in Figure 2.2. Components involved in a rational decision process are explained in the following paragraphs.

The first concept is *decision alternatives* (Figure 2.2a) representing a choice set of all possible actions or objects related to a particular decision (Arentze et al., 2008a; Gärling, Laitila, & Westin, 1998). Some literature refers to alternatives as decision strategies (e.g. Payne et al., 1993) and they can be formulated based on an individual's personal experience (Kruglanski, 1989) or through formal training (Larrick, Morgan, & Nisbett, 1990). Based on the nature of the task and the occurring circumstances, a decision maker evaluates the attractiveness of each alternative in the choice set (Harte & Koele, 1997). For instance, decision alternatives of travel modes to go fun-shopping in the city centre can be *car*, *bus*, or *bike*.

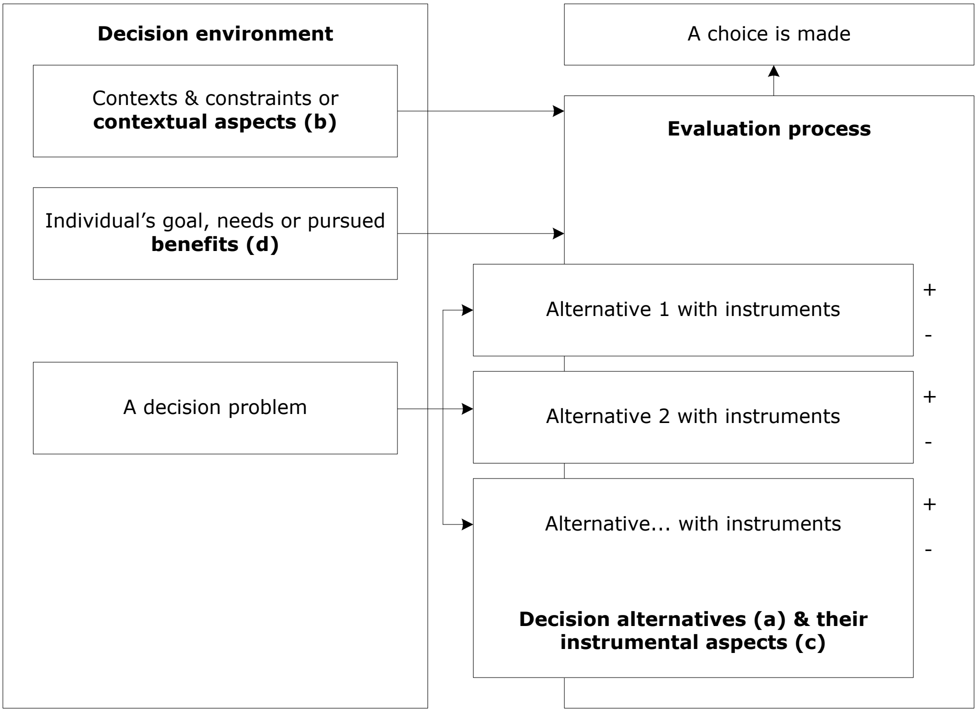


Figure 2.2 A rational decision making framework, including decision alternatives (a); contextual aspects (b), instrumental aspects (c) and benefits (d)

Secondly, *contextual aspects* (Figure 2.2b) are defined as all given circumstances, such as situations and constraints, taking place in the decision setting. Albeit strongly affecting decision outcomes, contextual aspects cannot be controlled by a decision maker (Arentze et al., 2008a). In travel behaviour, contexts and situational constraints play a significant role (Gärling & Axhausen, 2003; Gärling et al., 2002; Schlich & Axhausen, 2003; Stern & Richardson, 2005). Thus, this aspect cannot be discarded when studying travel decisions (Stauffacher et al., 2005). These contexts can be natural forces such as *weather conditions*, and other constraints (e.g. *budget*, *time availability*, *companionship*, etc.). Hägerstrand (1970) categorized various constraints surrounding individuals' travel-activities into *capability*, *authority* and *coupling constraints*.

Capability constraints are related to human's biological restrictions (e.g. the need to eat and sleep); coupling constraints rise because some activities require meeting other people in the same time-space; and authority constraints are related to external institutional regulations (e.g. shops opening hours) that urge individuals to change places using the given available transport modes (Algers, Eliasson, & Mattsson, 2005; Hägerstrand, 1970).

Thirdly, *instrumental aspects* (Figure 2.2c), also known as *attribute variables* (Harte & Koele, 1997), refer to any observable characteristics of alternatives in a choice set. In the example above, instrumental aspects of travel modes (car, bus, and bike) to go fun-shopping can be *travel time*, *cost*, *environment inside vehicles*, etc.

At last, *benefits* (or *utilities*) are related to individuals' pursued goals or needs. This aspect connects with any subjective evaluation of instruments of the choice alternatives given influencing contexts (Figure 2.2d). These utilities are summed up. It is assumed that an alternative that has the highest (overall) utility value is selected (Crozier & Ranyard, 1997). Even though these benefits could be the same across individuals, their weights depend on individuals' situation and subjective preferences. For instance, a busy person may prioritize gaining *efficiency* (benefit) over *saving some money* (benefit).

Decision alternatives, contextual aspects, instrumental aspects and benefits are considered together in an evaluation process, prior to making a choice. An individual decision maker weights up all pros and cons of decision alternatives concerning their instruments based on the arisen contexts and his pursued benefits. These aspects are linked together in a decision process, creating a MR of a decision problem, as discussed in Section 2.2.2.

2.2.2 Mental representation of a complex shopping trip decision

During a decision making process, a decision maker activates a temporary MR in his working memory based on his previous experiences or existing knowledge

(Kearney & Kaplan, 1997). Therefore, constructing a MR requires a decision maker to recall, reorder and summarize relevant information in his long-term memory (Cox, 1999). It may involve translating and representing this information into other forms, such as a scheme or diagram, supporting coherent reasoning in a connected structure (Kolloffel, Eysink, & de Jong, 2010; Tabachneck-Schijf, Leonardo, & Simon, 1997).

In a cognitive MR of travel decisions, different concepts, such as contextual aspects, instrumental aspects and benefits, are mapped and linked by causal relationships. In order to capture an individual's MR, the smallest component that composes this representation has to be obtained. This component is referred to as *cognitive subset*, comprising each basic need (pursued benefit) linked to its relevant context and instrument (Kusumastuti et al., 2010a), i.e. {*context, instrument, benefit*}. One subset of a certain decision can be linked to other subsets from the same or interrelated decision(s), constituting a complex MR of a particular decision problem.

However, it has been previously described in Section 2.2 that not every travel decision is made consciously and cautiously. In frequently repeated daily travels, travel decisions are often made out of habit (Hannes, Janssens, & Wets, 2008). Besides, certain instruments could also be considered regardless of the contexts, suggesting another cognitive subset type of *{normally, instrument, benefit}*, in "normal" conditions (or usual situations). In complex travel decisions, different decisions are interconnected. For instance, when planning a leisure-shopping trip, an individual initially decides upon the exact location to go to before thinking about the transport mode option, as shown in the example in Figure 2.3, or vice versa. In the MR example, the transport mode choice mainly depends on *weather conditions* (a context). This happens because various vehicles offer different protection or *shelter* (an instrument) in case of bad weather and due to an individual's pursued benefit of *having comfort* (a benefit). As a result, the transport mode subset of {*weather, shelter, comfort*} in this MR is registered. Using the same lines of thought, the cognitive subsets for the location choices are recorded.

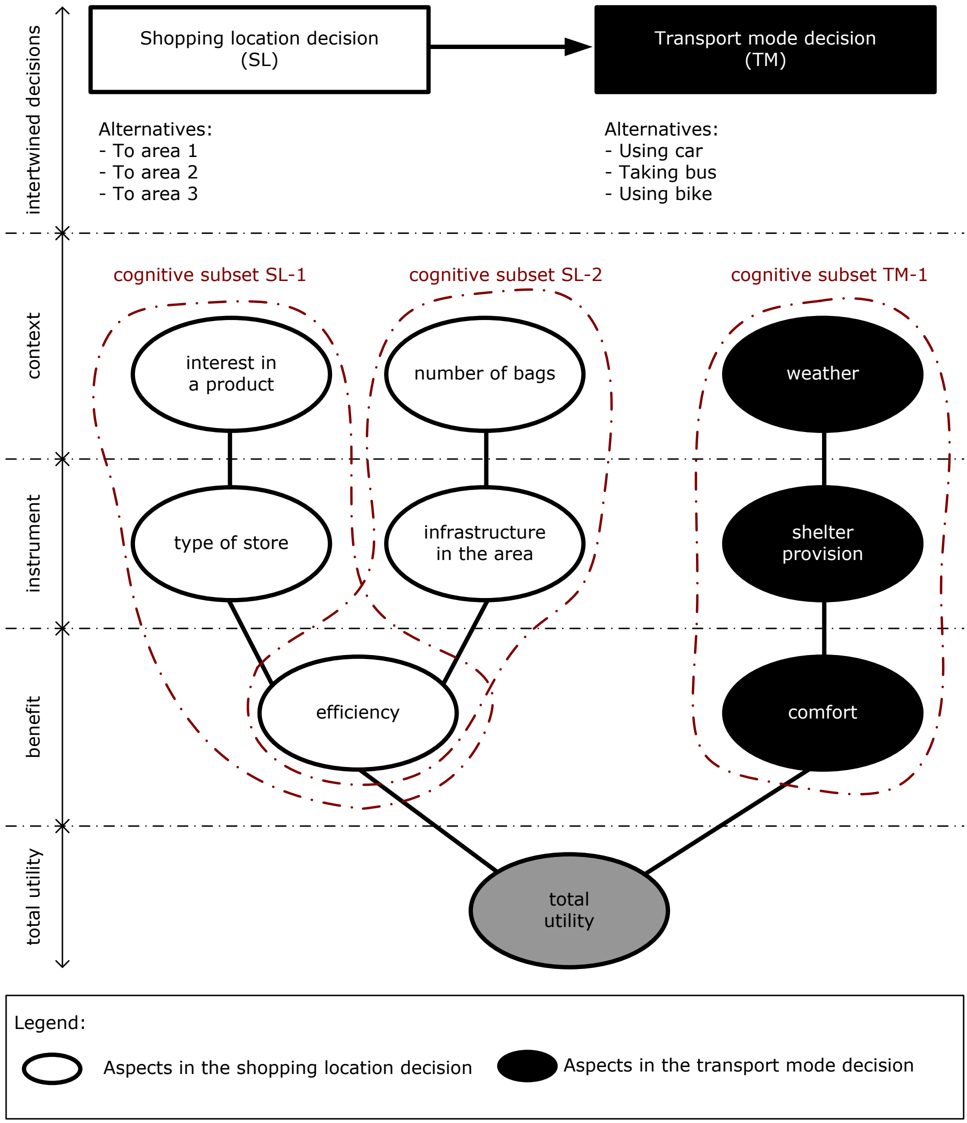


Figure 2.3 An individual's mental representation of fun-shopping decisions

The size of an individual's MR relies upon the importance of the decision problem to solve. A person's cognitive process when settling on crucial choices (e.g. buying a house) is generally much more complex and elaborate than when making trivial decisions (e.g. buying shoes) (Payne et al., 1993), resulting in a bigger MR and a longer choice process. Generating MR requires recalling episodic memories related to a certain decision problem and collecting some new information that can be used to solve the problem. Therefore, more mental effort is needed to create a bigger MR with more detailed information. Since human's cognitive capacity is limited, there is always a trade-off between the size of MR and working memory load (Johnson-Laird, 2001). Moreover, it is important to note that a decision maker is flexible enough to increase mental effort when more accurate decisions have to be made (Payne et al., 1993).

2.2.3 Habitual and script-based travel mode choices

People do not make rational decisions all the time. Once a deliberation is made in the past and a choice outcome is satisfactory, a decision maker may reuse that past solution to solve other similar problems under a stable environment. This is done to minimize cognitive load to evaluate all possible choice options (Baumeister, Bratslavsky, Muraven, & Tice, 1998). When such a solution (or an action) is reused all the time to solve the same problem task, an automatic response could be activated and a habit could eventually be formed. Habits are explained as "*…learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end-states*" (Verplanken & Aarts, 1999 p. 104). Hence, a habitual behaviour meets three principals (Verplanken, 2005): (1) it is a goal-oriented behaviour performed unconsciously, unplanned and with minimal intention (Aarts & Dijksterhuis, 2000a), (2) it is hard to control and yet (3) mentally efficient. The last concept means that actions are simplified and done without much thought and deliberation (Davidov, 2007).

A habitual behaviour is formed when a certain action is repeated frequently. However, a frequently repeated behaviour does not always lead to a habit formation (Verplanken, 2006). For instance, a bus driver who drives a bus all the time for a living does not mean that bus-use is his transport mode habit. Consequently, a habit is only established when a selected action gives satisfaction to a decision maker when pursuing a goal.

The frequency of a repetitive action plays a significant role in a habit formation. However, its minimum number to turn into a habit is not known. Some actions can easily become habits (e.g. smoking) while others have to go through long and difficult processes (e.g. changing sleeping time, learning to drive, etc.) (Verplanken, 2005).

Habits are often seen as an automatic goal-directed behaviour (Aarts & Dijksterhuis, 2000b; Bargh, 1989). Goals signify the desired or awaited result outcomes (or end states) (Austin & Vancouver, 1996; Elliot, 2007). Goals can also be seen as results of physiological needs or motives (Geen, 1994; Mook, 1995), such as the need to feel safe and secure, have efficiency, make friends, etc. Max-Neef (1992) defines these needs into nine categories: *subsistence*, *affection*, *understanding*, *participation*, *leisure*, *creation*, *identity*, and *freedom*.

The link between an action and a goal becomes stronger over time along with the frequency of executing an action to attain the goal. For instance, a goal (e.g. going fun-shopping) and an action (e.g. car-use) are linked together. Travel mode choice is often viewed as a habitual behaviour (e.g. Banister, 1978; Boe, Fujii, & Gärling, 1999; Gärling & Axhausen, 2003; Klöckner & Matthies, 2004; Davidov, 2007; Hannes, 2010). An obvious example is daily travel behaviours, such as commuting to work or school.

Hence, goals are the key to unconsciously activate the related actions (Aarts & Dijksterhuis, 2000a). Through the activation of a goal, a number of associated behaviours in the lower hierarchical levels of the MR are also actuated. For instance, shopping (the goal) may activate sequential behaviours of going to the city centre (shopping location choice) and using car (transport mode choice).

Habits are also defined as the proclivity to replicate past behaviours under stable contexts (Ouellette & Wood, 1998). Bargh (1997) argues that when an action is performed regularly in a given situation (to attain a goal), a link connecting this action to the activated MR for the given context will manifest itself. This is often referred to as *script-based choice* (Svenson, 1990; Fujii & Gärling, 2003; Gärling, Fujii, & Boe, 2001). Some research (e.g. Aarts & Dijksterhuis, 2000a) states that a situational cue can only trigger a goal-directed behaviour when that behaviour has already become habitual. However, other research (e.g. Abelson, 1981) argues that a script-based behaviour and habits are not equal. The first represents a knowledge structure whereas the latter resembles a response program. Despite these differences, both agree that actions can be tailored to certain contexts. Accordingly, choice sets are reduced or diminished to lessen mental effort. Since a link between a context and an action has been formed, deliberation about other possible actions or choice options is no longer needed. This link information is stored as a subset of information or a "*IF-THEN*" script in memory. For instance, when someone goes shopping (a goal), he normally uses his car (given a stable context). However, *IF* the weather is nice *THEN* he bikes (a situational triggered behaviour or a script-based choice).

Having habitual and/or script-based behaviours can be a good thing because people can save their cognitive effort. Existing research (i.e. Wood, Quinn, & Kashy, 2002) has shown that people's minds are more likely to wander when performing a habitual behaviour than when a non-habitual behaviour is carried out. Even though people's ability to efficiently multitask when conducting the task was not evaluated in that study, it can be assumed that this may likely be the case. Hence, when performing a habitual behaviour, people may use their time and effort to solve other problems.

While cognitive efficiency accounts for the major benefit of a habitual behaviour, having out-dated information is its main disadvantage (Jager, 2003). Habits may have given optimal results in past conditions but as new information becomes available, behavioural opportunities better suited to current situations may have been introduced without people being aware of them. It is also possible that people are informed about these opportunities at an attitudinal level but they are not willing to change their behaviour (Triandis, 1980), especially when there are conflicts between new information and habits. In this case, people tend to reject or underestimate the new information simply because it is easier than changing their habits (Jager, 2003). Habitual car-use can be seen as an example. Even though car users are commonly aware of the negative effects of excessive car-use on the environment, they do not easily give up this behaviour.

In daily travels, car-use habit has become a prominent problem along with the increase of air pollution and traffic jams, especially in urban regions. Generally, many studies have been conducted to investigate ways to break "bad" habits (e.g. Quinn, Pascoe, Wood, & Neal, 2010; Jager, 2003; Holland, Aarts, & Langendam, 2006). Since a habit is a goal-directed behaviour in a stable environment and a script-based behaviour is a situationally guided goal-oriented behaviour, breaking these behaviours may work when goals and benefits that people pursue are known (Holland et al., 2006).

Eliciting people's MR when facing a specific decision problem gives the opportunity to explore people's motivations that ground their choices. Accordingly, probing questions such as *how* and *why* people come to certain decisions (e.g. travel mode choices) may explain their behavioural processes that describe their habit occurrence. This can be used as additional information to develop TDM that can break a "bad" (car-use) habit.

2.3 Eliciting individuals' fun-shopping travel decisions

Previous sections (i.e. Section 2.2.1 to 2.2.3) have detailed different travel decision making styles. This section aims at discussing the methods to elicit those processes. Hence, this section is organized as follows: the *laddering technique* as the pioneer and well-known method to elicit individuals' values is discussed to start with. Following that, hard- and soft-elicitation techniques are compared. The research setting of fun-shopping in Hasselt and the sample are explained in Section 2.3.2. The CNET interview method and its application to extract the participants' leisure-shopping travel decisions are detailed in Section 2.3.3. Following that, the CNET card game is explained in Section 2.3.4. In Section 2.3.5, the participants' evaluations over the CNET interview and card game are presented. At last, Section 2.3.6 focuses on the intercoder reliability aspect of the CNET interview.

2.3.1 Elicitation methods

2.3.1.1 Laddering technique

The laddering technique is a well-established method in the marketing domain to elicit customers' motivations behind product selections. This technique is based on the *Means-End Theory* (Gutman, 1982). It emphasizes the link between product *attributes* (or also referred to as *instruments* in this study), *consequences* of attributes to customers (or defined as *benefits* in this research), and ultimate *values* that customers want to gain. The premise of the Means-End Theory states that customers are trained to select products that contain important attributes to attain desired consequences and define their personal values (Reynolds & Gutman, 1988).

In brief, laddering signifies an in-depth face-to-face interview technique, using a number of probing questions such as *"why is that important to you?"* (Reynolds & Gutman, 1988). The purpose of these questions is to elicit a range of intertwined *attributes* (A), *consequences* (C), and *values* (V), providing explanations of *how* and *why* product information is important. For instance, the ladder example in Figure 2.4 starts by eliciting the attribute of *sports car* (A) and ends after revealing the value of *having self esteem* (V).

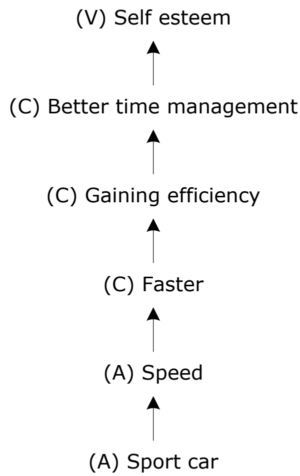


Figure 2.4 An example of laddering technique elicited data

The laddering technique probes about sequential concepts, from tangible (i.e. attributes) to intangible (i.e. values). Likewise, this approach can be applied in the transportation research field to elicit individuals’ MR that also consists of intertwined concrete (i.e. instruments) and abstract (i.e. benefits) concepts. However, in the travel decision making, contextual aspects play a significant role in determining travel outcomes, as described in Section 2.2.1. Consequently, literally implementing the laddering technique to investigate people’s travel choices may omit the elicitation of contextual aspects. Therefore, another method, namely CNET, is used for the purpose of this study. The CNET protocol has the underlying concept akin to the laddering technique, such as the use of similar probing questions. Nevertheless, it is designed particularly to elicit the decision making processes of people behind their travel choices. This technique is detailed later on in Section 2.3.3.

2.3.1.2 Soft- and hard-elicitation methods

From a methodological point of view, some relevant findings with regard to individuals’ responses to soft- and hard-elicitation techniques have been previously discussed in the literature, such as in Russell et al. (2004). They compare the results of a soft-laddering technique (i.e. face-to-face interviews) to the outcomes of hard-laddering methods (i.e. paper-and-pencil assessments and computer surveys). The results show that these various approaches generate different numbers of the elicited aspects, yielding distinct network complexity levels.

In the behavioural research, respondents are commonly asked about their past behaviours. As a consequence, the retrieval strategy of individuals' episodic memory during interviews plays a significant role. Cognitive research shows that an individual is likely to assess his perceived effort against the accuracy of the stored information (Zmud, 2001; Willis, 1999). This implies that the more important an event is to an individual, the more he is able to remember it correctly, and visa versa. When an event is less significant, it becomes harder to recall. Additionally, an individual's memory of salient events may deactivate the memory of less salient or habitual events.

In order to activate the correct episodic memory and to increase response accuracy, researchers should apply some manipulation strategies, such as by providing some cues in questions (Burton & Blair, 1991). With regard to this, it has been indicated that aided recalls (i.e. hard-elicitation technique or close-ended questions) generate better levels of accuracy of the reported behaviour in comparison to unaided recalls (i.e. soft-elicitation technique by using open-ended inquiries) (Cannell, Oksenberg, & Converse, 1979).

However, in order to accurately elicit people's behaviour, a pre-coded list used in a hard-elicitation technique should be made as extensive as possible, covering all possible variables from the least to the most salient. Despite being important, this could be cumbersome for researchers because an extensive literature review and some pilot studies with open-ended questions should be conducted prior to an actual experiment. Additionally, a close-ended format might not be as flexible as semi-open- and open-ended designs in obtaining new aspects from respondents, absent in a predefined list. Another disadvantage of a hard elicitation method is the possibility to introduce some bias due to the presentation of pre-coded variables to respondents, enabling them to varnish their actual behaviours.

With regard to the retrieval strategy, some studies (e.g. Burton & Blair, 1991) suggest that respondents should get more time to complete a memory task. This could improve their recall process and therefore enhance the accuracy of their answers. Besides, the order of questions plays an important role because prior questions may give cues to particular information in the memory (Converse & Presser, 1986; Schuman & Presser, 1996; Kalton & Schuman, 1982; Benton & Daly, 1991).

It should also be considered that in a face-to-face interview setting, respondents may feel obliged to give answers. High cognitive demand during the retrieval process may add up respondents' pressure to answer a question because they want to avoid feeling humiliated. This may make them give any (probably unrelated) answer that come to their mind at that moment (Beatty & Willis, 2007), or any reply that they can think of to satisfy their interviewers (Krosnick, 1991). In the end, all of these aspects determine the accuracy and reliability of data being gathered.

To summarize, the differences between soft- and hard-elicitation results suggest that researchers should be aware of the impact of implementing any elicitation technique on their research outcomes. The different nature of both elicitation methods may cause this distinctness. The self-initiated memory retrieval strategy plays a significant role in a soft-elicitation procedure while the variable recognition is the core of a hard-elicitation technique. Showing a priori aspects to respondents in a hard-elicitation method may give them some reminder of important constructs that are hard to recall instinctively but it may also limit their answers to predefined variables, preventing new concepts to be elicited as in a soft-elicitation procedure (Russell et al., 2004). Besides, it may evoke new aspects, irrelevant to the actual behaviour under investigation. Nevertheless, a hard-elicitation technique gives some advantages, such as reducing interviewers' bias in data collection and cutting cost and time for gathering them (Grunert & Grunert, 1995). These aspects should be considered when developing, selecting, and/or implementing an elicitation method.

2.3.2 Research setting and sample

An experiment is conducted to assess a number of elicitation methods, i.e. the CNET interview and card game methods. This experiment focuses on young adults' fun-shopping behaviour in the city centre of Hasselt. Hasselt is the capital city of the province of Limburg in Belgium that also represents a typical European historical city centre. The experiment is conducted in February to May 2008. To ensure the realism of the elicited thought processes in the study, respondents' familiarity with the research setting of fun-shopping in Hasselt is required. Therefore, 26 graduate students (age 22–23 years old) from the University of Hasselt are asked to participate in the survey. Such small sample sizes are typically used in qualitative research. This happens because qualitative data collection can be very demanding for both interviewer and respondent due to its intensity and time consumption (Bradley, 2006). The homogeneity of this research sample may give an additional advantage to give a general idea of substantial factors in young adults' fun-shopping decision making. Indeed, existing studies indicate the relevance of individuals' characteristics in shaping people's shopping behaviour (e.g. Rabolt & Drake, 1985; Solomon, 2007). Age is particularly important because research has shown that young adults tend to shop more than the older ones (Martin, 1976 in Seock & Sauls, 2008). Moreover, individuals in the same age group share distinctive norms and values, causing similarity and homogeneity in their behaviour (Assael, 1998).

Each respondent is interviewed using both elicitation methods. The first tested method is always the CNET interview. In the following day, the same respondent is re-interviewed using the CNET card game. This arrangement is made because of the characteristics of these elicitation techniques. The CNET interview encourages the respondents to elicit their considerations without any aid whereas the card game method relies on recognition of likely considerations. If the latter method would be used first, the respondents might simply try to remember their selected cards and use them as answers in the open-ended interview session the next day. Therefore, to eliminate this type of bias, the sequence of the tested methods is not randomized.

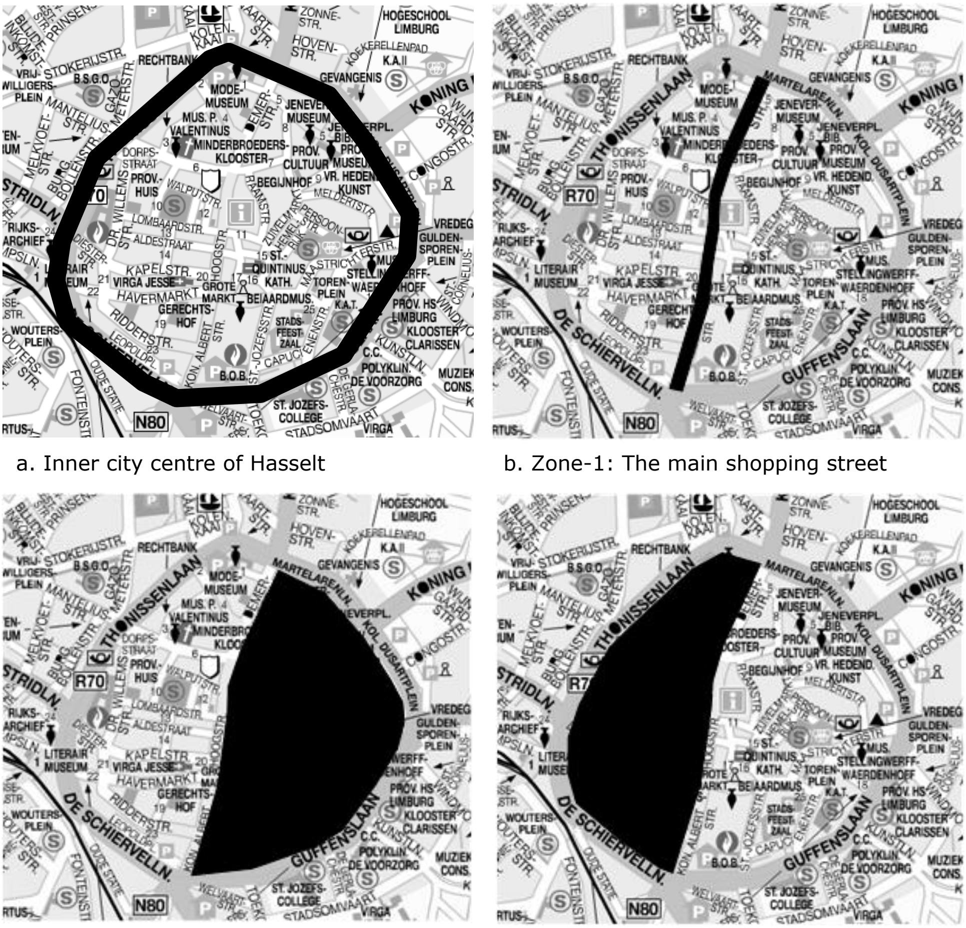
It is worth mentioning at this point that the interviews with the CNET interview protocol are always conducted in English while the native language of the participants is Dutch. Even though all participants are graduate students and they have taken English classes in the past years, it is acknowledged and anticipated that a few of them may have difficulties to express themselves in English. Therefore, a Dutch-English dictionary is provided during the interviews for anyone who needs it. The language barrier issue is solved in the card game interviews by applying *back translation method* (Brislin, 1970). This technique is commonly used in cross-cultural research with non-English speaking population and widely implemented with different variations (Willgerodt, Kataoka-Yahiro, Kim, & Ceria, 2005). Principally, it works by having the original document translated to the targeting language by a bilingual person and then having it translated back to the language of the original document independently by another bilingual person. The researcher has to check if there are some differences between the original document and the newly translated document. When some differences are found, both translators have to discuss about these until an agreement is reached. In this study, this back translation technique is applied on the cards used in the card game interviews. On each card, the variable names are written in English and Dutch.

In the beginning of each interview, the research scenario is given to the respondents, as follows:
"Imagine that you have a vague plan in mind to do fun-shopping in the centre of Hasselt in the near future. Besides, you need to buy a small present for your friend. It appears that you have some available time next Saturday. Thus, you may do it next Saturday afternoon as part of your recreational activities, or you may decide to choose another Saturday or a weekday. Note that fun-shopping is related to collecting some shopping information (e.g. availability of stores, products that are sold, price of goods, quality of goods, etc.)"

The respondents are asked to presume that they live in the outskirts of Hasselt, about 5 to 10 kilometres away from the city centre. Furthermore, their house is located within walking distance to the nearest bus stop. They are also asked to imagine that they own a driving license and a car, and that they are able to ride a bike. These imaginary contexts are set to ensure an equal probability of selection among a number of transport mode options, specifically *car*, *bus* and *bike*. Short-distance travel behaviour is especially targeted in the experiment because of the upsurge of car-use for these trips (e.g. Loukopoulos & Gärling, 2005). Accordingly, more insight is certainly needed to understand people's reasoning when engaging in such trips.

The destination choice options in the city centre are presented to the respondents by showing them a map of Hasselt city centre (Figure 2.5a). This area is divided into three district zones based on the results of a preliminary study on the participants' mental map about Hasselt. These divisions appear to match to the distinct shop characteristics in the city. The first area is *the main shopping street* where branches of store chains are located (Figure 2.5b), the second area is called *the gallery area* because several galleries can be found there (Figure 2.5c), and the third area is called *the boutique zone* due to the presence of exclusive shops (Figure 2.5d).

At last, the timing of the activity-scheduling decision is explained. In AB models, activity-scheduling is considered as an important element to understand how activities are chosen, planed, executed and adjusted in time and space (Doherty & Ettema, 2006). In this study, the timing decision simply focuses on the specific day to execute fun-shopping, i.e. *on the next Saturday*, *on another Saturday*, or *on a weekday*.



a. Inner city centre of Hasselt

b. Zone-1: The main shopping street

c. Zone-2: The gallery area

d. Zone-3: The boutique area

Figure 2.5 The shopping location zones: the inner city centre of Hasselt (a); the main shopping street (b); the gallery area (c); and the boutique area (d)

2.3.3 The CNET interview method

In brief, the CNET interview protocol is developed to reveal people's MR in a face-to-face semi-structured interview setting (Arentze et al., 2008a), starting from the elicitation of cognitive subsets (Kusumastuti et al., 2010a). To begin with, the research setting and choice alternatives are presented. Next, a participant is asked to describe the sequences of his decision making. Afterwards, the elicitation procedure begins by asking him questions according to a well-defined protocol, such as a question about considerations that come to his mind when making the first decision. The participant is encouraged to think aloud about his deliberations. An interviewer registers and converts (in-situ and on mutual agreement) the respondent's (verbal and non-verbal) responses in a structured format by means of an extensive predefined coding scheme. This scheme consists of an extensive list of contextual aspects, instrumental aspects and benefits, developed especially for the experiment. Depending on the type and category of an elicited variable, an interviewer asks further questions to probe about other related aspects, such as *how* and *why* such a variable influences the respondent's decision choice. These questions continue until a complete subset is elicited and recorded. Afterwards, an interviewer goes back to the first question to ask about the participant's other thought factors. Unforeseen factors are detailed and taken into account to update the scheme. This interview protocol is adapted to the leisure-shopping travel context as detailed in the following paragraphs.

Three decisions related to planning and executing fun-shopping are taken into account, namely *the transport mode*, *location*, and *timing decisions*. Each decision is explained initially to the respondent by detailing its available choice options, as previously explained in Section 2.3.2. Then, the respondent is asked to order these decisions from the one considered first to last. This is done by asking: *"What will you decide first when planning your fun-shopping trip to Hasselt?", and: "What will you decide next?"*

The respondent's thoughts related to each decision are elicited next, starting from the first decision in his decision making sequence. When the transport mode decision is selected first, the following question is asked: *"What are your considerations when deciding upon the transport mode (i.e. car, bus, or bike) to use for your fun-shopping trip to Hasselt?" Since* the respondent is free to bring up any consideration he can think of, any answer to this question will lead to the elicitation of a context, an instrument or a benefit.

Based on literature (e.g. Den Hartog, Arentze, Dellaert, & Timmermans, 2005; Doherty et al., 2002; Hägerstrand, 1970) and several pilot tests, an extensive coding scheme is developed, as shown in Appendix B. The interviewer uses that list to classify the respondent's answers. Depending on the categorization of the mentioned variable (i.e. context, instrument or benefit), different questions are asked next. For instance, the respondent indicates the importance of *weather conditions* (a context) in his transport mode consideration. In this case, the interviewer has to complete this respondent's cognitive subset by eliciting further instrument and benefit related to *weather conditions*. This is done by asking *how* or *why weather conditions* influence his choice. An answer to this question may reveal the variable of *having comfort* (a benefit). Next, the interviewer has to elicit the instrument connected with *weather conditions* and *having comfort* by asking: *"how do your transport mode choice give you comfort in different weather conditions?"* Here, another variable such as *shelter provision* (an instrument) could be uncovered. This way, the cognitive subset of {*weather, shelter, comfort*} is finalized.

Suppose that the interviewer repeats the first question of the elicitation process and in this case a benefit is elicited first. Here, the interviewer has to bring about the expression of an instrument or context associated with the mentioned benefit. For instance, the respondent indicates that *having efficiency* (a benefit) is important because of *time availability* (a context). Next, the interviewer continues by asking a question to elicit the related instrument(s), such as *travel time*, forming the cognitive subset of {*time availability, travel time, efficiency*}.

When an instrumental aspect is mentioned initially, the interviewer has to draw the respondent's consideration of its linked benefit(s) or context(s). Suppose the respondent's initial consideration is *vehicle speed* (an instrument). Thus, to elicit benefit(s) or context(s) related to that variable, the interviewer asks a *why* question. The answer to this question could be a benefit variable, such as *having freedom*. In this case, the cognitive subset of {*(normally), vehicle speed, freedom*} is registered, assuming that the instrument and benefit are considered in the normal situation. However, when the answer to the first *why* question is a contextual aspect (e.g. *time availability*), the interviewer has to ask another *why* question to reveal the underling benefit (e.g. *having freedom*) and to complete the subset of {*time availability, vehicle speed, freedom*}.

When the respondent cannot recall any more variables related to the first decision, the interviewer moves on to the next decision and repeats the whole procedure. It should be noted that different decisions may lead to the same thoughts of contexts, instruments and benefits. The interviewer has to keep track of the interrelationships between different types of aspects and decisions at any time. Besides, the interviewer is not allowed to interfere with the respondent's cognition even when the respondent is inconsistent in his answers (Arentze et al., 2008a).

The whole interview process can be very demanding for the respondents. They have to imagine the scheduling and execution of fun-shopping trips to Hasselt. Obviously, memory plays a significant role in eliciting reliable MR as discussed in Section 2.3.1. Therefore, it is important to create the right mindset and atmosphere during the interviews. In this experiment, a slideshow with images of Hasselt city centre, its shops and ambiance is continuously played as the interview background. The interview lasts for about 60 minutes on average per respondent, depending on the number of variables mentioned. Additionally, all the interviews are audio-recorded. These records are used later on to measure the reliability of the CNET interview method, as discussed in Section 2.3.6.

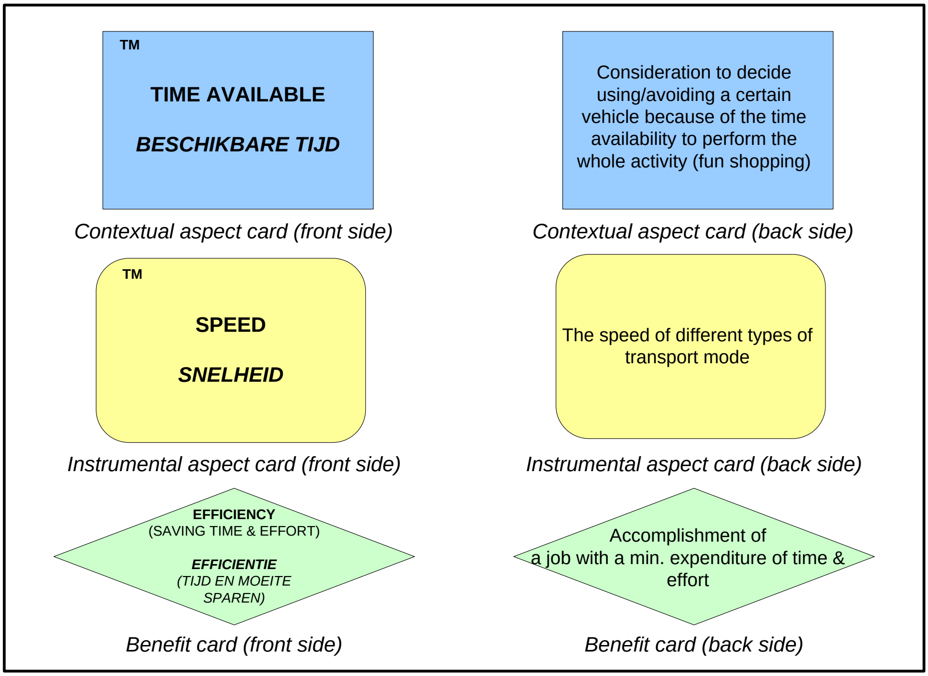
2.3.4 The CNET card game method

The CNET card game method is developed based on the coding scheme of the interview protocol. The card game resembles a stated response method in which predefined pick lists are shown to the respondents. Despite their different elicitation principles, both methods have a similar main purpose to elicit individuals' decision making processes by taking into account contexts, instruments, and benefits of certain decision problems. However, relevant variables in the card game only have to be recognized by the respondents and not recalled spontaneously. Thus, this method could reduce the respondents' burden in the elicitation process.

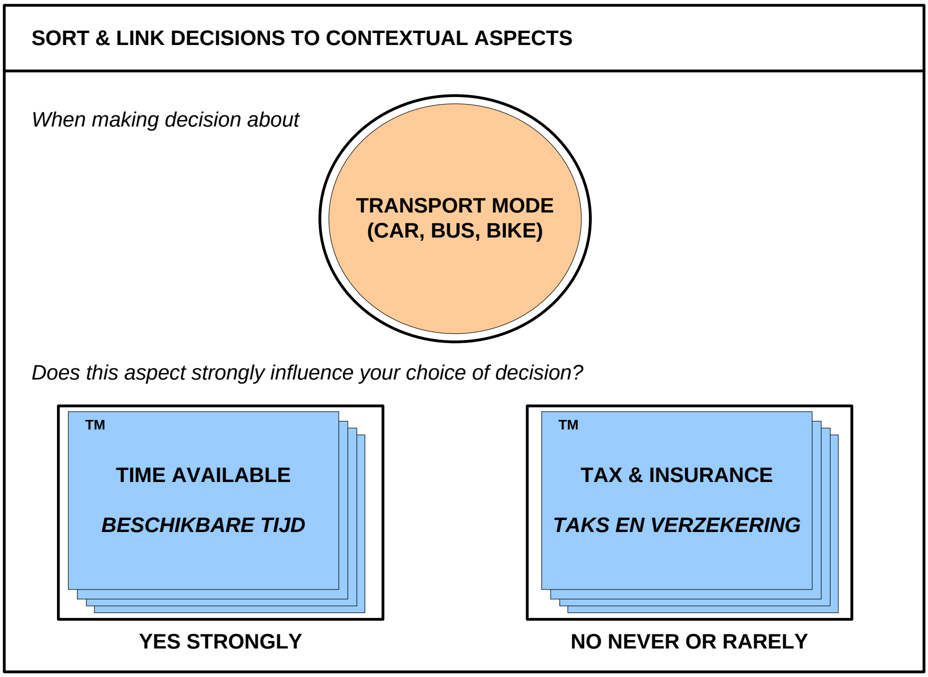
A display board is created for each step in the card game. These boards are presented in Appendix C. Additionally, a card is designed for each decision variable, containing a brief explanation and/or some examples on the backside of the card. The respondents are free to check that information during the interviews whenever they want. The examples of the cards can be seen in Figure 2.6a. The total numbers of 17 contexts, 26 instruments and 17 benefits are registered for the transport mode decision. Similarly, 15 contexts, 23 instruments and 17 benefits are predefined for the location choice. At last, 8 contexts, 13 instruments and 17 benefits are listed for the scheduling decision. These variables and their definitions are listed in Appendix B.

Similar to the CNET interview, this protocol is divided into two major parts: (1) ordering the decisions and (2) eliciting individuals' cognitive subsets. First, the respondent is asked to order his decisions as described in the CNET interview procedure. The next steps aim at eliciting individuals' considerations related to the investigated decisions. The respondent is guided until the end of the interview.

For each decision, a number of cards are shown to the respondent one by one. It starts with the recognition of the contextual variables. Here, the interviewer asks the respondent whether the variable mentioned on the card is considered when making the decision. Responses are categorized into two groups of "*no never or rarely*" and "*yes always*" (Figure 2.6b). After all variables are shown and sorted, the interviewer asks if there are other important but unmentioned contexts. New variables on new cards are added if necessary.



a. Examples of cards



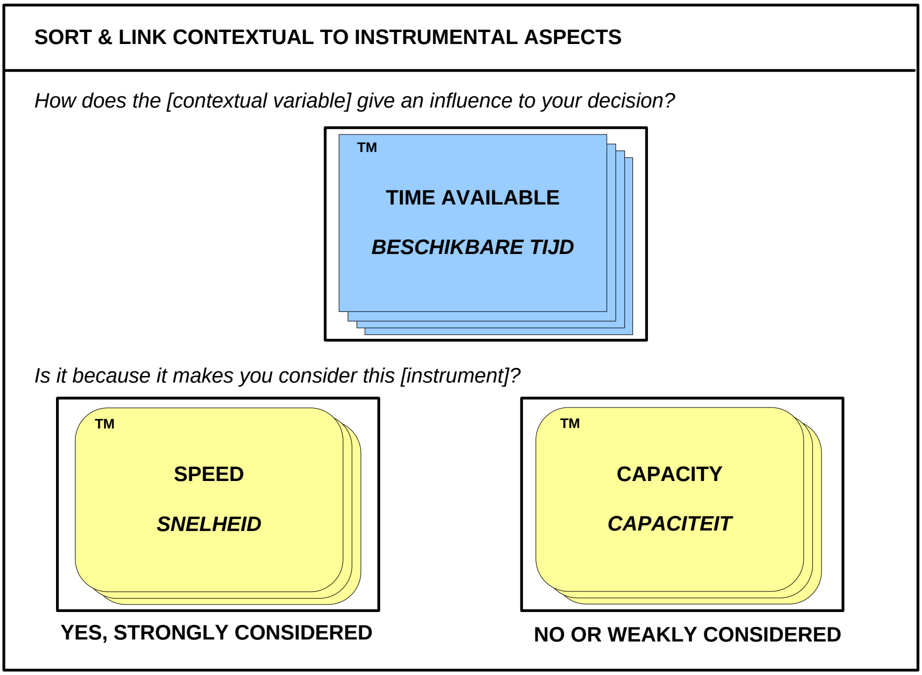
b. Eliciting contextual aspects

Figure 2.6 The CNET card game: Examples of cards (a) and eliciting contextual aspects (b)

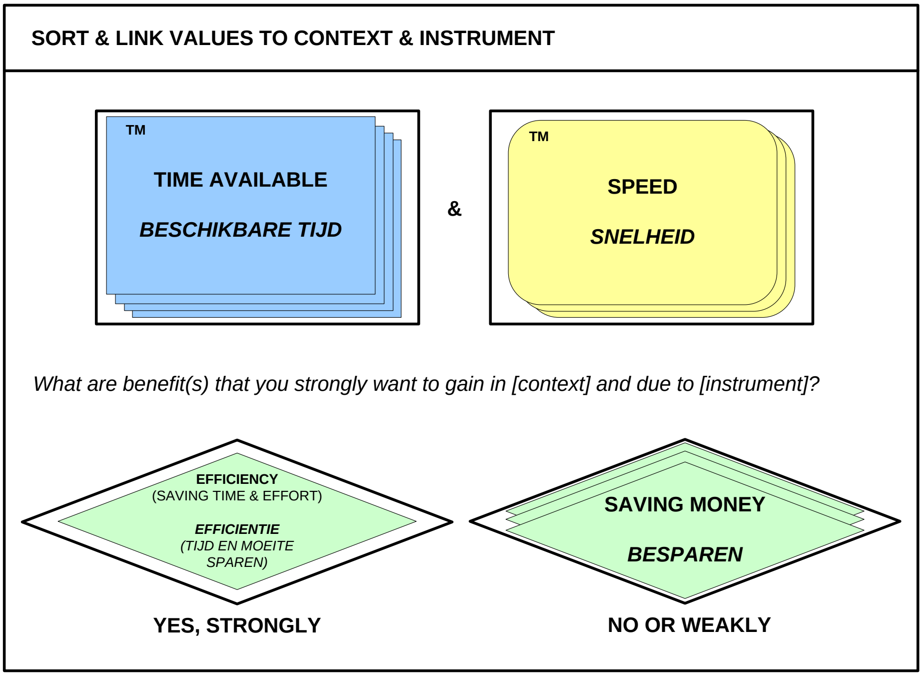
After identifying all important contexts in the decision, the interviewer has to investigate likely instrumental aspects associated with the selected contexts. In this case, all instrumental cards of that particular decision are arranged on the table. The interviewer takes a sorted context categorised in the "*yes always*" box, and the respondent is asked to pick instrumental features of the decision options that explain how that context influences the choice (Figure 2.7a). For instance, *time availability* (a context) is previously selected. This deliberation could be considered due to *vehicle speed* (an instrument).

Once a link is established between a context and instrument(s), their associations to the benefit variables are explored next, to complete the first cognitive subset type of {*context, instrument, benefit*}. All benefit cards are shown and the respondent is asked to indicate the strongest benefit(s) that he wishes to gain from the combination of the selected context(s) and instrument(s) (Figure 2.7b).

After completing one cognitive subset, the interviewer goes back to the previous game board to identify instrument(s) related to the next chosen contextual aspect and the whole procedure is repeated until all contextual aspects in the "*yes always*" box are investigated. When the respondent cannot relate any instrumental card to the selected context, the interviewer asks the respondent to verbally explain how his decision is influenced by that context. Based on his open answer, the interviewer selects the most relevant instrumental card(s) on mutual agreement with the respondent. If the interpretation of the respondent's answer is not available in the current cards, then a new card is added.



a. Eliciting instrumental aspects



b. Eliciting benefits

Figure 2.7 The CNET card game: Eliciting instrumental aspects (a) and benefits (b)

The interviewer has to specify another cognitive subset type of {*(normally), context, benefit*} when all cognitive subsets of {*context, instrument, benefit*} are identified. This is done by grouping unselected instrumental aspect cards in the previous procedure and asking the respondent to indicate whether each instrument is considered in his decision making. Afterwards, the interviewer guides the respondent to assess the associated benefit(s) for each sorted instrument. This whole procedure is summarized in Figure 2.8. On average, it takes about 90 minutes to interview one respondent using this protocol.

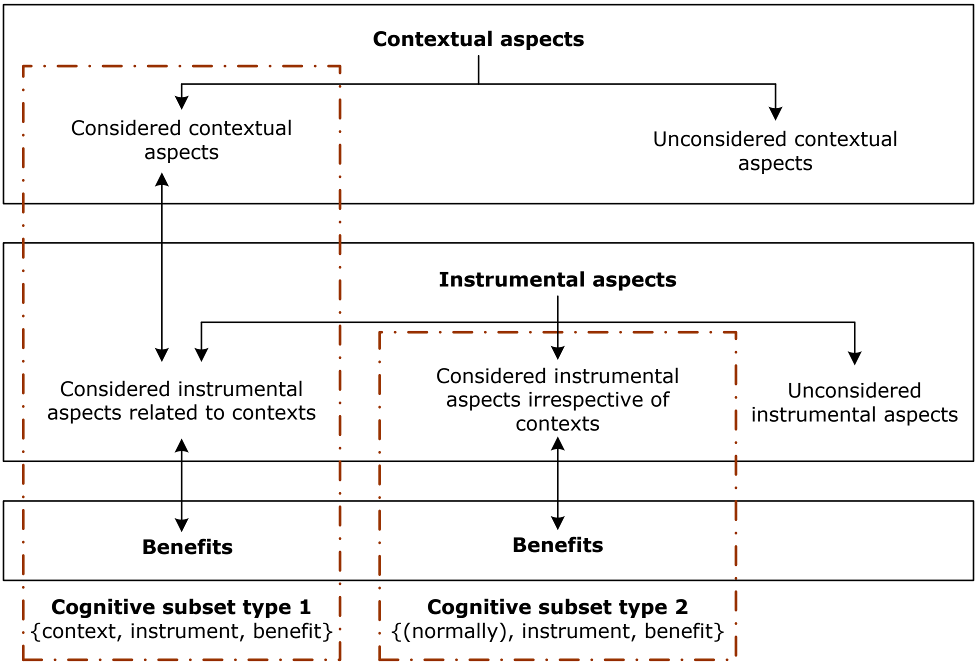


Figure 2.8 The CNET card game protocol stages

2.3.5 Methodological notes of the CNET interview and card game techniques

In order to gain insight into the CNET interview and card game methods from the respondents' account, each respondent is asked to complete a questionnaire and write a short report, comparing both methods in terms of *easiness*, *pleasantness*, *comprehensiveness* and *time consumption*. In addition, they are asked to indicate the method that they consider better in representing their actual decision making processes.

The results in Table 2.1 show that the CNET card game method is considered as easier, more pleasant and more comprehensive than the CNET interview technique. The respondents indicate that many aspects that they consider in real decision processes are often overlooked during the interviews with the CNET interview method. The benefit variable(s) attached to each instrument and context are the hardest one to recall (probably) because they signify an abstract concept, commonly considered unconsciously. Showing predefined variables during the card game interview may activate the memory related to the fun-shopping activity, making this method easier than its counterpart. This comes in line with previous studies (e.g. Burton & Blair, 1991; Cannell et al., 1979) that have indicated the usefulness of manipulation strategies, such as providing some cues to trigger respondents' episodic memory. In line with this, information provided on the back of the cards may give an additional advantage to the card game. Another plausible explanation of why the card game method is considered as easier and more pleasant is because the free format responses in the CNET interview may be hindered by an extra effort to express oneself in a foreign language. Therefore, the use of bilingual cards could also play a role in influencing the respondents' preferences over the card game. It should also be noted that the card game is always tested after the interview method and that both techniques are applied for the same scenario. Therefore, the respondents are already familiar with the research setting when they are interviewed with the card game. This could also influence their judgement of the easiness and comprehensiveness of the method.

The major drawback of the card game method is the longer time needed to complete the interview, as also indicated by the respondents. It takes them about 90 minutes to reveal their MR using the card game while the same task can be accomplished in only 60 minutes on average using the interview method. This longer time could affect the respondents' concentration on the task at hand.

Furthermore, some respondents state their difficulties to find the most representative card(s). In spite of these drawbacks, the respondents believe that the elicitation process using the card game method generates enriched and better representations of their thought processes.

Table 2.1 Individuals' evaluation of the CNET interview and card game techniques

Assessed aspects	*Pro to CNET interview*				*Neutral*	*Pro to CNET card game*			
	*5**	*4**	*3**	*2**	*1**	*2**	*3**	*4**	*5**
Easiness	0%	0%	8%	19%	4%	12%	42%	15%	0%
Total (n=26)	27%				4%	69%			
Pleasantness	0%	4%	12%	8%	8%	23%	27%	19%	0%
Total (n=26)	23%				8%	69%			
Comprehensiveness	0%	0%	4%	19%	31%	19%	23%	4%	0%
Total (n=26)	23%				31%	46%			
Time consumption	0%	0%	0%	8%	12%	31%	35%	12%	4%
Total (n=26)	8%				12%	82%			
Representativeness	0%	8%	19%	12%	8%	27%	23%	4%	0%
Total (n=26)	38%				8%	54%			

[*] The values in the table are rounded numbers
[1] Equally…(i.e. easy, pleasant, comprehensive, time consuming, representative)
[2] Moderately more…
[3] Strongly more…
[4] Very strongly more…
[5] Extremely more…

2.3.6 Measuring the reliability of the CNET interview method using the intercoder reliability techniques

In Section 2.3.3, the CNET interview technique has been detailed. It has been previously mentioned in the introduction (Chapter 1) that the CNET interview protocol is a relatively new qualitative approach, and it is applied only recently (Arentze et al., 2008a; e.g. Den Hartog et al., 2005; Kusumastuti et al., 2010a). Besides, qualitative research outcomes are often questioned due to researchers' subjective interpretations of participants' open answers in, for instance, face-to-face interviews. The same problem also applies to the research outcomes of the CNET interview method, highlighting the need to conduct a study to examine the quality of this technique.

Intercoder reliability can be used to investigate the quality of a qualitative technique by using a number of indices that count the degree of agreement between two or more coders (Lombard et al., 2008). Accordingly, when the result of an intercoder reliability test is high, it means that the coding instructions and process are good enough to produce reliable codes (Hak & Bernts, 1996). Even though higher values do not necessarily mean that the qualitative research method under study is valid, at least a condition towards good validity is fulfilled. Therefore, calculating the intercoder reliability indices gives more credibility to research outcomes of a qualitative method (Lombard et al., 2008). Moreover, it somehow ensures the transferability of that method to other contexts or samples.

In order to calculate the intercoder reliability of the CNET interview method, the audio-records of the CNET interviews are used, as mentioned in Section 2.3.3. A second coder is assigned to randomly select a number of interviews as the sample, hear the selected records, interpret the respondents' open answers, and code them using the same predefined code-list used in the actual interviews. The agreement between both researchers can be calculated accordingly.

Thus, Section 2.3.6 is organized as follows: different intercoder reliability techniques are explained to start with (Section 2.3.6.1). Additionally, the dataset (a), sample (b), measurement selection (c), and calculations (d) are described successively (Section 2.3.6.2). Next, the results are presented and discussed (Section 2.3.6.3).

2.3.6.1 Measuring intercoder reliability

There are a large number of intercoder reliability measures to handle nominal, ratio, and interval data. At least, 39 indices have been identified (Popping, 1988). However, only a few measures are widely used, such as *percent agreement*, *Cohen's kappa*, *Scott's pi*, and *Krippendorff's alpha*. These techniques have been previously detailed in other research (e.g. Lombard et al., 2002). Therefore, this section summarizes and highlights only the important characteristics and differences of these four indices.

The first index is *percent agreement*, or also referred to as *simple agreement*, *percentage of agreement*, *raw percent agreement*, and *crude agreement*. It works by simply calculating the percentage number of cases in which all coders have agreement, making it the easiest agreement index to compute. Accordingly, this index at 100% indicates perfect agreement among coders, whereas it implies otherwise (i.e. perfect disagreement) at 0%. This measure is often criticized because it does not take into account the possibility of agreement by chance (Lombard et al., 2008).

Scott's pi (Scott, 1955) solves the problem of the percent agreement index by allowing for agreement by chance. Moreover, this index includes the number of categories and their values in the calculations. The major drawback arises because it assumes that coders have identical distributions of values across those categories. If this is not the case, then the formula fails to count for proper agreement. Therefore, many consider this index as conservative. This coefficient is commonly used for nominal data, two coders, and relatively large sample sizes.

Cohen's kappa (Cohen, 1960, 1968) also considers agreement by chance, akin to the Scott's pi index. This measure takes the observed distributions of values as given, leading to possibilities to underestimate agreement of commonly used categories. Because of that, this index is also regarded as conventional. Another potential problem when using the Cohen's kappa coefficient is that even a perfect agreement has a maximum value less than 100%, making it hard to compare results with the ones calculated using the other coefficients. This index is used only for nominal data.

Krippendorff's alpha (Krippendorff, 2003) is another index to calculate agreement among coders. This coefficient can handle nominal and ratio data. Moreover, it can be used for any number of coders, and small sample sizes. It takes into account agreement by chance and furthermore "*proclivity*" of coders. "*Proclivity*" is coders' inclination to use the same codes repeatedly, for instance because they have used those codes before. Thus, the Krippendorff's alpha index can be considered as one of the most sophisticated agreement indices.

Once an intercoder reliability measure is selected, the next question is how to decide the minimum acceptance level of the coefficient. Lombard et al. (2008) argues that it depends on the nature of the study and the selected measure. The agreement value of 90% or higher is generally always acceptable. However, for an exploratory study, the agreement level of 70% is regarded as sufficient. A higher acceptance value should be employed when percent agreement is used because this index does not take many aspects into account. On the other hand, a lower acceptance value can be assigned for more conservative indices, such as the Krippendorff's alpha index.

2.3.6.2 Intercoder reliability of the CNET interview protocol

a. The datasets

A number of travel decisions are investigated in the experiment using the CNET interview method, namely the timing of activity-scheduling, transport mode and location decisions, as described in Section 2.3.2. Moreover, three types of aspects in the cognitive subsets are elicited, as explained in Section 2.2.2, 2.3.3, and 2.3.4. These aspects are referred to as contextual variables (or contexts), instrumental variables (or instruments), and benefits.

Therefore, a number of datasets can be arranged to calculate intercoder reliability of the CNET interview method. For instance, focusing on the travel decisions, each dataset contains one of the following data: the entire decisions (dataset number 1); timing of the activity-scheduling decision only (2); transport mode decision only (3); and shopping location decision only (4). Additionally, other datasets are managed in such a way that each of them includes the data of all decisions, but focuses only on contextual aspects (5); instrumental aspects (6); and benefits (7). Next, the datasets based on each decision and variable type are created. Each of them includes one of the following data: timing decision and contextual aspects only (8); timing decision and instrumental aspects only (9); and timing decision and benefits only (10).

Similar datasets are set for the transport mode decision for contexts (11), instruments (12), and benefits (13); and for the shopping location choice (14, 15, and 16).

Each dataset consists of researchers' assigned codes based on the participant's open answers. The example of a dataset can be seen in Appendix K1. There are a total number of 17 contexts, 26 instruments and 17 benefits for the transport mode decision; 15 contexts, 23 instruments and 17 benefits for the location choice; and 8 contexts, 13 instruments and 17 benefits for the timing decision. These yield large numbers of possible codes. Additionally, the first coder interviews the participants, code their answers, and audio-tapes the interviews. The second coder hears the interview records and independently codes the participants' open answers. It should be noted that the second coder does not know the codes assigned by the first coder. Only after the sample of audio-records is coded by the second coder and the intercoder reliability indices need to be calculated, the assigned codes by two researchers are compared. The selection of sample is explained in the subsequent paragraph. To sum up, the datasets consist of nominal data and a large number of codes. Moreover, the agreement between two coders is emphasized.

b. Selection of the sample

There are 26 respondents who participate in the experiment using the CNET interview method, yielding 26 participants' audio-records and assigned codes from the first coder (i.e. the interviewer). Each participant is asked to elicit their deliberation when making three travel decisions. The next issue to address here is whether all 26 records should be examined in order to draw some conclusions regarding the CNET interview reliability. Based on the existing research (i.e. Lombard et al., 2008), formal assessment of the reliability of full sample is not needed. A random sample can be selected and it is sufficient as long as it is larger than 10% of the total research sample. Therefore, the sample requirement can be calculated to assess the intercoder reliability of the CNET interview. Three participants' records are assigned randomly for each decision, yielding the total number of 9 participants' records. This sample size is relatively small, limiting the measurements that can be used to calculate the reliability index.

c. Selection of the measures

The description of the datasets (Section 2.3.6.2a) and the sample (Section 2.3.6.2b) concludes the following: there are only two coders (1), the sample is small (2) but consists of a large number of codes (3), and the datasets contain nominal records (4). Based on these characteristics, a number of intercoder reliability measures, as described in Section 2.3.6.1, can be evaluated.

First of all, the *percent agreement* index can be used because the large number of variables in this study reduces the possible agreement by random chance. This large number of codes makes the use of the *Cohen's kappa* index less beneficial. This index is more difficult to calculate, and its added value is relatively small due to the small possibility of agreement by random chance between the two coders. The *Scott's pi* index cannot be applied because the small sample size of this study violates one of its assumptions. At last, the Krippendorff's alpha index can be used. This measure is more flexible than the others as it can handle nominal data, small sample sizes and missing values. Additionally, it takes into account coders' proclivity.

d. Calculations

In order to calculate the percentage agreement, the number of cases when there is an agreement between the coders is divided by the total number of cases. The Krippendorff's alpha value is calculated by initially generate a coincidence matrix, recording the number of times when pairs of variables are coded by coders. Next, the following formula is used:

$\alpha = \dfrac{(n-1)\sum O_{cc} - \sum n_c(n_c - 1)}{n(n-1) - \sum n_c(n_c - 1)}$; Where α indicates the Krippendorff's alpha value; n donates the total number of cases in a coincidence matrix; O_{cc} signifies the total sum of the main diagonal cells; and n_c is the total value of each row c.

The details of how to calculate the percentage agreement and Krippendorff's alpha indices, along with an example, are shown in Appendix K1. In this research, the percentage agreement and Krippendorff's alpha values of the datasets previously explained and listed in Section 2.3.6.2a are calculated. In order to diminish the computational burden, R software package (R Project, n.d.) is used. Some adjustments are made, enabling the software to include missing values in the calculations.

e. Training

Some training is conducted before the actual coding with the selected sample. The second researcher is given the full list of variables with their definitions. Some records not selected as the sample are used for the exercise. The real coding on the sample data begins once the second coder feels familiar with the predefined code list, the variable definitions, and the interview procedure.

2.3.6.3 Results and discussions

The Krippendorff's alpha value is calculated for each decision and for all types of variables, resulting in nine alpha values (for the dataset number 8-16 as previously explained in Section 2.3.6.2a). Similarly, the percent agreement index is also calculated for each of them, allowing us to compare both measures.

However, an alpha value can only be calculated on a dataset that has the same list of variables, because a coincidence matrix has to be created accordingly. Consequently, calculating the alpha values cannot be done on the datasets that focus on the specific decision with the joint variable types (i.e. the dataset number 2-4), and the datasets of the certain variable type and the combined decisions (i.e. the dataset number 5-6). This happens because each of these decisions has its own list of contextual and instrumental variables. Similarly, the Krippendorff's alpha index cannot be used to calculate the agreement between coders for the entire decision dataset (the dataset number 1). As a result, only parentage agreement is used on the dataset number 1-6. The dataset number 7 consists of the benefit variables of the joint decisions. Since these benefits are the same for all the decisions, the alpha value can be calculated. The results are presented in Figure 2.9.

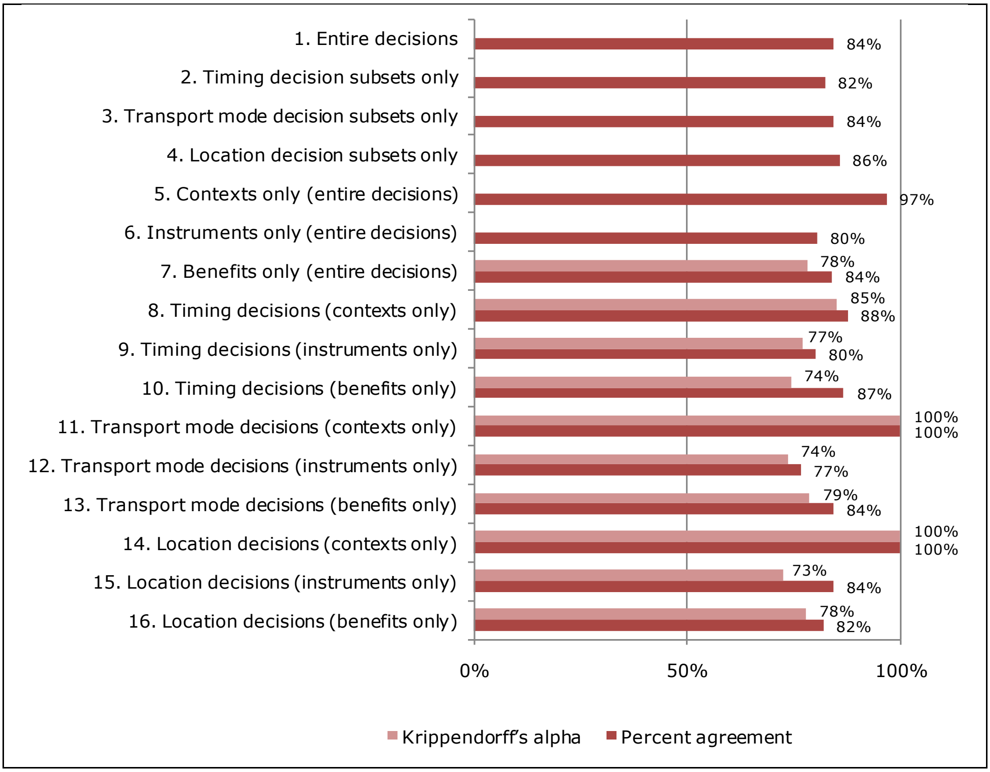


Figure 2.9 The results of Krippendorff's alpha and percentage agreement values (De Ceunynck et al., 2011)

The experiment using the CNET interview method is regarded as an exploratory study. Therefore, the minimum acceptance level of the percent agreement and Krippendorff's alpha indices is set to 70%. The results in Figure 2.9 show that all the calculated alpha values are higher than 70%, implying that the agreement between the two coders is acceptable. In general, the percentage agreement technique calculates better agreement values. This result is expected because this index does not take into account possible agreement by chance and proclivity. However, the differences between the calculated values using both measures are relatively small (0-12.4%). This happens because of the large number of variables, reducing the probability of agreement by chance. This low penalty also indicates that the coders' proclivity is also relatively low.

Moreover, the results show that the alpha values are substantially high for the contextual variables; i.e. 85%, 100%, and 100% for the timing, transport mode, and location decisions respectively. The alpha values for the instrumental and benefit variables are within the range of 70-80%. Additionally, the percent agreement values are calculated for the entire decisions, each decision, and each variable type. No significant differences are observed across those decisions (i.e. 82%, 84%, and 86% for the timing, transport mode and location decisions). The percent agreement value for the contextual variables (and for the joint decisions) is the highest (97%), whereas this agreement value reduces for the instrumental variables (80%) and the benefit variables (84%). These results confirm the previous alpha results.

The results indicate that contextual aspects are the easiest type of variables to code, whereas the instrumental and benefit variables are relatively harder to interpret. This could possibly happen because the instruments and benefits are more abstract than the contexts. Moreover, the results also point out that the differences among coders are real even though they are still within the acceptable level. The setting of this study may contribute to these results. The first coder has to immediately consider the participants' open answers in the interviews and convert these answers into codes in-situ. Consequently, fast and direct decision making is needed. On the other hand, the second coder interprets the participants' answers based of the audio-records, implying that he has more time and less pressure to rethink about the participants' answers.

However, despite some differences among the coders, it can be concluded that the coding list used in the experiment using the CNET interview is well defined. Moreover, the definitions of the codes are formulated clearly, allowing another coder to have similar interpretations of the variables. The results allow us to draw a general conclusion that the CNET interview protocol has a high level of reliability, giving more certainty to transfer this technique into other sample groups or decision types.

2.4 Modelling individuals' fun-shopping travel decisions using the influence diagram technique

The previous section (i.e. Section 2.3) describes different elicitation protocols from the methodological point of view. Further discussions of the content of the participants' elicited MR in the first experiment are presented later on in Chapter 3. Now, this section focuses on modelling individuals' MR using the ID technique. However, there is still a basic fundamental question regarding why models are needed. The following quote may offer good explanation of this issue: *"…we make sense of the world in order to predict how, all things being equal, the world will be in the future, and to decide how we might act or intervene in order to achieve what we prefer within that world…"* (Ackermann, Eden, & Cropper, 1992 p. 1). Hence, models can be used not only to predict the future, but also to understand the environment being modelled.

Individuals are unique beings, represented by their thoughts and considerations when making decisions. Each of them has his own mental state, consisting of beliefs, knowledge and preferences. Models that take into account these aspects are referred to as *mental-level models* (Brafman & Tennenholtz, 1997). Such behavioural models are useful to understand and/or predict behavioural changes of people in a defined period of time, and due to the variation of factors that appear in the decision environment.

There are a number of AI techniques that can be used to generate a mental-level model. One of them is ID or also called *decision network*. An ID model is an extension of a *Bayesian network* that combines *probabilistic reasoning* and *utilities*, allowing decision makers to estimate expected utility values of all choice alternatives. It enables us not only to model cognitive subsets in individuals' MR but also to represent sequential decision making. Both facets cannot be retained by more common knowledge representations, such as a DT classifier model.

In spite of ID unique properties mentioned above, studies concerning how to model individuals' MR using this modelling technique are still scarce. Arentze et al. (2008a) proposes a particular model structure to model an individual's MR by means of an ID model. This approach is used as a starting point to develop another structure best suited to address this PhD research objective. It should be noted that the main purpose of this section is not to compare both model structures, but to explain and demonstrate a number of ways to construct a mental-level model by using an ID technique. It is believed that how a mental-level model is configured should be tailored to the research setting and objective.

This section is organized as follows: ID model is explained to begin with (Section 2.4.1). The ID model structure suggested by Arentze et al. (2008a) is presented next (Section 2.4.2). Following that, the proposed model structure is shown and discussed (Section 2.4.3). Researcher's reflection of the modelling structures is briefly presented in Section 2.4.4. At last, an overview based on the researcher's experience with the CNET interview and card game to gather the data for the ID models is presented (Section 2.4.5).

2.4.1 Influence diagram

A Bayesian network is a *directed-acyclic-graph* (Korb & Nicholson, 2003). It contains *nodes* that represent a random set of variables in a specific field, and directed *arcs* that indicate inter-dependencies between the linked nodes. The strength of these relationships relies on conditional probability distributions of the joined nodes. Building a Bayesian ID requires some steps: (1) *determining nodes and their states*, (2) *revealing the network structure,* (3) *specifying conditional probabilities and utilities*, and (4) *evaluating the influence diagram*. These steps are detailed below successively.

2.4.1.1 Nodes and states

A Bayesian ID entails three types of nodes: *chance, decision* and *utility* nodes. *Chance nodes* represent random variables of interest, namely *contexts*, *instruments*, and *benefits* in individuals' MR. Each chance node takes *values* (or *states*), either discrete or continuous. The discrete values can be binary or Boolean values (e.g. *true* and *false*), ordered values (e.g. *low, medium, high*), and integral values (Korb & Nicholson, 2003).

In this PhD research, all possible aspects (i.e. context, instrument, benefit) and their states have been identified and listed by the researchers from the results of some preliminary in-depth studies. These variables are the ones used as the predefined coding scheme in the CNET interviews and written as cards in the card game interviews. Furthermore, all applied nodes are only limited to discrete nodes, meaning that variables must hold one of their states at a time. For instance, the contextual aspect of *weather conditions* has two states *{bad, good}*, the instrumental aspect of *vehicle speed* contains three states *{low, medium, high}*, and all benefits, such as *having comfort*, entail two states *{none, all}*.

Decision nodes represent the decisions being made, and its states indicate the choice alternatives or strategies used to solve the problem. At last, *utility nodes* symbolize subjective utility functions and they do not have any states. When there is more than one utility node in the network, the total utility is the sum of all partial-utilities.

2.4.1.2 Network structure

The network structure signifies the qualitative relationships between the defined nodes. An arc indicates a connection between its two linked nodes, and it goes from *a parent node* ("cause") to *a child node* ("effect"). When an arc goes to a decision node, it means that the parent node is known before making a decision. Moreover, an arc that goes from a decision node means that the child node is the outcome of the decision (Neapolitan, 2003).

The Bayesian ID allows us to model *sequential decision making*. Accordingly, it is suited to model individuals' MR of complex travel tasks that typically consist of interconnected decisions. An arc between two decisions is referred to as a *precedence* or *no-forgetting link*, implying that a decision maker considers previous decision(s) when making the next one(s).

In general, depending on the purpose of the study, the network structure can directly be specified by researchers, experts, or learned from a database. Since this study focuses on modelling individuals' MR at the disaggregate level, relevant aspects and their links in the cognitive subsets should be determined by individuals as experts in their daily travel decisions. However, standard ways to connect a context, an instrument and a benefit in a cognitive subset and to link a number of subsets in an ID model should be determined.

2.4.1.3 Conditional probability and utility table

The strength of the relationships between the linked nodes in a structured network has to be quantified in conditional probability tables (CPT). Each chance node contains a CPT, representing an individual's belief of occurrence of particular child states given the combination of states of its patents. This implies that the network structure determines the CPT that has to be filled in.

Each utility node has a utility table (UT). Since this type of nodes does not contain any states, it directly describes the utilities of its parent states. An individual may consider the importance of various benefits (or utilities) in reality differently (Dellaert et al., 2008). For instance, a busy person may prioritize having *efficiency* over *comfort*. Therefore, it is important to take the weight of partial-utilities into account in the UT.

2.4.1.4 Evaluating decision networks

Computing a Bayesian ID is done after all probabilities, utilities and their weights are inputted in the CPT and UT. Compiling a Bayesian ID combines utility and probability theories, allowing the *expected utility values* (EU) of all choice alternatives to be calculated. Evidence can be set when new information becomes available and the network can be updated accordingly by automatically recalculating the EU given the evidence (*e*) (Korb & Nicholson, 2003), using the following formula:

$EU(D \mid e) = \sum_i P(O_i \mid e, D) \times U(O_i \mid D)$; Where e is evidence; D is a non-deterministic decision alternative with possible outcome states; $EU(D \mid e)$ is the expected utility value, given evidence e is observed and action D is taken; $U(O_i \mid D)$ is the utility of each state of the outcomes O_i , given alternative D is taken; and $P(O_i \mid e, D)$ the conditional probability distribution over possible outcome states, given evidence e is observed and action D is taken.

2.4.1.5 Conclusions: Influence diagram

In this PhD research, modelling every individual's MR using an ID model is highlighted. Each individual's elicited cognitive subsets are used as input to his personalized ID model, implying that ID models differ from person-to-person. The nodes in the model depend on the participant's elicited variables and their states are predetermined by the researchers. Moreover, how these nodes are linked to each other, or called network structure, plays an important role in defining the CPT of each chance node and the UT of each utility node. Hence, considering its importance, the subsequent sections (i.e. Section 2.4.2 and 2.4.3) discuss different model structures.

2.4.2 The existing modelling approach

The existing approach described here is based on Arentze et al. (2008a). They develop the CNET interview method and use it to elicit individuals' travel-related MR in a hypothetical decision problem using predetermined contexts and constraints as scenarios. Moreover, the elicited representations are modelled using the ID technique.

Before explaining how every individual's MR is modelled, it should be noted that there are some differences between this PhD research and the existing study, concerning variable type interpretations. For instance, the existing approach regards the decision variables as an element of a system that can be chosen freely by a decision maker. There, the outcome variables are further differentiated into two categories. The first output relates to any observable states of a system, and it is referred to as *attribute variables*. The second output is *benefits* that signify a more abstract level, closer to an individual's needs. However, in some cases, the distinction between *attributes* and *benefits* is not always apparent. Despite these differences, some similarities between the two approaches can still be observed. For instance, *contextual aspects*, or also mentioned as *situational variables* (in Arentze et al., 2008a), are factors that are not influenced by decisions, either directly or indirectly.

Based on the lines of thought above, the existing network structure is explained by using the following example, taken from Arentze et al. (2008 p. 11):
"The imaginary individual considers a hotel near the work location and a hotel closer to the city center as alternative options for a place to stay. The business activity takes five weekdays and staying the weekend over for sightseeing is an option the individual considers. Expected costs of a hotel depend on the location and length of stay. The train and plane are the candidate transport modes for the trip to the city. Including a weekend in the trip reduces the price of a ticket for a flight. Only in case of the reduced flight tariff, the plane becomes competitive with the train in terms of travel costs. If train is chosen, the total time the person is away from home increases with two days due to the long travel time. The hotel location and length of stay determine the extent to which opportunities exist to go out and, in so doing, to entertain oneself outside working hours. A location near the center and a longer stay increase these opportunities. However, if the weather is bad, going out is not considered to be pleasant. Finally, the interests of the spouse are a concern. Staying long from home and spending much money on the trip are both not appreciated by the spouse."

The example above is modelled in Figure 2.10. The decision variables (or decision nodes) are *hotel location*, *length of stay*, and *transport mode*. The contextual aspect (and the chance node in the ID model) is the *weather* variable. Moreover, the variables of *hotel costs*, *travel costs*, *time from home* are regarded as the attribute variables (chance nodes). At last, the variable of *budget*, *entertainment*, and *spouse* are considered as the benefits (chance nodes) and the utilities (utility nodes).

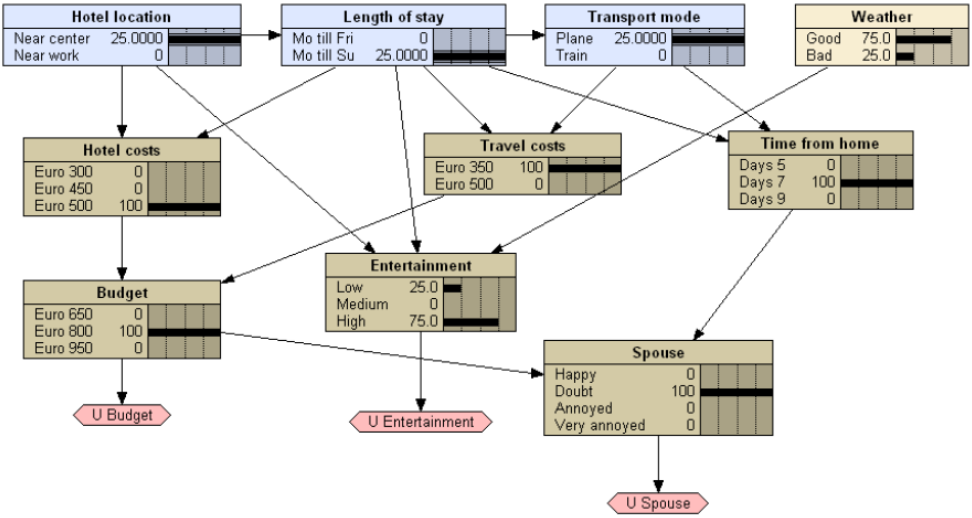


Figure 2.10 An example of the existing modelling approach (Arentze et al., 2008a)

The CPT behind each chance node and the UT behind each utility node are developed based on the network structure in Figure 2.10. However, they are not elaborated further in this section. This example intends to demonstrate that by inserting some evidence in the decision nodes, i.e. the *hotel location is located near the centre*, *the length of stay is from Monday to Sunday*, and *the transport mode is plane* (as shown in Figure 2.10), the benefits of *budgets*, *entertainment*, and *spouse* can automatically be calculated by the network.

2.4.3 The alternative modelling approach

The existing approach clearly demonstrates the application of such mental-level models to evaluate benefits that people want to gain based on their decisions, by means of backward reasoning on causal relationships. However, in many cases, a decision choice cannot be made freely because it is strongly affected by constraints and contexts in the decision environment. For the case of fun-shopping travel decisions for instance, contextual aspects such as *weather* *conditions* and *time availability* have been indicated as influential factors that contribute to people's actual choices, as discussed later on in Chapter 3. This underlies the reason to develop another model structure that aims at predicting behavioural changes of people based on substantial contexts in people's MR. To describe this approach in detail, this section is divided into some parts. In the beginning, the proposed network structure is initially explained (Section 2.4.3.1). The resulted CPT and UT are elaborated in Section 2.4.3.2, and the network calculations are presented in Section 2.4.3.3.

2.4.3.1 Network structure

The proposed model structure uses principles explained in the following example. Suppose that the cognitive subset of {*weather, shelter, comfort*} is elicited by a respondent when considering the *transport modes* {*car, bus, bike*} to go shopping. *Weather* {*bad, good*} represents weather conditions. *Shelter* {*not needed, needed*} symbolizes the need to have a shelter, as different transport modes vary in that respect. Logically, this need is driven by different weather conditions, i.e. when the weather is bad, the necessity to have shelter increases. *Comfort* corresponds to the benefit that someone wants to gain out of his transport mode choice. Hence, its states {*none, all*} are also influenced by weather conditions. This subset is modelled in Figure 2.11a.

The shopping location decision is influenced by *an individual's interest in a specific product* as well as *the number and size of goods being purchased* (Figure 2.11b). Both contexts and the decision lead to the benefit of *having efficiency*. In the model, the benefit of *having efficiency* gained in different situations is further differentiated, e.g. [*efficiency_1*] is linked to the first context of *an individual's interest in a specific product* and [*efficiency_2*] is connected to the second context. This way, the impact of every context on benefits can be assessed separately at the benefit level. In the end, both partial benefits lead to the same utility of *having efficiency*.

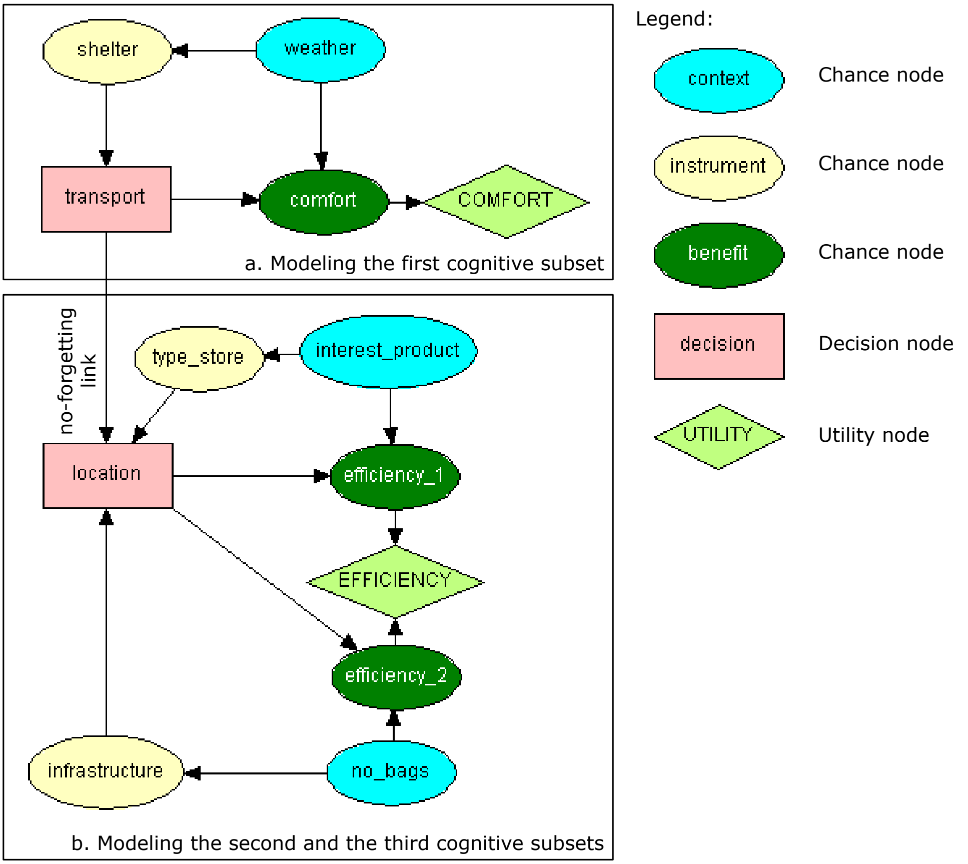


Figure 2.11 An example of the proposed modelling approach: Modelling the first cognitive subset of the transport mode decision (a); and modelling the second and the third subsets of the shopping location decision (b)

2.4.3.2 Conditional probability and utility table

To explain the CPT, the example in Figure 2.11a is reused. Consider the benefit of *having comfort* [*C*] {*none* [*N*], *all* [*A*]} in the cognitive subset example of {*weather, shelter, comfort*}. This benefit has *weather* [*W*] {*bad* [*B*], *good* [*G*]}) and *transport mode decision* [*TM*] {*car, bus, bike*} as its parents. The CPT of having *all comfort* takes the joint values {*P(C=A|W,TM)*}. Suppose that an individual estimates these values as {*<0.5>*, *<0>*, *<1>*, *<1>*, *<0.6>*, *<0>*} (Figure 2.12a), meaning that if a *car* is used when the weather is *good* then the chance to gain the benefit of having *comfort* is 50%, if a bus is used in that context then the probability to acquire this benefit drops to 0% (for instance because it is too hot inside the bus), and so forth. It should be noted that the joint values of all states in one node have to sum-up to 1. Therefore, the joint values for having *no comfort* are $\{P(C=N|W,TM)\}=1-\{P(C=A|W,TM)\}$.

CPT Shelter (S)	
W	P(S=N|W)
Bad [B]	1
Good [G]	0

CPT Weather (W)
P(W=G)
0.5

CPT Comfort (C)		
W	TM	P(C=A|W,TM)
G	Car	0.5
G	Bus	0
G	Bike	1
B	Car	1
B	Bus	0.6
B	Bike	0

UT COMFORT	
C=None [N]	0
C=All [A]	100

UT EFFICIENCY		
efficiency_1	efficiency_2	Utility
N	N	0
N	A	50
A	N	50
A	A	100

Legend:
B : Bad
G : Good
W : Weather
S : Shelter
TM : Transport Mode
C : Comfort
N : None
A : All

a. The CPTs and UTs

Utility		
W	TM	U(C|W,TM)
Good	Car	(0.5x100) + (0.5x0) = 50
Good	Bus	(0x100) + (1x0) = 0
Good	Bike	(1x100) + (0x0) = 100
Bad	Car	(1x100) + (0x0) = 100
Bad	Bus	(0.6x100) + (0.4x0) = 60
Bad	Bike	(0x100) + (1x0) = 0

b. The utilities of comfort

Figure 2.12 An example of the CPT and UT (a) and the calculated utility of comfort (b)

The CPT of a child node that has many parents (or when the parent nodes have many states) is very large. Imagine a child node with five parents. If each node has two states, the CPT of this child node requires $2^{5+1}=64$ probability assessments. Given the purpose of this study to individually model people's travel behaviour, each respondent's subjective probability judgments are needed for the CPT of his Bayesian ID model, implying great demand in data collection. This imposes a challenge to reduce respondents' burden. For this reason, each contextual variable is liked to only one partial benefit variable (Figure 2.11a and b), assuming that there are no interactions between different contexts that lead to the same desired benefit.

In the example, the utility node of "COMFORT" has the benefit of *having comfort* {*none*, *all*} as its parent. It is assumed that the utilities of having *no* benefit is always valued 0 and having *all* benefit is set at 100 (Figure 2.12a). When there are two identical partial benefits that lead to the same utility, such as the benefit of *having efficiency* in Figure 2.11b. The utility values are propagated equally, as shown in the "UT EFFICIENCY" table in Figure 2.12a.

2.4.3.3 Evaluating influence diagram

The calculations of an ID model are exemplified by assuming that an individual's ID model only contains the subset of {*weather, shelter, comfort*}. Using the CPT and UT in Figure 2.12a, and the calculated utilities of comfort {*U(C|W,TM)*} in Figure 2.12b, the EU for the transport mode options without (a) and with evidence (b) are calculated below.

a. No evidence

$$EU(TM) = \sum_i P(W) \times U(C \mid W, TM)$$
$$EU(car) = P(W = bad) \times U(C \mid W = bad, car) + P(W = good) \times U(C \mid W = good, car)$$
$$EU(car) = 0.5 \times 100 + 0.5 \times 50$$
$$EU(car) = 75$$
$$EU(bus) = P(W = bad) \times U(C \mid W = bad, bus) + P(W = good) \times U(C \mid W = good, bus)$$
$$EU(bus) = 0.5 \times 60 + 0.5 \times 0$$
$$EU(bus) = 30$$
$$EU(bike) = P(W = bad) \times U(C \mid W = bad, bike) + P(W = good) \times U(C \mid W = good, bike)$$
$$EU(bike) = 0.5 \times 0 + 0.5 \times 100$$
$$EU(bike) = 50$$

b. Evidence that the weather is bad

$$EU(TM \mid e) = \sum_i P(W \mid e) \times U(C \mid W, TM)$$
$$EU(car \mid e) = P(W = bad \mid e) \times U(C \mid W = bad, car) + P(W = good \mid e) \times U(C \mid W = good, car)$$
$$EU(car \mid e) = 1 \times 100 + 0 \times 50$$
$$EU(car \mid e) = 100$$
$$EU(bus \mid e) = P(W = bad \mid e) \times U(C \mid W = bad, bus) + P(W = good \mid e) \times U(C \mid W = good, bus)$$
$$EU(bus \mid e) = 1 \times 60 + 0 \times 0$$
$$EU(bus \mid e) = 60$$
$$EU(bike \mid e) = P(W = bad \mid e) \times U(C \mid W = bad, bike) + P(W = good \mid e) \times U(C \mid W = good, bike)$$
$$EU(bike \mid e) = 1 \times 0 + 0 \times 100$$
$$EU(bike \mid e) = 0$$

The calculations above show that given unknown weather conditions (i.e. 50-50% chance that the weather is good or bad), using car maximizes the utility (75), followed by bike (50) and bus (30). Additionally, some evidence can be entered in the network based on some observations and accordingly the network can be inferred. For instance, when the weather is (or expected to be) bad, the EU of choosing bike drops to 0. Using the same technique, the evidence that the weather is nice can also be entered, resulting in the new EU of each decision option.

The example illustrates the application of an individual's Bayesian ID model to predict his travel behaviour, assuming that he always takes the choice alternative with the highest utility value. However, this example is fairly simple, allowing for only one decision and one subset. In reality, individuals' MR can be more complex with multiple decisions and many subsets, as shown in Figure 2.13 and Figure 2.14. To compute complex networks, Bayesian software is commonly used, such as Hugin software (HUGIN EXPERT, n.d.).

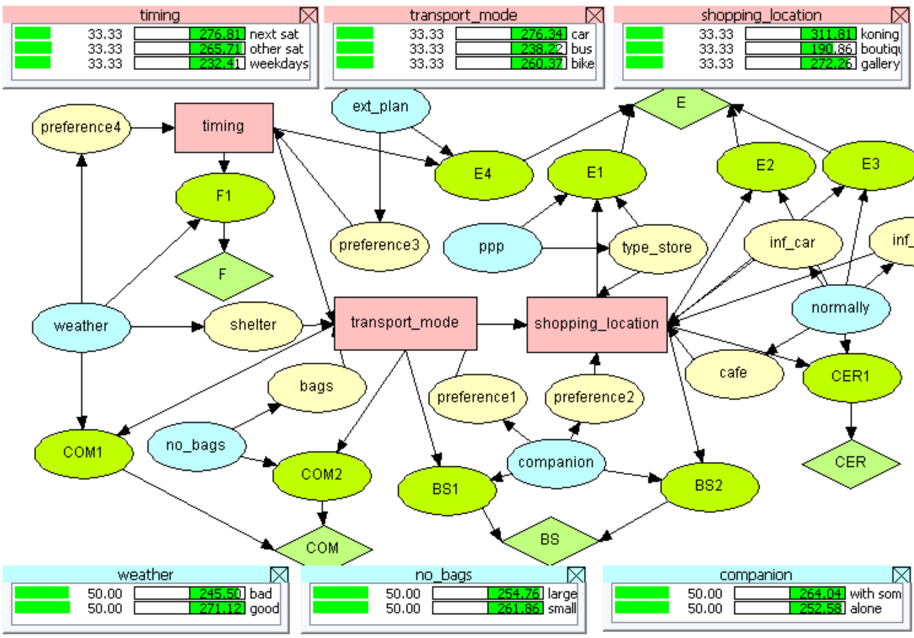


Figure 2.13 An example of the participant's elicited mental representation modelled using influence diagram technique (without evidence)

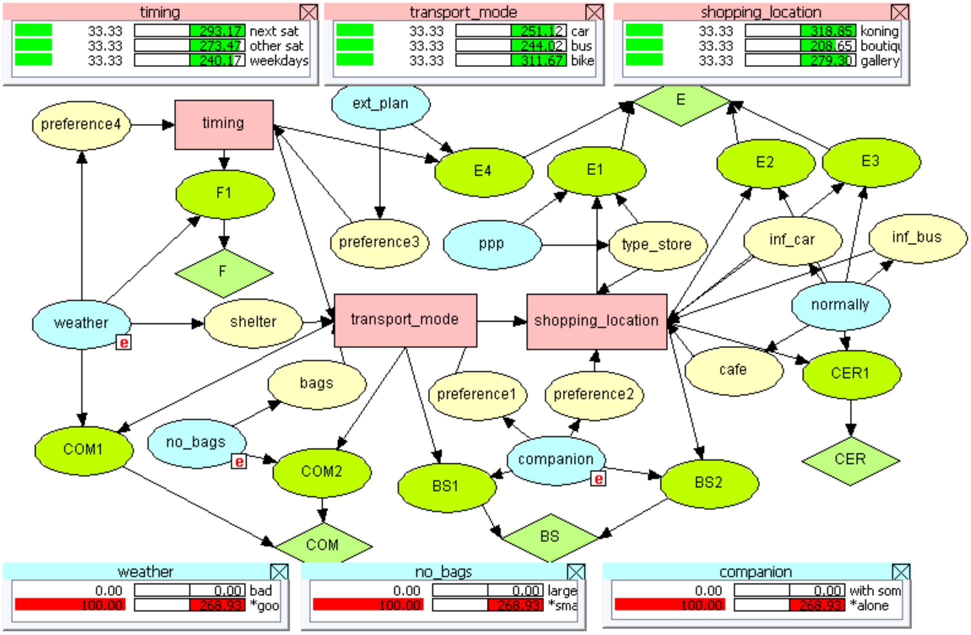


Figure 2.14 An example of the participant's elicited mental representation modelled using influence diagram technique (with some evidence)

The example in Figure 2.13 shows an ID model derived from the participant's MR elicited by means of the CNET interview method. Without any evidence, car maximizes the participant's utilities at 276.34. However, when some evidence is entered; i.e. *the weather is good*, *the number or size of goods to bring back home is small*, and *there is no companion*, the utility value of choosing car decreases to 251.12 while the utility of choosing bike is at maximum (311.67) (Figure 2.14). To end with, this section illustrates that such mental-level models can indeed be used to predict people's behavioural changes given the changeable and observable states of the world.

2.4.4 Some reflections on the model structures

Modelling individuals' MR as ID using different model structures has been shown in Section 2.4.2 and Section 2.4.3. Indeed, the existing and proposed models use similar types of variables (i.e. contextual, instrumental, and benefit variables). This means that conceptually, both models could be used for the same purpose, to calculate the expected utility values of choice options given the states of the contextual variables. However, it should also be noted, specifically in Section 2.4.3, that a network structure strongly determines the questions to gather parameter data. Therefore, the differences in the links connecting the nodes in both approaches cause different probability questions, resulting in different model outcomes. Which one of the model structures can best represent people's thought processes still remains unanswered. Future research should be done to elucidate this issue and to compare the results of different model structures.

2.4.5 Evaluating the CNET protocols to gather data for the influence diagram technique

The CNET interview and card game are used to elicit the participants' MR, as previously explained in Section 2.3. On average, the CNET interview lasts for about 1 hour, whereas the card game takes about 1.5 hours to complete. However, in order to model the elicited MR as ID, each respondent's ID graph has to be drawn manually based on every participant's elicited cognitive subsets. Furthermore, eliciting cognitive subsets is insufficient for the modelling purpose. Parameters (i.e. in CPT and UT) have to be gathered based on everyone unique network, preventing to capture such data immediately in face-to-face interviews. It means that post-questionnaires, designed for each individual, have to be sent after the interviews. Moreover, the gathered parameter data have to be inputted in each individual's network.

The whole procedure can take at least 8 hours of the researcher's time to complete (for one participant), added with additional 2 hours of the participant's time to answer the post-questionnaire. The inability to ask parameter questions directly in the interview may add-up the respondents' burden to recall the decision problem and reactivate the MR. Overall, the data collection procedure requires considerable time and effort, enhancing the need to automate the entire process by means of a computer-based elicitation interface. This interface is described Chapter 4.

2.5 Conclusions

In general, this chapter is organized into two major parts. The first part (Section 2.3) describes the implementation of the CNET interview protocol and the development of the CNET card game to elicit various contexts, instruments, and benefits in the participants' fun-shopping travel decisions. Both techniques are used to assess people's leisure-shopping activities, using a small sample group of 26 young adults. Three fun-shopping travel-related decisions are further investigated, namely *when* to fun-shop (the activity-scheduling decision), *what* transport mode to take (the transport mode decision), and *where* exactly to go to (the shopping location decision).

The differences between the CNET interview (soft-elicitation technique) and card game (hard-elicitation method) are discussed from the theoretical point of view and with regard to the participants' personal evaluation based on their experiences over both interfaces. The card game method is considered as easier, more pleasant and more comprehensive in comparison to the interview method. The respondents argue that the card game method generates better representations of their thought processes. This happens because of the cues, provided on the cards of predefined variables, may help activating the correct episodic memory in the respondents' mind (Burton & Blair, 1991) and hence, reducing the respondents' burden and effort to remember their past behaviours (Zmud, 2001). However, it should be noted that this study is cross-cultural research with non-English speaking population as the sample. The card game method gains more advantage over the CNET interview technique as it can presents the predefined variables in bilingual presentations. The CNET interview requires the respondents to express their idea in an open-ended format, hindering some respondents with insufficient English capability to confidently express their idea. This could contribute to the participants' preferences over the card game method. A disadvantage of the card game technique is that it is more time consuming than the interview method, yielding the respondents' difficulties to always stay focus on the task at hand. Besides, there is also a possibility of bias due to the presentation of predefined variables to the respondents, allowing them to varnish their actual behaviour.

The two tested elicitation methods in this experiment are fundamentally different, for instance in terms of using strategy for retrieving the participants' episodic memory. This may cause the disparities in the research outcomes. Therefore, the results should be compared not only based on the respondents' experiences with both methods but also based on the content of the participants' MR. Further analyses and their results with regard to the aspects elicited with both techniques are elaborated in Chapter 3.

In order to check the reliability of the CNET interview protocol, intercoder reliability measures are employed, i.e. the percentage agreement and Krippnedorff's alpha indices. The results indicate high percentage of agreement between the two coders. This implies that the CNET interview is indeed reliable and accordingly transferable to other sample groups and/or to elicit other decision making types.

The second part of this chapter (i.e. Section 2.4) demonstrates the use of the ID technique to model decision making. In this part, the existing modelling structure is initially explained along with the justification of why the alternative modelling structure is developed. Next, the elicited MR using the CNET interview and card game along with the additional parameter data are used as input for the modelling exercise, allowing us to create a mental-level model for each individual that can foresee his behavioural variations through his MR. However, to generate theoretically sound research outcomes, a sufficient number of participants should be used as the sample. Consequently, the CNET interview and card game cannot be used for this purpose. The extensive demand in data collection using both techniques leads to large investments in researchers' and participants' time and effort, as described in Section 2.4.5. In order to apply this research on a large sample group, the data collection procedure should be done quantitatively. Therefore, a computer-based elicitation technique is developed to automate this process, starting from eliciting individuals' MR until collecting parameter data for additional model input. This computer-based protocol is detailed in Chapter 4.

3 Scrutinizing individuals' leisure-shopping travel decisions: An exploratory study

3.1 Introduction

AB models for modelling individuals' travel demand have come to a new era in addressing individuals' and households' travel behaviours at an individual's level. Quantitative data are mainly used in this domain to enable a realistic representation of individuals' choices and a true assessment of the impact of different TDM. However, it is believed that qualitative approaches in data collection are the ones that can describe aspects in individuals' travel behaviour, such as detailed decision making process information. Accordingly, qualitative methods may deepen our insight into human's travel behaviour from the agent-based perspective.

This chapter presents the results of the elicited aspects obtained by means of the CNET interview and card game, previously explained in Chapter 2. In this chapter, the differences of the 26 participants' MR data obtained by both techniques are highlighted. The concept of MR and cognitive subset has been explained in Chapter 2. The AR analysis is done next to investigate intertwined aspects in *cognitive subsets*. AR is a data mining technique to discover patterns and associations among variables in data. The results of the AR analysis on both the CNET interview and card game datasets are used further to inform AB modellers and policy makers about constructs and beliefs commonly considered in people's travel decisions. These results can be used to ground assumptions in AB models of travel demand and to analyse TDM that could encourage people to predominantly shift their transport mode choice from car to other more sustainable forms of transport modalities, such as bus and bike.

However, due to the methodological differences between the CNET interview and card game protocols, as detailed in Chapter 2, it is expected that there are some discrepancies of the analysis results of the data gathered by both techniques. Despite the underlying question of which one of the two methods generates a more accurate cognitive representation of human's mind, the results of both studies are useful to explain the reasoning behind every individual's travel behaviour. Thus, the AR results of the CNET interview data are used to ground the assumptions in AB models. Next, the AR results of the card game data are employed to analyse a number of TDM measures in line with people's decision making. These policies could be effective in reducing a number of problems caused by excessive car-use, such as traffic jams, car emissions, accidents, and the overuse of energy and land (Gärling, 2005).

The rest of Chapter 3 is organized as follows: the elicited aspects using the CNET interview and card game are presented to start with (Section 3.2). Following that, AR as the method is explained (Section 3.3). The data analysis using AR is described in Section 3.4. Afterwards, the AR results of the CNET interview dataset are discussed to inform AB models (Section 3.5), whereas the results of the CNET card game are set as the basis to analyse a number of TDM measures (Section 3.6). At last, the general conclusions of this chapter are drawn and presented in Section 3.7.

3.2 The elicited aspects in cognitive subsets

The aim of this study is to test different elicitation techniques and highlight their similarities and differences. In this section, comparisons are made with regard to the average number of the revealed variables and their types. They are discussed below subsequently.

3.2.1 The average number of elicited variables

The average number of variables is calculated by registering the total number of revealed variables (per decision type and per elicitation method) and dividing it by the total number of respondents. The results are presented in Table 3.1. These results indicate that the respondents on average consider almost twice as many relevant aspects in the CNET card game as in the interview, implying that more information can be extracted by the card game. However, this can also be caused by some non-considered factors selected by the respondents simply because they want to varnish their actual behaviours, to avoid feeling humiliated, to satisfy the interviewer, etc. This issue has been previously discussed in Chapter 2 (Section 2.3.1.2).

Table 3.1 The average number of variable types being elicited per respondent (n=26 respondents)

Fun-shopping decision	*Variable types*	*CNET interview*	*CNET card game*
Activity-scheduling decision	Context	1.69	2.81
	Instrument	3.23	5.69
	Benefit	2.81	4.31
Transport mode decision	Context	3.42	6.85
	Instrument	6.36	12.85
	Benefit	4.46	6.46
Shopping location decision	Context	2.19	5.50
	Instrument	5.31	11.31
	Benefit	3.50	6.46
	Total	32.97	62.24

Furthermore, Table 3.1 shows that the numbers of (contextual, instrumental, and benefit) aspects are generally the highest for the transport mode decision, whereas they are the lowest for the activity-scheduling decision. This may happen because there are quite significant and noticeable differences in the characteristics of the transport mode options (i.e. car, bus and bike) and the variety of contexts in which each of the transport mode features is searched for. On the other hand, timing choice options are much less divers and more finite. Indeed, the limited number of considerations related to the activity-scheduling shows that people are restricted by fixed commitments and routines such as going to school on weekdays and playing football on Saturday. This may cause people's inflexibility with regard to time, making fewer aspects left to consider.

3.2.2 The elicited aspects in fun-shopping decisions

This section focuses on the differences of the results of the elicited aspects using both the CNET interviews. Accordingly, this section is organized as follows: the order of people's decision making is presented to start with (Section 3.2.2.1). Next, the elicited variables in the activity-scheduling (Section 3.2.2.2), transport mode (Section 3.2.2.3), and shopping location decisions (Section 3.2.2.4) are emphasized. At last, some reflections from the methodological point of view are discussed (Section 3.2.2.5).

3.2.2.1 The order of decision making

In the beginning of the interviews with both the CNET protocols, the participants are asked to indicate the order of their decision making by assigning ranking to each travel decision. Their responses are recorded and the average scores of ranking are calculated for all decisions, as shown in Table 3.2. These results point out that the respondents firstly decide when to execute their fun-shopping plan before choosing where exactly to go to or how to get there. These results are used later on in Section 3.5.2.1 to discuss assumptions in AB models.

Table 3.2 The average ranking of decision making order (n=26 respondents)

Fun-shopping decision	*Scheduling activity*	*Location*	*Transport mode*
The CNET interview	1.12	2.5	2.38
The CNET card game	1.12	2.62	2.27

3.2.2.2 The activity-scheduling decision

With regard to the activity-scheduling decision, the results in Figure 3.1 show that the contextual variable of *weather conditions* is elicited by most of the respondents (the CNET interview [I]: 57.7% of the respondents; the CNET card game [CG]: 65.4% of the participants). However, the consensus of the *weather* variable for this decision is less clear than for the transport mode choice, as described in the subsequent section (i.e. Section 3.2.2.3).

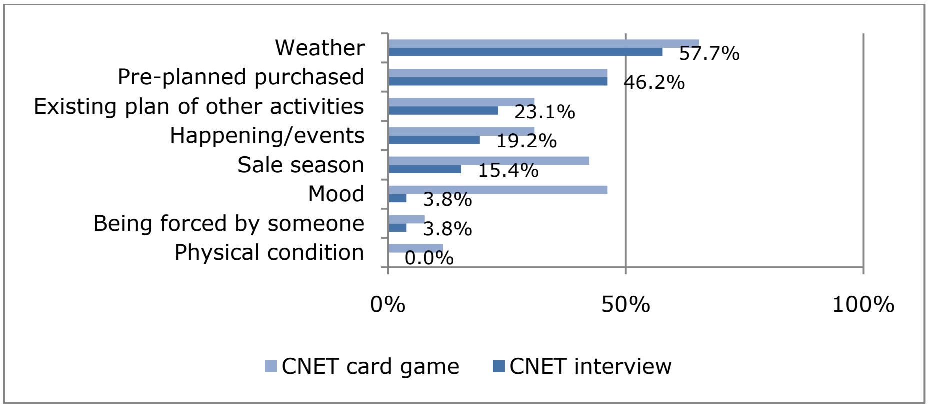


Figure 3.1 Contextual aspects in the activity-scheduling decision

With respect to the benefits (Figure 3.2), the respondents mostly want to maximize *having fun* (I: 69.2%; CG: 69.2%) and *efficiency* (I: 61.6%; CG: 80.8%) from the scheduling of fun-shopping. Moreover, *reducing stress* (CG: 73.1%) and *being sociable* (CG: 50%) turn out to be important benefits as well, at least in the card game data.

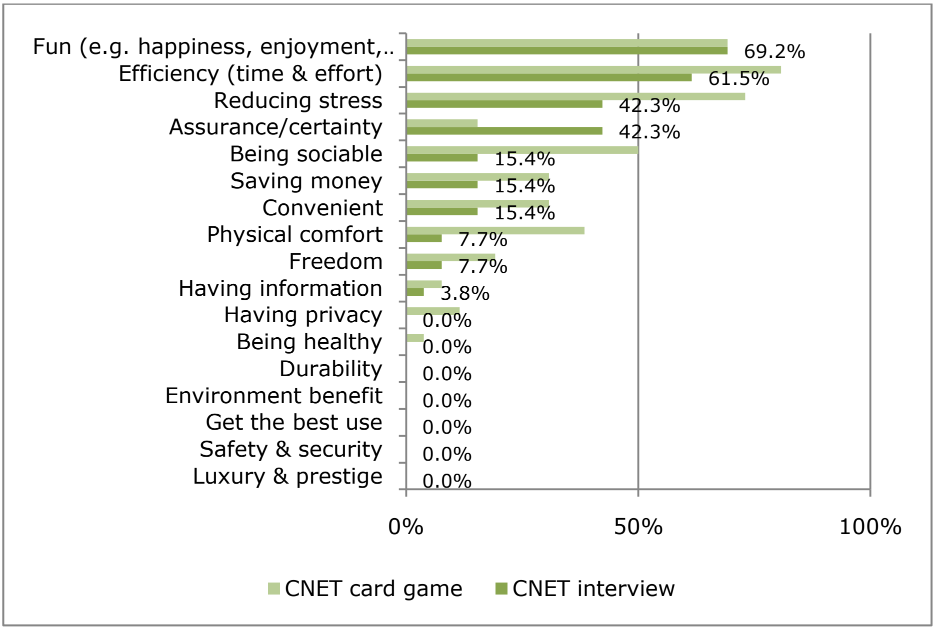


Figure 3.2 Benefits in the activity-scheduling decision

Furthermore, the results (Figure 3.3) show that *time availability* (I: 80.8%; CG: 73.1%), *preference of day* (I: 76.9%; CG: 88.5%) and *presence of companionship* (I: 57.7%; CG: 73.1) are the most notable instruments influencing the respondents' selection of day. This may be due to the fact that fun-shopping is a discretionary leisure activity. Therefore, *time availability* and *the respondent's preference of day* play major roles. The importance of *companion* in determining the time plan to do the activity shows that the respondents usually execute this type of pastime together with friends or family members. This comes in line with results of other studies (e.g. Carrasco & Miller, 2006) that show the role of companionship and detailed social networks in social activities.

In addition, there are other instrumental aspects, highly considered based on the card game data. These aspects are *the urgency of the activity* (66.5%), *crowdedness in Hasselt* at the day when the activity is scheduled (61.5%), *the duration of fun-shopping* (53.8%), *scheduling effort* (50%) and *budget availability* (50%). These results are shown in Figure 3.3.

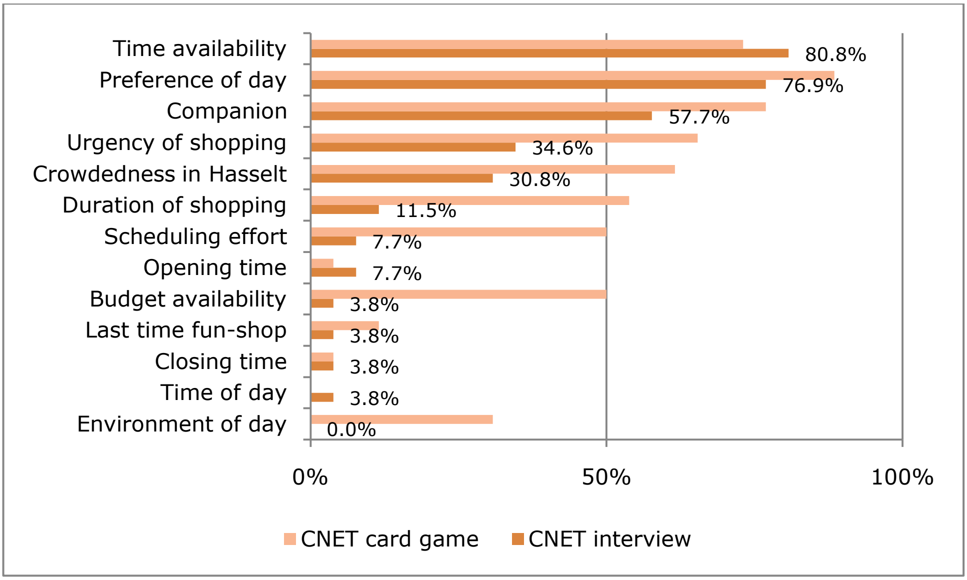


Figure 3.3 Instrumental aspects in the activity-scheduling decision

Some instruments of the activity-scheduling decision such as *time availability*, *companion*, *crowdedness in Hasselt*, etc. are in fact the contextual aspects of the transport mode and location decisions. This happens because in the scheduling context, these factors signify the characteristics of different days in a week. For instance, when a respondent plans to go shopping on Saturday, he usually has someone to accompany him, but this is not the case when the activity is planned on a weekday. Also, time availability on weekends can be different than on weekdays. On the other hand, these variables are considered as given situations in the transport mode and location choice decisions, implying that they are contextual aspects for these decisions. This example further demonstrates the complexity and interdependency among decisions in the activity-travel plans.

3.2.2.3 The transport mode decision

The participants' choices of transport modes strongly depend on the contextual constraint of *weather conditions* (or *precipitation*), as indicated by the highest percentage of respondents who elicit this variable in both CNET interview (84.6%) and card game data (92.3%). *Companionship* is also an important contextual aspect in both interview data (I: 61.5%; CG: 65.4%). These results are shown in Figure 3.4. The finding of this experiment signifies the importance of *weather conditions* and *companionship* as contextual factors that affect travel choices. The latter aspect (i.e. *companionship*) supports the initial idea of Hägerstrand (1970) regarding coupling constraints.

The CNET interview method unveils that *the number or size of goods* that the respondents have to carry back home is a quite important aspect (50%). To a lesser extent, this result is shown in the card game data (46.2%). This variable can be considered as a capability constraint, again supporting Hägerstrand's theory. Furthermore, there are some additional influential contexts in the CNET card game data, such as *time availability* (88.5%), *the availability of parking space* (76.9%), *existing plan of other activities to do* (65.4%), and *crowdedness inside bus* (53.8%).

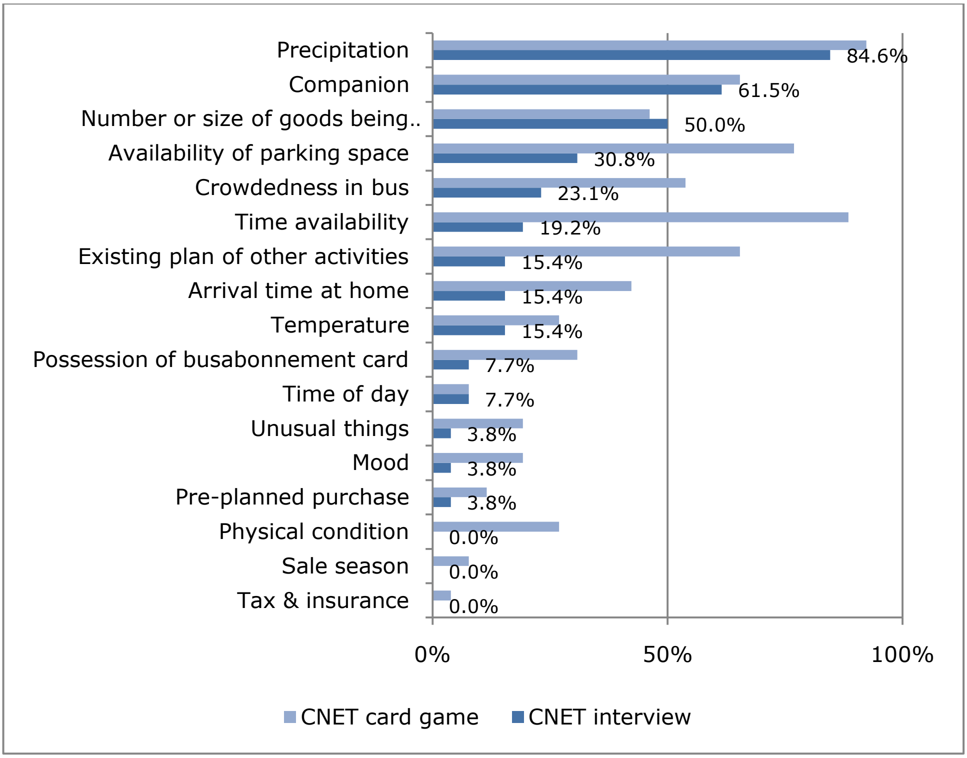


Figure 3.4 Contextual aspects in the transport mode decision

With regard to the benefits in the transport mode decision (Figure 3.5), the respondents mainly want to maximize *having efficiency* (I: 88.5%; CG: 96.2%) and *physical comfort* (I: 80.8%; CG: 92.3%). *Saving money* is a fairly important benefit in the CNET interview data (50%) and this result is somehow confirmed by the card game (42.3%). Other additional benefits in the card game data are *having convenience* (73.1%), *having freedom* (53.8%), *having certainty* (50%), and *being sociable* (50%).

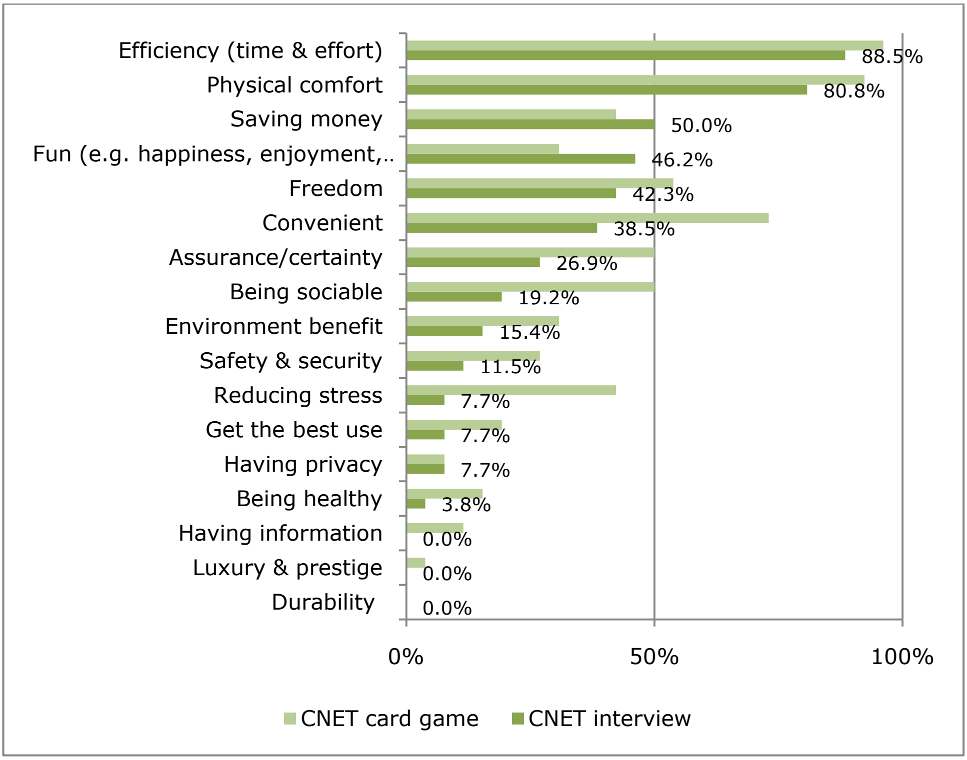


Figure 3.5 Benefits in the transport mode decision

The benefits above are fulfilled by a number of instruments of the transport mode options (car, bus and bike) (Figure 3.6), such as *shelter provision* (I: 80.8%; CG: 88.5%), *transport mode availability* (I: 73.1%; CG: 84.6%), *individual's transport mode preferences* (I: 65.4%; 92.3%), and *travel time* (I: 53.8%; CG: 84.6%). Surprisingly, *the transport mode availability* is still frequently considered even though it is mentioned in the research setting (in Section 2.3.2) that car, bus, and bike are available to use. This could happen because buses in Hasselt to certain destinations are not operated after a certain time at night (usually around 8 PM), adding up the respondents' concerns when considering to take a bus.

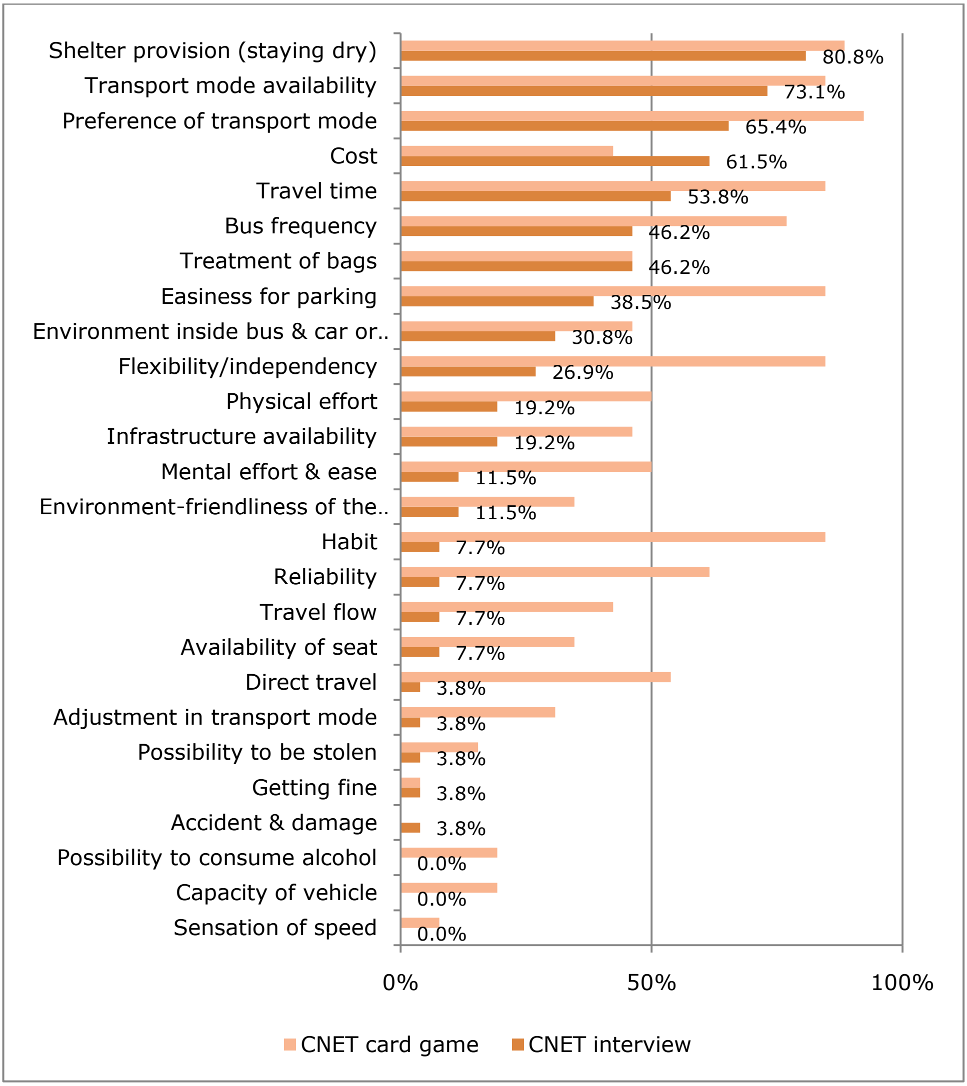


Figure 3.6 Instrumental aspects in the transport mode decision

According to the interview data, *cost* is an important factor (61.5%). However, this variable is not selected that much in the card game data (42.3%). Additional commonly selected instruments in the card game data are *individual's habit to use a certain transport mode* (84.6%), *flexibility/independency offered by the vehicle* (84.6%), *easiness for parking* (84.6%), *bus frequency* (76.9%), *reliability of the vehicle* (61.5%), *direct travel* (53.8%), *physical effort* (50%), and *mental effort* (50%). *Direct travel* is considered because busses often make detours. Besides, the respondents sometimes have to change from one bus to another one to reach their final destinations.

In traditional utility-based transport demand models, *travel time* and *cost* are often used as decisive factors. With regard to the fun-shopping travel decision, this study confirms that indeed *travel time* and *cost* are important decision aspects. However, there are other more significant factors that people consider as well, such as *shelter provision*, *transport mode availability,* and *preference over certain modes of transport*. These variables are often overlooked in other common utility-based transport demand models.

3.2.2.4 The shopping location decision

The destination choice in the city centre is strongly determined by contextual aspects such as *a pre-planned purchase in mind* (I: 66.4%; CG: 84.6%). Other aspects, for instance *companion* (38.5%), *time availability* (26.9%), *individual's interests in specific products* (11.5%), and *information from other people about a particular shop or shopping area* (11.5%) are less significant in the interview data but they are important in the card game data (57.7 %, 57.7%, 84.6%, and 53.8% respectively). High frequency of elicitation of *a pre-planned purchase in mind* in both datasets reveals that even though fun-shopping is a recreational activity, individuals tend to perform it when necessary, such as when there is the actual need to buy something. Similarly, this result is also unveiled in the previous activity-scheduling part (in Section 3.2.2.2). Additionally, a number of major contexts are considered in the card game data, namely *time availability*, *individual's interests,* and *companionship*. These results are presented in Figure 3.7.

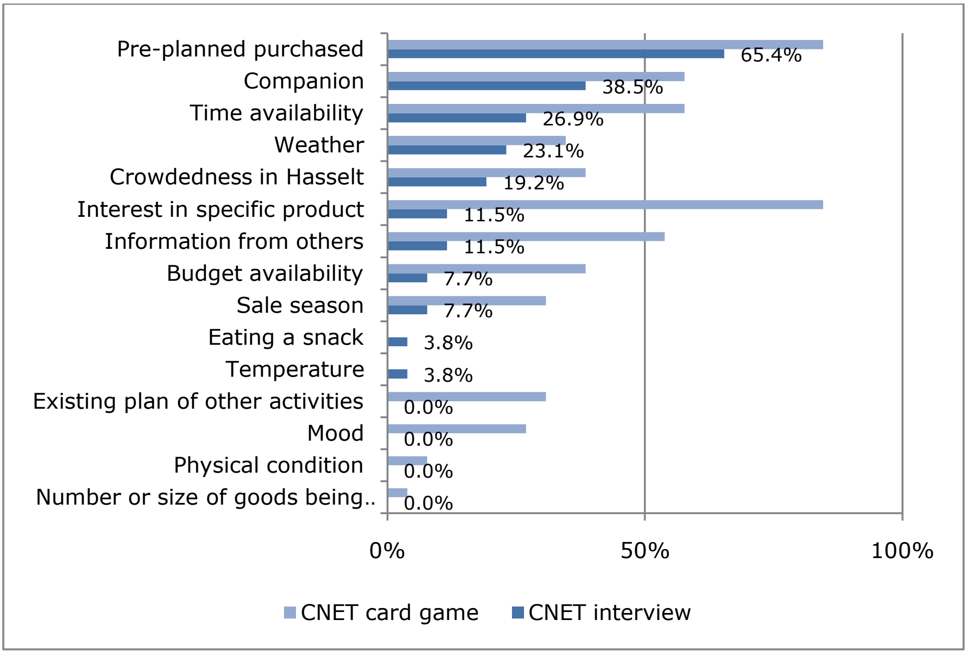


Figure 3.7 Contextual aspects in the shopping location decision

With respect to the benefits, the results (Figure 3.8) show that the destination choice is made to gain *efficiency in time and effort* (I & CG: 96.2%), *certainty* (I: 53.8%; CG: 80.8%) and *fun* (I: 53.8%; CG: 73.1%). In addition, the card game reveals other pursued benefits such as *saving money* (73.1%) and *having information* (57.7%). These results correspond to other findings in literature regarding leisure-shopping: a fun-shopper aims to have *fun* and *enjoyment* as well as to satisfy *information needs* (Dellaert, Borgers, & Timmermans, 1995; Lesser & Hughes, 1986). From the perspective of urban planning, it should be noted that people, at least in the observed sample group, want to gain more efficiency from the shopping area.

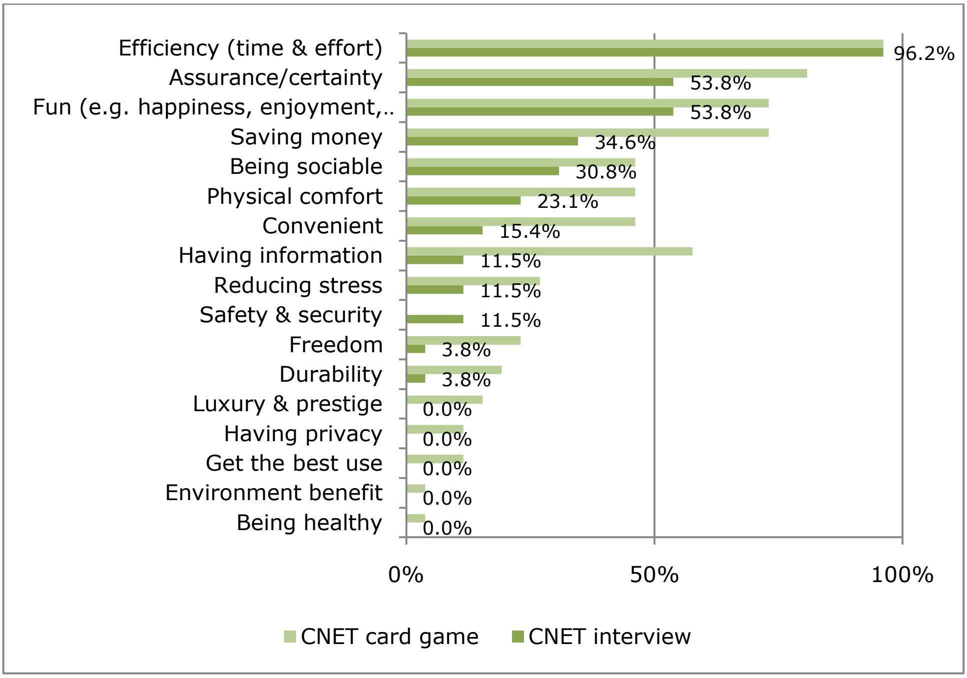


Figure 3.8 Benefits in the shopping location decision

This study brings about the important instrumental aspects of the shopping locations (Figure 3.9); namely *the type of stores in the area* (I: 69.2%; CG: 92.3%) and *accessibility for bus* (I: 57.7%; CG: 50%). To some extent, *accessibility for car* (I: 50.0%; CG: 46.2%) can also be considered as an important attribute of the location choice. Accessibilities for bus and car indicate the closeness and easiness to reach certain areas when using these modes of transport. This depends on the availability of bus stops and car parking in or very close to the area being considered. High elicitation of the accessibilities for car and bus for short distance trips related to this activity type can be a guide to develop policy measures to encourage public transport use by making the shopping areas more reachable for bus users and less accessible for car users. Further discussions concerning TDM to encourage the use of more sustainable transport modes can be found in Section 3.6.

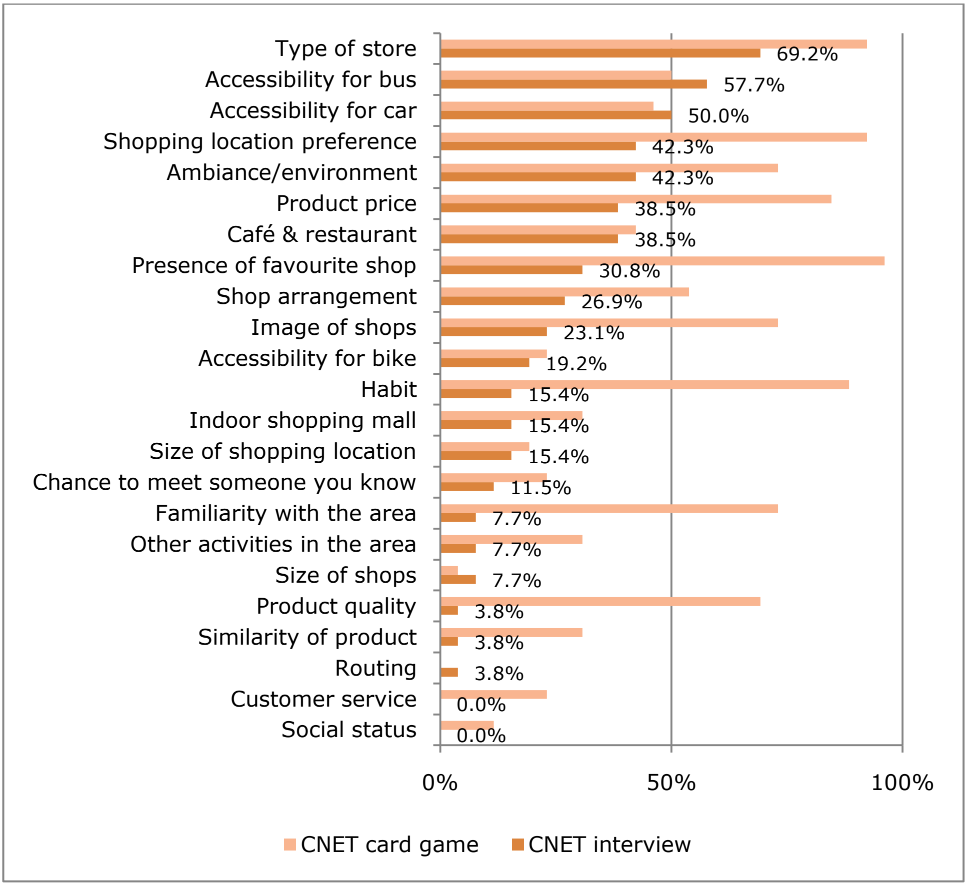


Figure 3.9 Instrumental aspects in the shopping location decision

Further instruments elicited by the card game method are *the presence of an individual's favourite shop in the area* (96.2%), *individual's preference over shopping location* (92.3%), *individual's habit* (88.5%), *product price in the area* (84.6%), *familiarity with the area* (73.1%), *image of the shopping location* (73.1%), *ambiance and environment of the shopping location* (73.1%), *quality of the product* (69.2%), and *shop arrangement* (53.8%). The high percentages of elicitation of these aspects indicate that the participants' personal judgments, perceptions, values, and habits play significant roles in determining their location choices. Further discussions of aspects elicited in the shopping location decision from the marketing point of view can be read in Chapter 5 (Section 5.4.3).

3.2.2.5 Some reflections from the methodological perspective

The results presented in Figure 3.2 to Figure 3.9 clearly indicate that there are some differences of the numbers of respondents who elicit each decision variable in the CNET interviews and card game interviews. These differences are calculated and presented in Figure 3.10 for the activity-scheduling decision, Figure 3.11 for the transport mode decision, and Figure 3.12 for the shopping location decision. The positive value in these figures means that the corresponding variable is elicited by more respondents in the CNET card game interviews, whereas the negative value indicates otherwise. Hence, from the results in Figure 3.10 to Figure 3.12, it can be seen that the respondents are often add more variables when interviewed with the CNET card game technique, previously unseen in the interviews with the CNET interview method.

In the transport mode decision (Figure 3.11), the contextual variable of *time availability* is elicited by 19.2% of the participants during the CNET interviews. This variable is picked by 88.5% of the respondents in the CNET card game interviews. This results in 69.3% (or 88.5%-19.2%) of the respondents who actually miss to indicate the importance of this variable in their decision making using the CNET interview method. Similarly, the differences of the number of respondents who elicit the contextual variable of *the existing plan of other activities* are 50%. The same cases can also be observed for the transport mode instruments of *habit* (77%), *flexibility/independency* (58%), *reliability* (54), and *direct travel* (50%). In the shopping location decision (Figure 3.12), these variables are *interest in a specific product* (73%), *habit* (73%), *presence of favourite shop* (65%), *product quality* (65%), *familiarity with the area* (65%), *shopping location preference* (50%), and *image of shop* (50%). However, smaller differences are seen in the activity-scheduling decision variables (Figure 3.10).

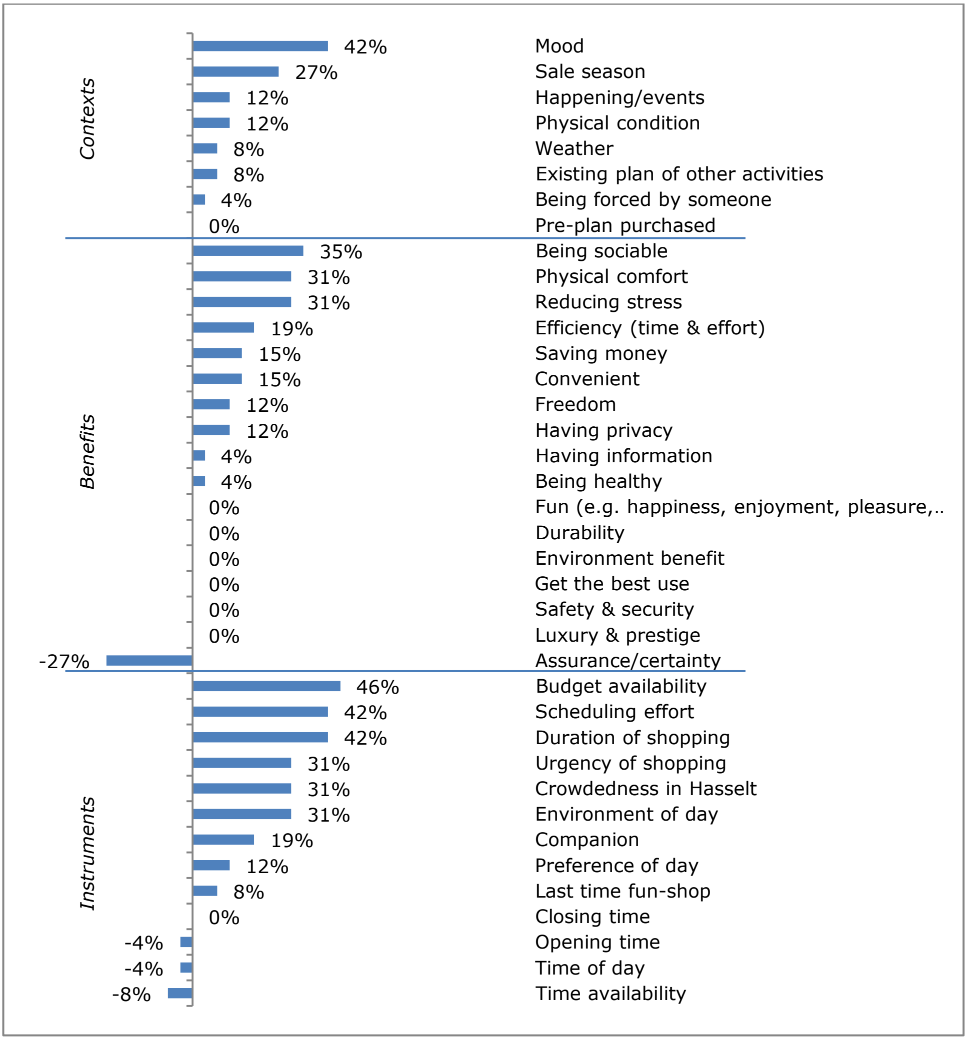


Figure 3.10 The differences of the number of respondents who elicit the activity-scheduling decision variables

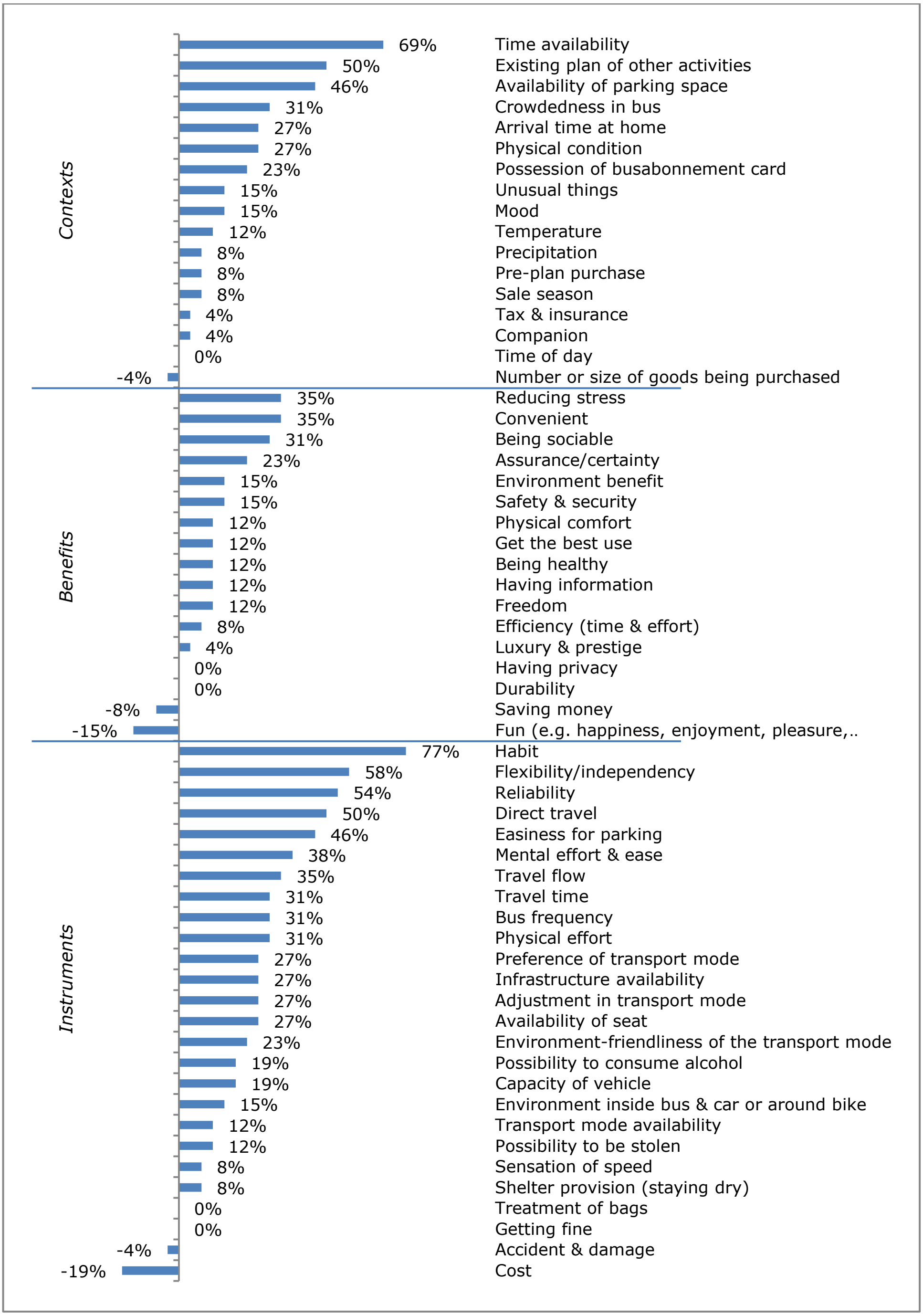


Figure 3.11 The differences of the number of respondents who elicit the transport mode decision variables

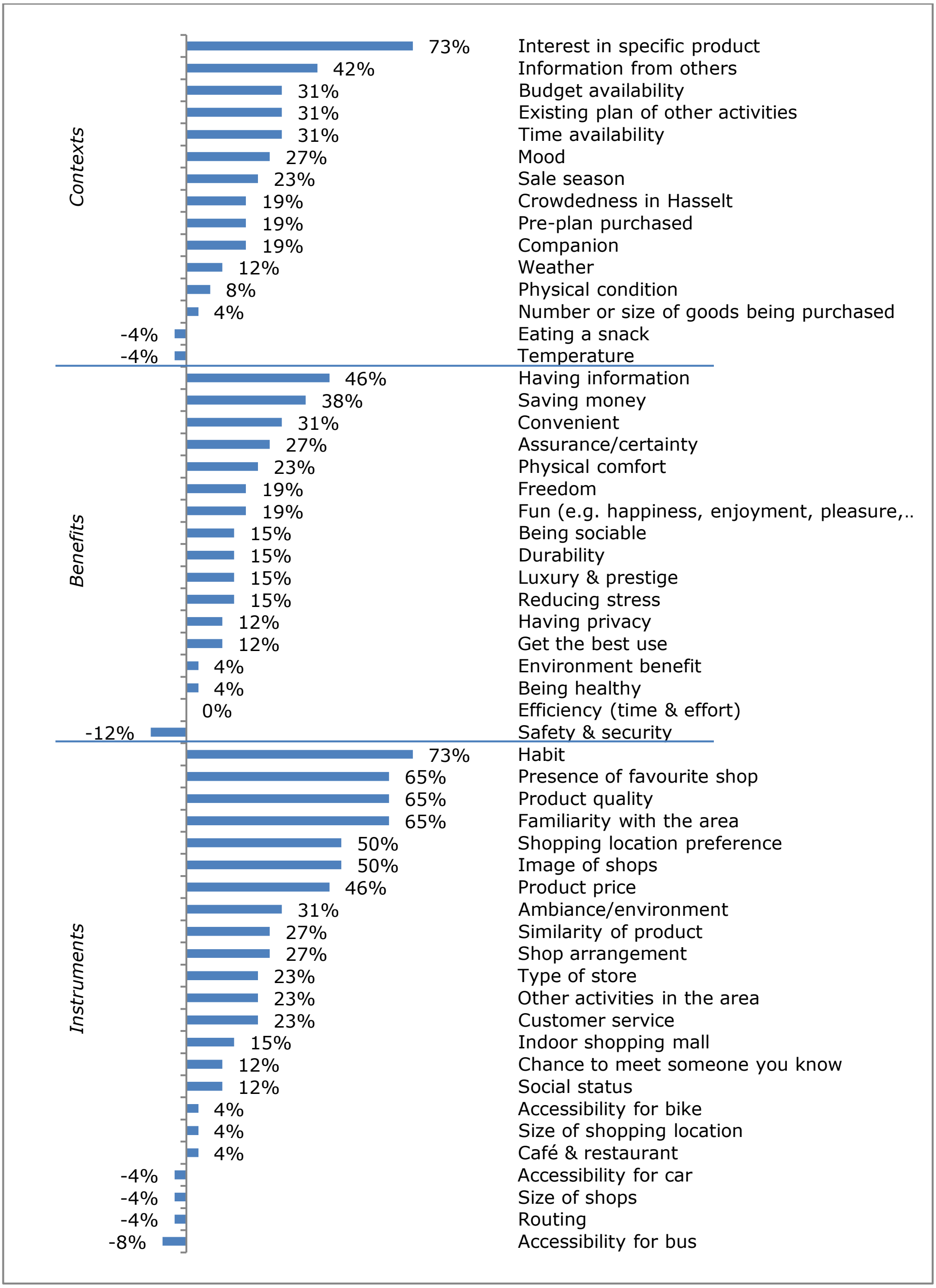


Figure 3.12 The differences of the number of respondents who elicit the shopping location decision variables

The results may give an indication of aspects often forgotten by people. However, due to the nature of the card game protocol, thoughts that are not actually present in the individuals' MR could be also be evoked or induced during the interviews, giving an indication of why these variables are only recognized in the card game interviews. The results show that these cases are more common in the transport mode and location decisions than in the activity-scheduling decision. This could be caused by a larger variety of aspects that could be taken into account in the transport mode and shopping location decisions. Interestingly, the differences of the elicited benefits are smaller than the contexts and instruments. This may suggest that benefit variables are more finite rather than the other variable types (i.e. contexts and instruments).

3.3 Association rules

Previous section (i.e. Section 3.2) has shown the differences between aspects elicited using different methods. Nonetheless, in the framework explained in Chapter 2 (Section 2.2), a context, an instrument, and a benefit are connected and formed a cognitive subset. This information is needed to understand how different benefits can be gained through a number of choice set instruments and due to certain affecting contexts. However, the previous analysis cannot learn these interlinking variables from the data. For this reason, the AR technique is employed, as detailed in this section.

The AR analysis is a widely used data mining technique for efficiently discovering relationships between variables in a dataset in the form of "*IF-THEN*" statements. This method is initially introduced to find regularities in transaction data in supermarkets (Agrawal, Imieliński, & Swami, 1993). To date, the AR technique has been successfully applied in many different fields, such as marketing (e.g. Changchien & Lu, 2001), e-commerce (e.g. Lin, Alvarez, & Ruiz, 2002), health (e.g. Brossette et al., 1998), bioinformatics (e.g. Creighton & Hanash, 2003), transportation (e.g. Gong & Liu, 2003) and traffic safety (e.g. Geurts, Thomas, & Wets, 2005).

In this study, the AR algorithm is applied as an analysis tool to find robust and frequently elicited cognitive subsets that constitute the participants' MR, derived from the elicited and revealed considerations using the CNET interview and card game methods. Some terminologies are commonly used in this domain, as follows: firstly, items (I) is defined as a set of k binary attributes ($I=i_1,i_2,i_3,\ldots,i_k$). All contextual aspects, instrumental aspects and benefits are examples of items in the fun-shopping database, such as the variable of *weather conditions* (a context), *shelter* (an instrument), *and comfort* (a benefit). Next, a database (D) consists of a set of transactions (t) so that $D=\{t_1,t_2,\ldots,t_m\}$. Each transaction (t) in a database (D) comprises of a set of binary attributes or a subset of items (I). A rule $X \Rightarrow Y$ is derived, where $X,Y \subseteq I$ and $X \cap Y = \emptyset$. X and Y are defined as *itemsets*, the short form of *sets of items*, and they are defined as the *antecedent* and *consequent* of the rule successively. An itemset can be a single or a set of combined binary attributes in a dataset, such as the size-one itemset of {*weather*}, the size-two itemset of {*weather, shelter*}, and the size-three itemset of {*weather, shelter, comfort*}.

Generally, two important steps are needed in order to generate rules from a database using AR: (1) determining frequent itemsets and (2) determining rules from frequent itemsets. The word "frequently" in the frequent itemsets is determined by a user-specified *minimum support value* (for short *minsup*). A support value (S) is expressed as a percentage of the total number of transactions (t) in a dataset (D) which contains an itemset (e.g. X or Y). A high percentage of support value indicates that a combination of items can commonly be found in a dataset, and vice versa.

When all frequent itemsets have been recognized, the next stage is aimed at searching "strong" rules from these itemsets. To do that, a user-specified *minimum confidence value* (for short *minconf*) has to be set. When a confidence value (C) of a rule $X \Rightarrow Y$ is 50%, it means that when itemset X appears in the transaction, there is 50% probability that itemset Y also occurs in that transaction. This implies that higher confidence values yield better rules. A confidence value is calculated using the following formula:

$C(X \Rightarrow Y) = \frac{S(X \cup Y)}{S(X)}$; Where *C* signifies the confidence value; *S* is the support value; and *X* and *Y* are the itemsets.

Another important measure in AR is called *improvement* (also termed *lift*). This measure indicates the level of accuracy of a rule by giving information whether itemsets *X* and *Y* appear together in the transaction by a random chance or not. *Improvement* is calculated by the following equation:

$I(X \Rightarrow Y) = \frac{S(X \cup Y)}{S(X) \times S(Y)}$; Where *I* donates the improvement value; *S* signifies the support value; and *X* and *Y* are the itemsets.

When the improvement value equals 1, it means that *X* and *Y* are independent itemsets, and they may appear in the transaction by a random chance. When this value is bigger than 1, *X* and *Y* may be present together in a transaction because they are dependent itemsets. For instance, beer and chips could be dependent itemsets in a transaction database of a supermarket, because from that database it is seen that when beer is bought then chips is also purchased.

Based on this principal, the fun-shopping database is organized as follows. Suppose that for the transport mode decision, Respondent A and B in succession elicit 5 and 4 subsets. Each subset from each respondent is registered as one transaction. Therefore in total there are 9 transactions in the database (see Figure 3.13).

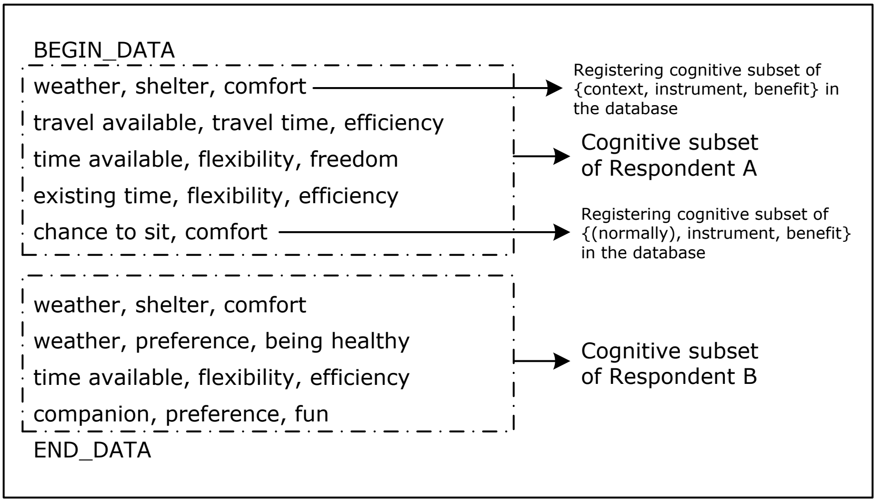


Figure 3.13 A database example containing elicited cognitive subsets

In the example database in Figure 3.13, an itemset {*weather, comfort*} has a support of 2/9=0.222, which means that this itemset appears in 2 out of 9 transactions (22.2% of all transactions). Similarly, the support of an itemset {*weather*} is 0.333. On the same basis, itemsets containing more combined items (e.g. {*weather, shelter, comfort*}) can be calculated. When a user specifies a minsup value to 0.030, it means that the itemset of {*weather, comfort*} is not considered as a frequent itemset and therefore will not be used as an itemset in the rules.

The confidence and improvement values of the rule *weather⇒comfort* from the example database are calculated below.

$$C(weather \Rightarrow comfort) = \frac{S(weather \cup comfort)}{S(weather)}$$

$$C(weather \Rightarrow comfort) = 0.222 / 0.333 = 0.667$$

$$I(weather \Rightarrow comfort) = \frac{S(weather \cup comfort)}{S(weather) \times S(comfort)}$$

$$I(weather \Rightarrow comfort) = 0.222 / 0.333 \times 0.333 = 2$$

3.4 Data analysis

The example of the dataset in Figure 3.13 is fairly small and simple, consisting of only 9 transactions. In reality, the database derived from the CNET interview contains a total numbers of 177 transactions for the transport mode decision, 139 transactions for the location choice and 98 transactions for the activity-scheduling decision. The numbers of transactions registered in the CNET card game datasets are even larger; i.e. 381, 350, and 171 transactions for the same decisions respectively. Therefore, a specialized data mining software for AR is used, namely ARtool (Cristofor, n.d.). *Apriori* is one of the most commonly used algorithms in the AR, and it is selected in this analysis as well.

For this data type, a low minsup value is expected because several transactions in the database come from the same respondents, as it is explained in the following example. Suppose that a database containing 100 transactions of cognitive subsets is generated from 20 respondents. This implies that on average, every respondent contributes to 100/20=5 transactions in this dataset. It is assumed that in every 5 transactions, each itemset is elicited once. Next, presuming that one itemset is considered as important when at least 50% of the respondents elicit it in the interview, it means that there should be at least 10 transactions in the dataset comprising this itemset. Accordingly, the user-specified minsup can be calculated: 10/100=10%.

Using the same principal and the assumption that the itemsets are important when 1/3rd of respondents elicit them, the user-specified minsups used in the datasets derived from the CNET interview method are calculated as 8.9%, 6.3% and 5% for the timing, location and transport mode decisions respectively. Similarly, when applied in the card game datasets, the minsup values of that sequence of decisions are 5.10%, 2.50%, and 2.30%. Additionally, the minconf in the analysis is always set to 50%.

The results of analysis using the AR method are presented next. The discussions of these results are split into two parts: the results of the CNTE interview data are used to highlight the differences among factors in people's decision making and variables appear in the FEATHERS of travel demand model (Section 3.5), whereas the results of the CNET card game are used to analyse high impact TDM policies (Section 3.6). Section 3.5 starts by giving a short introduction to the AB theory.

3.5 The CNET interview results and discussions: Informing the activity-based of travel demand

The AB approaches to model individuals' and households' travel behaviours have been developed in the past decades as an alternative to the conventional 4-step models for forecasting travel demand (Davidson et al., 2007). From a technical point of view, two main system designs dominate the agent-based micro-simulation of AB models (Algers et al., 2005): econometric, discrete choice models based on random utility maximization (RUM) on the one hand, and on the other, computational process models (CPM) comprising a set of scheduling rules and decision heuristics. From a behavioural perspective, the RUM model type is criticized for depending on unrealistic behavioural principles such as perfectly rational decision makers (e.g. Gärling, 1998), whereas sequential decision making of CPM models are questioned with regard to their theoretical basis (Svenson, 1998) and their empirical foundation (Roorda & Miller, 2005).

AB models commonly use different sources of *quantitative data* on activity-patterns, such as travel diaries, computer simulations, and conjoint experiments (Arentze, Timmermans, Hofman, & Kalfs, 1997). However, previous study has indicated that the accuracy of the results of current AB models is not ideal (Arentze, Hofman, & Timmermans, 2003) and beyond doubt should be enhanced, such as by improving the behavioural realism of the models. Hence, various AB models try to further accommodate complex *decision making* *processes* involved in travel behaviour (Gärling, 1998). This is an enormously difficult task to do but it is of crucial importance to increase modelling accuracy.

Regardless of the significance of quantitative data in defining travel patterns, travel surveys are further criticized for providing inadequate information to understand decisions processes that underlie the measured choice outcomes (Pendyala & Bricka, 2006). In other words, quantitative data may answer questions such as *what, when, where, whose* (or *with whom*) activity-travel plans are executed, but they cannot sufficiently explain *why* and *how* a person comes to a certain decision (Bradley, 2006).

Qualitative methods on the other hand, including focus groups, in-depth interviews and participant-observer techniques, could fill in the gap left by quantitative approaches since these methods enable the integration of behavioural planning process information inside the data used to develop AB models (Doherty & Miller, 2000). Certainly, they can extract individuals' beliefs and decision processes (Goulias, 2003) by addressing the reasons of *why* and *how* certain choices are made (Bradley, 2006). This topic has been discussed in Chapter 1 (Section 1.1) and Chapter 2 (Section 2.1). Hence, the CNET interview method is suited in this case, to extract people's decision making processes before travelling.

The AR analysis enables us to map out the intertwining aspects in the decision making, allowing us to understand not only important aspects in decisions but also how they are interconnected to each other in a complex MR of a particular decision problem. Therefore, the results of the AR analysis can be used as a means to deepen the insight into aspects that should be taken into account in an AB model from a behavioural decision making perspective. For instance, this study reveals the importance of the cognitive subset of {*weather, shelter, comfort*} in the decision to engage in fun-shopping, and in the choice of transport mode. However, *weather conditions* have never been taken into account in current AB models (Cools, Moons, & Wets, 2010).

The remainder of this section is organized as follows: the theory of AB modelling is presented to start with (Section 3.5.1). Following that, the AR results of the CNET interview are shown and discussed (Section 3.5.2).

3.5.1 The theory of activity-based modelling

Originating from concepts introduced by Hägerstrand (1970) and Chapin (1974), AB models of travel demand describe how people engage in different types of activities and how consequent travel plans are organized in time and space. This point of view largely determines the understanding of the derived and constraint nature of travel. Most of agent-based micro-simulation models have integrated space-time prisms and constraints introduced by Hägerstrand and Chapin (Bhat & Koppelman, 1999). However people's decision making processes behind their underlying activity-travel scheduling in these models remains a vexed question (Bowman & Ben-Akiva, 2001).

Some AB models, e.g. Bowman & Ben-Akiva (2001), are fairly close to conventional models, since they use a similar probabilistic discrete choice framework grounded on RUM (Algers et al., 2005). Another type of AB models, such as CPM models, emphasizes the activity-travel scheduling process. The first fully operational CPM model is ALBATROSS, an acronym for *A Learning-BAsed TRansportation Oriented Simulation System*. It is used to assess policy impact in the Netherlands (Arentze & Timmermans, 2008). Only recently, the ALBATROSS approach is transferred to the region of Flanders in Belgium in the FEATHERS project (Arentze et al., 2008b; Bellemans et al., 2010). FEATHERS stands for *Forecasting Evolutionary Activity-Travel of Households and their Environmental RepercussionS*. These CPM models frame the issues addressed in this chapter, i.e. MR involved in complex leisure-shopping decision making and its proper implementation in an AB model of travel demand. Accordingly, the subsequent paragraphs briefly discuss the ALBATROSS architecture and its main differences with the FEATHERS model.

The ALBATROSS architecture applies a set of *IF-THEN* rules, representing thought processes in which heuristics are used and updated based on individuals' experiences (Arentze & Timmermans, 2008). These rules are accommodated in the rule-based engine to derive individuals' activity schedules in a household context. In detail, these rules take into account different space and time aspects, possible scheduling constraints, as well as decision trees derived from individuals' daily activity-travel diaries, as shown in Figure 3.14.

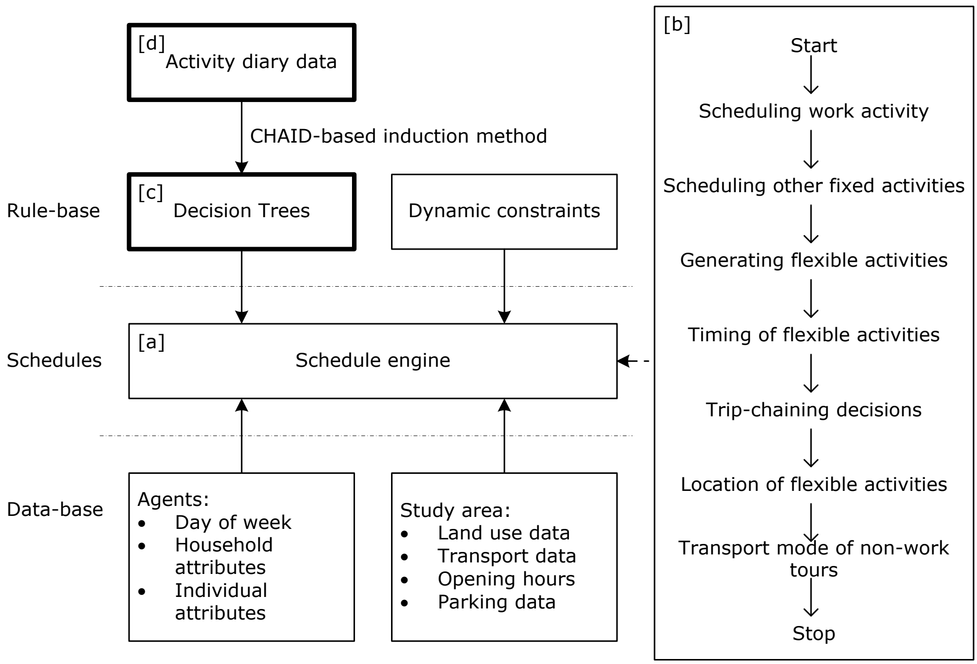


Figure 3.14 An overview of the scheduling engine in ALBATROSS (adapted from Arentze & Timmermans, 2008)

In the scheduling engine ([a] in Figure 3.14), a fixed sequential decision process is assumed in which mandatory activities such as working and other fixed activities are scheduled prior to discretionary activities. Furthermore, each activity is detailed; i.e. a *specific type of activity to perform*, *its starting time*, *duration*, *likely trip-chaining*, *location* and *transport mode choice* (if needed) are determined in a priority-based sequential order. This scheduling process is summed up in [b] in Figure 3.14. The ALBATROSS only distinguishes out-home activities in detail whereas in-home activities are not differentiated. Activity categories relatively connected to the fun-shopping example in this study are shopping for non-daily goods and discretionary leisure trips.

A Chi-squared Automatic Interaction Detector (CHAID)-based induction method is applied to generate decision trees from activity-travel diary data. A decision tree can be used to identify all meaningful antecedents (*IF*-conditions) in the data given a certain decision outcome (*THEN*-action) under inspection. Thus, this method allows large sets of attribute variables to be considered in each scheduling decision. These attributes refer to individuals' and households' socio-economic variables, the current state of the schedule in the scheduling process, the space-time settings and choice alternatives.

Decision trees ([c] in Figure 3.14) are commonly derived only from quantitative observed data ([d] in Figure 3.14). From a point of view of *AB modellers*, decision trees do not necessarily characterize individuals' thought processes because they are generated to optimize model fit. However, from a *behavioural decision making perspective*, actual considered aspects in the thought process may be useful to be integrated in the activity-travel diary data and accordingly in the decision trees to improve model fit.

The ALBATROSS model is a static model, whereas the main goal of the FEATHERS project is to develop a dynamic AB model, taking into account agents' perceived utilities on scheduling options and thus allowing for the changes in the schedule. Besides, the fact that an agent learns from his experiences and updates his knowledge is an issue that will be elaborated inside FEATHERS (Bellemans et al., 2010). In order to develop a fully dynamic model, FEATHERS project consists of consequent stages, as follows: developing a static model, a semi-static model, and finally a fully dynamic model. This issue has been previously detailed in Bellemans et al. (2010). The present working version of FEATHERS is a static model, using a similar scheduling engine as it is used in ALBATROSS. Currently, the main differences between both modelling approaches lay on the rule-based modelling approaches. While the ALBATROSS model uses CHAID, the FETAHERS can integrate different rule-based techniques, such as CHAID, Bayesian networks (Janssens et al., 2004, 2006), simple classifiers (Moons, 2005), association rules (Keuleers, Wets, Arentze, & Timmermans, 2001), etc. There are other differences between FEATHERS and ALBATROSS models, such as the use of modular system design in the FEATHERS framework, which enables a straightforward and modular transfer of the model towards other study areas. In addition, the development of a novel road assignment solution is in progress. However, this issue is not anymore relevant for the purpose of this study, i.e. to address people's MR and its possible behavioural feedback to an AB model. This part only wants to demonstrate that the basic behavioural assumptions in the current scheduling engine of FEATHERS and ALBATROSS are in fact similar.

The subsequent Section 3.5 specifically highlights the differences between aspects taken into account in the decision trees and in the individuals' MR. Therefore, the decision trees derived from the data of 602 households in Flanders are compared to the outcomes of the CNET interview protocol. These results should be addressed as feedback to improve design of the current activity-travel diaries, yielding a better modelling accuracy.

3.5.2 Informing the activity-based models

3.5.2.1 The order of decision making

In the interviews using the CNET interview method, the participants are initially asked to rank their decisions, as described earlier in Section 3.2.2.1. Their responses are recorded and the average scores of ranking for all decisions are calculated. The results are presented in Table 3.2 (in Section 3.2.2.1). With the average ranking of 1.12, the results show that the participants firstly plan the actual day to go fun-shopping. This result supports the assumption in AB models in which the actual activity-scheduling is addressed before modelling other tour- or trip-related matters (Doherty et al., 2002; Davidson et al., 2007).

After this, the respondents tend to think about how to get to the city centre (the average ranking is 2.38) and then to decide about the precise location to go to (the average ranking is 2.5). However, these average ranking values have a fairly small difference, meaning that both decisions are made interchangeably. Considering the small sample size in the study, further vigorous conclusions regarding this issue are still too soon to draw. In the ALBATROSS system, it is assumed that the location choice is made before the transport mode choice (Arentze & Timmermans, 2008), as it has been described in the previous section (i.e. Section 3.5.1). Clearly, the relationship between these decisions is complex in nature and further study is needed to untie the sequence of decisions. This issue is discussed further in Chapter 5, when discussing the results of the second experiment using the CB-CNET interface. The interface itself is detailed in Chapter 4.

3.5.2.2 The activity-scheduling decision

Learning the data using AR, strong associations between antecedents and consequents of timing decisions are retrieved. However, to get more meaningful information, the results have to be brought back to the perspective of cognitive subsets. This is done qualitatively, for instance, several AR results indicated in the shaded rows in Table 3.3a constitute the cognitive subset of {*weather, preference of day, fun*} in the hatched cell in Table 3.3b. The same way to interpret the AR results is applied to the other rules in Table 3.3a, and the other decisions.

The AR results show that the contextual aspect of *weather conditions* is frequently considered when deciding upon the time to do the activity. This context is strongly associated with *the individual's preference of the execution day* (an instrument) and *having fun* (a benefit). *Companion* (an instrument) appears to be an important aspect associated with the same benefit of *having fun*. Additionally, *having efficiency* is also aimed at, related to *crowdedness in Hasselt on different days* (an instrument). As a reminder, it is explained in Section 3.2.2.2 that some instrumental aspects of the timing decision are actually contextual aspects of the other decisions, such as the variable of *crowdedness in Hasselt.*

Table 3.3 The association rules results of the activity-scheduling decision (a), and the deduced cognitive subsets using the CNET interview data (b)

a. AR results of the activity-scheduling decision				
Antecedent	*Consequent*	*SV*[1]	*CV*[2]	*Lift*
Weather (C[3])	Preference of day (I[4])	14.29%	87.50%	2.86
Weather (C)	Fun (B[5])	12.24%	75.00%	2.04
Weather (C), Fun (B)	Preference day (I)	11.22%	91.67%	2.99
Preference day (I), Fun (B)	Weather (C)	11.22%	78.57%	4.81
Preference day (I), Weather (C)	Fun (B)	11.22%	78.57%	2.14
Weather (C)	Preference day (I), Fun (C)	11.22%	68.75%	4.81
Crowdedness in Hasselt (I)	Efficiency (B)	9.18%	90.00%	3.83
Companion (C)	Fun (B)	9.18%	60.00%	1.63

[1] Support value
[2] Confidence value
[3] Contextual variable
[4] Instrumental variable
[5] Benefit variable

b. Deduced cognitive subsets of the activity-scheduling decision
{weather, preference day, fun}
{(context/normally), crowdedness, efficiency}
{(context/normally), companion, fun}

The results above are compared with the decision making principals in the FEATHERS model. From 602 households' data in Flanders, 9226 observations regarding the inclusion of a flexible activity into the daily schedule of each individual in the model are recorded, and thus the decision tree is derived. Variables in the decision tree represent various aspects of socio-economic status, space-time settings, choice alternatives as well as the current state of the schedule. Examples of antecedents in the decision tree of flexible activities from the Flanders data are: *urban density*, *children category*, *day of the week*, *work status, time availability in a day*, and *duration of mandatory activities (work/school/voluntary work) in the current schedule*. There are other variables in this tree. However, none of these variables corresponds to the results of elicited considerations.

The AR results reveal the significance of *weather conditions* in the individuals' MR related to fun-shopping, an activity that can be considered as a part of non-work flexible activities in AB models. Nevertheless, *weather conditions* are not present in the decision tree (as listed above). Even more, this aspect has never been taken into account in current AB models in general (Cools et al., 2010), at least to the best of our knowledge. The actual *weather conditions* are not recorded in activity-travel surveys, albeit being one of the most important inputs to develop an AB model.

Other influential characteristics of the day of execution, such as *sheer individual's preference to fun-shop* on a certain day, or likely *crowdedness* on a given time, turn out to be important aspects as well, but they have not been elaborated in any AB model to date. The same case applies for different *benefits* that people look for in specific contexts and instruments, such as *having fun* and *efficiency*.

On the other hand, *companionship* is an element that is clearly taken into account in most AB models. In ABLATROSS for instance, the presence of *companion* is one of the decisions that is modelled in the activity-scheduling process, besides inclusion, duration, location, transport mode and trip chaining, supporting Hägerstrand's initial idea of coupling constraints.

The interlocking aspects in cognitive subsets are clearly a part of an individual's MR that constitutes a decision process. However, typical AB models only take into account single attribute decision trees. Further study is needed to check if multi-attribute decision trees and decision rules can be integrated in rule-based AB models and if they can further increase modelling accuracy. These multi-attribute decision trees have been tested in other studies and in other domains (e.g. Lee & Olafsson, 2006).

3.5.2.3 The transport mode decision

The AR results in Table 3.4 show that *weather conditions* are an important contextual consideration in the participants' transport mode choices. This is related to the instrument of *shelter provision* and the benefit of *having comfort*. Furthermore, *companionship* is mapped together with *individual's preference for a specific transport mode* (an instrument), showing that people tend to make leisure-shopping trips with others. This is related to the issue of using groups of people (e.g. households) as a unit of analysis in AB models instead of an individual. This topic is an actual area of research in AB modelling (Davidson et al., 2007). The results of this study support the unit of analysis in ALBATROSS (Arentze & Timmermans, 2008).

The respondents also care about *the number or size of goods that they have to carry back home* (a context). This context is mapped with *the easiness to treat bags when using different types of transport* (an instrument) and *having comfort* (a benefit). Besides, *travel time* (an instrument) is a consideration that causes the evaluation of *having efficiency* (a benefit). Finally, *travel cost* (an instrument), specifically for parking, fuel and bus tickets, is an additional significant aspect, linked to *saving money* (a benefit).

However, the decision tree of the transport mode choice for non-work activities in the AB model for Flanders, derived from 185 number of observation in the travel diary data, emphasizes different decision criteria, for instance *the number of cars in a household*, *presence of social activities in the current schedule*, as well as *the actual choice to bike & walk, to drive or being car driver, to take public transport and to be a car passenger*.

Table 3.4 The association rules results of the transport mode decision (a) and the deduced cognitive subsets using the CNET interview data (b)

a. AR results of the transport mode decision

Antecedent	*Consequent*	*SV*[1]	*CV*[2]	*Lift*
Weather (C[3])	Shelter (I[4])	12.43%	91.67%	7.37
Shelter (I)	Weather (C)	12.43%	100.00%	7.37
Weather (C)	Comfort (B[5])	11.30%	83.33%	2.95
Shelter (I)	Comfort (B)	10.73%	86.36%	3.06
Weather (C), Comfort (B)	Shelter (I)	10.73%	95.00%	7.64
Shelter (I), Comfort (B)	Weather (C)	10.73%	100.00%	7.38
Shelter (I), Weather (C)	Comfort (B)	10.73%	86.36%	3.06
Weather (C)	Shelter (I), Comfort (B)	10.73%	79.17%	7.38
Shelter (I)	Weather (C), Comfort (B)	10.73%	86.36%	7.64
Travel time (I)	Efficiency (B)	8.47%	83.33%	2.89
Saving money (B)	Cost (I)	7.34%	76.47%	8.46
Cost (I)	Saving money (B)	7.34%	81.25%	8.46
Companion (C)	Preference TM (I)	7.34%	81.25%	6.85
Preference TM (I)	Companion (C)	7.34%	61.90%	6.85
Number bags (C)	Treatment of bags (I)	7.34%	92.86%	12.64
Treatment of bags (I)	Number bags (C)	7.34%	100.00%	12.64
Number bags (C)	Comfort (B)	5.08%	64.29%	2.28

[1] Support value
[2] Confidence value
[3] Contextual variable
[4] Instrumental variable
[5] Benefit variable

b. Deduced cognitive subsets of the transport mode decision

{weather, shelter, comfort}

{number or size of goods being purchased, treatment of bags, comfort}

{(context/normally), travel time, efficiency}

{(context/normally), cost, saving money}

{companion, transport mode preference, (benefit)}

A fairly small number of observations in the data may result in the unreliability of the decision tree. When there is a trip-chaining in the schedule, this decision follows the transport mode choice used in the work activity. Besides, the transport mode choice for non-work fixed activities and non-work flexible activities are not further differentiated, making it even more difficult to have an idea about aspects particularly considered in the mode choice decision of the flexible activity, such as in fun-shopping. Furthermore, the differences between aspects taken into account in individuals' MR and in decision trees may happen because some variations of person and household attributes (e.g. the number of cars in a household) will never appear in individuals' MR albeit important for the choice modellers.

3.5.2.4 The shopping location decision

The shopping location results in Table 3.5 indicate that the shopping location decision is often influenced by *a pre-planned purchase in mind* (a context) that raises a consideration of the *type of stores in a certain area* (an instrument) and *having efficiency* (a benefit). Furthermore, *accessibilities for car and bus* (instruments) are frequently elicited and both have a strong association with *having efficiency* (a benefit). These results clearly highlight the importance of *having efficiency* when deciding upon the actual place to go fun-shopping in Hasselt.

However, in the ALBATROSS framework for Flanders, the location choice is not modelled at such a detailed level yet, but in aggregate zones. In the modelling process, these zones are used to calculate origin-destination matrices to assign travel demand to the transportation network. To date, they are much wider than the detailed shopping areas in the inner city of Hasselt shown in this case study. Accordingly, the results of this decision are probably more suitable to inform urban planners on the improvement of the shopping location from a city-marketing point of view, to increase the attractiveness of the city centre.

Table 3.5 The association rules results of the shopping location decision (a) and the deduced cognitive subsets using the CNET interview data (b)

a. AR results of the shopping location decision

Antecedent	*Consequent*	*SV*[1]	*CV*[2]	*Lift*
Pre-planned purchase (C[3])	Type of store (I[4])	10.07%	66.67%	5.45
Type shop (I)	Pre-planned purchase (C)	10.07%	82.35%	5.45
Pre-planned purchase (C)	Efficiency (B[5])	10.07%	66.67%	1.49
Accessibility for car (I)	Efficiency (B)	8.63%	92.31%	2.07
Accessibility for bus (I)	Efficiency (B)	7.91%	73.33%	1.64
Type of store (I)	Efficiency (B)	7.91%	64.71%	1.45
Pre-planned purchase (C), Efficiency (B)	Type of store (I)	6.47%	64.29%	5.26
Type of store (I), Efficiency (B)	Pre-planned purchase (C)	6.47%	81.82%	5.42
Type of store (I), Pre-planned purchase (C)	Efficiency (B)	6.47%	64.29%	1.44
Type of store (I)	Pre-planned purchase (C), Efficiency (B)	6.47%	52.94%	5.26

[1] Support value
[2] Confidence value
[3] Contextual variable
[4] Instrumental variable
[5] Benefit variable

b. Deduced cognitive subsets of the shopping location decision

{pre-planned purchase in mind, type of store, efficiency}
{(context/normally), accessibility for car, efficiency}
{(context/normally), accessibility for bus, efficiency}

3.6 The CNET card game results and discussions: High impact TDM measures

TDM is defined as strategies that bring about the efficiency of transportation resources by managing travel demand. TDM is used to solve a number of transportation problems by reducing current transportation demand or redistributing this demand in time or in space. Thus, it is often referred to as *mobility management* (Victoria Transport Institute, 2010).

It is argued here that high impact TDM can be formulated by having a better understanding of individuals' thought processes. Therefore, the aim of this study is to understand individuals' leisure-shopping behaviours and their underlying decision making processes before carrying out the fun-shopping activity. The results are discussed within the perspective of mobility management. Since most of TDM try to influence individuals' travel behaviour towards more sustainable transport modes (Gärling et al., 2002; Loukopoulos & Scholz, 2004; Stauffacher et al., 2005), the results of the transport mode decision are presented in the beginning (in Section 3.6.1). For having a complete understanding of individuals' MR when planning their shopping trips, the location and timing decisions are presented next in sequence (in Section 3.6.2 and Section 3.6.3).

3.6.1 The transport mode decision

Similar to the CNET interview data analysis, the AR algorithm is applied on the CNET card game data, allowing us to identify strong associations between antecedents and consequents related to the transport mode decision. Furthermore, using the same lines of thought, these results are translated to the cognitive subset forms. The AR results of the transport mode decision can be seen in Appendix D1. However, the retrieved cognitive subsets of this decision are listed in Table 3.6.

High lift values of the rules (in Appendix D1) explain that the antecedents and consequents of those rules do not appear together in the transaction merely by a random chance. Accordingly, important cognitive subsets of this decision can be interpreted (in Table 3.6). The results show that the respondents search for some benefits from their transport mode choices, such as *having comfort, efficiency,* and *convenience. Individuals' comfort* is very much affected by *weather conditions* (a context) due to *shelter provisions* (an instrument) of the transport mode options. The contextual factor of *the crowdedness of the shopping location* also plays a role in affecting people's transport mode choices because of the pursued benefit of *having comfort*. Other instruments, such as *physical effort*, *availability of seats*, and *environment inside transport modalities*, are related to that benefit as well. *Having efficiency* (a benefit) is linked to the combinations of *time availability* (a context) and *travel time* (an instrument), and *parking availability* (a context) and *easiness for parking* (an instrument). The benefit of *having efficiency* can also be gained from an assortment of transport mode instruments, such as *bus frequency* and *directness of the travel* (e.g. bus usually makes detour). The benefit of *having convenience* is mapped out together with the instrument of *mental effort*.

Table 3.6 The deduced cognitive subsets of the CNET card game data for the transport mode decision

List of revealed cognitive subsets
{time availability, travel time, efficiency}
{availability of parking space, easiness for parking, efficiency}
{weather, shelter, comfort}
{companion, transport mode preference, sociable}
{(context/normally), cost, saving money}
{(context/normally), bus frequency, efficiency}
{(context/normally), direct travel, efficiency}
{(context/normally), physical effort, comfort}
{(context/normally), availability of seat, comfort}
{(context/normally), environment inside bus & car or around bike, comfort}
{(context/normally), mental effort, convenient}
{crowdedness in bus, (instrument), comfort}
{number or size of bags, treatment of bags, (benefit)}

Besides the factors above, there are other sought after benefits, such as *being sociable* and *saving money*. The benefit of *being sociable* is considered because the *presence of companions* during the trips (a context) affects *individuals' preferences over certain transport mode* (an instrument). The benefit of *saving money* is frequently considered along with the instrumental aspect of *cost*, such as *parking cost*, *fuel price*, and *bus fares*. Learning from the transport mode dataset, *the number or size of goods being purchased* (a context) is also important related to *the treatment of bags* (an instrument). However, the benefit strongly associated with these aspects cannot be identified.

Victoria Transport Institute (2010) has developed an online TDM Encyclopaedia in which different strategies are categorized based on how they influence trips (Table 3.7), as follows: (1) TDM to improve transport options, (2) to give incentives to use alternative mode choices and reduce car driving, (3) to manage land use and parking, and (4) to guide policy and institutional reform. Various policies in each group are explained in the website, and summarized in Table 3.7.

Since this study focuses only on leisure trips, specifically fun-shopping, not all policies in the table are relevant to discuss the results. Some high impact policies can be learnt based on the individuals' cognitive subsets. These policies are indicated in the shaded cells in the table and each of them is discussed further in the following paragraphs.

Table 3.7 The categorization of different TDM strategies (Victoria Transport Institute, 2010)

(1) Improved transport options	*(2) Reducing car driving*	*(3) Managing land use & parking*	*(4) Policy & institutional reform*
Address Security Concerns	Carbon Taxes	Bicycle Parking	Asset Management
Alternative Work Schedules	Commuter Financial Incentives	Car-Free Planning	Car-Free Planning
Bus Rapid Transit	Congestion Pricing	Strong Commercial Centres	Change Management
Cycling Improvements	Distance-Based Pricing	Connectivity	Comprehensive Market Reforms
Bike/Transit Integration	Fuel Taxes	Land Use Density and Clustering	Context Sensitive Design
Car sharing	HOV (High Occupant Vehicle) Priority	Location Efficient Development	Contingency-Based Planning
Flex-time	Multi-Modal Navigation Tools	New Urbanism	Institutional Reforms
Guaranteed Ride Home	Parking Pricing	Parking Cost, Pricing and Revenue Calculator	Least Cost Planning
Individual Actions for Efficient Transport	Pay-As-You-Drive Insurance	Parking Management	Operations and Management Programs
Light Rail Transit	Road Pricing	Comprehensive Parking Management Strategies, Evaluation and Planning	Prioritizing Transportation
Non-motorized Planning	Road Space Reallocation	Parking Pricing	Regulatory Reform
Non-motorized Facility Management	Speed Reductions	Parking Solutions	
Park & Ride	Transit Encouragement	Parking Evaluation	
Pedestrian Improvements	Vehicle Use Restrictions	Shared Parking	
Pedways	Walking And Cycling Encouragement	Smart Growth	
Public Bike Systems		Smart Growth Reforms	

(1) Improved transport options	*(2) Reducing car driving*	*(3) Managing land use & parking*	*(4) Policy & institutional reform*
Ridesharing		Comprehensive Smart Growth Reforms	
Shuttle Services		Streetscape Improvements	
Small Wheeled Transport		Transit Oriented Development (TOD)	
Transit Station Improvements		Land Use Impacts on Transport	
Taxi Service Improvements		Land Use Impacts on Transport - Comprehensive	
Telework			
Traffic Calming			
Transit Improvements			
Transit Examples			
Universal Design (Barrier Free Planning)			

The results (Table 3.6) show that the cognitive subset of {*weather, shelter, comfort*} is an important consideration when deciding to use car, bus or bike to go fun-shopping. This happens because various transport modes offer different types of protection (*shelter*) when facing the ever changing *weather conditions*. This factor has been previously indicated as an important element that may influence travel decisions (Khattak & De Palma, 1997) and accordingly may impact on traffic intensity (Cools et al., 2010). This study reveals that *weather conditions* have a strong association with the benefit of *having comfort*. Therefore, to encourage the use of public transport, transit improvements are significant to boost passengers' comfort. The online TDM Encyclopaedia (Victoria Transport Institute, 2010) defines transit improvements as increasing the quality of public transit service by improving the level of comfort, convenience, speed, frequency, etc. Therefore, increasing the level of comfort and convenience especially in transportation terminals, such as bus stations or stops, are also focused on in the transit improvement program. This can be done, for instance, by providing clean and comfortable stations and stops that can protect passengers from dust, wind, rain, and other types of exposure. Furthermore, stations and stops should be provided with real-time information of vehicle's arrival time to reduce passengers' stress caused by uncertainty during the waiting period. This policy can be linked to the cognitive subsets of {*(context/normally), mental effort, convenient*}. Moreover, such improvements may create a pleasant and comfortable waiting experience for passengers. Besides, the environment inside public transports, specifically buses, should be enhanced as well; for instance by providing sufficient compartments above or below seats to store passengers' luggage. Since the results of the AR analysis emphasizes the importance of comfort as a benefit that people aim at, improving comfort in public transport services may likely increase their ridership.

Furthermore, the results also reveal that *cost* is a crucial consideration because people want to maximize *saving money* in their leisure-shopping trip. This comes in line with results of existing studies (e.g. Meyer, 1999) that highlight the importance of cost-related variables associated with trips. There are various cost-related TDM measures that can be implemented to increase the attractiveness of public transport and to reduce car-use, especially for short distance trips, namely *carbon taxes*, *congestion pricing*, *distance-based pricing*, *fuel taxes*, *parking pricing*, *pay-as-you-drive insurance*, and *road pricing*. Additionally, it turns out from the results that companion is an important influential aspect for the transport mode decision. Accordingly, giving incentives for people to travel by public transport in groups (e.g. group discount tickets) could be a successful policy.

However, applying *comfort* and *pricing-related strategies* alone is probably not enough to make people give up their intensive car-use behaviour. The results unveil that individuals need to have *efficiency* from their trips, particularly related to *travel time*. Accordingly, public transport such as buses should be able to fulfil this need. A number of strategies can be applied, such as *giving priority to HOV* (High Occupant Vehicles), *improving connectivity*, and *encouraging public transit use*. Dedicating one lane of the street especially for buses (also known as busway or Bus Rapid Transit) can be a means to give priority to buses as part of HOV, leading to the reduction of travel time by bus. Improving connectivity by establishing more connections in the road network will contribute to shorter travel distances and bigger route choices. At last, transit encouragement includes enhancement of public transport services, such as increasing bus frequency to minimize waiting time. Additionally, parking availability turns out to be an important contextual aspect as well. Thus, limiting the number of free-parking spaces could be effective to make parking less accessible for everyone, encouraging people to use other transport mode options such as bus and bike. Undoubtedly, this policy should work together with the improvement of public transport systems, such as longer service hours, wider service coverage and more frequent service provisions.

Due to the fact that cycling is an effective travel mode for short distance trips with multiple stops (Victoria Transport Institute, 2010), it is important to implement policies that connect with the individuals' goal of *having efficiency* to promote bicycle-use. Some strategies for cycling improvement can be implemented, for instance, by *improving bicycle paths or lanes* as well as *bicycle parking*, and *implementing public bike systems* (PBS). PBS (also called bike sharing/community bike programs) is a system that provides well-located bicycle rentals, targeting for short distance urban trips of up to 5 kilometres. This system consists of an armada of bicycles and points (or stations), where bikes are stored, redistributed and maintained (Victoria Transport Institute, 2010). Points, usually using self-service docking systems, are located at important hubs (e.g. bus and train stations, city centre, etc.) and the distance between two points is about 300 meters. Bicycles can be taken from one point and returned to the others. Furthermore, the use of a bicycle within a short period of time (first 30 minutes) is free of charge or inexpensive. This will have an effect on the overall efficiency of urban day trippers as they can be easily move within the city. Furthermore, it is cheaper to use bicycle because people do not need to purchase, store and maintain a bike (Victoria Transport Institute, 2010).

3.6.2 The shopping location decision

The AR interpreted results in Table 3.8 indicate that the participants mainly want to *save some money* (a benefit) from their shopping trips due to *budget restriction* (a context) and differences in *product prices* (an instrument). The individuals also want to *have some fun* (a benefit), derived from *the crowdedness of particular shopping locations in Hasselt* (a context) and its *environment* (an instrument). People also seek after the benefit of *having efficiency* out of *type of stores* (an instrument) and *shop arrangement in the area* (an instrument), due to *time availability* (a context). *Having efficiency* is also associated to *the existing plan of other activities* (a context). The benefit of *having comfort* in the chosen shopping location is pursued because of numerous *weather conditions* (a context). The actual AR results of the shopping location decision based on the CNET card game data can be seen in Appendix D2.

Table 3.8 The deduced cognitive subsets of the CNET card game data for the shopping location decision

List of revealed cognitive subsets
{budget availability, product price , saving money}
{crowdedness in Hasselt, ambiance/environment, fun}
{time availability, shop arrangement, efficiency}
{(context/normally), type of store, efficiency}
{weather, (instrument), comfort}
{existing plan of other activities, (instrument), efficiency}

The research findings can be used to inform urban planners about aspects that can boost the attractiveness of the shopping locations from a city marketing perspective. This can be done for instance by encouraging urban planners to develop vibrant and strong commercial centres with mixed urban activities; i.e. business, civic, and cultural services (Victoria Transport Institute, 2010) to boost the sought after benefit of *having efficiency* and *fun*. Moreover, shopping areas should be provided with places, comfortable enough to wait when raining or to sit and enjoy the sun when the weather is nice. Further results and discussions of aspects considered when making the shopping location decision in the second experiment, from the marketing point of view, are presented in Chapter 5 (Section 5.4.3).

3.6.3 The activity-scheduling decision

The AR deduced results in Table 3.9 show that the choice of day to carry out a fun-shopping activity is made because people want to maximize *being sociable* as well as *having fun*, *efficiency* and *comfort*. The benefit of being sociable is related to *the presence of companions* on certain days (an instrument). The benefit of *having fun* is strongly affected by *individuals' mood* (a context), and the benefit of *having comfort* is linked to *weather conditions* (a context). Additionally, *having efficiency* is an important benefit that people aim at related to *flexibility to schedule fun-shopping activity on certain days* (an instrument), *scheduling effort* (an instrument), and *a pre-planned purchase that someone has in mind* (a context). The AR results of the activity-scheduling decision from the CNET card game data are shown in Appendix D3.

Table 3.9 The deduced cognitive subsets of the CNET card game data for the activity-scheduling decision

List of revealed cognitive subsets
{(context/normally), scheduling effort, efficiency}
{(context/normally), companion, being sociable}
{weather, (instrument), comfort}
{mood, (instrument), fun}
{pre-planned purchase, (instrument), efficiency}

The results presented in the previous paragraph are strongly related to the activity-scheduling aspects. Therefore, they are more relevant to give feedback to AB modellers. Travel is a derived demand from different activities. Knowing the underlying reasoning of *why* such activities are performed can be used as behavioural input to AB models of travel demand (Gärling, 1998), specifically in the rule-based model such as FEATHERS and ALBATROSS. This issue has been previously detailed in Section 3.5.

3.7 Conclusions

Chapter 3 addresses the results of the experiment using the CNET interview and card game methods to elicit individuals’ complex reasoning and associations between different decisions involved in a fun-shopping activity. These decisions are the choice of day to do fun-shopping, the destination choice in the city centre and the transport mode choice. Using the background of Hasselt historical city centre, 26 young adults systematically reveal their considerations regarding these three travel decisions.

Section 3.2 discusses the revealed variables in the CNET interview and card game data, highlighting their similarities and differences. From the methodological point of view, this implies that researchers should be aware of the impact of the method selection on research outcomes. This study demonstrates that implementing different research methods on the exact same sample and setting gives dissimilar outcomes, at least with regard to people’s reported considerations. The card game method is able to extract more information from the respondents with respect to their thought processes, resulting in more complex and elaborate representations. However, this higher complexity could also represent varnished MR, not representing the actual MR of people.

Furthermore, aspects often elicited by the respondents are identified. For instance, *weather conditions* emerge as a context in the activity-scheduling and transport mode decisions, revealed by most of the respondents. Moreover, *presence of companions* also comes out as a frequently considered context in determining the transport mode choice, and as an instrument in the activity-scheduling decision. The fundamental benefits in people’s fun-shopping travels are also extracted, such as *having fun* and *efficiency*.

However, a number of contexts, instruments and benefits are intertwined in people’s MR. Accordingly, the AR analysis is used to investigate the associations among aspects that form cognitive subsets, using the CNET interview and card game data. This issue is addressed in Section 3.4.

Section 3.5 highlights the complexity in the travel-related decision making process, by using the CNET interview data. In particular, this section demonstrates how different aspects of a decision problem are mapped in an individual's MR. This provides a better understanding of possible behavioural interpretations of AB models of (leisure) travel demand. Therefore, the results can be a foundation to empirically ground or extend assumptions in AB models and to add insight into aspects that should also be considered in activity-travel diary, specifically in a rule-based approach, such as FEATHERS and ALBATROSS. It is believed that such integrations could improve model fit.

To start with, the ordering of decisions indicates the sequence of different sub-choices in scheduling activity-travel. It is clear that activities are planned before making other related decisions, such as where to go and how to get there. However, this study shows that the location choice is not always made before the transport mode choice, as it is commonly assumed in CPM models. Obviously, further study is needed to elucidate this issue. Therefore, another experiment is conducted using a computer-based elicitation method, focusing only on these two travel decisions. The results of the experiment relating to this topic can be found in Chapter 5 (Section 5.4.1).

With regard to the significant aspects that people think about when making fun-shopping decisions, the results clearly indicate the importance of *weather conditions*, especially when deciding upon the time and the transport mode. This aspect is overlooked in AB models to date (Cools et al., 2010). Furthermore, the results highlight the importance of *companionship*, supporting the original idea of coupling constraints by Hägerstrand (1970). Besides, this research underscores individuals' search for values when making choices, such as *having fun* and *efficiency* in the timing of the activity, and *having comfort*, *efficiency* and *saving money* in the transport mode choice. Ultimately, instrumental and contextual aspects influencing these goals are also successfully mapped out.

The results illustrate fundamental differences between aspects appear in individuals' MR elicited by means of the CNET interview protocol and factors in the decision trees of the FEATHERS model. These results are highlighted specifically for the activity-scheduling and transport mode decisions. Accordingly, to have a more realistic representation of individuals' decision making in such a CPM model, qualitative in-depth explorations, as shown in this study, constitute a vital tool to identify critical components and causal links in individuals' thought processes.

This study clearly demonstrates the complex nature of the individuals' travel decisions. However, future research still needs to be done to implement such results in an AB model, to improve activity-travel surveys and empirically ground behavioural assumptions in the model. Due to the small sample size of this experiment and its restriction to a particular group of people, the research outcomes cannot yet be generalized. However, some clear points of attention are marked to test in further research on larger sample sizes.

Section 3.6 emphasizes a number of TDM measures along the lines of the CNET card game results. For instance, it is revealed that people want to maximize *having comfort*, *efficiency* and *convenience*, *being sociable*, and *saving money*. Accordingly, specific TDM that may influence these underlying benefits should be implemented to boost the attractiveness of low-impact travel modes, particularly bus and bicycle. As an example, *having efficiency* is a benefit that people desire related to *travel time*, therefore transit improvement strategies should focus on how to make passengers gain more efficiency. This can be done for instance by giving priority to HOV, improving connectivity and encouraging public transit use. Additionally, other pricing policies can also be implemented, since they are connected with individuals' considerations of *cost* and the benefit of *saving money*. These measures could be carbon taxes, congestion pricing, distance-based pricing, fuel taxes, parking pricing, pay-as-you-drive insurance, and road pricing. Furthermore, bike sharing can be an additional policy to increase bicycle-use. Jointly, these transport policies could affect people's travel behaviours towards more sustainable forms, improving the quality of urban living environment.

4 An interactive computer-based interface to support the discovery of individuals' mental representations and preferences

4.1 Introduction

Growing emphasis is currently given in modelling decision making based on behavioural process data. Nevertheless, advanced applications to elicit such data are still lacking. The CNET interview and card-game methods, both face-to-face interviews, are examples of methods to obtain individuals' decision making by eliciting temporary MR of decision problems. However, to portray and model these representations into formal modelling approaches such as Bayesian ID, an extensive set of parameters has to be gathered for each individual, as explained in Chapter 2. Hence, the data collection procedure for large sample sizes can be considerably costly and time consuming, highlighting the need to transform the current elicitation procedures into a computer-based protocol.

For the reason mentioned above, this chapter reports on the methodological conversion and enhancement of the face-to-face CNET interview protocols to an advanced computer-based survey, named as CB-CNET. The CB-CNET survey shows predefined variables to the respondents as cues. The dynamic nature of the interface allows us to ask different questions to the respondents depending on their previous variable selections. This procedure gives some insight into the associations between contexts, instruments and benefits. The protocol also captures different decision making styles and discerns MR driven by habitual choices or conscious considerations. Moreover, the interface has an automatic question generation feature for parameters (i.e. probabilities and weights) based on the elicited MR, enabling these representations to be modelled as Bayesian ID, DT, FCM, etc. This PhD research also highlights the modelling of MR data using ID models, an AI technique that supports decision making. ID separately models every individual's decision process. This technique is compared to the DT model that learns the aggregate representation from survey data. The comparison of those modelling techniques is further elaborated in Chapter 7.

The automation of the computerized elicitation procedure and respondents' independent contribution can significantly reduce interviewers' bias (Grunert & Grunert, 1995; Russell et al., 2004). Furthermore, data collection can be administered easier and cheaper for large sample groups (e.g. in group sessions). Just like a web-based survey, a computer survey enables extra design choices and reduces data entry time (Booth-Kewley, Larson, & Miyoshi, 2007; Fan & Yan, 2010). The CB-CNET interface has been successfully implemented to assess 221 respondents' fun-shopping travel decisions in the city of Hasselt, Belgium, focusing on the *transport mode* and *location* choices. This sample and the behavioural data gathered using the CB-CNET interface is further described in Chapter 5.

The remainder of this chapter is structured as follows: the next section presents some general reviews of the computer-based surveys (Section 4.2). The description of the CB-CNET interface is presented next (Section 4.3). At last, some conclusions are drawn (Section 4.4).

4.2 Computer-based surveys

The increased use of computers in day-to-day life (Maxwell, 2001) enlarges the use of computer interfaces in survey questionnaires. Previous study reports that respondents prefer computer surveys over traditional paper-and-pencil administrations (Booth-Kewley, Edwards, & Rosenfeld, 1992). This may happen because of participants' anonymity in a computer administration, increasing the feeling of security and safety when answering personal and sensitive matters (Paperny, Aono, Lehman, Hammar, & Risser, 1990), such as in a study related to drug uses, sexual practices and criminal offences (Donohue, Powell, & Wilson, 1999).

Computer administrated questionnaires are widely accepted (e.g. Schriger, Gibbons, Langone, Lee, & Altshuler, 2001). Such computer administrations give participants a greater control over the tempo of the survey (Donohue et al., 1999), making it less stressful than its traditional counterparts (Davis & Cowles, 1989). It provides standardization and reliability (Donohue et al., 1999), and offers great flexibility of presentation (Booth-Kewley et al., 2007). Therefore, it has been previously applied in memory interviews involving children (Steward, Farquhar, Driskill, & Steward, 1996) and people with poor literacy abilities (Barber, 1990). Because of its degree of flexibility, the number of questions can be adjusted, focusing solely on relevant questions based on respondents' previous answers (Smith, Velikova, Wright, Lynch, & Selby, 2006).

Another major advantage of computer administration surveys is its significant cost reduction in comparison to conventional surveys (Weber et al., 2003). It eliminates possible errors, as well as time and cost needed for data entry (Booth-Kewley et al., 2007; Fan & Yan, 2010). Computer surveys can be administered easily (Booth-Kewley et al., 2007), especially for large sample groups, and can provide direct results.

Eliciting individuals' MR using computers may grant the mentioned benefits in the previous paragraphs. For instance, the automation and anonymity of the data collection procedure can minimize the interaction between researchers and respondents and thus diminishing interviewers' bias (Grunert & Grunert, 1995; Russell et al., 2004). Furthermore, research is feasible to be administered for large sample groups at a lower cost. Both the data gathering and data entry processes can be conducted faster. The flexibility of the computer survey allows questions to be generated automatically based on respondents' variable selections, making it more focus and diminishing researchers' error.

4.3 Computer-based elicitation technique

The computer interface to capture and model individuals' MR should be divided into several stages, as already described and concluded in Chapter 2 (Section 2.4.1). These steps are summarized in Figure 4.1, along with the information regarding in which subsections they are discussed in this chapter. An additional step is added to the interface to capture participants' actual preferences in different scenarios, enabling model validations. Moreover, some screenshots of the English version of the interface can be seen in Appendix E.

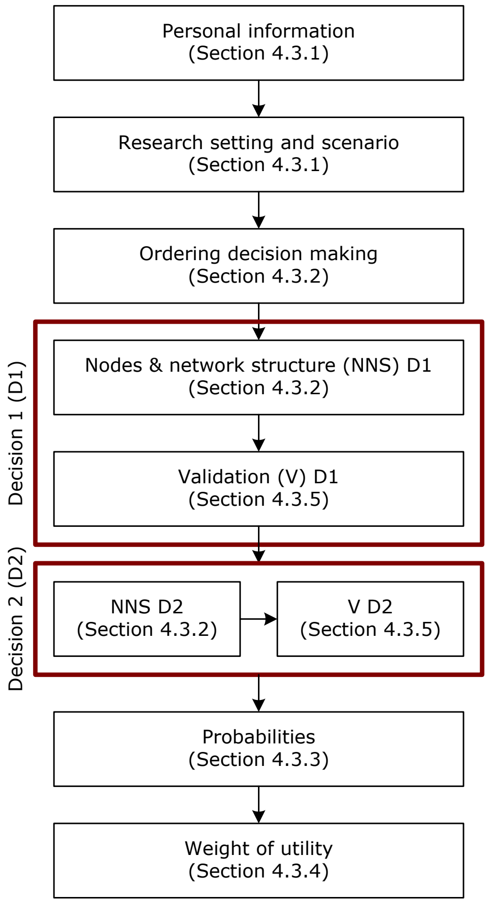


Figure 4.1 The elicitation stages of the CB-CNET protocol

4.3.1 Research setting and scenarios

The survey starts by asking the participants to give their personal information, such as their residence, education, and occupation. These data are used in Chapter 5 to describe the sample. Afterwards, the research scenarios are explained.

Akin to the first study, the second experiment also aims at eliciting individuals' leisure-shopping travel decision making processes. This is done by revealing MR that describes these processes. Additionally, the CB-CNET interface is also designed to capture the shift of participants' MR due to *time pressure*. The reasons to focus on the contextual constraint of time pressure and an analysis concerning this matter are explained later on in Section 5.6. Hasselt is again chosen as a case study to implement the interface. Since Hasselt is located in the Dutch speaking part of the country, the whole survey is conducted in Dutch. However, some preliminary versions of the interface are developed in English. Two scenarios are tested, namely shopping with and without time constraints. Accordingly, these scenarios divide the sample into two groups at random. Half of the sample faces the time pressure scenario whereas the other half encounters the no-time pressure scenario. These scenarios can be seen below. A short description of the assigned scenario is always shown in the interface as a reminder throughout the whole survey, as illustrated in Appendix E.

Scenarios:
"Your friend has a party this Sunday evening. Even though it is not obligatory, you think that it will be nice to buy something for the occasion (a gift and/or something to wear)."

*<u>Scenario 1:</u> "Today is a Friday night in autumn and it appears that **you have plenty of time available on Saturday afternoon.** You can use this spare time to go fun-shopping in the city centre of Hasselt to look for an item for the occasion."*

<u>Scenario 2:</u> *"Today is a Friday night in autumn and it appears that **you have a very busy schedule on Saturday**. Nevertheless there is a small time gap in your afternoon schedule that you can use to go fun-shopping in the city centre of Hasselt to look for an item for the occasion."*

"Fun-shopping" is a leisure activity related to collecting some shopping information; e.g. stores that are available, products that are sold, price of the products, etc. It can be related to actually buying goods, but this is not necessarily the case. It relates to goods you do not buy every day, like clothing, electronics, etc."

In the experiment using the CB-CNET interface, only two travel decisions are focused on, namely the decisions to use certain *transport modes* and go to *particular shopping locations* in the city centre. In this experiment, the time planning decision is not anymore considered as something to think about by the respondents. Instead, it is fixed in the scenarios. This is done because leisure-shopping is a non-mandatory activity type. Therefore, it is usually carried out rather spontaneously or planned closer to the day of execution. It is also rather easily adjusted (shifted, or even more deleted) when other more urgent activities have to be performed. Because of this, the respondents in the first experiment state their difficulties in eliciting aspects related to this decision.

All decision alternatives are explicated next. The transport mode choices are explained by reminding the respondents that they are living in Hasselt outskirts, 3-10 kilometres away from the city centre. All the respondents are in fact reside in this area. Further explanations of the sample recruitment procedure and characteristics can be seen in Chapter 5 (Section 5.2). Every respondent owns a driving license and at least a bike. A bus stop is located within walking distance to everyone's home, which is the case in the selected area. Accordingly, different predefined transport mode options (i.e. *car, bus,* and *bike*) can equally be considered. The *location choices* are elucidated by showing a map of Hasselt city centre divided into three zones, derived from the results of the preliminary study on the participants' mental map; i.e. *the main shopping street* (Zone-1), *the gallery area* (Zone-2), and *the expensive boutique area* (Zone-3). These zonings have been previously illustrated in Chapter 2 (Section 2.3.2).

4.3.2 Eliciting nodes and specifying network structure

The elicitation procedure begins after describing the research setting and scenario. Initially, the participants have to rank their decisions from the one that they think of first to last. Based on this, the respondents are asked to contemplate their decision making styles, i.e. whether their decisions vary depending on certain circumstances, indicating *heuristic* or *rational decision making*, or whether a choice is made spontaneously, representing *habitual decision making*. This part is defined as the *split-elicitation procedure* because based on the respondents' indications ([a] in Figure 4.2), different elicitation paths are followed ([b-i] and [b-ii] in Figure 4.2).

Suppose that a respondent indicates that his transport choice depends on some contexts then revealing these factors is targeted next, forming *situational models* (Wyer, 2007). For instance, a participant reasons that he bikes whenever the *weather* is good and takes his car when the *time* is limited. In that case, *weather conditions* and *time availability* are registered as his influencing contexts. To elicit these variables, the participants are asked to sort out all contexts that could affect their transport choices from the predefined list of contexts ([c-i] in Figure 4.2). This list contains a wide variety of contextual aspects, ranging from coupling constraints (i.e. *companionship*), natural forces (e.g. *weather conditions*, *wind*, etc.), TDM (e.g. *bus frequency*, *parking cost*, *bus fare,* etc.), to other contexts and constraints (*time availability*, *parking availability*, etc.). This list is developed from the predefined list of variables in the previous experiment using the CNET interview and card game methods, with some modifications. In total, 27 and 15 contextual variables are registered for the transport and location decisions respectively.

Split elicitation procedure [a]
(The example below is applied when the transport mode decision is selected first in the ordering decision stage)

Q: *Which of the following statements represents the way you make your choice out of different transport mode options (bus, bike and car)?*
R: *My transport mode choice depends on certain circumstances or*
R: *I would directly choose to go by...*

Heuristic and rational decision making [b-i]
R: *My transport mode choice depends on certain circumstances*

Cognitive subset type-1

Eliciting contexts (contextual aspects) [c-i]
Q: *What are specific circumstances that could affect your transport mode choice when you go fun-shopping?*
R: (A full list of contextual aspects is shown to respondents)

Eliciting benefits from each selected context **[d-i]**
Q: *What are benefits that you certainly want to gain from your chosen transport mode given the influence of "(CONTEXTUAL VARIABLE)" when you go fun-shopping?*
R: (A full list of benefits is shown to respondents)

Eliciting instruments (instrumental aspects, attributes, or characteristics) for each interconnected context-benefit **[e-i]**
Q: *Which attribute(s) of different transport modes will help you in achieving the benefit of "(BENEFIT VARIABLE)" given the influence of "(CONTEXTUAL VARIABLE)" when you go fun-shopping?*
R: (A short list of instrumental aspects is shown to respondents. The associations between contexts and instruments in the list are generated based on the results of qualitative pilot interviews)

Eliciting cognitive subset type-2 (if any) **[f-i]**
Q: *You have indicated that your choice of transport mode to go fun-shopping depends on certain circumstances. However, there may be, in general, certain benefits that you want to gain IN ANY CIRCUMSTANCES. What are benefits that you certainly want to gain from your chosen transport mode in any circumstances when you go fun-shopping?*
R: (A full list of benefits is shown to respondents)

Habitual decision making [b-ii]
R: *I would directly choose to go by...*

Cognitive subset type-2

Eliciting benefits [d-ii]
Q: *What are benefits that you certainly want to gain from your chosen transport mode in any circumstances when you go fun-shopping?*
R: (A full list of benefits is shown to respondents)

Eliciting instruments (instrumental aspects, attributes, or characteristics) for each interconnected context-benefit **[e-ii]**
Q: *Which attribute(s) of different transport modes will help you in achieving the benefit of "(BENEFIT VARIABLE)" in any circumstances when you go fun-shopping?*
R: (A full list of instrumental aspects is shown to respondents)

Eliciting cognitive subset type-1 (if any) **[f-ii]**
Q: *You have indicated that you will directly choose a certain transport mode to go fun-shopping. However, there could be specific circumstances that may affect your choice. What are specific circumstances that could affect your transport mode choice when you go fun-shopping?*
R: (A full list of contextual aspects is shown to respondents)

Eliciting other considerations [g]
Q: *Do you have any other strong considerations with regard to the TRANSPORT MODE decision that are not presented in previous pages?*
R: (Open answer that can be used for future research)

How do people come to a decision? [h]
Q: *Do you consciously consider different aspects when you actually make your transport mode decision?*
R: (Continuous scale bar from "habit [no consideration]" to "careful consideration")

Figure 4.2 The network structure elicitation stages in the CB-CNET protocol

In order to ensure that the respondents have uniform interpretations of the variables, the definition is shown in the CB-CNET interface whenever the respondents pass their mouse on each of them. The predefined contextual variables and their definitions for the transport mode and shopping location decisions are listed in Appendix F1 and Appendix F4 respectively.

Afterwards, the respondents have to reveal the interconnected *benefits* for each elicited context ([d-i] in Figure 4.2). For this purpose, 15 benefits in the predefined benefit list are shown (e.g. *having fun, physical comfort*, etc.). The list of the benefit variables and their definitions can be seen in Appendix F7.

Next, the full cognitive subsets are revealed by interrogating the intertwining *instrument(s)* for each selected *context-benefit* ([e-i] in Figure 4.2). The interface automatically generates questions depending on the respondents' previous variable selections. Here, the short lists of instrumental aspects appear. These lists contain various numbers of instruments depending on the chosen context, previously identified using the CNET card-game method. For instance, *precipitation (*or *weather conditions)* connects with 15 instruments (the longest list for the transport mode decision) whilst *tax and insurance* links to only 3 instrumental aspects (the shortest list for the same decision). The short lists of instruments for the contextual variables are presented in Appendix F3 (the transport mode decision) and Appendix F6 (the shopping location decision). After this procedure is completed, *the first cognitive subset type* of {*context, instrument, benefit*} can be registered.

When a respondent initially points out that he would directly choose a certain transport mode regardless of specific contexts, another elicitation path is carried out to obtain the *generalized representations* from values (Wyer, 2007) ([b-ii] in Figure 4.2). The procedure begins with extracting all pursued *benefits* from the chosen transport mode, followed by revealing the linked instruments. The full list of instruments is shown, containing 25 and 22 variables for the transport and location choices, presented in Appendix F2 (the transport mode decision) and Appendix F5 (the shopping location decision). As a result, *the second cognitive subset type* of {*normally, instrument, benefit*} can be noted down.

Additionally, the participants are asked if they have other considerations not presented in the lists. An additional question of how the participants actually make choices is also asked ([h] in Figure 4.2) to re-confirm their previous answers in the split-elicitation page ([a] in Figure 4.2). Detailed stages and explanations of the CB-CNET elicitation part can be seen in Figure 4.2.

4.3.3 Probabilities

The probabilities are gathered next for the ID modelling purpose (see Chapter 2, Section 2.4 for detailed explanation of the ID model). They are assessed based on the relationships between the parent and child nodes. Each variable is normally represented as a discrete node with two or three states. Specifically, cost-related variables usually have three states, such as *parking cost* {*free, <2 Euro/hour, >2 Euro/hour*}. The maximum number of seven states is observed for the contextual aspect of *having information from others {no advice, positive advice for area 1, negative advice for area 1, + area 2, - area 2, + area 3, - area 3}* in the shopping location decision. The states of all contextual variables are listed in Appendix G.

Theoretically, the probabilities should be gathered for each node. Practically, this is infeasible, considering a considerable number of questions that the respondents have to answer. Therefore, some assumptions are made as follows: first, the probabilities of certain contexts to occur should be assessed based on individuals' beliefs. However, these contexts are observed or expected at the decision time. For instance, when deciding upon the transport mode, an individual already has preliminary knowledge of the (expected) *weather conditions* during the trip (bad or good), allowing some evidence to be set in the network. The initial probabilities before entering the evidence are distributed equally across the variable states, e.g. *weather {bad, good} = <0.5, 0.5>*. Hence, the participants are not asked to indicate these values, solving the problem when the participants' initial probability knowledge is lacking. Next, the probabilities of the instruments rely on the context states. However, from the calculations shown in Chapter 2 (Section 2.4.3.3) those values are not used to calculate the utilities of choice alternatives. It implies that any inputted values in these nodes do not change the calculated utilities. Therefore, they are not collected. This node type is elicited only to find out about which attributes of the decision alternatives are important to gain certain benefits in particular contexts.

The mentioned considerations let us focus solely on the probabilities of the benefits, based on the contexts and decisions. Since the benefits always have two states (i.e. {*none, all*}), the probabilities can be assessed only for one state. The CB-CNET allows questions to be generated automatically based on the participants' preceding variable selections. For instance, when the benefit of having *comfort* {*none, all*} is elicited due to *weather conditions* {*bad, good*} and the *transport mode* options {*car, bus, bike*}, the following question is asked: *"Imagine that the weather is bad when you go fun-shopping in Hasselt. In this case, how big is the chance that you will gain the benefit of having comfort when you use car/bus/bike?"*

A sliding bar ranging from 0 to 100% is presented for each choice alternative. Subsequently, the participant is asked to indicate the probabilities of acquiring the benefit for another context state (i.e. good weather). Similar questions are asked to capture the benefit values in a normal situation (or habitual decision making).

4.3.4 Weight of utility

The utility weights are calculated in two ways: rating of single-benefit profiles (1) and combined-benefit profiles in a conjoint experiment using fractional factorial design (2). The first approach asks the participants to indicate the importance of gaining every benefit (in the benefit list) when they go fun-shopping. The respondents can freely indicate their answers in continuous response bars, ranging from *not important* (0) to *extremely important* (100).

Each value is divided by the sum of the elicited benefit values, yielding each utility weight. The second approach is explained in the subsequent paragraphs. The ID results calculated using both weighting techniques are compared. This issue is discussed later on in Chapter 7 (Section 7.6).

Experimental designs, such as conjoint experiments, have been used in industrial marketing, pricing and advertising (Gustafsson, Herrmann, & Huber, 2003; Mahajan & Wind, 1992) to realistically represent the way consumers make some trade-offs in their decision processes involving multi-attribute products or services (Huber, 1987). This is done for instance by using full factorial design experiments. However, such a design requires a large number of runs, albeit having a small number of attributes. For instance, a product is assessed based on five attributes (*k*), each having two levels. This implies that the number of full-profiles to measure is $2^k=2^5=32$. Thus, the research can be costly and respondents' burden also grows. To solve this issue, a fraction of the full factorial runs is used, commonly called as fractional factorial design (FFD).

FFD allows us to economically assess "causal-effect" relationships between factors in an experiment, because instead of running 32 full factorial designs a ½ fractional run of 18 or a ¼ fractional run of 8 can also be sufficient. These designs should fulfil adequate properties of being *balanced* and *orthogonal*, meaning that all combinations of levels (or states), e.g. *high [+]* and *low [-]*, appear as frequently in the design and the correlations between all attributes are "0". Nevertheless, it can only assess the *main-effects* while the *interaction-effects* are assumed to be "0". The *main-effect* shows the effect of single factors on the dependent variable and the *interaction-effect* indicates the effect of combined independent variables. In this study, FFD is used to calculate the partial-utility weights.

FFD is written in a notation 2_R^{k-p}, where 2 represents the *number of attribute levels*; *k* symbolizes *the number of attributes*, *k-p* stands for the *extent of fractionation*, and *R* signifies the *resolution*. The resolution indicates the shortest length of "word" in the generator set (see e.g. NIST/SEMATECH, n.d. for detailed explanations). This study implements 2^{7-3}_{IV} design (Table 4.1), meaning that seven benefits are assessed in the total number of 16 runs (profiles), each benefit has two levels, and a resolution IV design is used. Such designs can be obtained from other literature (e.g. Box, Hunter, & Hunter, 1978; Montgomery, 2000; NIST/SEMATECH, n.d.).

The respondents are asked to value the profiles separately concerning their chances to execute the leisure-shopping activity (0-100%) given the profiles. Each profile contains combinations of seven-benefit states. These benefits are taken from the survey. Thus, the same FFD is used for all the participants, but the assessed benefits differ from one respondent to another. The response column in Table 4.1 shows an example of a respondent's answers.

Table 4.1 The FFD design with the participant's response

Profile	*X1*	*X2*	*X3*	*X4*	*X5*	*X6*	*X7*	*Response*
1	+	+	+	+	+	+	+	1
2	+	+	+	-	+	-	-	0,1
3	+	+	-	+	-	+	-	0,49
4	+	+	-	-	-	-	+	0,07
5	+	-	+	+	-	-	-	0,34
6	+	-	+	-	-	+	+	0
7	+	-	-	+	+	-	+	0
8	+	-	-	-	+	+	-	0
9	-	+	+	+	-	-	+	0,13
10	-	+	+	-	-	+	-	0,12
11	-	+	-	+	+	-	-	0,79
12	-	+	-	-	+	+	+	0,08
13	-	-	+	+	+	+	-	0
14	-	-	+	-	+	-	+	0
15	-	-	-	+	-	+	+	0
16	-	-	-	-	-	-	-	0

The total utility is calculated as the sum of the part-worth factors that construct it (Hair, Black, Babin, Anderson, & Tatham, 2005):

TotalUtility=part_worth_X1+part_worth_X2+…+part_worth_Xn

Part-worth utilities are calculated by firstly coding the levels with *effect coding* (i.e. -1 and +1) and employing a linear regression analysis next. Statistical software, e.g. SPSS (SPSS, n.d.), can be used to obtain the regression equations, as shown below.

Assessment=C+b1X1+b2X2+…+b7X; Where *C* is the constant value, representing basic use or average assessment of profiles; *Xn* is the assessed benefits; and *bi* is the estimated part-worth.

The example of the regression equation from the example in Table 4.1 is shown below. The values (i.e. *C, b1,…,b7*) are taken from Table 4.2. Partial-utilities are defined as *factor importance* or the effect of attributes on the utility. To calculate these values, the range of part-worth for each benefit is estimated, divided by the sum of part-worth ranges, multiplied by 100% (Table 4.3).

Utility=0.195+0.055X1+0.153X2+…-0.035X7

Table 4.2 An example of regression coefficients

Model	*Unstandardized Coefficient*		*Standardized Coefficient*	*t*	*Sig.*
	B	Std. Error	Beta		
(Constant)	0.195	0.067		2,898	0.020
B1	0.055	0.067	0.184	0.817	0.437
B2	0.153	0.067	0.511	2.267	0.053
B3	0.016	0.067	0.054	0.242	0.815
B4	0.149	0.067	0.499	2.211	0.058
B5	0.051	0.067	0.172	0.762	0.468
B6	0.016	0.067	0.054	0.242	0.815
B7	-0.035	0.067	-0.117	-0.520	0.617

Table 4.3 Calculating factor importance of each benefit variable

Estimating Part-Worths			*Calculating factor importance*	
Attributes	Levels	Estimated part-worth	Range part-worth	Factor importance
X1	+	0,055	0,11	11,58%
X1	-	-0,055		
X2	+	0,153	0,306	32,21%
X2	-	-0,153		
X3	+	0,016	0,032	3,37%
X3	-	-0,016		
X4	+	0,149	0,298	31,37%
X4	-	-0,149		
X5	+	0,051	0,102	10,74%
X5	-	-0,051		
X6	+	0,016	0,032	3,37%
X6	-	-0,016		
X7	+	-0,035	0,07	7,37%
X7	-	0,035		
Total range part-worth			0,95	

The limitation of this study is the use of fixed seven-attribute FFD, implying that when the respondent elicits less than seven benefits, additional random benefits from the predefined list have to be added to make the number of attributes in the design equals seven. On the other hand, if more than seven benefits are selected, the respondent is asked to indicate the seven most important ones.

Traditional conjoint experiments using full-profiles are commonly used for less than 10 attributes (Hair et al., 2005). It is believed that the accuracy of full-profile designs reduces as the number of attributes grows beyond 10 due to respondents' fatigue, memory limitation, and information overload (Pullman, Dodson, & Moore, 1999). However, the maximum number of attributes that a respondent can assess has never been determined (Pullman et al., 1999). A benchmark of maximum 30 attributes is often used (e.g. Green & Srinivasan, 1990). This study applies a seven-attribute design because the results of the previous study using the CNET card game (for the transport mode and location decisions) show that the respondents tend to indicate six or seven benefits (as shown in Chapter 3, Section 3.2.1). The survey data of 221 respondents confirm this finding as the average number of the selected benefits equals seven (see Chapter 5, Section 5.3).

4.3.5 Model validation

The last part of the survey is designed to gather sufficient data for model validations. Every respondent's actual transport mode preferences are asked according to his initial selected contexts. For instance, a respondent elicits *weather conditions*, *time availability*, and *companionship* as contexts that affect his transport mode choice. Accordingly, different schemes are shown and the following question is asked:

"Which transport mode (car, bus or bike) will you choose given the following scenario?"

Scenario 1:

- *It is raining*
- *You have plenty of time available*
- *You go fun-shopping alone*

Scenario 2:

- *It is sunny*
- *You have plenty of time available*
- *You go fun-shopping with someone*

Etc.

The respondent's transport mode preferences given the scenarios above are compared with the prediction results of his ID model to check its accuracy. Similarly, the accuracy of 221 participants' ID models can be assessed, allowing us to conclude about the general accuracy of ID model in predicting behavioural changes of people. This issue is further elaborated in Chapter 7.

4.3.6 Compiling influence diagram models

Specialized Bayesian network software, i.e. Hugin Researcher 7.2 (HUGIN EXPERT, n.d.), is used to compute all the ID networks. Beforehand, an additional Java-based program is written under application programming interface (API) in Hugin to automate the generation of every participant's ID model from the corresponding MR data. An example of an individual's ID model derived from the CB-CNET survey can be seen in Figure 4.3 and Figure 4.4. This example also illustrates the use of an ID model to predict travel behaviour. Furthermore, behavioural changes due to some influential contexts can be assessed. For instance, with no evidence, the individual network predicts that taking the car maximizes the utility value at 53.30 (Figure 4.3). However, when some evidence is entered (i.e. *there is plenty of time available, car is not available, it is not a windy day,* and *the weather is good*), taking the bike gives the highest utility value at 41.64 (Figure 4.4). Additionally, the utility value of taking the car decreases to 35.80, given the evidence.

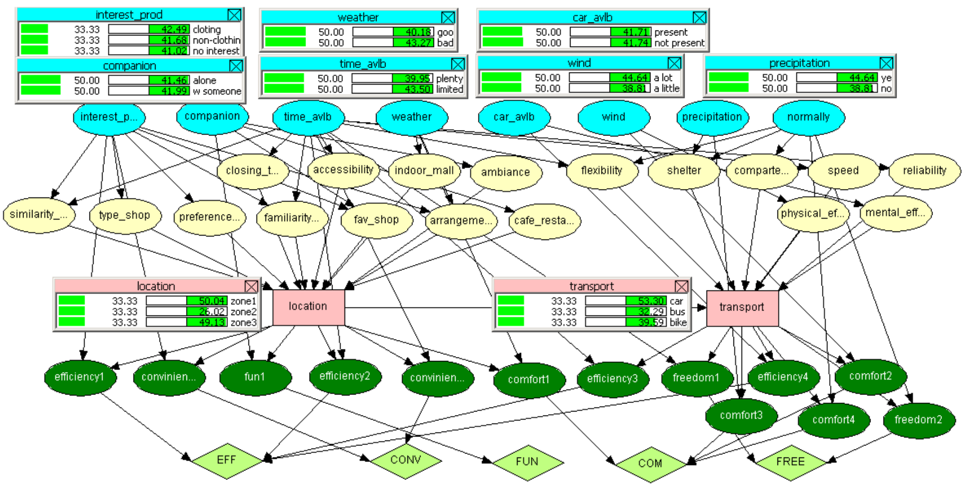


Figure 4.3 An example of the participant's influence diagram model (without evidence)

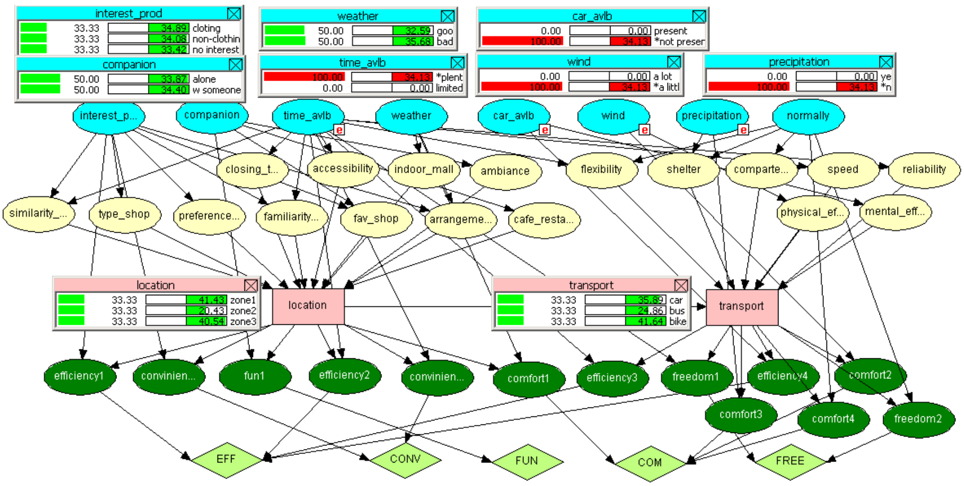


Figure 4.4 An example of the participant's influence diagram model (with evidence)

4.3.7 Experiences on the CB-CNET survey

This section has detailed the development of the CB-CNET protocol and its application in eliciting individuals' leisure-trip decisions. This interface has been used to gather the data from 221 respondents. The use of the interface significantly reduces the time to collect the data in comparison to the face-to-face CNET interview protocols because the parameters can automatically and directly be gathered. In average, the whole survey lasts for about 2-3 hours, per group session of about 16 respondents, in comparison to the CNET interview methods that took about 10 hours to finish, per respondent (as previously explained in Chapter 2, Section 2.4.5).

4.4 Conclusions

The CB-CNET protocol allows us to construct MR interactively with the respondents, measure their preferences, and generate their mental-level decision models (i.e. Bayesian ID). For this purpose, the protocol is broken down into several stages and implemented in the interface accordingly.

The first stage aims at eliciting considered aspects, constructs, beliefs and their interconnections in the decision process using probing questions. They are represented as the *cognitive subsets*, consisting of the interconnected *contexts*, *benefits, and instruments*. Accordingly, the individuals' MR can be revealed and used to generate their ID network structures. These networks are used in the second stage to generate the questionnaires for collecting probability and utility data. Subsequently, the utility weights have to be set. The application allows for two ways to generate these weights; i.e. separate rating assessments of single-utility profiles and rating evaluations of combined seven-utility profiles by means of FFD. At last, the interface formulates some questions to investigate the participants' actual preferences, enabling the constructed models to be validated.

This chapter further highlights the advantages of using a computer survey for this type of behavioural study. For instance, the questions can be automatically generated, and the interviewers' bias can be lessened. Moreover, the data can be collected easier, quicker and cheaper for large sample groups. The CB-CNET survey is applied to assess leisure-shopping travel behaviour in the city centre of Hasselt, in Belgium, focusing on the individuals' *transport mode* and *location* choices. This interface has successfully been applied to gather the data from 221 people who live in the outskirts of Hasselt.

However, there are some research limitations. First, the activity-scheduling decision is given in the scenario, implying that the participants cannot opt not to go shopping. The model also assumes that there are no interaction effects among various contexts that yield the same pursued benefit, as it has been explain in Chapter 2, Section 2.4.3. For instance a respondent indicates that contextual aspects of *weather conditions {bad, good}* and *wind conditions {not windy, windy}* are linked to the same benefit of *having comfort*. Suppose the respondent indicates that if the *weather condition* is *good* and it is *windy* then his chance of having the *benefit of comfort* when biking is really *low*. However when the *weather* is still *good* but it is *not windy*, the *probability to gain comfort increases* when bike is used. This signifies an interaction between the variables of *weather* and *wind conditions*. Future research should address this issue to improve ID modelling accuracy. At last, one way to calculate utility weights in the survey is using the fixed seven-utility design. Needless to say, the latter problem can be fixed in the future research if needed, based on the results of calculations of the current data.

Further analyses on the ID models are presented in Chapter 7. In that chapter, the predictive accuracy of the individuals' models are shown and discussed. Additional analyses are done to compare the accuracy of the ID models with the DT model. Both modelling techniques use the MR data gathered using the CB-CNET survey. The assessment of different methods to generate utility weights is also presented in Chapter 7; i.e. rating of single-benefit profiles versus rating of joined seven-benefit profiles in FFD experiment. The data obtained by the CB-CNET interface are described in Chapter 5. In that chapter, the impact of time availability to perform leisure-shopping activities on cognitive representations is also analysed. The same data are also used to generate the typology of fun-shopping travellers. By doing so, a number of TDM effective for specific groups of people can be emphasized. This issue is discussed in Chapter 6. Undoubtedly, the CB-CNET interface can be adapted to assess different activities as well.

5 Individuals’ mental representations of leisure-shopping trip decisions: A descriptive study

5.1 Introduction

Capturing individuals’ MR of travel-related decision problems, especially when planning leisure-shopping trips to a city centre, has been previously discussed in Chapter 2. For that purpose, the first experiment is conducted, comparing the two CNET qualitative face-to-face interview methods using 26 young adults as the participants; i.e. the CNET interview and card game. The data derived from that experiment have been analysed, presented, and discussed in Chapter 3. However, due to its small sample size, any statistical analysis cannot be performed on the gathered MR data. Moreover, comparing the performance of computational mental-level models that use MR as input data cannot be done. For that reason, the second experiment is conducted, intending to be a follow-up of the first test using a larger sample size. The CB-CNET interface is developed for this purpose based on the CNET interview and card game methods, as explained in Chapter 4. This computerized interface has successfully been used to gather MR and other additional data form 221 participants.

The subsequent chapters (i.e. Chapter 6 and 7) aim at performing some analyses and modelling on the data gathered in the CB-CNET survey. Hence, this chapter focuses on giving an introduction to its succeeding chapters, covering the sample recruitment and description (Section 5.2). Moreover, the complexity of the participants’ MR is described (in Section 5.3), along with the elicited aspects (in Section 5.4) and the revealed cognitive subsets (in Section 5.5). In these sections, the results of the preliminary study (using the CNET protocols) are compared with the outcomes of the CB-CNET data. Furthermore, two scenarios are tested in the survey; i.e. fun-shopping with and without time constraints. The impact of these scenarios on the size and content of the participants' MR is investigated in Section 5.6. At last, some conclusions are drawn in Section 5.7.

5.2 Sample

5.2.1 Sample recruitment

In Chapter 4 (Section 4.3.1), the research setting and task of the CB-CNET survey have been detailed, as summarized below. The second survey is developed based on the CNET interview and card game. Accordingly, some parts of the previous research setting remain the same. There are two travel-related decisions which are investigated, namely the transport mode decision to use car, bus, or bike; and the shopping location decision in the city centre to go to Zone-1, Zone-2, or Zone-3. The choice set of the shopping location decision has been previously explained in Chapter 2 (Section 2.3.2) and Chapter 4 (Section 4.3.1). To enable a realistic interpretation of the research setting, especially concerning the transport mode decision, the target respondents are people who actually live in the neighbourhood area of Hasselt, about 3-10 kilometres away from the city centre. This area has relatively good bus infrastructure (i.e. bus stops within walking distance). People who live in this zone may actually consider using a bike to go to the city centre. Additionally, the respondents are obliged to possess a driving licence in order to be considered to participate in the survey. These prerequisites allow us to develop a sample of people who in reality consider the predefined transport mode alternatives (i.e. car, bus, and bike).

A sufficient number of respondents who meet the requirements above have to be gathered for the CB-CNET survey. Additionally, it should be noted that this survey is carried out in small guided group sessions in a computer room of Hasselt University. This is done in order to have a better control on the quality of the data. Based on its nature, the survey takes about 2 hours to complete. Consequently, it is infeasible to let people take the survey online without any help due to the expected large number of respondents' drop out. This is why the survey is held in Hasselt University. This also implies that the participants have to travel to the university, adding more difficulties to find such dedicated people who are willing to spend about 2-3 hours of their time and effort to participate in the study. Thus, a supermarket voucher valued 20 Euro is given for each respondent as an incentive.

Due to the specific characteristics of the sample (i.e. living in Hasselt outskirts, having a driving license, and willing to participate), a combination of sampling methods is used. The first approach is the snowballing method. It works by initially recruiting a small number of people who fulfil the sample requirements. They are asked to help spreading the "call for respondents" further to their spouse, colleagues, friends, relatives, etc. who also meet the criteria. The announcement of the call for respondents is also published in some local newspapers. Furthermore, flyers are placed in public places, informing the readers about the survey and the call.

Using the combination of techniques above, a total number of 221 participants are recruited. These participants are categorized into 19 group sessions. Each session has about 16 participants and 2 researchers to assist them. This survey is held on December 12th-23rd 2009, on Saturdays and weekdays, and in the morning, afternoon, and evening.

It should be noted that the second experiment is conducted as a joint project, involving a number of researchers who would use the gathered data for different purposes. Hence, some practical details about the sample recruitment can be found in De Ceunynck (2010).

5.2.2 Sample characteristics

In the beginning of the survey, the respondents are asked to give their socio-demographic information, such as their age, gender, education, income, residence location, etc. Moreover, they are questioned about their transport mode and leisure-shopping behaviours. The data are described in Section 5.2.2.1 (i.e. socio-demographic characteristics), Section 5.2.2.2 (i.e. travel behaviour characteristics), and Section 5.2.2.3 (i.e. shopping behaviour characteristics). At last, some conclusions regarding the sample taking and characteristics are presented in Section 5.2.3.

5.2.2.1 Socio-demographic characteristics

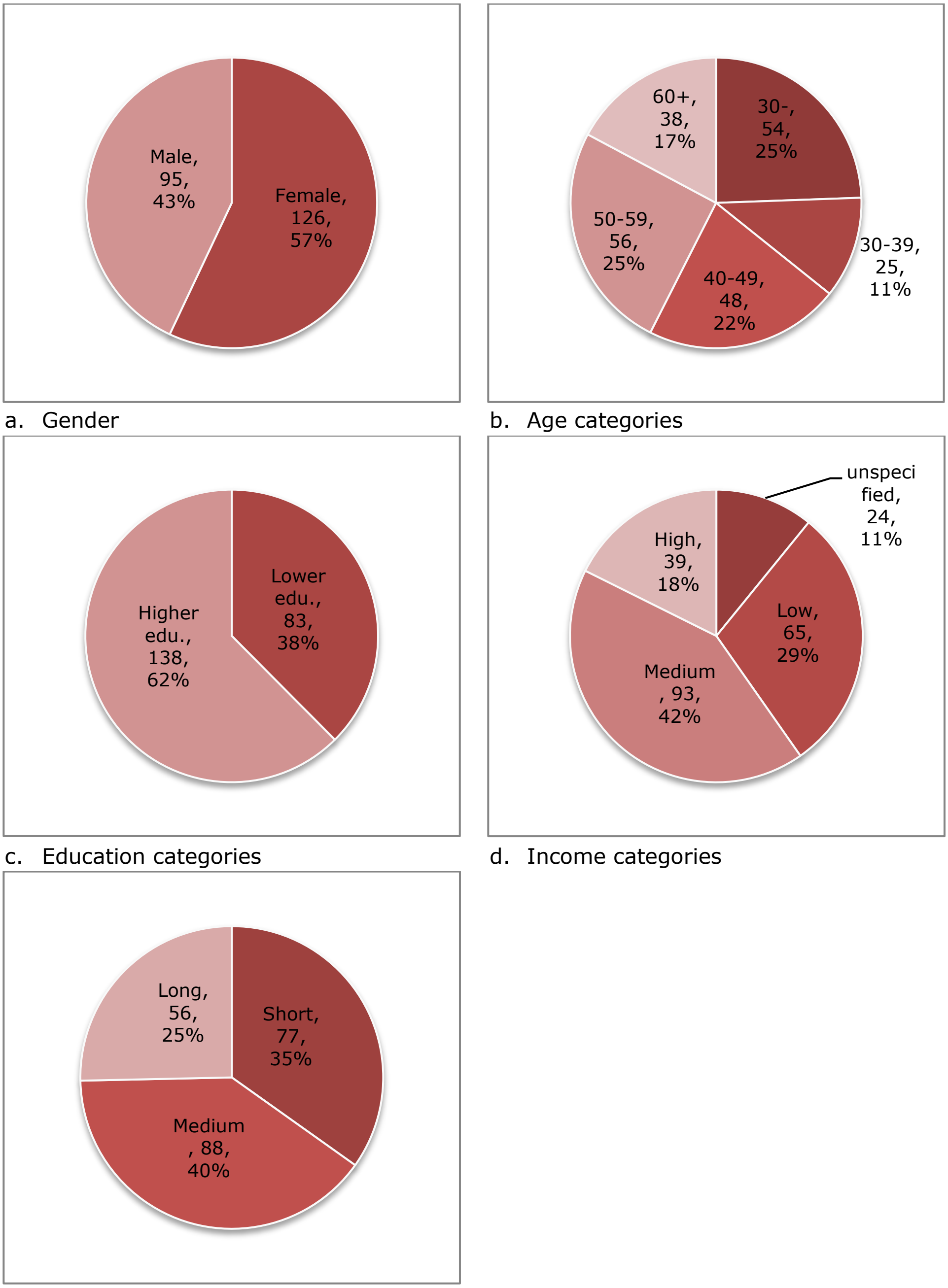
It has been previously explained in Section 5.2.1 that the respondents are recruited using a number of sampling techniques. Therefore, the socio-demographic characteristics of the participants are needed to describe the sample. These characteristics are summarized in Figure 5.1, focusing on: *gender* (a), *age categories* (b), *education categories* (c), *income categories* (d), and *residence categories* (e). There are other socio-demographic aspects questioned in the survey, i.e. *household size*, *occupation*, and the respondents' *position in the household*. However, the five categories indicated above are considered sufficient to describe the sample.

a. Gender

The composition of male and female respondents can be seen in Figure 5.1a. Even though the number of female participants is slightly larger than the number of male respondents, it still can be concluded that both gender categories are well represented in the sample.

b. Age categories

The respondents' age are aggregated into the following categories (Figure 5.1b): *below 30 years old* (1), *between 30 and 39* (2), *between 40 and 49* (3), *between 50 and 59* (4), and *above 60 years old* (5). In general, these groups are equally portrayed in the sample. However, the second (30-39) and the last (>60) groups are slightly under represented. This should be taken into account when drawing some conclusions from any quantitative analysis that uses the data.



a. Gender

b. Age categories

c. Education categories

d. Income categories

e. Residence location categories

Figure 5.1 The participants' socio-demographic characteristics: Gender (a), age categories (b), education categories (c), income categories (d), and residence categories (e) *c. Education categories*

The respondents are asked to indicate their education level; i.e. *not educated* (1), *primary school* (2), *general secondary school, not completed* (3), *other types of secondary school, not completed* (4), *general secondary school, completed* (5), *other types of secondary school, completed* (6), *higher education non-university* (7), and *university* (8). These categories are aggregated into two broader groups of *lower education* (comprising of group number 1 to 6) and *higher education* (including group number 7 and 8) (Figure 5.1c). Overall, high educated people dominate the sample (62%). This sample does not well represent the education level of people in Belgium, which indicates the proportion of 26% and 74% of high and low educated people respectively, based on the data in 2009 (Statbel, n.d.).

d. Income categories

The participants are asked to indicate their household monthly income based on the following predefined categories: *I would rather not specify* (1), *0-1000 Euro* (2), *1001-2000* (3), *2001-3000* (4), *3001-4000* (5), *4001-5000* (6), *more than 5000 Euro per month* (7). They are aggregated further into groups of *unspecified income* (i.e. including group number 1), *low income* (i.e. group 2 and 3), *medium income* (i.e. group 4 and 5), and *high income* (i.e. group 6 and 7) (Figure 5.1d).

Figure 5.1d shows that the *medium income* people with the salary of 2001-4000 Euro per month dominate the sample (42%), followed by the *lower income* people (29%), the *higher income* group (18%), and the *unspecified income* group (11%). Household income indeed can be used as an indicator of wealth status. However, this variable alone may not be adequate to give a fair indication of the prosperity of a household, as explained in the following example. A household comprising one person with an income of 1800 Euro per month could be wealthier than a household containing 6 people with an income of 4200 Euro per month. Thus, this issue should be considered when interpreting results of analysis using the data.

e. Residence location categories

It has been previously explained in Section 5.2.1 that this study focuses on people who live in Hasselt outskirts, consisting of a number of municipalities. The respondents are recruited from seven municipalities (i.e. 10 post codes), as shown in the coloured areas in Figure 5.2.

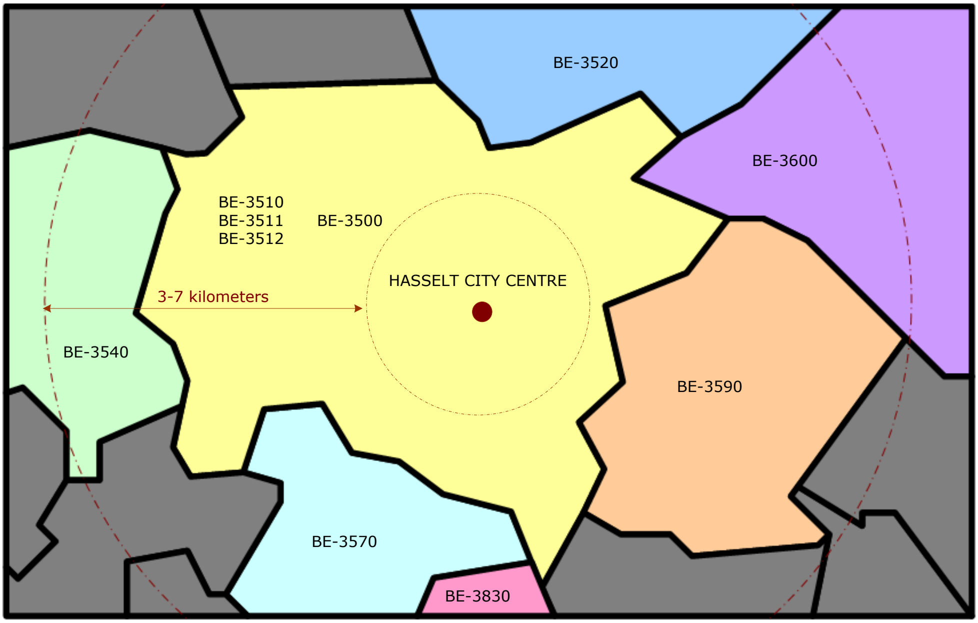


Figure 5.2 The participants' housing area and postcodes

The postal code can be used to roughly estimate the distance between the respondents' home location and the city centre. For instance, BE-3500 is the post code of Hasselt municipality. The respondents who come from this post code zone are considered living 3-4 kilometres away from the city centre (i.e. short distance area). Moreover, BE-3510, BE-3511, and BE-3512 cover the independent municipalities in the suburban area of Hasselt, around 4-7 kilometres from the city centre (i.e. medium distance area). The rest of the post codes (i.e. BE-3520, 3540, 3570, 3590, 3600, 3830) are located 7-10 kilometres away from the city (i.e. long distance zone).

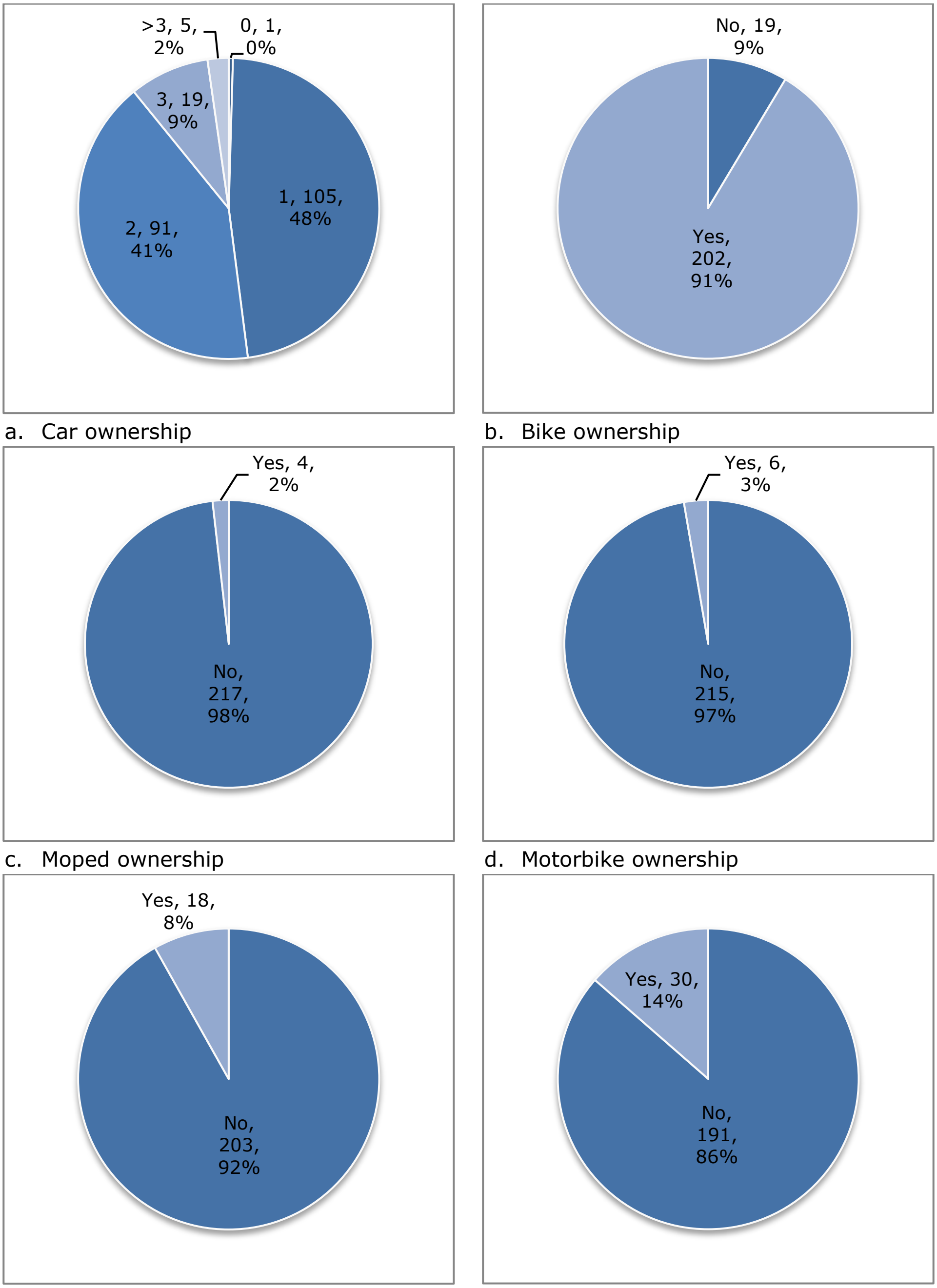
The distribution of the respondents who come from the short, medium and long distance areas can be seen in Figure 5.1e. In general, the percentages of the respondents are relatively equal across the distance categories, with the medium distance group being slightly overrepresented (i.e. 40%).

5.2.2.2 Travel behaviour characteristics

The respondents’ travel behaviour characteristics are explained by using the following indicators: *car ownership and other transport mode options* (a), *parking behaviour* (b), *yearly kilometres of travel by car* (c), and *transport mode habits* (d). Moreover, the participants’ *transport mode behaviour to Hasselt city centre* is further asked for, specifically regarding *the frequency of going to Hasselt by car, bike, and bus* (e). These aspects are described below in turn, and illustrated in Figure 5.3 (i.e. transport mode options) and Figure 5.4 (i.e. other travel behaviour characteristics).

a. Car ownership and other transport mode options

The majority of the participants own at least one car in their household. As a matter of fact, there is only one respondent who indicates no car ownership (Figure 5.3a). Moreover, 91% of the respondents own at least one bicycle. Based on the Decree of Basic Mobility in Flanders, the inhabitants of Hasselt and its surrounding area have a bus stop within walking distance, offering a good and direct connection to Hasselt Station (Mobiel Vlaanderen, n.d.). Accordingly, these data confirm that people in the sample may actually consider using the predefined choice set (i.e. car, bus and bike) to go to Hasselt.



e. Busabonnement card

f. Bus reduced ticket

Figure 5.3 The participants' transport mode options: Car (a); bicycle (b), moped (c), motorbike (d), busabonnement card (d), bus reduced ticket (e)

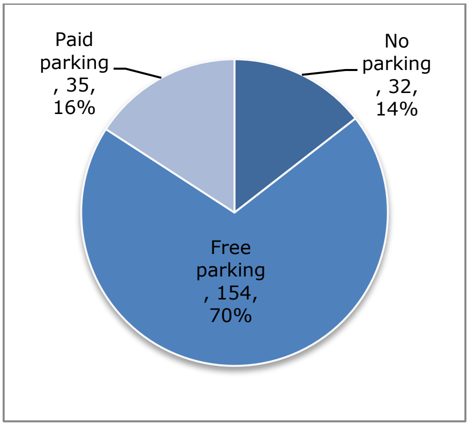
Moreover, 2% and 3% of the respondents own a moped and a motorbike respectively (Figure 5.3c and d). Some of the participants (8%) possess a busabonnement card (Figure 5.3e). A busabonnement card is a prepaid card using monthly, 3-monthly, 6-monthly, or yearly payment schemes. Someone can travel with bus as much as he wishes by using that card within its validity. 14% of the participants own a bus reduction ticket. It is a bus ticket valued 8 Euro bought in a ticket vendor in the bus station. Using that ticket, a passenger gets a direct (up to 50%) discount of the price of a bus ticket bought inside the bus. The reduction ticket can be reused until all values that it contains are consumed. There are other transport mode options asked in the survey but not discussed here; i.e. the possession of trainabonnement card, train reduction card, and others.

b. Parking

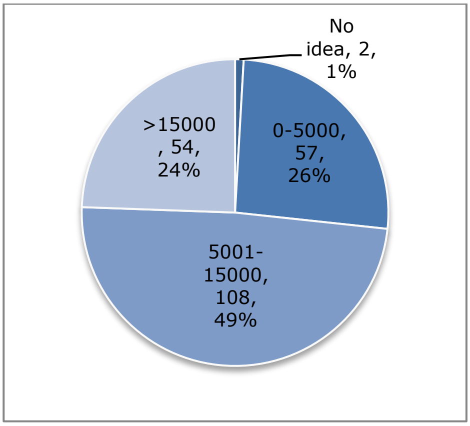
The respondents are asked about parking places in Hasselt where they usually park their car based on the predefined categories: *no parking needed* (1), *in the free parking area* (2), and *in the paid (indoor or outdoor) parking zone* (3) (Figure 5.4a). Only 14% of the respondents state that parking is not needed because the car has never been used to go to Hasselt. 70% of them park their car in the free parking space provided by Hasselt municipality in the surrounding area of the city centre, demonstrating high attractiveness of the free parking zone.

c. Yearly kilometres of travel by car

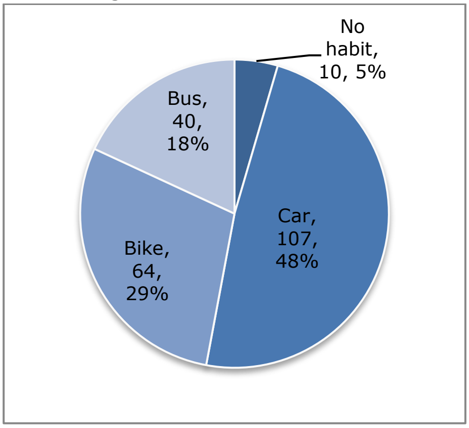
The respondents are asked to specify the average numbers of yearly kilometres travelled by car for any purposes. Their numeric responses are further discretized into four groups (Figure 5.4b): *no idea* (1%), *short distances of 0-5000 kilometres* (26%), *medium distances of 5001-15000 kilometres* (49%), and *long distances of larger than 15000 kilometres* (24%). These groups also represent the respondents' car usage. Hence, it can be concluded that a large number of respondents (49%) moderately drive their car.



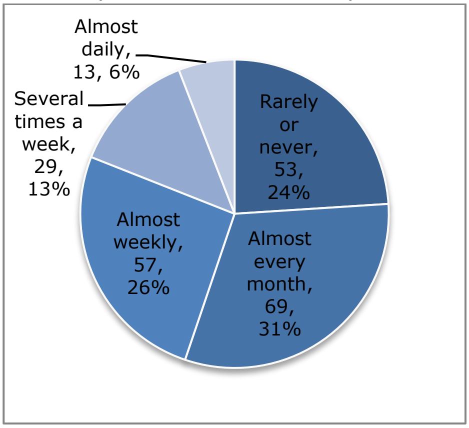
a. Parking



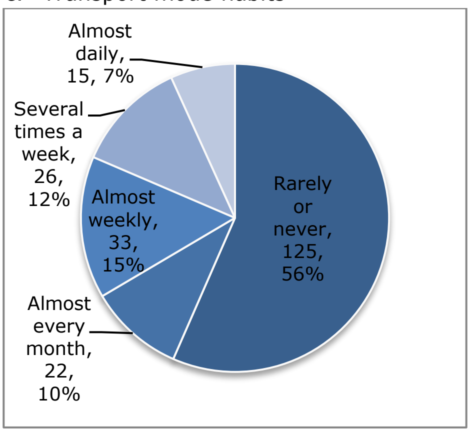
b. Yearly kilometres of travel by car



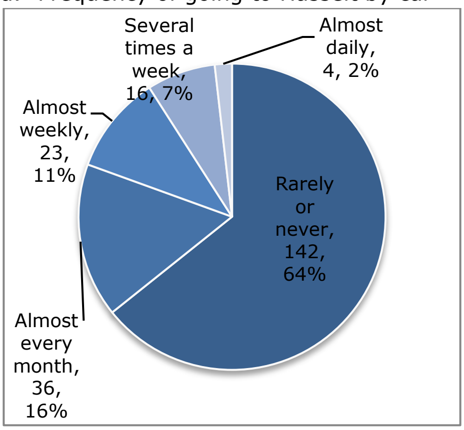
c. Transport mode habits



d. Frequency of going to Hasselt by car



e. Frequency of going to Hasselt by bike



f. Frequency of going to Hasselt by bus

Figure 5.4 The participants' travel behaviour characteristics: Parking (a), yearly VKT (b), habits (c), frequency of going to Hasselt by car (d), by bike (e), and by bus (f) *d. Transport mode habits*

The respondents are questioned about the probability of using each transport mode option (i.e. car, bus, and bike) in the normal situation, given the fun-shopping scenario. The choice options with the highest assigned probability values are regarded as the respondents' transport mode habits. These results are presented in Figure 5.4c. In general, car is the most preferable transport mode option (48%), followed by bike (29%), and bus (18%). Only 5% of the participants do not have strong transport mode habits for leisure-shopping trips to Hasselt city centre. Accordingly, the data imply that the respondents have relatively high dependency on car-use to go to leisure-shopping locations, especially for short to medium distances of 3-10 kilometres.

e. The frequency of going to Hasselt by car, bike, and bus

At last, the respondents are asked to indicate the frequencies of going to the city centre of Hasselt by using car (Figure 5.4d), bike (Figure 5.4e), and bus (Figure 5.4f) for any purposes. 24% of the respondents state that they rarely or hardly ever go there with car. 19% of them express their frequent use of car (almost daily or several times per week). 56% of the respondents rarely use bike to go to Hasselt. However, 19% of them state their quite frequent use of bike, akin to percentage of the frequent car-use. A similar trend can also be observed for the frequent use of bus (18%). However, more respondents (64%) state that they rarely (or never) use a bus as their transport mode choice to go to Hasselt.

5.2.2.3 Shopping behaviour characteristics

Some questions are asked in the survey to investigate the participants' fun-shopping behaviour; i.e. *how frequent they execute the activity in a year* (a), *when the last time was that they performed the activity* (b), and *what their shopping location habits are* (c). These aspects are described below subsequently and illustrated in Figure 5.5. Moreover, the respondents' favourite shops and favourite shopping cities are questioned in the survey, but they are not presented here.

a. Yearly frequency of fun-shopping

The respondents are questioned about their frequency of performing leisure-shopping activities in a year. 6% of them rarely and probably never carry out the activities (Figure 5.5a). The rest of the respondents (94%) go leisure-shopping at least several times a year, implying that the sample is adequate for the purpose of the study to investigate individuals' leisure-shopping travel behaviour.

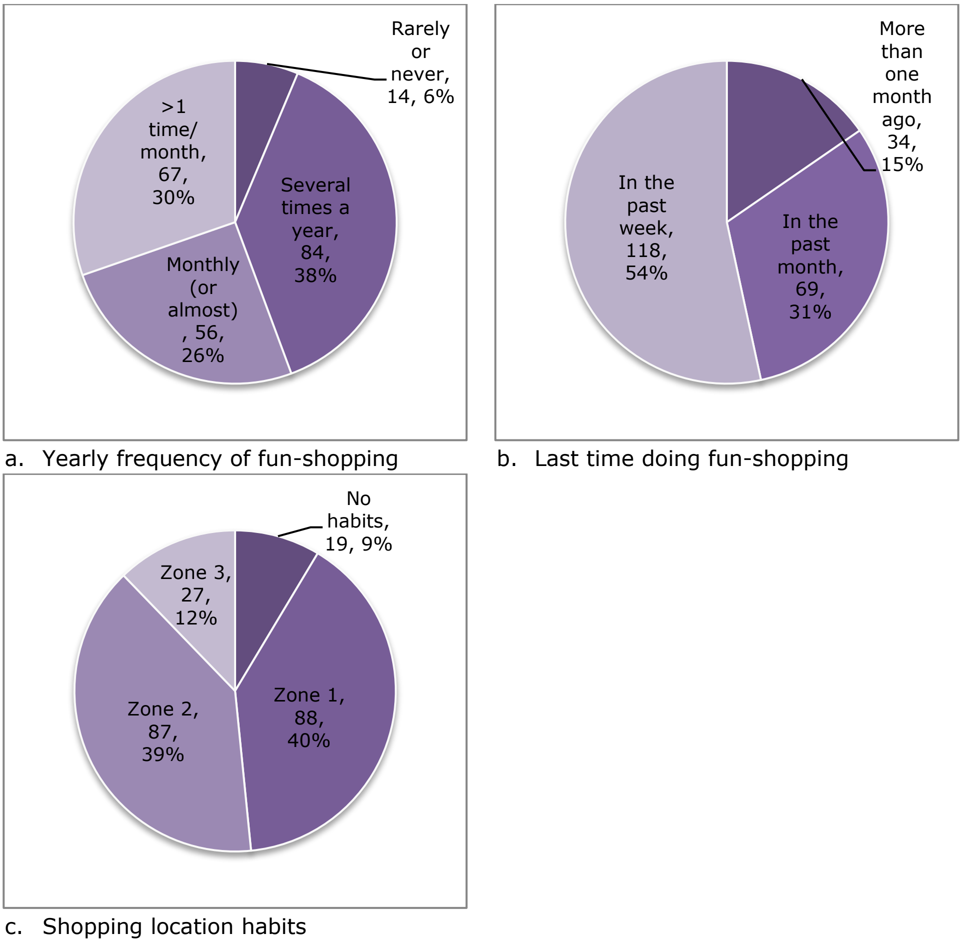


Figure 5.5 The participants' fun-shopping behaviour characteristics: Yearly frequency of fun-shopping (a), last time doing fun-shopping (b), and shopping location habits (c)

b. Last time doing fun-shopping

More than half of the respondents indicate that they have performed the fun-shopping activity in the week prior to the survey. Additionally, 31% of them conducted the activity in the past month (Figure 5.5b). This implies that leisure-shopping has been carried out quite recently by most of the respondents. Therefore, it can be assumed that the participants still have good memory regarding their travel decision processes when performing the leisure-shopping activity.

c. Shopping location habits

The respondents are asked to specify the probability of going to each shopping location (i.e. Zone-1, Zone-2, and Zone-3) in a normal situation. The location habits are assigned based on the highest probability values. The results can be seen in Figure 5.5c. It can be seen form the figure that Zone-1 (i.e. the main shopping street) and Zone-2 (i.e. the gallery area) are normally chosen by 40% and 39% of the respondents respectively. Additionally, 9% of them do not state strong location habits.

5.2.3 Conclusions: The sample

Section 5.2.1 describes the sample requirements based on the research setting. Due to the specific criteria of the respondents and the high demand of the survey, finding people to participate becomes a major challenge. To solve the problem, a number of sample taking techniques are used, i.e. snowballing method, announcement in some newspapers and flyers. Accordingly, it is important to investigate the sample characteristics to ensure that different socio-demographic groups are well represented.

Section 5.2.2 gives detailed descriptions of the sample, covering a number of issues namely *the participants' socio-demographic characteristics* (such as gender, age categories, etc.), *their travel behaviour* (such as car ownership and other transport mode options), and *fun-shopping behaviour* (such as yearly frequency of fun-shopping, etc.). Based on the socio-demographic data, the gender categories (i.e. male and female) are well represented in the sample. The age categories of 30-39 years old and older than 60 years old are slightly underrepresented. To some extent, high educated people dominate the sample. The medium income category is also overrepresented in the sample whereas higher income category is underrepresented. Comparatively, the distance categories are equally portrayed.

With regard to the travel behaviour, the sample confirms the predefined transport mode choice set (i.e. car, bus, and bike). Additionally, the percentages of the respondents who frequently go to Hasselt by car, bus, and bike are equivalent. However, the ones who indicate that they never go to Hasselt by bus account for the largest percentage of the sample. Furthermore, it is revealed that car is preferred by most of the respondents regardless of the contexts, followed by bike and bus. At last, based on the participants' fun-shopping behaviour, it can be concluded that the respondents are people who frequently shop for leisure purposes.

5.3 The complexity of the individuals' mental representations

This section aims at describing the elicited MR, focusing on the number of elicited variables (Section 5.3.1) and the revealed cognitive subsets (Section 5.3.2). They are discussed below subsequently.

5.3.1 The number of elicited aspects

The data derived from the CB-CNET survey let us investigate the complexity of the participants' MR based on the number of aspects being elicited, i.e. contexts, instruments, and benefits of the transport mode and location decisions. The results of the descriptive analysis are shown in Table 5.1 and discussed below.

With regard to the transport mode decision, each respondent picks on average 4.36 contextual variables (Table 5.1a). The maximum number of contexts chosen by a respondent equals 25, implying that the corresponding respondent selects almost all contextual variables in the list (containing 27 contexts). However, 11 respondents do not indicate any contexts as their influential factors. On average, each participant reveals 5.31 benefits. The maximum number of the benefits being selected equals 14. Instrumental aspects are the type of variables with the highest average number of elicitation (i.e. 9.51). This result is expected because the instruments are revealed based on the combination of each context and benefit. Other estimates to describe the data can be seen in Table 5.1, i.e. median, mode, sample variance, confidence interval, etc.

Table 5.1 The number of elicited contexts, instruments, and benefits for the transport mode decision (a), shopping location decision (b), and all decisions (c)

	a. Transport mode			*b. Shopping location*			*c. All decisions*
	C[1]	*I*[2]	*B*[3]	*C*	*I*	*B*	*B*
The CB-CNET data (n=221)							
Mean	4.36	9.51	5.31	3.19	8.11	4.47	7.30
Standard Error	0.23	0.30	0.16	0.13	0.31	0.16	0.18
Median	4	9	5	3	8	4	7
Mode	5	7	4	3	8	3	5
Std. Deviation	3.39	4.40	2.43	1.86	4.53	2.34	2.70
Sample Variance	11.46	19.36	5.90	3.46	20.56	5.47	7.29
Kurtosis	9.85	0.33	1.78	0.35	0.00	0.75	-0.29
Skewness	2.56	0.71	1.09	0.64	0.58	0.79	0.34
Range	25	24	14	9	21	13	13
Minimum	0	1	1	0	1	1	2
Maximum	25	25	15	9	22	14	15
Sum	964	2101	1174	706	1793	987	1614
Count	221	221	221	221	221	221	221
95% CI[4]	0.45	0.58	0.32	0.25	0.60	0.31	0.36
The CNET interview data (n=26)							
Mean	3.42	6.36	4.46	2.19	5.31	3.50	-
The CNET card game data (n=26)							
Mean	6.85	12.85	6.46	5.50	11.31	6.46	-

[1] Contextual variable
[2] Instrumental variable
[3] Benefit variable
[4] Confidence interval

The average number of variables considered in the shopping location decision is lower than in the transport mode decision (Table 5.1b); i.e. 3.19 contexts, 4.47 benefits, and 8.11 instruments. These results indicate that people have slightly more factors to consider when making their transport mode decisions in comparison to their location decisions.

Both the transport mode and location decisions use the same list of benefit variables. Thus, some descriptive statistics is also applied on the benefits of both decisions. The results are presented in Table 5.1(c). On average, each respondent selects seven benefits, confirming the fixed seven-benefit design of FFD to calculate the utility weights (discussed in Chapter 4, Section 4.3.4).

In general, the average numbers of aspects elicited with the CB-CNET survey are lower than with the CNET card game method, but they are larger than with the CNET interview technique. The results of the analysis using the card game and interview methods have been previously described in Chapter 3. These results are again represented in Table 5.1, as follows: using the card game method, each respondent selects 6.85 contexts, 12.85 instruments, and 6.46 benefits for the transport mode decision; and 5.50 contexts, 11.31 instruments, and 6.46 benefits for the location decision. With regard to the CNET interview data, participants on average reveal 3.42 contexts, 6.36 instruments, and 4.46 benefits for the transport mode choice; and 2.19 contexts, 5.31 instruments, and 3.50 benefits for the shopping location decision.

5.3.2 The average number of elicited cognitive subsets

Table 5.2 presents some descriptive statistics (i.e. mean, median, mode, range, minimum, maximum, sum, count, and 95% confidence interval) based on the number of the cognitive subsets revealed in the CB-CNET survey data, for the transport mode (a) and shopping location decisions (b). On average, each respondent elicit 32.91 transport mode subsets (95% CI: 5.72) and 24.56 shopping location subsets (95% CI: 4.41). In total, there are 7274 and 5427 subsets for the transport mode and location decisions respectively. The maximum number of subsets elicited by a respondent are 400 (the transport mode decision) and 414 (the shopping location decision). Many respondents reveal 11 subsets in both decisions (mode). The median values are 22 and 18 for the transport mode and location decisions in turn.

Table 5.2 The number of elicited cognitive subsets for the transport mode (a), and shopping location (b) decisions

	a. Transport mode decision	*b. Shopping location decision*
Mean	32.91	24.56
Median	22	18
Mode	11	11
Range	399	413
Minimum	1	1
Maximum	400	414
Sum	7274	5427
Count	221	221
95% CI[1]	5.72	4.41

[1] Confidence interval

Moreover, there are two types of cognitive subsets; i.e. type-1 of {*context, instrument, benefit*} and type-2 of {*normally, instrument, benefit*}. Therefore, to get a complete idea of the distribution of the data based on the subset types, some descriptive statistics is applied. The results are presented in Table 5.3.

Table 5.3 The number of cognitive subset types for the transport mode (a), and shopping location (b) decisions

	a. Transport mode decision		*b. Shopping location decision*	
	Type-1	*Type-2*	*Type-1*	*Type-2*
Mean	16.81	16.10	13.86	10.69
Median	11	9	10	6
Mode	3	4	2	5
Range	161	239	137	277
Minimum	0	0	0	0
Maximum	161	239	137	277
Sum	3715	3559	3064	2363
Count	221	221	221	221
95% CI[1]	2.69	3.62	1.93	2.82

[1] Confidence interval

Table 5.3 shows that both subset types of the transport mode decision have almost the same mean values (i.e. 16.81 and 16.10 for the cognitive subset type-1 and type-2 in turn). In the shopping location dataset, it appears that the cognitive subset type-1 is revealed more frequently than the type-2. Other estimates of the descriptive statistics can be seen in Table 5.3.

5.3.3 Conclusions: The complexity of the individuals' mental representations

Based on the number of variables and subsets being revealed in the survey, it can be concluded that the transport mode decision is more complex and elaborate than the location decision (Table 5.1 and Table 5.2). The lower complexity of the shopping location decision may happen because the predefined choice set of that decision is limited to the city centre area. Even though the division of the city centre area into a number of zones are made based on their distinct characteristics, their sizes are still relatively small. Besides, people probably do not have so much deliberation when making their shopping location decisions because of the proximity of one shopping zone to the others. The results may also imply that the complexity of the transport mode decision is resulted from the obvious distinctness of the transport mode options in the choice set (i.e. car, bus and bike). This highlights the importance of the interactions between the occurring contexts and the instruments in achieving the individuals' sought after benefits.

5.4 The elicited contexts, instruments and benefits

In this section, the content of the individuals' MR are shown. This section starts by describing the results of the decision making sequence (Section 5.3.1). Following that, the participants' MR related to the transport mode decision is disclosed (Section 5.2.2.2), highlighting the differences between aspects elicited using different elicitation techniques. The outcomes of the shopping location decision are presented next (Section 5.4.3). The results of this decision type have not yet been elaborated previously, despite being important in the marketing domain. Therefore, in this section, these results are discussed, focusing on outcomes of other studies done in the marketing field. At last, some conclusions regarding the revealed variables are given in Section 5.4.4. It should be noted that these elicited considerations come from two scenarios of leisure-shopping with and without time constraints, as previously stated in Chapter 1, Section 1.2, and explained in Chapter 4, Section 4.3.1. The differences between aspects considered in these scenarios are highlighted in Section 5.6.

5.4.1 The order of decision making

The respondents are asked to rank two determined travel decisions from the one that they make first to last; i.e. the transport mode and location choices. Based on their responses, Table 5.4 is generated. The result indicates that 68% (rounded) of the respondents firstly make their transport mode decisions before thinking about the exact location to go to (Table 5.4).

Table 5.4 The ordering of decision making based on the count data

	Transport mode	*Shopping location*	*Total (N)*
First decision	150 (67.87%)	71 (32.13%)	221 (100%)
Second decision	71 (32.13%)	150 (67.87%)	221 (100%)
Total (N)	221 (100%)	221 (100%)	

The result above clarifies the issue discussed in Chapter 3 (Section 3.5.2.1). In that section, the order of decision making taken from the CNET interview data is used to give feedback to AB models, in particular to FEATHERS (and ALBATROSS). Form the previous CNET interview data, it cannot be concluded that the transport mode decision is made prior to the location decision. The CB-CNET data reveal that the transport mode choice is made first. However, in the ALBATROSS and FEATHERS systems, that decision is assumed to be made after the location choice (Arentze & Timmermans, 2008). It should be noted that for the purpose of this study, the predetermined shopping locations are located near to each other in the city centre. On the other hand, location choices in AB models are commonly distributed across a larger geographical space (i.e. the whole city, region, or country). Accordingly, similar studies are certainly needed to give a solid ground to the assumption of the order of decisions in AB models, particularly in CPM models such as FEATHERS and ALBATROSS.

5.4.2 The transport mode decision

Figure 5.6 shows the percentages of respondents who select contextual variables. In total, 27 contexts are present in the predefined list of variables. The respondents can freely indicate contexts that influence their decision making. Another variable of *normally* is automatically added afterwards in the dataset when the respondents go through the split elicitation procedure and opt to indicate the cognitive subset type-2 of {*normally, instrument, benefit*}, previously explained in Chapter 4 (Section 4.3.2).

Figure 5.6 indicates that in general 97% of the respondents want to gain certain benefits in any circumstances, making them elicit the second type of subsets and adding the *normally* variable in their MR. Moreover, the variable of *time availability* is elicited by 48% of the respondents and the variable of *precipitation* (or *weather conditions*) is elicited by 46% of them. Other frequently chosen contexts are *the number or size of goods being purchased* (39%) and *the availability of parking space* (36%).

To some extent, these results verify the previous results of the CNET card game (Figure 5.6). For instance, based on the card game data, the contextual variable of *precipitation* is elicited by the highest percentage of the respondents (92%), followed by the variable of *time availability* (89%), and *parking availability* (77%).

It is worth pointing out here that there are some differences between the predefined list of variables used in the CB-CNET survey and in the previous interviews (with the CNET interview and card game). Some variables are added in the list (e.g. *crowdedness in the centre*, *car availability*, etc.), whereas some others in the old list are deleted or modified.

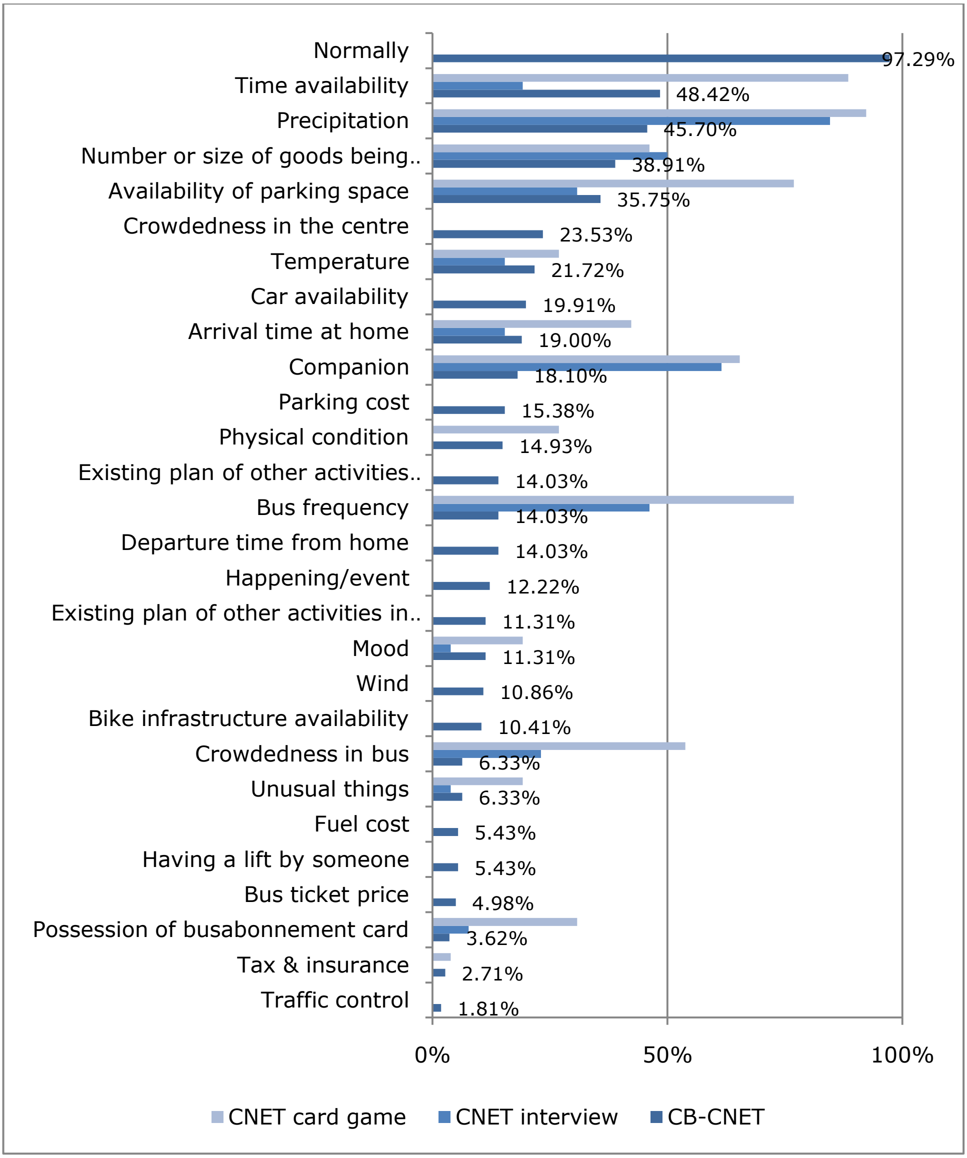


Figure 5.6 Contextual variables of the transport mode decision

The CB-CNET results in Figure 5.7 signify the high frequency of benefit elicitation of *having efficiency* (83% of the participants). Additionally, the benefit of *having freedom* is revealed by 76% of the respondents, followed by *having physical comfort* (63%), and *having convenience* (57%). These results are also similar to the most frequently chosen benefit variables in the card game data, even though the percentages of the respondents who elicit these benefits in the CB-CNET survey are generally lower. In the card game data, the most frequently chosen benefits are *having efficiency* (96%), *physical comfort* (92%), and *having convenience* (73%). Additionally, the benefit of *having freedom* is revealed by 54% of the respondents in the CNET card game interviews and 42% of the participants in the CNET interviews.

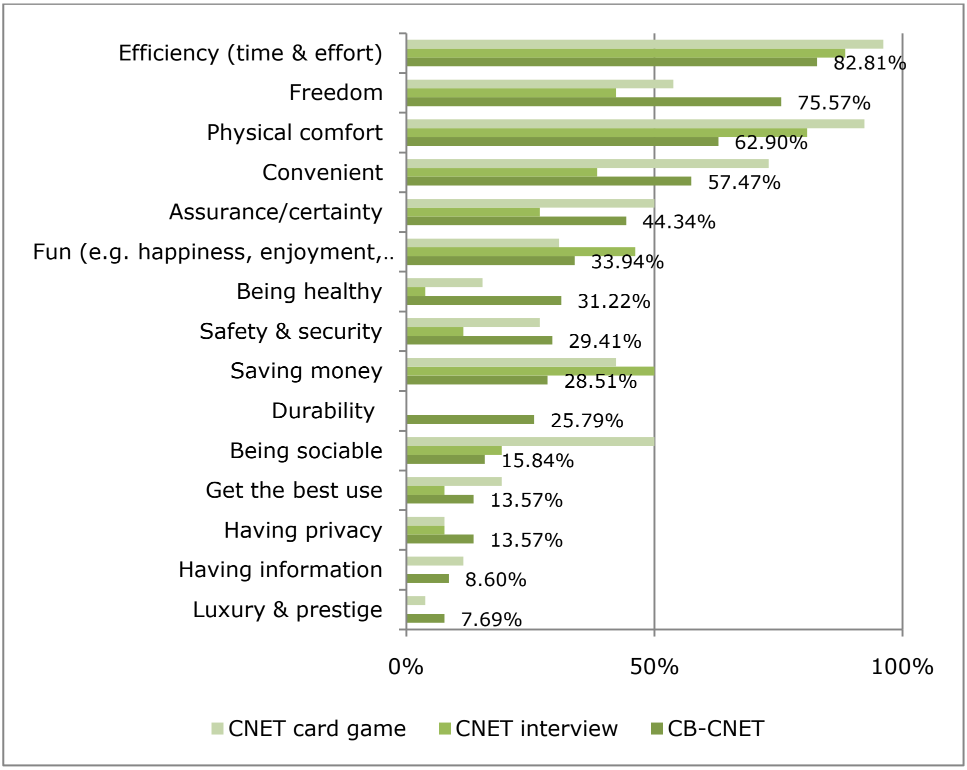


Figure 5.7 Benefit variables of the transport mode decision

Furthermore, the instrumental variables chosen by most of the participants are examined (Figure 5.8). Based on the CB-CNET data, these instruments are: *flexibility/independency* (78%), *travel time* (77%), *accessibility* (73%), *easiness for parking* (72%), etc. These instruments are different than the ones obtained in the CNET interviews; i.e. *shelter provision* (*staying dry*) (81%), *transport mode availability* (73%), *preference of transport mode* (65%), *cost* (62%), and *travel time* (54%). Based on the card game data, the following instruments are elicited most: *preference of transport mode* (92%), *shelter provision* (88%), *transport mode availability* (85%), *travel time* (85%), *easiness for parking* (85%), *flexibility/independency* (85%), and *habit* (85%). The variable of *habit* is not present in the new instrumental variable list because the individuals' transport mode and location habits are taken into account in the split elicitation procedure discussed in Chapter 4. Despite some variance in the lists, it can be seen in Figure 5.8 that the instruments revealed by different elicitation methods do not exactly match.

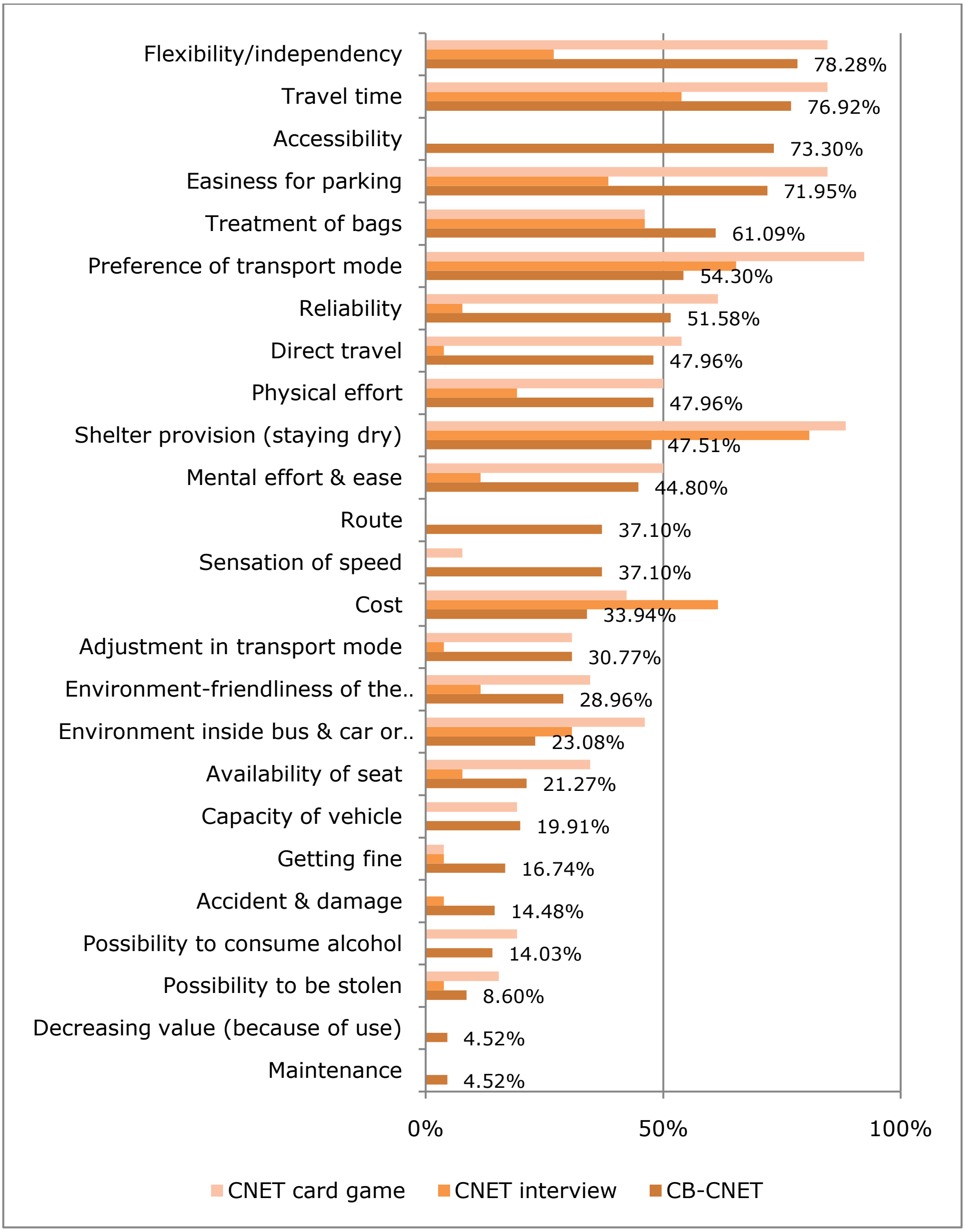


Figure 5.8 Instrumental variables of the transport mode decision

5.4.3 The shopping location decision

The CB-CNET results of the shopping location decision in Figure 5.9 indicate that the contextual variable of *interest in a specific product* is chosen by most of the respondents (68%). The *normally* variable, added automatically in the database, accounts for the largest percentage of the respondents (97%). Moreover, the contextual variable of *time availability* is also frequently selected (49%).

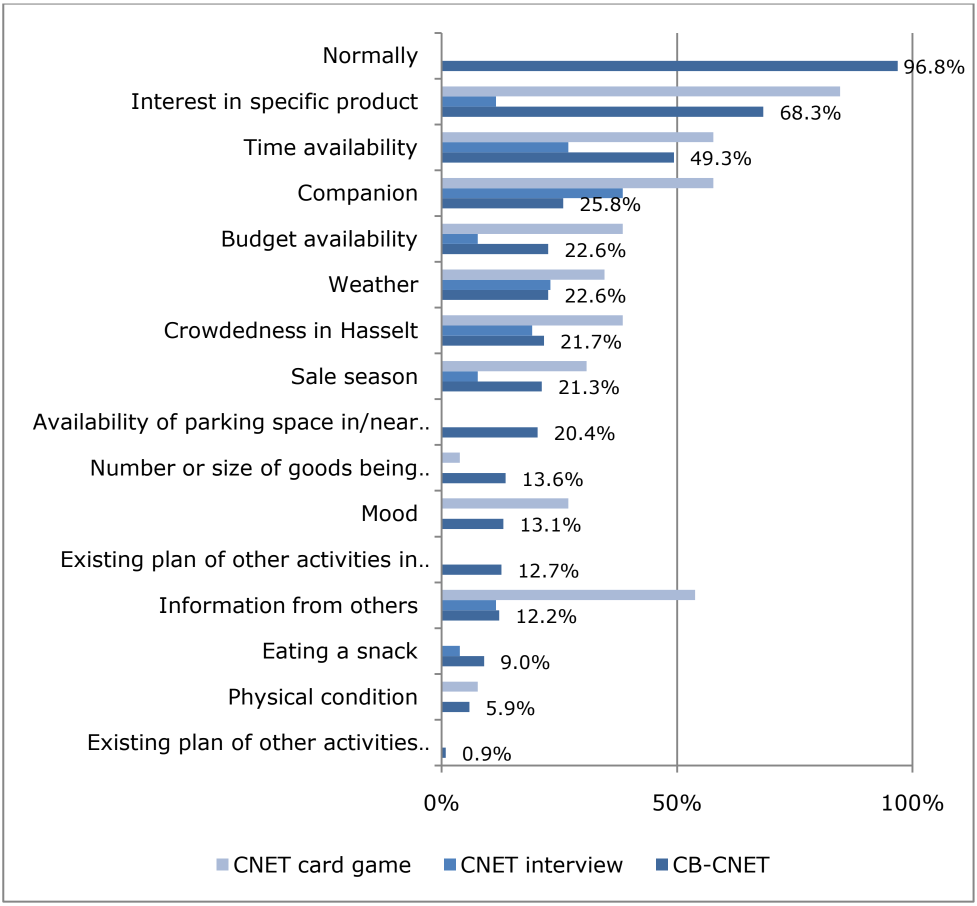


Figure 5.9 Contextual variables of the shopping location decision

Similarly, *interest in a specific product* is also revealed by most of the respondents in the card game interviews (85%), followed by *time availability* (58%) and *companion* (58%). However, these variables are not revealed so frequently in the CNET interviews; i.e. only 12%, 27%, and 39% of the respondents elicit them respectively (Figure 5.9).

Generally, the CB-CNET data show that the most pursued benefits of the shopping location decision are: *having efficiency* (77%), *having assurance or certainty* (45%), *having convenience* (45%), *saving money* (43%), and *having fun* (43%). The exact benefits (except the benefit of *having convenience*) are also frequently elicited in the card game interviews. The differences in both datasets only relate to the percentage of the participants who elicit every benefit variable (Figure 5.10).

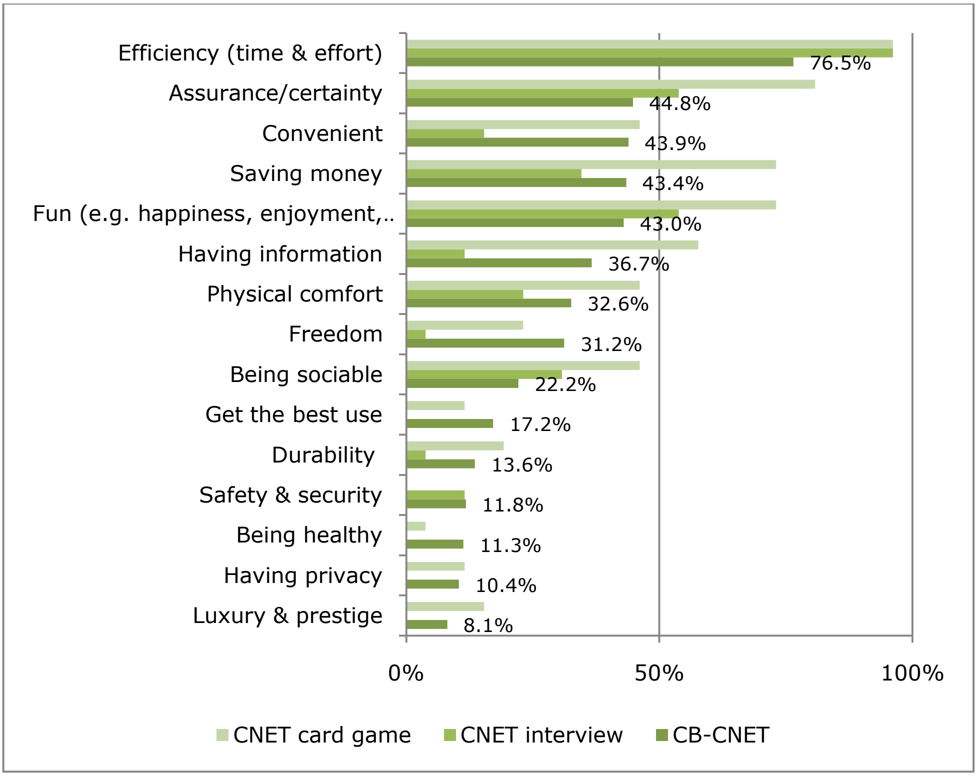


Figure 5.10 Benefit variables of the shopping location decision

Moreover, the following instruments are repeatedly chosen in the CB-CNET survey: *presence of favourite shops* (83%), *familiarity with the area* (70%), *type of store* (67%), *product price* (58%), *accessibility of the area* (55%), *and* *product quality* (55%) (Figure 5.11). The percentages of elicitation of these instruments based on the card game and interview data can also be seen in Figure 5.11. For instance, *the presence of favourite shops* is also frequently picked in the card game interviews (96%), followed by *the type of store* (92%), *shopping location preference* (92%), and *product price* (85%). Besides, *ambience or environment*, *familiarity with the area,* and *product quality* are selected by 73%, 73%, and 69% of the respondents in turn.

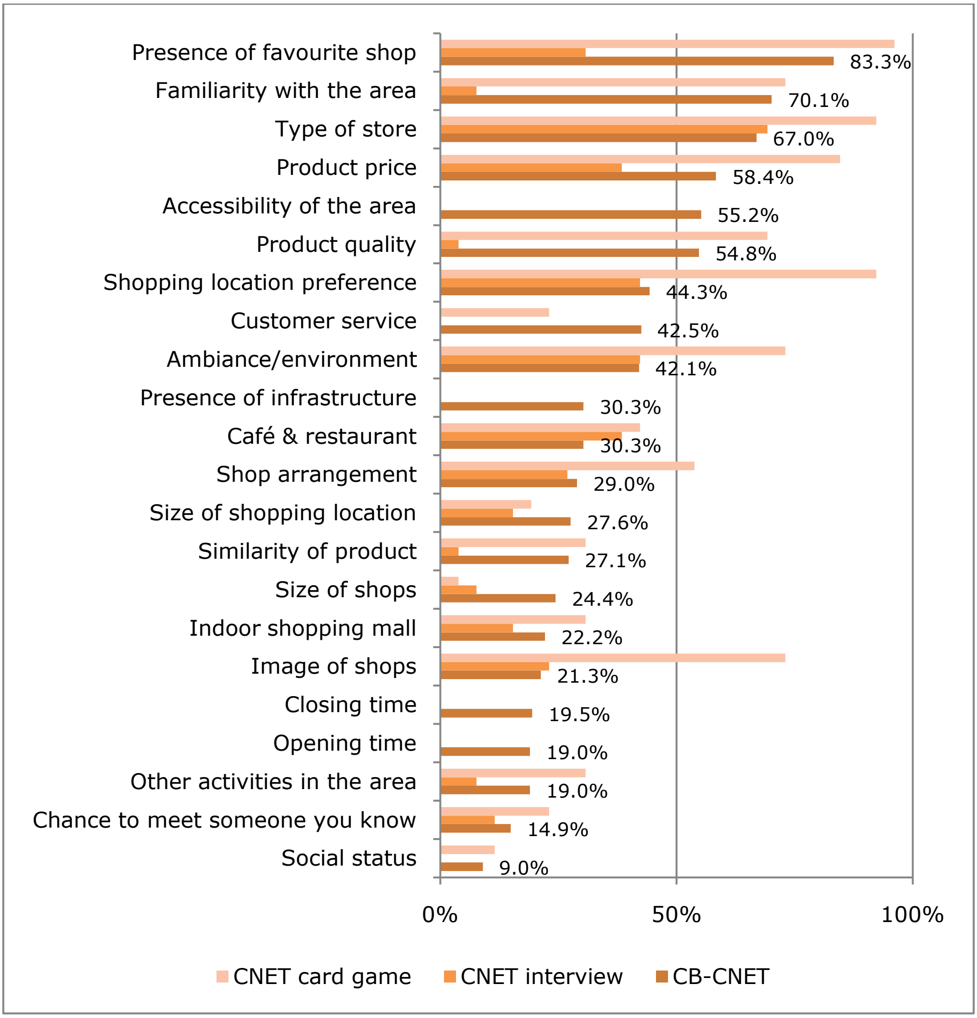


Figure 5.11 Instrumental variables of the shopping location decision

In general, the research outcomes presented in Figure 5.9-Figure 5.11 support research findings of Dawson, Bloch, & Ridgway (1990). They conclude that there are correlations among people's motivations, their actual shopping experiences, and shopping outcomes (such as satisfaction). Certain contexts, such as *people's interests in specific products*, drive them to go shopping. However, emotion-related variables (such as *favourite shop*) are the ones that in fact affect people's location choices (Nevin & Houston, 1980). Nevin & Houston (1980) also reveal that shopping area itself is often regarded as a secondary choice after this specific attractive shop. The results of this study support that finding. The instrument of *the existence of a favourite shop* is strongly considered when making shopping location choices, implying that people go to particular shopping areas because of the presence of particular shops that interest them. Other emotion-related instruments, such as *familiarity with the area* and *preference of particular locations*, are also often considered by people in this study.

Another emotion-related aspect that plays an important role in determining people's shopping behaviour based on existing literature is *mood* (an instrument). Arnold & Reynolds (2009) indicate that *individuals' mood* play an important role in determining people's decision to go shopping. People generally go shopping when they are in good mood and retailers try their best to ensure that to happen, as happy shoppers tend to purchase more goods. However, based on the results of this study, only a small number of participants (i.e. 13.1% based on the CB-CNET survey) indicate that mood affects their decisions to go to certain shopping areas. This result may be obtained because people do not consciously understand their mood nor pay attention to it. Therefore, they tend to think that mood does not play an important role to them. Considering the importance of mood based on existing research, some studies have been conducted in order to turn people's negative mood towards the positive one (e.g. Arnold & Reynolds, 2009; Erber & Tesser, 1992). For instance, Arnold & Reynolds (2009) suggest retailers to apply some strategies to defuse customers' negative feelings. This can be done by giving nostalgia-related stimuli related to positive mood. Besides, creating correct ambiance may also work in altering customers' negative emotions.

Another important shopping aspect based on the results of this study is people's conscious consideration of *product price* (an instrument). This variable is considered important by 58.4% of the respondents (based on the CB-CNET survey). This result also supports other existing research outcomes (e.g. Babin, Gonzalez, & Watts, 2007; Lichtenstein, Ridgway, & Netemeyer, 1993; Sinha & Prasad, 2004). Those studies explain how product prices affect customers' shopping behaviour.

This research has shown important aspects that people think about when making their shopping location decisions. Another study is done in order to investigate different groups of shoppers based on those aspects and their complex relationships that shape people's MR, presented in Chapter 6. The discussions concerning those results can be read in Section 6.6.

5.4.4 Conclusions: The elicited variables

Some conclusions can be drawn with regard to the elicitation methods (i.e. the CNET interview, card game, and CB-CNET). One important methodological finding of this research shows that the most frequently elicited variables using the CB-CNET and card game methods are fairly alike, indicating the stability of these variables across different methods and samples (see Figure 5.6 to Figure 5.11). However, the results of the CNET interview protocol reveal different variables, although some degree of similarity can still be observed to some extent. This could happen because the similar nature of the CB-CNET and card game methods; i.e. using variable recognition instead of self-initiated memory recall. The most similar results of both methods are observed particularly for the contextual and benefit variables. Some disparities are more apparent in the results of the instrumental variables revealed by both techniques.

5.5 The underlying elicited cognitive subsets

The frequently elicited contextual, instrumental, and benefit variables have been described in Section 5.4. In that section, a strong resemblance between the CB-CNET and card game results is discovered. However, the associations among contexts, instruments, and benefits in the participants' cognitive subsets are still concealed. Thus, this section focuses on the AR (i.e. frequent itemset) analysis, emphasizing the differences between the cognitive subsets elicited by means of the CB-CNET interface and card game protocol. Hence, this section is organized as follows: the association rules and frequent itemset analyses are briefly explained to start with (Section 5.5.1). Following that, the analysis and dataset are described (Section 5.5.2). The results are discussed in Section 5.5.3. At last, some conclusions on the underlying cognitive subsets are presented in Section 5.5.4.

5.5.1 Association rules and frequent itemset

Frequent itemset (FI) is a component of association rules (AR) analysis that has been previously described in Chapter 3. AR is a data mining technique commonly used to discover associations between items in a dataset. This method was initiated to look for patterns in transaction data in a supermarket using the form of *"IF-THEN"* statements (Agrawal et al., 1993). For instance, customers' buying records in a supermarket show that *IF* beers are bought *THEN* chips are also purchased.

In brief, the AR analysis consists of two consecutive steps. The first step is done in order to obtain all frequent itemsets from a dataset above a user-specified value, referred to as *minimum support value* or *minsup*. These itemsets are a single variable or known as a size-one itemset (e.g. {*weather*}, etc.) and combined variables. The latter could be a size-two itemset (e.g. {*weather, shelter*}, {*weather, comfort*}, {*shelter, comfort*}, etc.), or a size-three itemset (e.g. {*weather, shelter, comfort*}, etc.). The *support value* indicates the proportion of the data that contains an itemset. Once all frequent itemsets are identified, the next stage is to generate rules from these itemsets based on another user-specified value named as *minimum confidence value* or *minconf*. The *confidence value* measures the certainty of the rules. An example of the rule is *weather⇒{shelter,comfort}*, implying that *IF* the itemset of {*weather*} is present *THEN* the itemset of {*shelter, comfort*} is also observed.

The AR technique has been previously detailed in Chapter 3. Moreover, its application on the CNET interview and card game datasets has been demonstrated. The rules are learned from those datasets and in order to obtain the cognitive subsets, some interpretation has to be made from the results. This is only possible when the number of important rules is still manageable. When a large number of rules are acquired from the analysis, this process can be quite cumbersome. To solve this problem, only FI is used in this analysis. Special emphasis is given to size-three frequent itemsets that also signify the cognitive subsets.

Indeed, employing only FI analysis to learn about the underlying cognitive subsets can speed up the analysis. This happens because only the first stage of the AR analysis is done instead of having to run the whole stages of the analysis. However, this also means that some cognitive subsets could be overlooked, especially with regard to the incomplete subsets. Bearing that drawback in mind, the FI analysis is used to gain some general insight into the most frequently elicited cognitive subsets in the CB-CNET data. Moreover, the differences between these results and the results of the CNET card game analysis are shown and discussed. Details of the AR and FI analyses can be read in Chapter 3.

5.5.2 The dataset and analysis

The cognitive subset datasets are formed based on the cognitive subsets revealed in the card game interviews and CB-CNET survey. It has been previously stated in Section 5.3.2 that there are two types of subsets and both types account for considerable parts of the CB-CNET data (Table 5.3).

Accordingly, the data are split into four datasets (i.e. *the transport mode decision subset type-1*, *the transport mode decision subset type-2*, *the shopping location decision subset type-1*, and *the shopping location decision subset type-2*). Similarly, the data derived from the card game interviews are also divided into four datasets.

The descriptive statistics of the number of subsets from the CB-CNET datasets is shown in Table 5.3. Some basic statistics (i.e. *count* [*w*] and *sum* [*x*]) in that table is used to calculate the minsup value, as presented in Table 5.5a and Table 5.5c. Moreover, the description of the card game data can be seen in Table 5.5b and Table 5.5d. *Count* (*w*) represents the number of respondents in each experiment, whereas *sum* (*x*) signifies the total number of cognitive subsets revealed using each elicitation method.

A number of assumptions (i.e. *y* in Table 5.5) are tried out initially on the datasets. For the purpose of comparing the CB-CNET and card game results, *y* is set at 10%. This implies that a cognitive subset is considered as important when at least 10% of the participants elicit it in the survey. By fixing the assumption value at 10%, a sufficient number of subsets are generated, enabling the results of all datasets to be compared. At last, the user-specified minsup values (*z* in Table 5.5) are calculated using the following formula:

$z = {y \times w}/{x}$; Where *z* is the support value; *y* signifies the assumption; *w* donates the total number of respondents in the dataset; and *x* indicates the total number of cognitive subsets in the dataset.

In order to conduct the FI analysis, a specialized AR software named ARtool (Cristofor, n.d.) is used. The calculated minsup values are specified in ARtool and as results, all itemsets with the support values above the specified minsup are shown. It should be noted that special emphasis is given to all generated size-three itemsets. In order to have a better notion of the results, the support values of the (size-three) itemsets are converted into the percentages of the respondents who elicit these items. This is done by using the formula below.

The results of the analysis are presented in the subsequent section (i.e. Section 5.5.3).

$\%\_respondent = {(support\_value \times x)}/{w}$; Where *%_respondent* signifies the total percentage of the respondents who elicit a subset; *support_value* donates the calculated support value of a subset; *x* indicates the total number of cognitive subsets in a dataset; and *w* is the total number of respondents in a dataset.

Table 5.5 Minsup values for the transport mode and shopping location decision datasets

	Cognitive subset type-1	*Cognitive subset type-2*
Transport mode decision (the CB-CNET data) (a)		
Count (*w*)	221	221
Sum (*x*)	3715	3559
Minimum number of respondent (*y*)	10%	10%
Minimum support (*z*)	0.006	0.006
Transport mode decision (the card game data) (b)		
Count (*w*)	26	26
Sum (*x*)	234	147
Minimum number of respondent (*y*)	10%	10%
Minimum support (*z*)	0.01	0.02
Shopping location decision (the CB-CNET data) (c)		
Count (*w*)	221	221
Sum (*x*)	3064	2363
Minimum number of respondent (*y*)	10%	10%
Minimum support (*z*)	0.007	0.009
Shopping location decision (the card game data) (d)		
Count (*w*)	26	26
Sum (*x*)	227	123
Minimum number of respondent (*y*)	10%	10%
Minimum support (*z*)	0.01	0.02

5.5.3 Results

5.5.3.1 The transport mode decision

The results of the frequent itemset analysis are presented in Figure 5.12 (based on the CNET card game data) and Figure 5.13 (derived from the CB-CNET data).

The underlying cognitive subsets are presented on the left hand side of the figures, whereas the percentages of the respondents who elicit those subsets are shown on the right hand side. In these figures, similar subsets in the card game and CB-CNET data are indicated using black percentage bars.

From the results of the transport mode decision in Figure 5.12 and Figure 5.13, some similarities (and dissimilarities) among the cognitive subsets in the card game and CB-CNET datasets can be observed. With regard to the cognitive subset type-1, the subset of {*precipitation, shelter provision, physical comfort*} is elicited by 22% and 81% of the respondents in the CB-CNET survey (CB) and card game interviews (CG), making it the most frequently elicited subset in both datasets. This result further highlights the importance of *weather conditions* as one of the determinant factors in people's decision making. Furthermore, {*time availability, travel time, efficiency*} accounts for another recurrent subset (CB: 16%; CG: 58%). The cognitive subsets of {*number and size of goods being purchased, treatment of bags, physical comfort*} (CB: 15%; CG: 15%) and {*availability of parking space, easiness for parking, efficiency*} (CB: 13%, CG: 31%) are also revealed. In total, there are 21 important (type-1) subsets in the card game dataset and 5 subsets in the CB-CNET data.

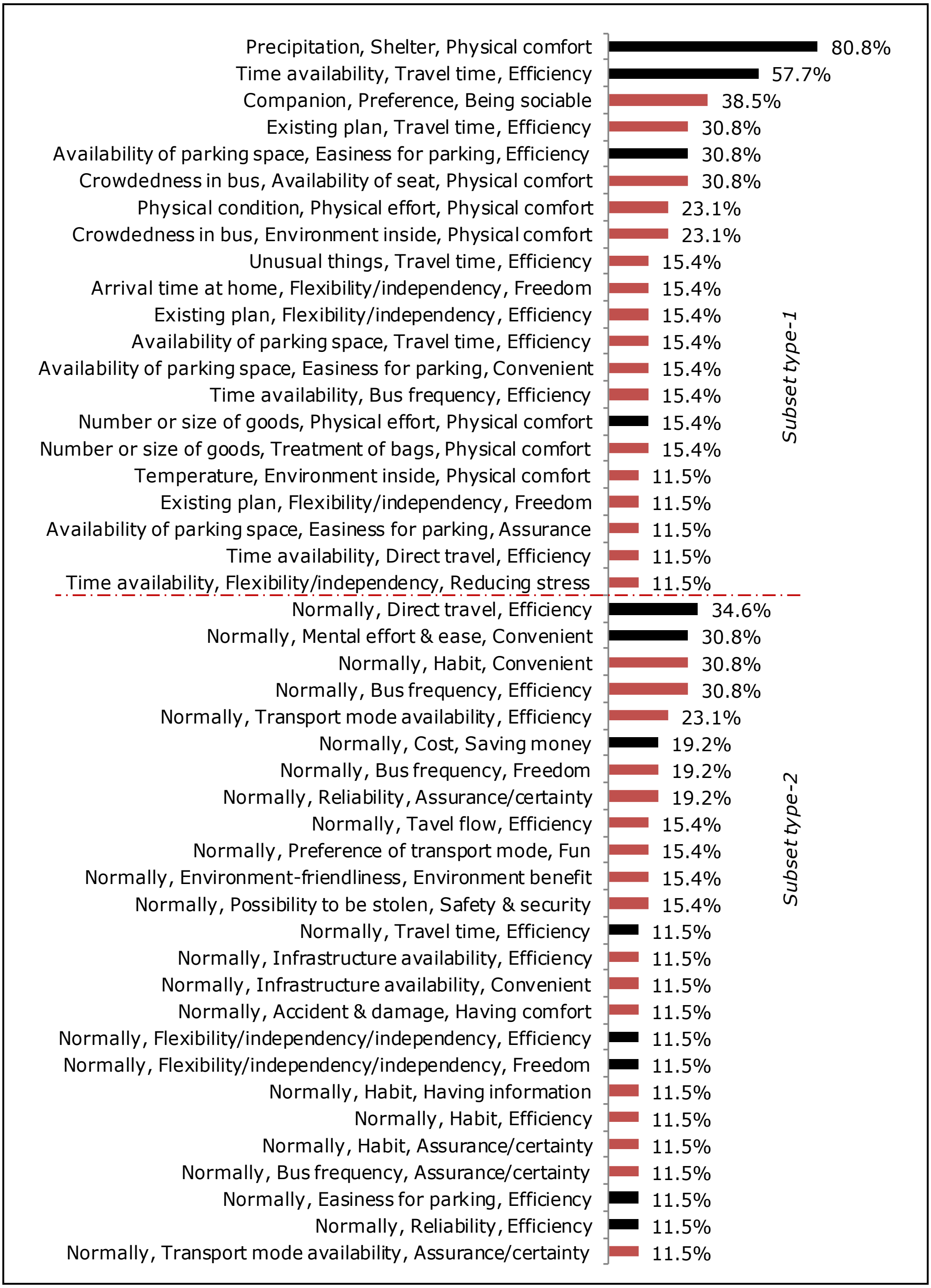


Figure 5.12 Cognitive subsets type-1 and type-2 of the transport mode decision (CNET card game)

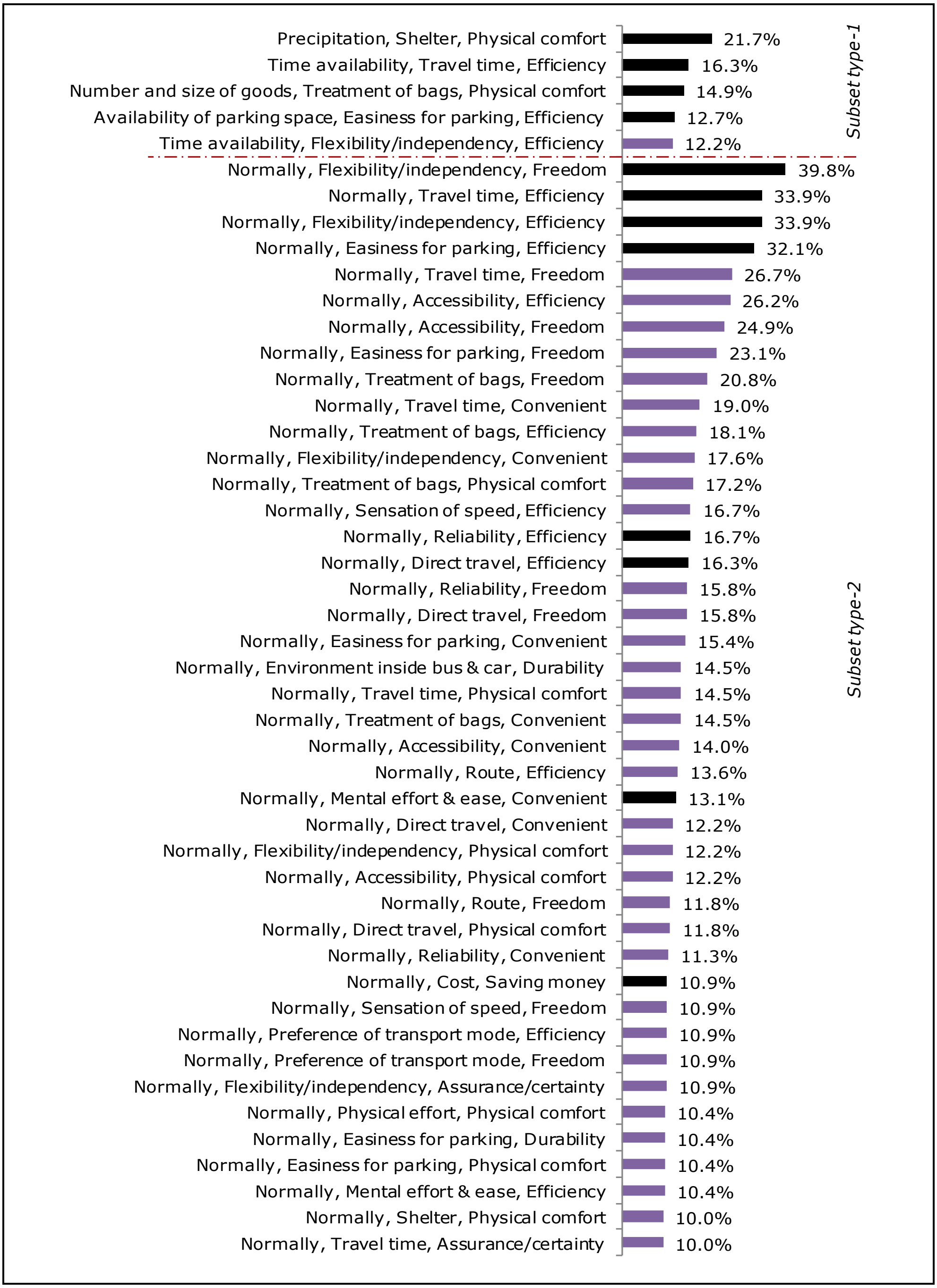


Figure 5.13 Cognitive subsets type-1 and type-2 of the transport mode decision (CB-CNET)

The second type of cognitive subsets is examined next. The results of the analysis are shown in Figure 5.12 and Figure 5.13. It can generally be seen that there are some similarities between the cognitive subsets of the CB-CNET and card game. These subsets are: {*normally, flexibility/independency, freedom*} (CB: 40%, CG:12%); {*normally, travel time, efficiency*} (CB: 34%, CG: 12%); {*normally, flexibility/independency, efficiency*} (CB: 34%, CG:12%); {*normally, easiness for parking, efficiency*} (CB: 32%, CG:12%); {*normally, reliability, efficiency*} (CB: 17%%, CG:12%); {*normally, direct travel, efficiency*} (CB: 16%, CG: 16%), {*normally, mental effort & ease, convenient*} (CB: 13%, CG: 31%); and {*normally, cost, saving money*} (CB: 11%, CG: 19%). It can be observed that these subsets are mostly related to the benefit of *having efficiency*. Additionally, there are other benefits as well, with a lower number of subsets, such as *having freedom*, *having convenience*, and *saving money*. In total, there are 25 subsets in the card game results and 42 subsets in the CB-CNET outcomes.

Furthermore, it can be seen in Figure 5.12 that the number of the cognitive subset type-1 is less than the type-2, specifically in the CB-CNET data. This implies that there are more varieties in the CB-CNET data concerning the type-1 subsets. The same trend cannot be observed in the card game data, in which the numbers of frequently revealed subsets (type-1 and type-2) are relatively equal.

5.5.3.2 The shopping location decision

With regard to the shopping location decision, the results of the frequent itemset analysis are presented in Figure 5.14 (i.e. the card game data) and Figure 5.15 (i.e. the CB-CNET data). Similar to the transport mode decision results, some similarities of the results of both elicitation methods can be observed, denoting as the black percentage bars in the figures.

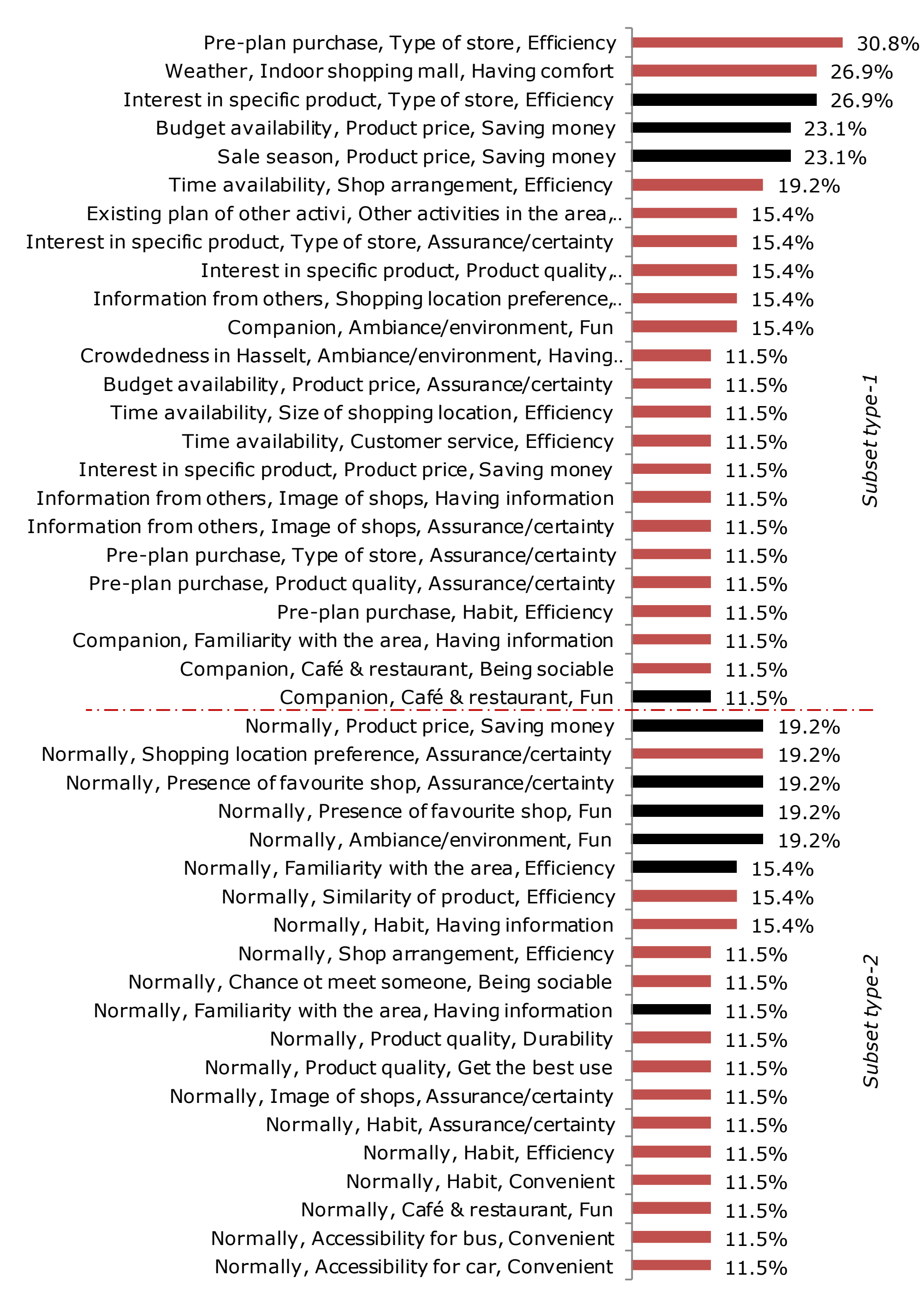


Figure 5.14 Cognitive subsets type-1 and type-2 of the shopping location decision (CNET card game)

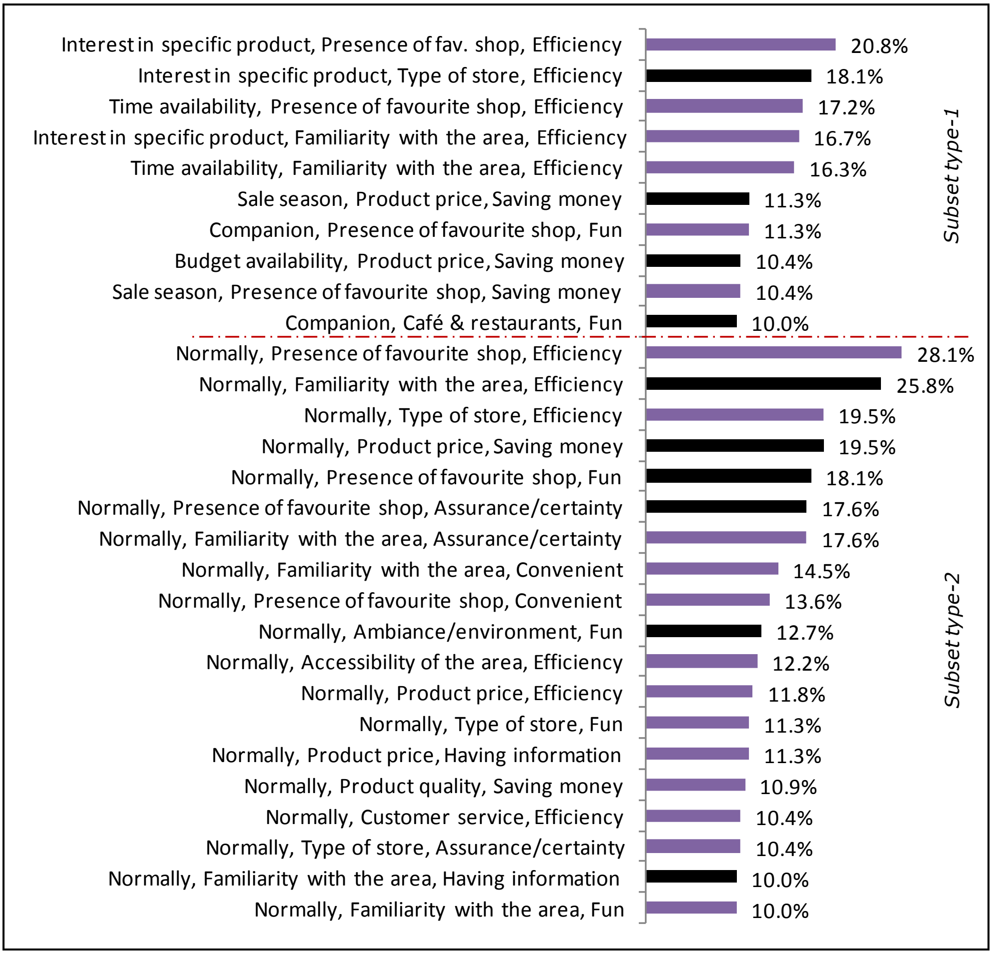


Figure 5.15 Cognitive subsets type-1 and type-2 of the shopping location decision (CB-CNET)

The following (type-1) cognitive subsets are registered: {*interest in specific products, type of store, efficiency*} (CB: 21%, CG: 27%); {*sale season, product price, saving money*} (CB: 11%, CG: 23%); {*budget availability, product price, saving money*} (CB: 10%, CG: 23%); and {*companion, café & restaurants, fun*} (CB: 10%, CG: 12%). In total, 24 and 10 (type-1) subsets are recorded in the card game and CB-CNET results in turn.

The results of frequently elicited (type-2) cognitive subsets are shown in Figure 5.14 and Figure 5.15. A total number of 20 and 19 (type-2) cognitive subsets are presented in the figures, derived from the card game and CB-CNET datasets. Similar subsets in both datasets are: {*normally, familiarity with the area, efficiency*} (CB: 26%, CG: 15%); {*normally, product price, saving money*} (CB: 20%, CG: 19%); {*normally, presence of favourite shops, fun*} (CB: 18%, CG: 19%); {*normally, ambiance/environment, fun*} (CB: 13%, CG: 19%); and {*normally, familiarity with the area, having information*} (CB: 10%, CG: 12%).

5.5.4 Conclusions: The cognitive subsets

In the CB-CNET and card game results, some similarities of the elicited cognitive subsets can be observed to some extent. It should be noted that the lists of the predefined variables in both experiments are not exactly identical, making the exact matching of the results less likely to occur.

From a content point of view, it can be concluded that *having efficiency* and *comfort* are the benefits strongly pursued by people when making the transport mode decision. With regard to the shopping location decision, the benefits of *having efficiency*, *saving money*, and *having fun* are important. Additionally, the benefit of *having information* is also aimed at regardless of the occurring contexts (e.g. related to *the familiarity of the shopping area*).

Furthermore, the FI analysis of AR allows us to gain insight into the transport mode instruments that can be used to satisfy individuals' needs, in any circumstance or given some affecting contexts. This information can be used to improve public transport systems and to make people shift their transport mode choices from car to bus or bike, as previously highlighted in Chapter 3.

5.6 The impact of time pressure on individuals' mental representations

Time availability is considered as an important context that influence people's travel-related decision making processes related to leisure-shopping activities, as previously shown in Section 5.4.2 and Section 5.4.3. This result in fact supports research outcomes of many existing studies, such as a study by Maule, Hockey, & Bdzola (2000), investigating the significant effect of time pressure on people's decision making.

Time pressure itself can be seen as an undesired condition caused by limited time to accomplish a task (Thomas, Esper, & Stank, 2010), causing stress (Iyer, 1989; Ordóñez & Benson, 1997; Park, Iyer, & Smith, 1989). In the marketing literature, time pressure is seen as a factor that influences customers' shopping behaviour (Mattson, 1982). It makes people become less-engaged with impulsive buying activities (Iyer, 1989), as it reduces information search and decreases people's satisfaction (Putrevu & Ratchford, 1997). Other research by McDonald (1994) states that emphasis on customers' sensitivity to time availability should also be given as a part of marketing research efforts. This is not just related to the actual shopping time, but also to travel time (to and from stores).

Hence, considering the importance of time pressure in effecting people's leisure-shopping behaviour, this study further investigate the influence of this variable on people's MR. For this purpose, two scenarios are tested using the CB-CNET interface, dividing the sample into two groups at random. These two scenarios are set in order to investigate the impact of time pressure on individuals' leisure-shopping travel behaviour. It is expected that the individuals' cognitive representations under time pressure are more simple and straightforward than the ones activated in the situation without time constraint. Moreover, the content of the individuals' MR in these two distinct scenarios is further investigated. Hence, the remainder of this section is structured as follows: the research scenarios are explained to start with (Section 5.6.1). The sizes of individuals' mental representations in different scenarios are studied next, in Section 5.6.2. Furthermore, the content of the individuals' MR in both scenarios is investigated, along with the associations among aspects in the elicited MR (Section 5.6.3). At last, some conclusions on the impact of time constraint on MR are presented and discussed in Section 5.6.4.

5.6.1 Research scenarios

The first scenario is shopping without time constraint. In the second scenario, the respondents are asked to imagine that they have limited time available to fun-shop. These scenarios have been shown in Chapter 4, Section 4.3.1, and can be seen again below.

Scenarios:

"Your friend has a party this Sunday evening. Even though it is not obligatory, you think that it will be nice to buy something for the occasion (a gift and/or something to wear)."

Scenario 1: *"Today is a Friday night in autumn and it appears that* ***you have plenty of time available on Saturday afternoon.*** *You can use this spare time to go fun-shopping in the city centre of Hasselt to look for an item for the occasion."*

Scenario 2: *"Today is a Friday night in autumn and it appears that* ***you have a very busy schedule on Saturday****. Nevertheless there is a small time gap in your afternoon schedule that you can use to go fun-shopping in the city centre of Hasselt to look for an item for the occasion."*

"Fun-shopping" is a leisure activity related to collecting some shopping information; e.g. stores that are available, products that are sold, price of the products, etc. It can be related to actually buying goods, but this is not necessarily the case. It relates to goods you do not buy every day, like clothing, electronics, etc."

The respondents are assigned to one of the scenarios above in a random order. In total, 111 respondents experience the no time pressure scenario, whereas 110 respondents are subjected to the time pressure scenario.

5.6.2 The complexity of individuals' mental representations in different scenarios

The complexity of the participants' MR in different scenarios is examined by means of the numbers of the elicited aspects and (type-1 and type-2) subsets. The results of some descriptive statistics based on the number of aspects are presented in Table 5.6. These results show that in general, there are no major differences between the numbers of aspects in different scenarios, unlike the expectations. The number of contexts in the time pressure scenario is slightly larger than in the no time pressure setting. Similarly, the average number of instruments in the time pressure context is also slightly larger than in the no time pressure scenario. The rest of the average numbers of the variables are relatively similar.

Table 5.6 The number of aspects in different settings: no time pressure (a) and time pressure (b) scenarios

	Transport mode			*Shopping location*		
	C[1]	*I*[2]	*B*[3]	*C*	*I*	*B*
a. No time pressure scenario						
Mean	3.95	9.23	5.29	3.17	7.87	4.41
Median	4	8	5	3	8	4
Mode	3	7	4	3	8	3
Range	17	22	12	9	21	9
Min.	0	1	1	0	1	1
Max.	17	23	13	9	22	10
Sum	439	1025	587	352	874	490
Count	111	111	111	111	111	111
95% CI[4]	0.52	0.80	0.43	0.35	0.85	0.41
b. Time pressure scenario						
Mean	4.77	9.78	5.34	3.22	8.35	4.52
Median	4	9	5	3	7.5	4
Mode	5	7	3	3	7	5
Range	25	23	14	9	21	13
Min.	0	2	1	0	1	1
Max.	25	25	15	9	22	14
Sum	525	1076	587	354	919	497
Count	110	110	110	110	110	110
95% CI	0.73	0.86	0.48	0.35	0.86	0.47

[1] Contextual variable
[2] Instrumental variable
[3] Benefit variable
[4] Confidence interval

Additionally, the same analysis is redone based on the number of cognitive subsets elicited by the respondents. The results are presented in Table 5.7; i.e. for all types of subsets, and for the first and the second types of subsets. The results in Table 5.7 unveil that the average numbers of (all-type) subsets are larger in the time pressure scenario for both the transport mode and location decisions. In order to check whether there is a statistically significant difference between the average numbers of contexts in the time pressure and no time pressure scenarios, t-test statistics of two sample is conducted (i.e. assuming unequal variances). The results of the t-test analysis are shown in Table 5.8, indicating that both p-values (two-tail) are larger than 0.05 (i.e. 0.10 and 0.27 for the transport mode and shopping location decisions in turn). This means that there is no sufficient evidence to reject the null hypothesis of equal means. In other words, the means of (all-type) subsets in both scenarios are equal, for the transport mode and location decisions.

Table 5.7 The number of cognitive subsets in different settings: no time pressure (a) and time pressure (b) scenarios

	Transport mode			*Shopping location*		
	All types	*Type-1*	*Type-2*	*All types*	*Type-1*	*Type-2*
a. No time pressure scenario						
Mean	28.14	14.16	13.98	22.06	12.59	9.47
Median	20	10	8	18	10	6
Mode	10	0	4	5	2	2
Range	179	65	138	134	58	108
Minimum	1	0	0	1	0	0
Maximum	180	65	138	135	58	108
Sum	3124	1572	1552	2449	1398	1051
Count	111	111	111	111	111	111
95% CI[1]	4.99	2.66	3.38	3.94	2.15	2.49
b. Time pressure scenario						
Mean	37.73	19.48	18.25	27.07	15.15	11.93
Median	23.5	12	10	18.5	10	7
Mode	15	9	5	15	8	4
Range	398	161	239	413	137	277
Minimum	2	0	0	1	0	0
Maximum	400	161	239	414	137	277
Sum	4150	2143	2007	2978	1666	1312
Count	110	110	110	110	110	110
95% CI	10.36	4.69	6.47	7.97	3.24	5.12

[1] Confidence interval

Table 5.8 T-test statistics of two-sample assuming unequal variances: transport mode (a) and shopping location (b) decisions

	a. Transport mode		*b. Shopping location*	
	No time pressure	*Time pressure*	*No time pressure*	*Time pressure*
Mean	28.14	37.73	22.06	27.07
Variance	703.89	3006.04	438.39	1777.70
Observations	111	110	111	110
df	157		159	
t Stat	-1.65		-1.12	
P(T<=t) one-tail	0.05		0.13	
t Critical one-tail	1.65		1.65	
P(T<=t) two-tail	0.10		0.27	
t Critical two-tail	1.98		1.97	

5.6.3 The elicited cognitive subsets in different scenarios

This section highlights the differences of the aspects in different (time constraint) scenarios. For this reason, FI analysis is used once more to discover important associations among aspects in the participants' MR. The similar types of information and assumption as previously shown in Table 5.5 are used to calculate the minsup value using the formula below. The calculated minsup values are shown in Table 5.9.

$z = {}^{y \times w}\!/_{x}$; Where *z* is the support value; *y* is the assumption; *w* is the total number of respondents in a dataset; and *x* is the total number of cognitive subsets in a dataset.

Table 5.9 Minsup values for the transport mode (a) and shopping location (b) datasets in different time pressure scenarios

	a. Transport mode		*b. Shopping location*	
	No time pressure	*Time pressure*	*No time pressure*	*Time pressure*
Count (*w*)	111	110	111	110
Sum (*x*)	3124	4150	2449	2978
Minimum number of respondent (*y*)	10%	10%	10%	10%
Minimum support (*z*)	0.004	0.003	0.005	0.004

Furthermore, ARtool software is employed. The results are the (size-three) itemsets with the support values above the calculated minsup values. Hence, using the formula below, the percentages of the respondents who elicit the subsets can be obtained. The final results are presented in Figure 5.16 (for the transport mode decision) and Figure 5.17 (for the shopping location choice).

$\%\_respondent = {}^{(support\_value \times x)}\!/_{w}$; Where *%_respondent* signifies the total percentage of the respondents who elicit a subset; *support_value* donates the calculated support value of a subset; *and x* and *w* signify the total numbers of cognitive subsets and respondents in the dataset, subsequently.

5.6.3.1 The transport mode decision

The results of the most frequently elicited cognitive subsets in the time pressure and no time pressure scenarios for the transport mode decision are presented in Figure 5.16. The figure shows that the number of cognitive subsets in the time pressure scenario is larger than in the no time pressure setting. Furthermore, there are some similarities of the subsets being revealed in both scenarios, as indicated by the overlapping percentage bars in Figure 5.16. For instance, the cognitive subset of {*precipitation, shelter provision, physical comfort*} is revealed by 17% and 26% of the participants in the no time pressure (NTP) and time pressure (TP) scenarios successively. Furthermore, the following subsets are disclosed: {*time availability, travel time, efficiency*} (NTP: 14%, TP: 19%), {*availability parking, easiness for parking, efficiency*} (NTP: 14%, TP: 12%), and {*number or size of goods, treatment of bags, physical comfort*} (NTP: 12%, TP: 18%).

With regard to the second type of cognitive subsets, the subsequent subsets are extracted: {*normally, flexibility & independency, efficiency*} (NTP: 29%, TP: 39%), {*normally, easiness for parking, efficiency*} (NTP: 31%, TP: 34%), {*normally, travel time, efficiency*} (NTP: 34%, TP: 34%), and {*normally, flexibility & independency, freedom*} (NTP: 41%, TP: 3%) There are other (type-2) subsets that are unveiled as well, as shown in Figure 5.16. However, the subsets mentioned above account for the highest percentages of the respondents who elicit them.

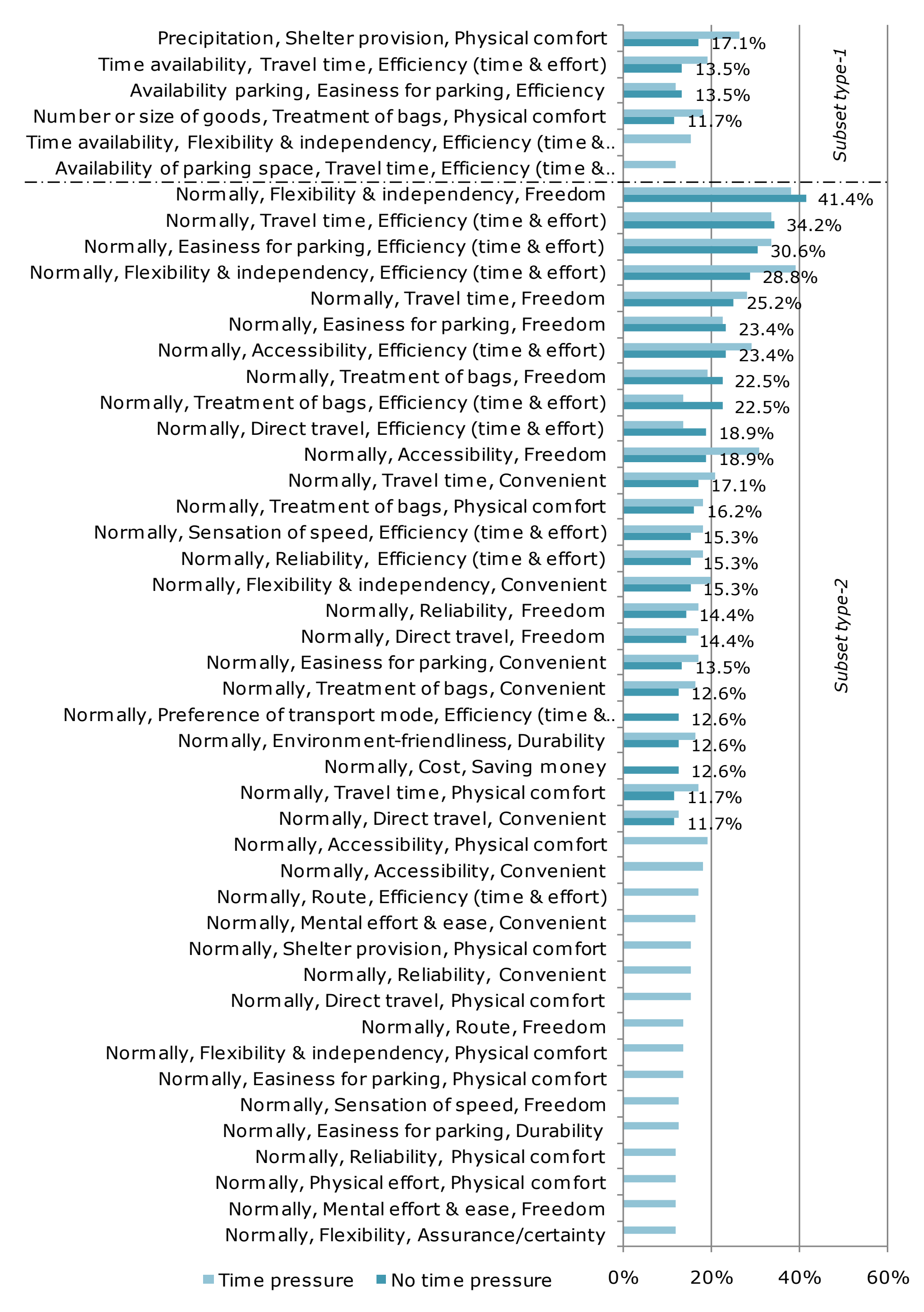


Figure 5.16 Cognitive subsets of the transport mode decision in different time pressure scenarios

5.6.3.2 The shopping location decision

The results of the shopping location decision can be seen in Figure 5.17. In general, the results of this decision show a similar trend to the outcomes of the transport mode decision; i.e. a larger number of important subsets are revealed under the time pressure scenario.

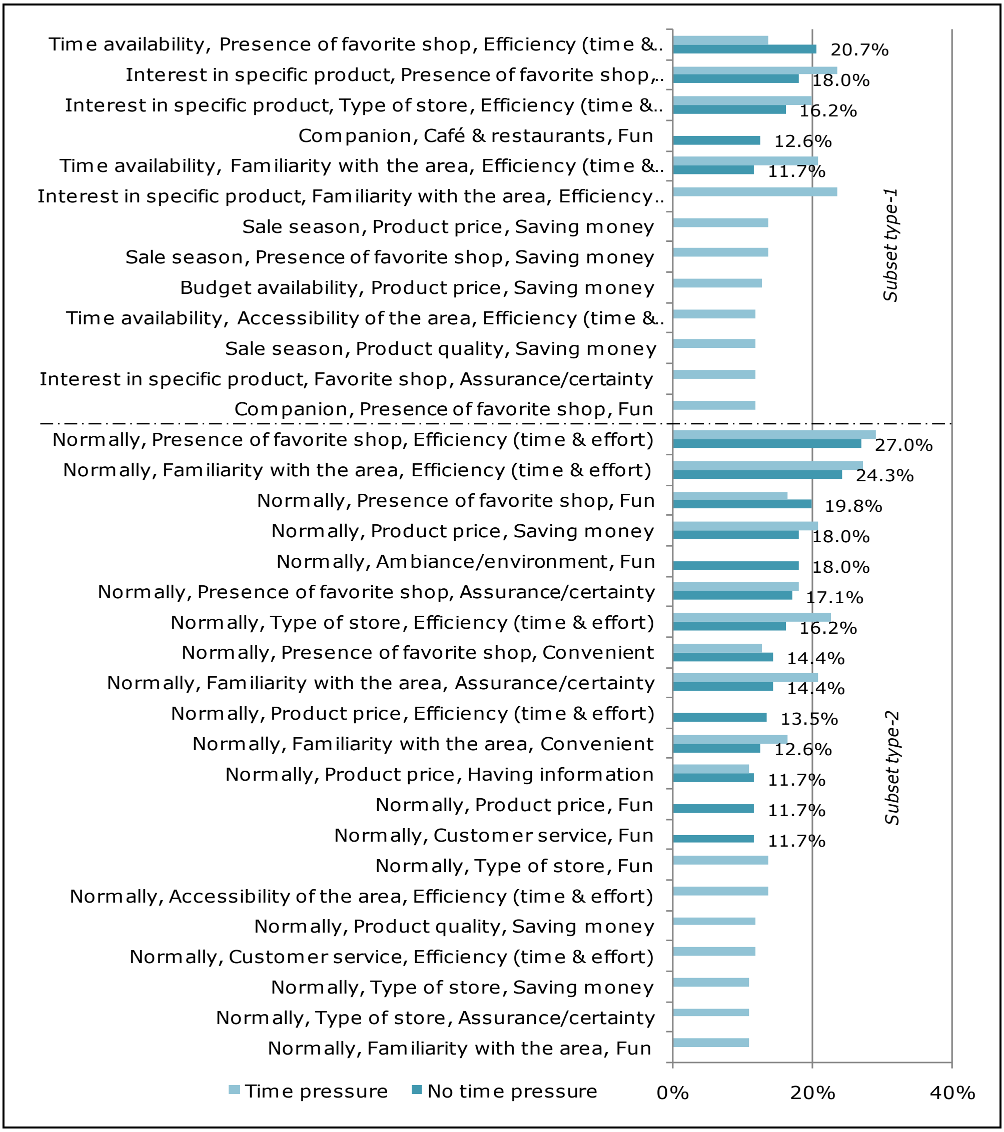


Figure 5.17 Cognitive subsets of the shopping location decision in different time pressure scenarios

The crucial (type-1) shopping location subsets are: {*time availability, presence of favourite shops, efficiency*} (NTP: 21%, TP: 14%), {*interest in a specific product, presence of favourite shop, efficiency*} (NTP: 18%, TP: 24%), {*interest in a specific product, type of store, efficiency*} (NTP: 16%, TP: 20%), and {*time availability, familiarity with the area, efficiency*} (NTP: 12%, TP: 21%). With regard to the second type of cognitive subsets, a number of subsets are uncovered: {*normally, presence of favourite shop, efficiency*} (NTP: 27%, TP: 29%), {*normally, familiarity with the area, efficiency*} (NTP: 24%, TP: 27%), {*normally, presence of favourite shop, fun*} (NTP: 20%, TP: 16%), and {*normally, product price, saving money*} (NTP: 18%, TP: 21%).

5.6.4 Conclusions and discussions: The impact of time pressure scenarios on individuals' mental representations

The analyses conducted in Section 5.6 aim at investigating the differences of individuals' MR of leisure-shopping travel decisions under different time constraint scenarios; i.e. shopping with and without time pressures. Time pressure is particularly chosen because it is expected that an individual decision maker activates much simpler MR in that context. Accordingly, the numbers of aspects and cognitive subsets revealed in the survey are examined. The results of t-test of two-sample indicate that the sizes of the participants' MR in both scenarios are in fact alike.

The second analysis of FI is conducted to study the content of the elicited cognitive subsets in the time pressure and no time pressure scenarios. From the content point of view, it can be concluded that there are some similarities between the cognitive subsets considered in the time pressure scenario and the ones deliberated in the no time pressure context. However, the number of important subsets (i.e. above the pre-set assumption of 10%) is larger in the time pressure scenario. This may happen because the participants are actually not asked to plan their fun-shopping travel under real time pressure. Instead of that, they are asked to imagine what their deliberations would look like when they have to plan an execution of an activity in a very busy day. Therefore, the results indicate that there are more important aspects to consider because of the time restriction that is imposed. When imagining an activity execution under time limitation, people tend to think more about aspects that may help them fulfilling their needs (pursued benefits). Because of that, the interaction between the time constraint and other possible occurring contexts becomes more important, as well as the relations between the time pressure and the instruments and benefits. In other words, when facing a more complex and demanding decision problem (i.e. shopping under time pressure), an individual decision maker activates a more complex MR in order to find the most satisfactory solution to solve the problem, given the uncertainty in the decision environment caused by the occurrence of a large number of other possible contexts.

5.7 Conclusions

This chapter highlights a number of issues to describe the sample and to take a first look at the data. It is divided into five main sections. The first part discusses the sample recruitment procedure and further describes the characteristics of the sample. The second and the third parts subsequently focus on the complexity of participants' MR and aspects considered in it, comparing the analysis results of the CB-CNET data and the other CNET protocols. The last part examines people's MR when making trips with and without time constraints. Detailed conclusions are presented in the end of each section, and briefly summarized here below. To start with, the sample criteria are explained, followed by the description of the sampling techniques. The sample is further described based on the participants' socio-demographic characteristics, their travel behaviour and fun-shopping behaviour. Some categories of the socio-demographic characteristics are over- or under-represented. However, in general the sample representatively portrays all the predefined categories (i.e. age, income categories, education levels, etc.).

Furthermore, the MR data are explored. In the beginning, the complexity of the participants' MR is depicted by means of some descriptive statistics on the numbers of aspects and subsets being elicited in the survey. It can be concluded that the individuals' MR of the transport mode decision is commonly more complex and elaborate than the MR of the shopping location decision.

The next analysis aims at studying the content of the participants' MR. Moreover, the results of the CB-CNET data are compared to the results of the CNET interview and card game datasets. From those comparisons, it can be seen than the outcomes of the CB-CNET survey correspond to the results of the card game interviews. This indicates strong correlations between different elicitation methods (i.e. CB-CNET and card game protocols) which have the same basic principal (i.e. variable recognition). The results of the CB-CNET survey can, to some extent, verify the results of the card game interviews. Moreover, the FI analysis is conducted on the CB-CNET datasets. The results are compared to the card game results.

The last analysis in this chapter focuses on the impact of different time pressure scenarios on the participants' MR (i.e. shopping with and without time constraints). The sizes of the participants' MR in different scenarios are studied. It can be concluded that the sizes of the elicited MR are relatively stable across different scenarios. An additional analysis is done to uncover the underlying subsets in both settings. The results show that people have stronger deliberation when planning an activity that has to be carried out under time pressure. This also indicates that in fact people have more worries due to the unfavourable context imposed in the planning of the fun-shopping activity. Consequently, a decision maker seems to activate a more complex MR to come out with the best possible solution that can satisfy his needs given the demand of the task and the uncertainty in the decision environment caused by the variety of other possible occurring contexts. However, it is believed that when the activity is carried out impulsively, individuals most likely activate simpler MR (e.g. by using a habitual or script based behaviour) under the time pressure in order to gain more efficiency in their decision making. Unfortunately, this issue cannot be answered in this current research.

The results of the descriptive statistics and FI analysis on the cognitive subset data show the diversity of the sizes and the content of the important cognitive subsets, based on the CB-CNET data. This may give an indicator that the participants can be further categorized into a number of groups, based on their MR. This issue is examined in the next chapter (i.e. Chapter 6). Different groups of participants based on their elicited MR are analyzed, highlighting the differences among groups of people and aspects that are important to them. The results are discussed concerning a number of TDM policies that could be effective to alter travel behaviour of people with car-use habit into other, more sustainable, transport mode use behaviours.

6 The typology of fun-shopping travellers

"An unfortunate thing about this world is that the good habits are much easier to give up than the bad ones."

W. Somerset Maugham

6.1 Introduction

A computer-based elicitation interface named CB-CNET has been developed to gather behavioural process data of individuals, particularly when making travel decisions to perform leisure-shopping activities in a city centre. The interface has been used in a survey involving 221 participants. Hasselt city centre is chosen as a case study. The interface is detailed in Chapter 4. Moreover, the sample is explained in Chapter 5, along with the general description of the participants' MR.

The gathered behavioural data allow for clustering people based on their MR. This approach is fairly different than the one commonly used in the transportation research field. There, a priori socio-demographic characteristics are typically used to classify people into meaningful sub-groups (e.g. Shay & Khattak, 2007). Members of each group share similar (socio-demographic) characteristics. A number of strategies (or policies) are formulated accordingly and people's responses are predicted. However, this segmentation type may lead to bias in understanding behavioural tendencies (Anable, 2005). Segmenting people based on socio-demographic characteristics assumes that that people with comparable background have similar travel behaviour, which is not always the case. For this reason, in this study, the typology of fun-shopping travellers is learned from the MR data. People in the same group share similar way of thinking concerning their transport mode and location choices, making it more realistic to assess their behavioural changes due to certain policies.

This chapter gives emphasis to the typology of fun-shopping travellers based on the transport mode decision. Hence, *cluster analysis* is employed sequentially to generate the clusters. An additional *Fisher's test* is used to check if there is an association between these clusters and people's (transport mode) habit. Moreover, *frequent itemset* (FI) analysis is conducted to learn the general MR associated with these groups. This information is relevant to transportation planners, to break car-use habit by analyzing TDM that can boost the attractiveness of bike-use and bus-use and reduce the attractiveness of car-use. Similar analyses are also performed on the shopping location decision dataset and the results are also presented. The results of this decision are discussed from the marketing point of view, highlighting aspects considered by people when making their shopping location choices.

The remainder of this chapter is structured as follows: the first analysis is presented in Section 6.2. This section aims at clustering the participants based on their MR. The complexity of the participants' MR in the clusters are presented next, in Section 6.3. In Section 6.4, the underlying cognitive subsets in each cluster are illustrated. Furthermore, another analysis is conducted in Section 6.5 to check the differences among clusters, concerning the participants' characteristics, such as socio-demographic aspects, travel behaviour and fun-shopping behaviour. In the next section (i.e. Section 6.6), some results are drawn and discussed. The discussions concerning the transport mode decision emphasize TDM policies that work best for different groups of people. At last, the results of the shopping location decision are discussed from the marketing point of view. Some conclusions are drawn in Section 6.7.

6.2 Clustering the participants' mental representations

This section is organized as follows: the dataset to cluster the participants' MR is explained to start with (Section 6.2.1). In Section 6.2.2, a number of clustering techniques are described and one method is selected. In Section 6.2.3, the results of the analysis are shown.

6.2.1 The dataset

In order to apply cluster analysis on the MR data, a dataset is arranged, as shown in Figure 6.1. Each row in the figure represents a participant's record. Since there are 221 participants in the survey, the total number of rows in the dataset equals 221. Each column symbolizes a variable, in this case the presence (1) or absence (0) of a combination of {*context, instrument, benefit*}, or known as a cognitive subset, in the participants' MR. The example of a subset is {*precipitation, shelter provision, comfort*}. Two travel decisions (i.e. *the transport mode* and *location choices*) are investigated in the survey using the CB-CNET protocol, resulting in two separate datasets. A total number of 28 contexts (including the "*normally*" variable), 25 instruments and 15 benefits are listed for the transport mode decision, leading to 28x25x15=10500 possible cognitive subsets. However, only 1799 cognitive subsets are elicited by the participants. Thus, they are registered as the variables in the transport mode decision dataset. The dataset of the shopping location decision consists of 1342 variables (signifying the total number of occurring subsets) derived from the combinations of 16 contextual aspects (including the "*normally*" variable), 22 instrumental aspects and 15 benefits. The whole lists of variables and variable definitions are recorded in the appendices (i.e. Appendix F). In order to select a clustering method suited to this study, a technique for binary variables is looked for. This is explained in Section 6.2.2 below.

Participants' ID

$C_xI_yB_z$: {context-x, instrument-y, benefit-z}

ID	$C_{10}I_{48}B_{84}$	$C_{10}I_{48}B_{86}$	$C_{10}I_{48}B_{88}$	$C_{10}I_{48}B_{89}$
1	0	1	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
5	0	1	0	1
6	0	0	0	0
7	0	0	1	0
8	0	0	1	0
9	0	1	0	0

...1799 variables

Binary variables
1: The cognitive subset is elicited (present) in MR
0: The cognitive subset is not elicited (absent) in MR

.
.
.
221 participants

Figure 6.1 An example of a mental representation dataset for cluster analysis

6.2.2 Cluster analysis

Cluster analysis (CA) is an unsupervised learning method that aims at exploring a dataset. "Cluster analysis" terminology was firstly used by Tryon (1939). This technique finds groups in a dataset based on the degree of associations among its entities. Thus, the relationship between two objects is maximal when they are in the same group and minimal otherwise (StatSoft, Inc., 2010). This technique has commonly been used to develop taxonomies, to investigate valuable conceptual schemes for grouping entities, to explore the data, and to generate or to test hypothesis (Aldenderfer & Blashfield, 1984). Accordingly, it has been widely applied in biology, archaeology, psychology and other domains. This research applies *the tree-clustering technique* to discover groups of participants based on their MR. However, there are other available clustering techniques. Therefore, *the tree-clustering method* is framed within these techniques and its selection is justified in the following paragraphs. The results are used to generate new datasets for further analyses.

There are different types of clustering methods, such as *joining* (*the tree-clustering* or *the agglomerative hierarchical method*), *two-way joining* (*block clustering*), and *k-means clustering* (Lloyd, 1982; Macqueen, 1967; Steinhaus, 1956), etc. *The joining technique* sees each case (e.g. individual) as one cluster on its own. Each cluster is combined into successively larger clusters by using some measures of similarity or distance. Results are typically presented in a *dendrogram*. *Two-way clustering* is used when researchers are interested in grouping cases and variables simultaneously. *K-means clustering* works by specifying a fixed number of *k* desired (or hypothesized) clusters. Hence, it is commonly used when the number of *k* clusters is known a priori. The algorithm assigns cases to clusters in such a way that the means across clusters (for all variables) are as distinct as possible from each other. However, the best number of clusters that leads to the greatest separation in this case is not known before computing the data. *V-fold-cross-validation* can be used to solve this problem by automatically determining the number of clusters. Some software has incorporated this technique into their analysis. There are other more sophisticated methods, such as *Expectation Maximization* (*EM*) (Dempster, Laird, & Rubin, 1977). However, they are not elaborated in this chapter.

Hierarchical clustering gives some advantages over other flat clustering methods, such as *k-means*, because it gives informative outputs in a hierarchical form. Moreover, it does not require the number of clusters to be specified beforehand. Another advantage of hierarchical cluster comes from its simplicity, as the complexity of the most common *tree-clustering* algorithm is much simpler than *k-means* and *EM* (Manning, Raghavan, & Schütze, 2008). Besides, this study focuses on clustering the participants, and not the variables, making EM not applicable. Hence, the hierarchical clustering technique allows us to understand the hierarchical relationships among cases, or in this case among the participants. It also allows us to group the participants while retaining their identification numbers, enabling to trace back to their cognitive subset and personal data to perform the subsequent analyses.

A few steps are followed when applying *the tree-clustering technique*. It begins by identifying and selecting variables to measure the entities (Aldenderfer & Blashfield, 1984). A matrix of inter-individual similarity or distance measures is calculated next. This matrix is used to search for the most similar (or the closest) pair of individuals (e.g. *i* and *j*). A new cluster *k* is formed by merging *i* and *j* and the matrix is modified to accommodate the change. The closest pair is searched again from the updated matrix and the process is repeated until all individuals are merged into one big cluster (Lorr, 1983). This procedure is referred to as SAHN, an acronym for *sequential*, *agglomerative*, *hierarchical* and *non-overlapping* (Sneath, 1973). In general, there are two groups of measurements to perform tree-clustering. The first category is the similarity (or distance) measure to generate a matrix and the second one is the sorting method to define the similarity/dissimilarity between clusters.

There are a number of similarity or distance measures, such as well-known Euclidean distance. However, they mainly work based on an initial assumption that variables to cluster individuals are continuous in nature (Anderberg, 1973). Research that uses binary or dichotomous variables, such as clustering individuals' MR, should apply other alternative measures for separation, referred to as *matching coefficients* (Dillon & Goldstein, 1984) or *association coefficients* (Everitt, 1980). Matching coefficient calculates the degree of similarities between individuals based on common patterns among the variables (i.e. present or absent) (Snijders, Dormaar, van Schuur, Dijkman-Caes, & Driessen, 1990).

Matching coefficient for binary data is based on values in a two-way association table derived from two individuals, *i* and *j*, over *K* number of variables as shown in Figure 6.2. In the table, *a* represents positive matches or the number of counts when both individuals have the variables present in the data, *b* and *c* signify the number of times when one individual has the attributes present and the other one has them absent. At last, *d* denotes the negative matches of having the variables absent for both individuals.

		Individual i		
		1	0	
Individual j	1	a	b	$a+b$
	0	c	d	$c+d$
		$a+c$	$b+d$	p

Where $p=a+b+c+d$

Figure 6.2 A two-way association table for two individuals

There are a large number of proposed matching coefficients. Some of them are listed in Table 6.1. This large variety of coefficients happens because of the uncertainty over incorporating negative matches and the vagueness surrounding the weight of perfectly matched and unmatched pairs (Everitt, 1980). For instance, *the Russell/Rao index* (Rao, 1945) calculates only the proportion of cases that has positive matches, *the simple matching coefficient* (Sokal & Michener, 1958) takes into account the sum of positive and negative matches in the numerator and all types of matches in the dominator, *the Jaccard's coefficient* (Sneath, 1957b) leaves out negative matches from the denominator, and *the Dice's* (or *Czekanowski's* or *Sorenson's*) *coefficient* (Dice, 1945) gives positive matches twice the weight of mismatches. The selection of association coefficients to use significantly determines research outcomes (Everitt, 1980).

Table 6.1 Matching coefficients (adapted from SPSS Help Manual, n.d.)

Coefficient	*Equation*
Binary Euclidean distance	$\sqrt{b+c}$
Binary squared Euclidean distance	$b+c$
Simple matching coefficient	$\frac{a+d}{p}$
Russell and Rao	$\frac{a}{p}$
Jaccard's coefficient	$\frac{a}{a+b+c}$
Dice or Czekanowski or Sorenson	$\frac{2a}{2a+b+c}$
Sokal and Sneath 1	$\frac{2(a+d)}{2(a+d)+b+c}$
Sokal and Sneath 2	$\frac{a}{a+2(b+c)}$
Sokal and Sneath 3	$\frac{a+d}{b+c}$
Rogers and Tanimoto	$\frac{2(a+d)}{a+d+2(b+c)}$
Kulczynski	$\frac{a}{b+c}$
Hamann	$\frac{(a+d)-(b+c)}{p}$
Ochiai	$\sqrt{\left(\frac{a}{a+b}\right)\left(\frac{a}{a+c}\right)}$

Different matching coefficients result in dissimilar coefficient values for the same dataset, yielding different conclusions. This is shown in the example in Figure 6.3. Using *the* Russell/Rao *index*, association coefficients of individual 1-2, 1-3, and 2-3 are 0.2, 0, and 0.1 respectively, which are relatively low. However, the simple matching coefficient calculates relatively high matches for those pairs of individuals (i.e. 0.7, 0.5, and 0.8).

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
Individual 1 (I1)	1	0	1	0	1	1	0	0	0	0
Individual 2 (I2)	0	1	1	0	1	0	0	0	0	0
Individual 3 (I3)	0	1	0	0	0	0	0	0	0	0

a. Raw data

Individual 2 (I2) \ *Individual 1 (I1)*	1	0	
1	2	1	3
0	2	5	7
	4	6	10

Individual 3 (I3) \ *Individual 1 (I1)*	1	0	
1	0	1	1
0	4	5	9
	4	6	10

Individual 3 (I3) \ *Individual 2 (I2)*	1	0	
1	1	0	1
0	2	7	9
	3	7	10

b. 2-way matrices between 2 individuals

Russell/Rao Index (i)

	I1	*I2*	*I3*
I1	1	0.2	0
I2		1	0.1
I3			1

Simple Matching Coef. (ii)

	I1	*I2*	*I3*
I1	1	0.7	0.5
I2		1	0.8
I3			1

Jaccard's Coefficient (iii)

	I1	*I2*	*I3*
I1	1	0.4	0
I2		1	0.3
I3			1

Dice's Coefficient (iv)

	I1	*I2*	*I3*
I1	1	0.6	0
I2		1	0.5
I3			1

Ix=Individual x

c. Matching coefficient matrices across all individuals

Figure 6.3 An example of raw data (a), calculating 2-way matrices (b), and calculating matching coefficient matrices (c)

This study clusters the participants' MR based on the elicited cognitive subsets. During the survey, the participants are asked to indicate strong affected aspects in their decision making. Thus, unselected variables are regarded as not (or less) considered in the decision processes. For this reason, negative matches are not essential and they should not be taken into account in the denominator, leading us to consider the Jaccard's and Dice's coefficients. The latter coefficient seems to be better suited because of the double weight that it gives to the positive matches.

Once a coefficient matrix of inter-individuals is calculated, the clustering technique or sorting method to generate tree-clustering has to be selected. Generally, the most common techniques are *the nearest neighbour* or *single linkage* (Florek, Lukaszewicz, Perkal, Steinhaus, & Zubrzycki, 1951; Johnson, 1967; McQuitty, 1956; Sneath, 1957a), *the furthest neighbour* or *complete* *linkage* (Macnaughton-Smith, 1965), *the centroid cluster analysis* (Sokal & Michener, 1958; King, 1965a, 1965b), *the median cluster analysis* (Gower, 1967), *the group average method* (Sokal & Michener, 1958; Lance & Williams, 1966), and *the Ward's method* (Ward, 1963). The differences among these techniques, including their strengths and weaknesses, have been previously discussed (e.g. Everitt, 1980; Lance & Williams, 1967). Therefore, they are only explained very briefly in this chapter.

The single linkage method forms clusters by simply taking the closest distance of its members whereas the complete linkage merges cases by taking the furthest distance between them. The most prominent drawback of the single linkage method is its tendency to form chains of long and elongated clusters (Aldenderfer & Blashfield, 1984). The complete linkage gives better results than the single linkage. However, low concordance is found when comparing the result of the complete linkage with a known-structure (Aldenderfer & Blashfield, 1984). The group average method takes the average distance of the merged group members. This technique is aimed at providing solutions to the problems faced when using the single and complete methods. There are several variants of this technique, such as *within-group average* and *between-group average*. The centroid cluster analysis combines groups based on the distance between their centroid. The median cluster analysis calculates the median of each cluster and applies a certain likelihood measure to join groups with the highest likelihood. At last, the Ward's method uses the loss of information system (i.e. error sum of squares or ESS). The fusion of two individuals with the minimum increase of ESS is selected as the first group. The Ward's method, the centroid analysis, and the median cluster analysis commonly use squared Euclidean distance to calculate a matrix of similarity or distance. Thus, they are normally applied to continuous data. Employing these techniques on binary data may violate the nature of the formula. For instance, using the Ward's method on binary data results in equal-sized clusters instead of similar-characteristic clusters. Based on these considerations, the group average method seems to be best suited for the purpose of this study.

6.2.3 The results of cluster analysis

SPSS PASW Statistics 17.0 software (SPSS, n.d.) is used to analyse the raw data of the participants' MR, discussed in Section 6.2.1. *The Dice's matching coefficient* is selected to generate inter-individuals' coefficient matrices. Additionally, *the average group cluster*, i.e. *within-group average*, is chosen as the clustering technique as previously explained in Section 6.2.2. It should be noted that a combination between *the Dice's coefficient* and *the between-group average technique* is also tested on the data. However, this does not give satisfactory results since one cluster is fairly big in size while the others are small-sized groups.

Figure 6.4 shows an example of how to define the clusters from the resulted dendrogram. Using the cutting line shown in Figure 6.4, six clusters are retrieved. Regrettably, due to the large size of the dendrogram, the full tree cannot be presented here. The dendrogram allows us to register the respondents who belong to specific clusters. Cluster-1 to Cluster-6 are groups of 73, 51, 27, 18, 19, and 33 participants successively. *The Jaccard's coefficient* is also tried out on the same dataset as a comparison, resulting in seven slightly smaller groups of 73, 46, 26, 25, 23, 14, and 14 respondents. When the same analysis using *the Dice's coefficient* is applied on the shopping location dataset, nine clusters are formed. Similar to the result of the transport mode data, *the Jaccard's coefficient* constructs 14 smaller clusters. Descriptive statistics of all transport mode and shopping location decision clusters is presented in Section 6.3.

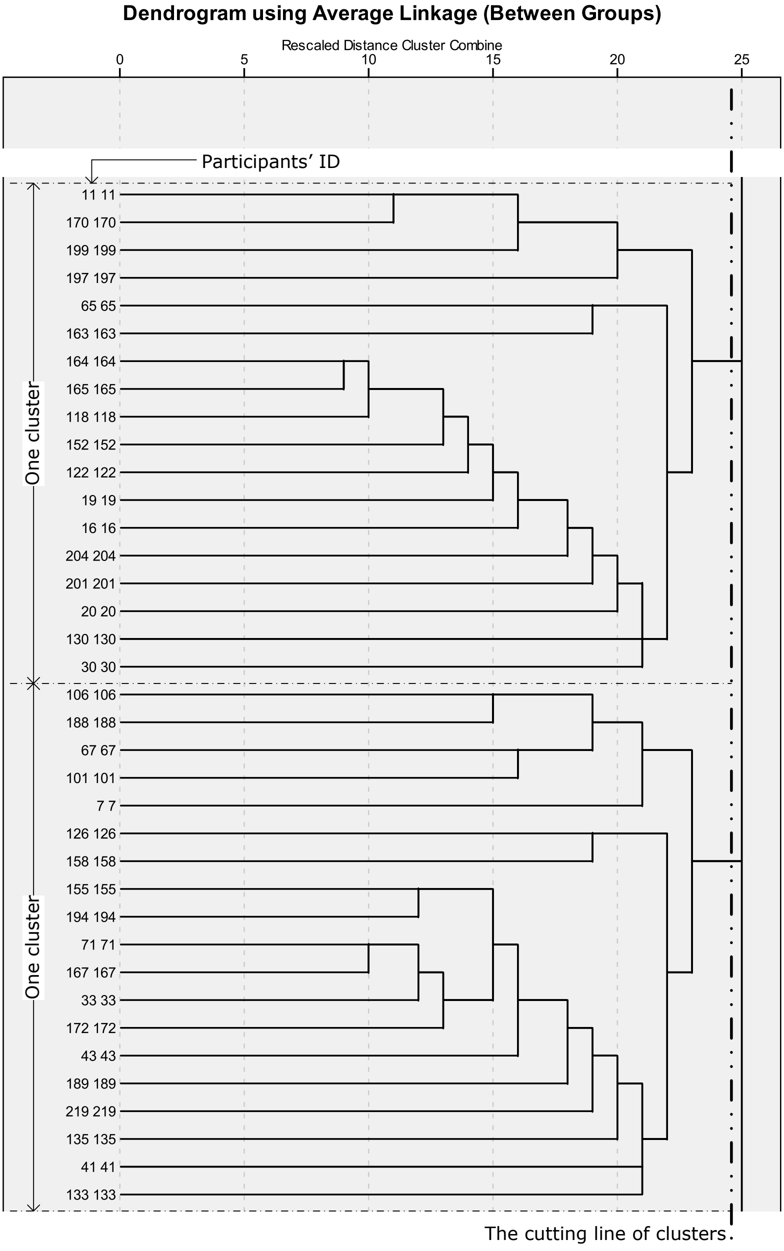


Figure 6.4 An example of cluster interpretation from the dendrogram

6.3 The complexity of the participants' mental representations in the clusters

Using the tree-clustering technique described in Section 6.2, the respondents in specific clusters are identified. Furthermore, these clusters are examined, emphasizing their descriptive statistics. For this purpose, SPSS PASW Statistics 17.0 software is used. The results are shown in Table 6.2a (for the transport mode decision) and Table 6.2b (for the shopping location decision). In the table, *cluster* donates the cluster number, *count* represents the total number of respondents, and *sum* indicates the total number of cognitive subsets. Furthermore, the mean of the cognitive subsets per respondent in a cluster, standard deviation, standard error, 95% confidence interval (CI), minimum, and maximum values are also presented in the table.

Table 6.2 The descriptive statistics of the transport mode (a) and shopping location (b) clusters

Cluster	*Count*	*Sum*	*Mean*	*Std. Deviation*	*Std. Error*	*95%CI for Mean*		*Min.*	*Max*
						Lower bound	*Upper bound*		
				a. The transport mode decision					
1	73	2461	33.71	27.479	3.216	27.30	40.12	1	131
2	51	1407	27.59	17.861	2.501	22.56	32.61	2	87
3	27	516	19.11	11.085	2.133	14.73	23.50	6	45
4	18	1887	104.83	113.122	26.663	48.58	161.09	2	400
5	19	351	18.47	13.818	3.170	11.81	25.13	6	56
6	33	652	19.76	13.984	2.434	14.80	24.72	4	77
Total	221	7274	32.91	43.178	2.904	27.19	38.64	1	400
				b. Shopping location decision					
1	31	410	24.39	22.400	4.023	16.17	32.60	2	95
2	18	204	22.17	15.542	3.663	14.44	29.90	2	59
3	28	556	35.25	38.397	7.256	20.36	50.14	6	180
4	41	1107	37.24	62.277	9.726	17.59	56.90	5	400
5	16	169	21.25	19.838	4.959	10.68	31.82	5	87
6	26	818	54.00	71.988	14.118	24.92	83.08	10	294
7	34	561	21.91	19.025	3.263	15.27	28.55	1	87
8	9	143	26.00	21.570	7.190	9.42	42.58	6	76
9	18	1459	49.00	31.376	7.395	33.40	64.60	18	123
Total	221	5427	32.91	43.178	2.904	27.19	38.64	1	400

It can be observed in Table 6.2 that there are some disparities in the numbers of subsets in the clusters. Therefore, *one-way ANOVA* test is employed to check whether these differences are statistically significant. This statistical analysis aims at testing the equality of at least three means at once by using variances. The null hypothesis states that the means of all populations are equal. Thus, the significance value (or *p-value*) gives information whether to reject or to accept the null hypothesis. The null hypothesis is rejected when the p-value is less than 0.05, and otherwise when this value is larger than 0.05. Statistical discussion regarding how to conduct one-way ANOVA test can be read in many statistical handbooks (e.g. Hill & Lewicki, 2005). In this study, one-way ANOVA is used to investigate the differences of the mean values of the number of cognitive subsets across the clusters.

The results of one-way ANOVA test are shown in Table 6.3. Since the calculated *p-value* for the transport mode decision is less than 0.05 (Table 6.3a), the null hypothesis can be rejected, implying that there are significant differences among clusters concerning their numbers of cognitive subsets. A similar test is done for the shopping location decision (Table 6.3b). In this case, the *p-value* equals 0.053 which is slightly larger than the critical value of 0.05. This implies that the calculated p-value is in the limit to reject the null hypothesis. Even though statistically it cannot be concluded that the there are significant differences among clusters, some disparities can still be observed to some extent, as shown in Table 6.2b.

Table 6.3 The ANOVA test results: The mean differences of the number of cognitive subsets across the transport mode (a) and shopping location (b) clusters

	Sum of Squares	*df*	*Mean Square*	*F*	*Sig.*
a. The transport mode decision					
Between Groups	109414.091	5	21882.818	15.644	.000
Within Groups	300745.276	215	1398.815		
Total	410159.367	220			
b. Shopping location decision					
Between Groups	28194.965	8	3524.371	1.956	.053
Within Groups	381964.401	212	1801.719		
Total	410159.367	220			

Hence, it can be concluded that there are some differences among clusters with regard to the number of registered subsets, especially for the transport mode decision. Cluster-4 of the transport mode decision is the most complex cluster. Cluster-5 appears to be the simplest one, even though the number of subsets in that cluster is relatively close to the numbers of subsets in Cluster-3 and Cluster-6. With regard to the shopping location decision, Cluster-6 is slightly more complex than the other clusters. Additionally, the rest of the clusters are relatively similar in size.

The next analysis focuses on the general content of the cognitive subsets in each cluster. Accordingly, the FI analysis is employed. The analysis and its results are described in the subsequent section below (i.e. Section 6.4).

6.4 Learning the underlying cognitive subsets in the clusters

6.4.1 The datasets and the frequent itemset analysis

In line with the CA results, the MR data is split into smaller datasets. Each of them consists of a number of cognitive subsets belong to a specific cluster. The total numbers of six and nine datasets for the transport mode and location decisions are prepared successively. An example of this dataset can be seen in Figure 3.13, slightly modified from the dataset example in Chapter 3 (i.e. Section 3.3).

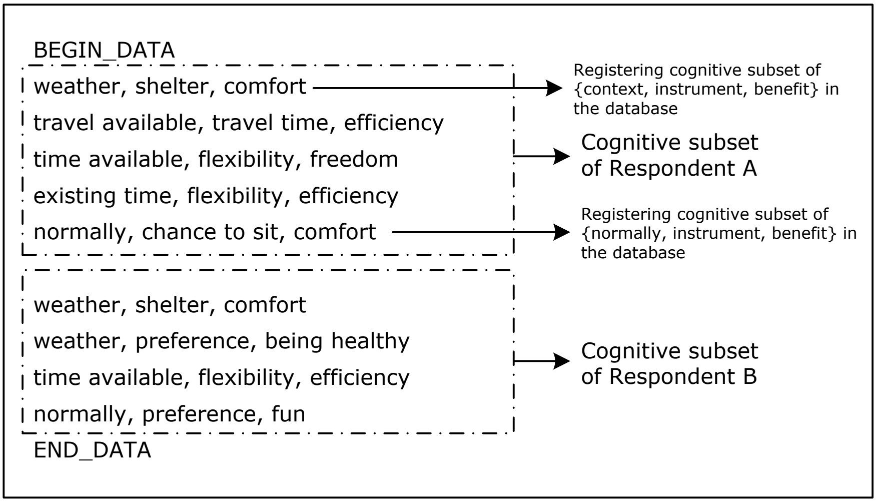


Figure 6.5 An example of a database containing the elicited cognitive subsets

The FI analysis is applied next. This analysis is previously detailed in Chapter 3 and Chapter 5. Similar to the previous analysis in Chapter 5, the minsup values for all datasets are calculated. These values are presented in Table 6.4. It is assumed here that a set of cognitive subset is important when at least one-third of participants in each cluster elicit the subset (y in Table 6.4). *Count* (w) signifies the total numbers of participants who belong to the clusters. *Sum* (x) indicates the total numbers of elicited cognitive subsets. The values of w and x in Table 6.4 are taken from Table 6.2. Additionally, the minsup values are calculated using the following formula:

$z = {y \times w}/{x}$; Where z is the support value; y is the assumption; w is the total number of respondents in the dataset; and x is the total number of cognitive subsets in the dataset.

Table 6.4 Minsup values for the transport mode (a) and shopping location decision (b) datasets

Cluster	*Count* (w)	*Sum* (x)	*Assumption* (y)	*Minsup* (z)
		a. The transport mode decision		
1	73	2461	33.3%	0.010
2	51	1407	33.3%	0.012
3	27	516	33.3%	0.017
4	18	1887	33.3%	0.003
5	19	351	33.3%	0.018
6	33	652	33.3%	0.017
		b. The shopping location decision		
1	31	410	33.3%	0.025
2	18	204	33.3%	0.029
3	28	556	33.3%	0.017
4	41	1107	33.3%	0.012
5	16	169	33.3%	0.032
6	26	818	33.3%	0.011
7	34	561	33.3%	0.020
8	9	143	33.3%	0.021
9	18	1459	33.3%	0.004

6.4.2 The results of frequent itemset analysis

ARtool software is used for the computation, using the minsup values in Table 6.4. Akin to the previous FI analysis in Chapter 5, only the size-three itemsets of {*context, instrument, benefit*} and {*normally, instrument, benefit*} above the specified minsup values are taken into account. Furthermore, to bring the results back to the percentages of the respondents who elicit the subsets, the formula below is applied on the results.

$\%\_respondent = (support\_value \times x) / w$; Where *%_respondent* is the total percentage of the respondents who elicit a subset; *support_value* is the calculated support value of a subset; *x* is the total number of cognitive subsets in a dataset; and *w* is the total number of respondents in a dataset.

6.4.2.1 The transport mode decision

The results of FI analysis for the transport mode decision are summarized in Figure 6.6 (i.e. Cluster-1 to Cluster-3) and Figure 6.7 (i.e. Cluster-4 to Cluster-

6), derived from the FI results presented in Appendix H1. The cognitive subset of {*normally, flexibility/independency, freedom*} is important in Cluster-1. Furthermore, *having efficiency* is an additional sought after benefit in this cluster. Both benefits are linked to the instruments of *flexibility/independency*, *treatment of bags*, and *travel time*. Similar to Cluster-1, Cluster-2 also places great emphasis on the subset of {*normally, flexibility/independency, freedom*}. The differences between both clusters rest on the instruments of the secondary subsets; i.e. *easiness for parking* and *accessibility*. In Cluster-3, all subsets are revealed by less than 50% of the members of this group. Besides *normally*, the contextual aspect of *time availability* also plays a moderately important role in determining the participants' transport mode choices. *Having convenience* and *efficiency* are the benefits looked for in this group. These benefits are obtained through the instruments of *flexibility/independency* and *travel time*.

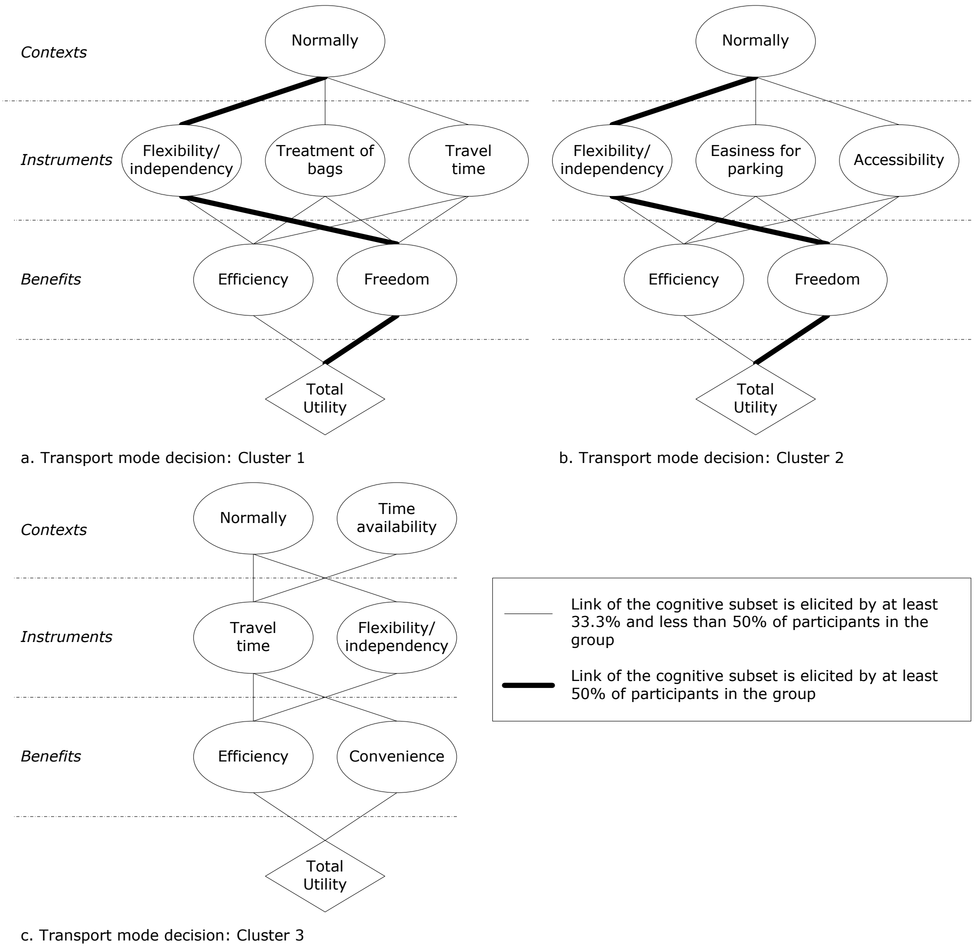


Figure 6.6 The transport mode decision cognitive subsets: Cluster 1(a) to 3(c)

There are many important subsets in Cluster-4 (Figure 6.7). This could be related to the fact that the participants in this group on average elicit 104.8 subsets, resulting in a more complex generalized MR. Furthermore, the benefits of *saving money*, *feeling safe and secure*, *having assurance and certainty*, and *durability* (including *environmental benefit*) are searched for most. They are linked to the instruments of *cost*, *easiness for parking*, *environmental-friendliness of the transport mode*, and *reliability*. Moreover, *parking cost* is moderately considered as an influential context. Cluster-5 highlights the cognitive subsets of {*precipitation, shelter provision, comfort*} and {*number or* *size of goods being purchased, treatment of bags, comfort*}. In *Cluster-6*, the cognitive subset of {*normally, easiness for parking, efficiency*} is essential.

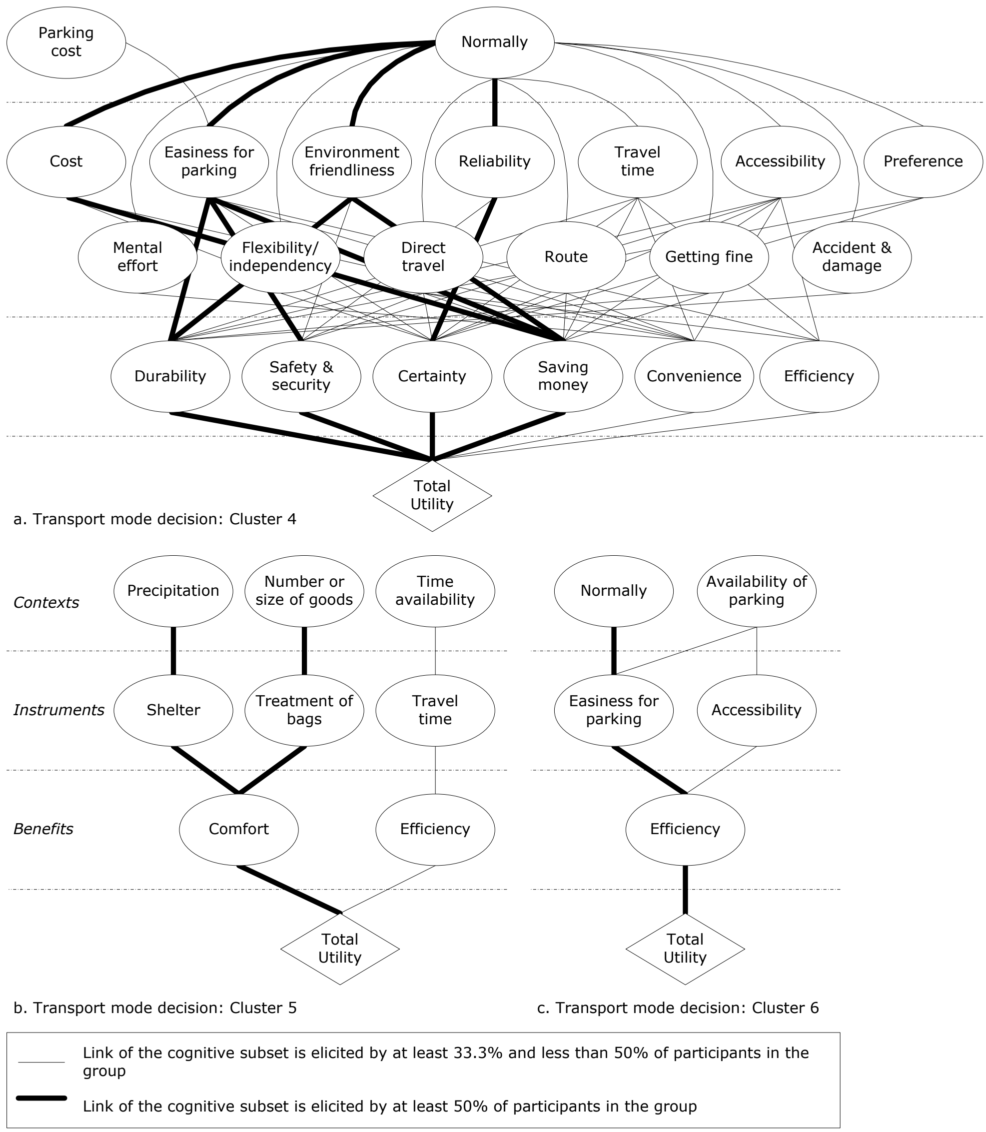


Figure 6.7 The transport mode decision cognitive subsets: Cluster 4(a) to 6 (c)

6.4.2.2 The shopping location decision

The results of the FI analysis for the shopping location decision are summarized in Figure 6.8 (i.e. Cluster-1 to Cluster-6) and Figure 6.9 (i.e. Custer-7 to Cluster-9), generated from Appendix H2. The cognitive subset of {*interest in a specific product, type of store, efficiency*} is elicited by at least 50% of the participants in Cluster-1 (Figure 6.8). Additionally, the instrument of *favourite shops in the area* is also linked to the benefit of *having efficiency*. Cluster-2 is dominated by the respondents who activate their MR in *normal circumstances*. In general, the benefit of *having efficiency* is sought out through the instruments of *type of store*, *favourite shops* and *participants' familiarity with the area*. In Cluster-3, the benefit of *having convenience* seems important. This benefit is linked to the instrument of *familiarity with the area*. In Cluster-4, the most significant cognitive subset is {*interest in a specific product, familiarity with the area, efficiency*}. However, there are other important subsets in this group, related to the contexts of *time availability* and *normally*. In Cluster-5, the benefit of *having fun* is mostly gained by means of *type of store* and *favourite shops*. *Companion* appears as an important context in Cluster-6. The benefit of *having fun* also dominates this cluster. This benefit is gained through the instruments of *ambiance of the area*, *favourite shops*, *product price*, and *presence of café and restaurant in the area*.

The benefit of *having certainty* is essential for the participants in Cluster-7, whereas the benefit of *saving money* is crucial for the respondents in Cluster-8 (Figure 6.9). Reasonably, the instrument of *product price* and the context of *budget availability* are frequently elicited by the participants in Cluster-8. It turns out that the participants in Cluster-9 activate a more complex MR in comparison to the other groups. There are five benefits that are mostly considered in this group; i.e. *having efficiency*, *having fun*, *having information* and *saving money*. These benefits are gained through various instruments. The contextual aspects of *normally*, *interest in a specific product* and *sale season* are frequently chosen.

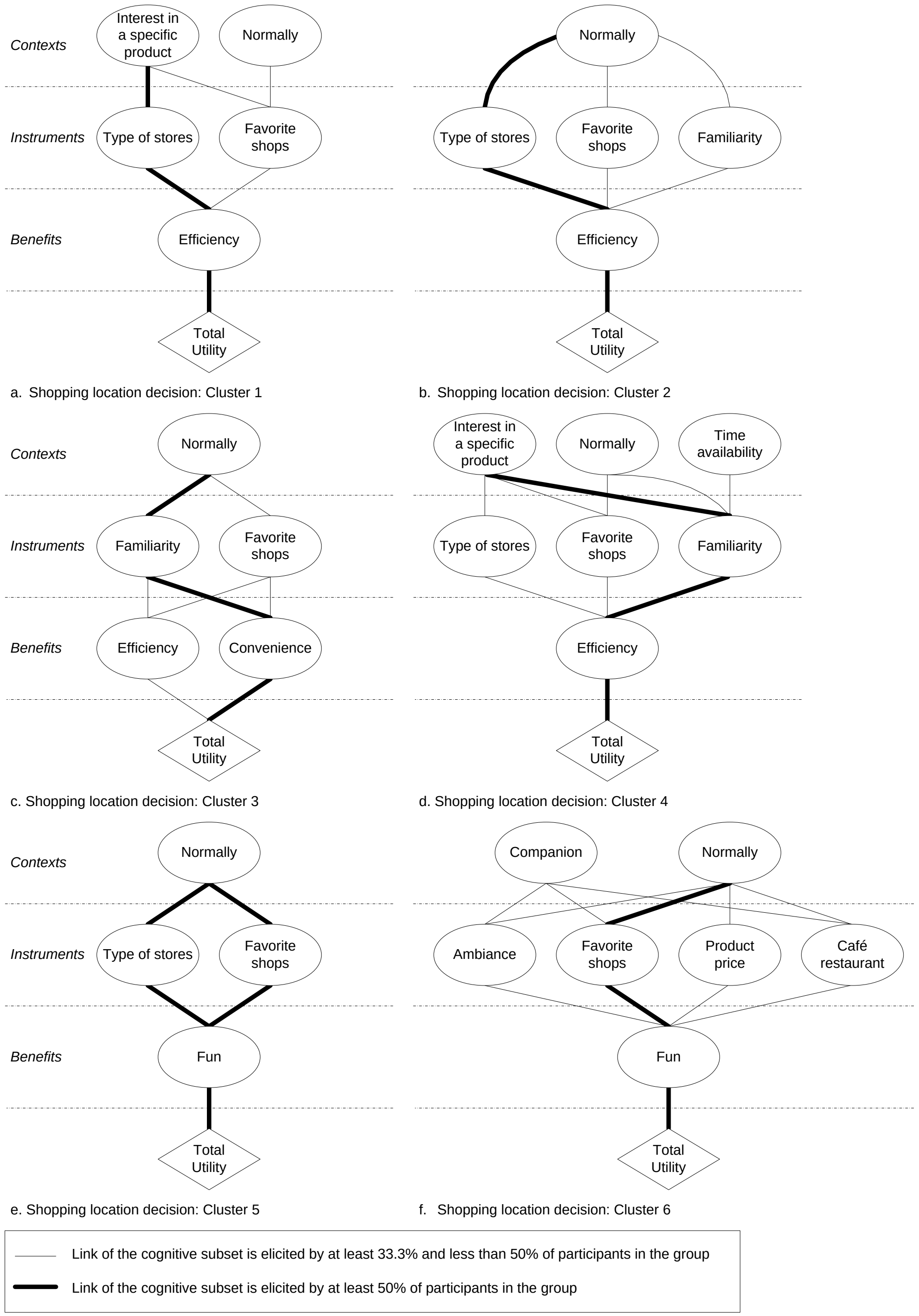


Figure 6.8 The shopping location decision cognitive subsets: Cluster 1(a) to 6(f)

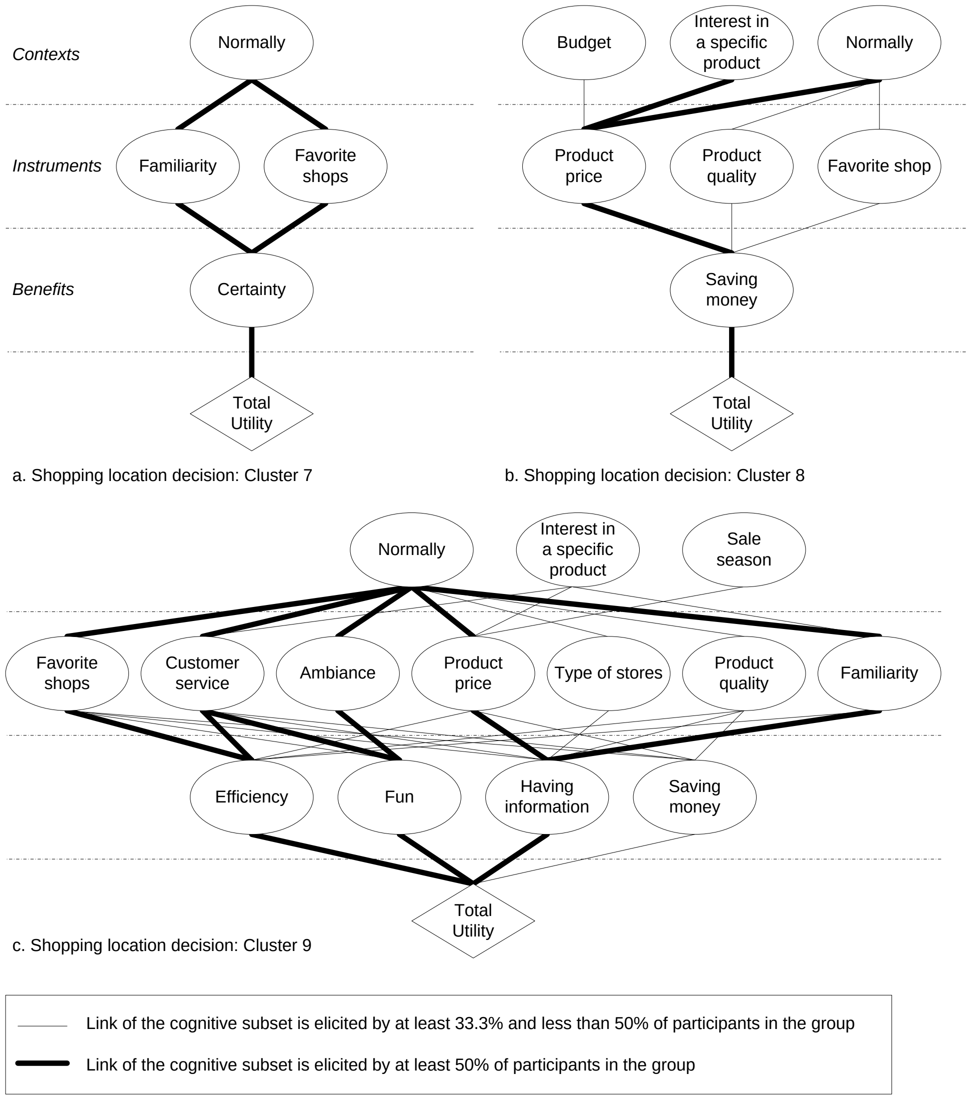


Figure 6.9 The shopping location decision cognitive subsets: Cluster 7(a) to 9(c)

6.5 Socio-demographic characteristics of each cluster

Previous analyses illustrate how the participants are categorized into a number of clusters, how these clusters differ in size, and what aspects are important for these groups. However, to generate a complete idea of the clusters, their differences concerning the participants' socio-demographic characteristics, travel behaviour, and fun-shopping behaviour should also be examined. It should be noted that these attributes have been deeply described in Chapter 5. An analysis should be done to examine associations between the cluster variables of the transport mode and shopping location decisions and the participants' personal data. However, since the clusters of different decisions may relate to dissimilar sets of attributes, only a few associations are focused on. To be precise, correlations between the transport mode clusters and each of the following variables are investigated: *gender* (TM-a), *age categories* (TM-b), *education categories* (TM-c), *income categories* (TM-d), *residence location categories* (TM-e), *car ownership* (TM-f), *bike ownership* (TM-g), *moped ownership* (TM-h), *motorbike ownership* (TM-i), *possession of a busabonnement card* (TM-j), *possession of a bus reduced ticket* (TM-k), *parking* (TM-l), *yearly kilometres of travel by car* (TM-m), *transport mode habits* (TM-n), and *the frequency of going to Hasselt by car* (TM-o)*, bus* (TM-p)*, and bike* (TM-q).

Similarly, associations are checked for the shopping location clusters and the following variables: *gender* (SL-a), *age categories* (SL-b), *education categories* (SL-c), *income categories* (SL-d), and *residence location categories* (SL-e), *yearly frequency of fun-shopping* (SL-f), *last time doing fun-shopping in Hasselt* (SL-g), and *shopping location habits* (SL-h). Since all variables are categorical data, *contingency tables* are generated. Moreover, some inferences are calculated based on those tables, e.g. a test of independence.

6.5.1 Contingency table and chi-square test

Contingency table, or often referred to as *cross-tabulation* (*crosstab*) *or cross-classification table*, is a table that comprises a number of variables under study, their (categorical) values, and their frequencies of observation. Creating this table is the first step to display relationships between two or more categorical variables (Agresti & Finlay, 1997). For instance, X and Y are two categorical variables that consist of I and J categories respectively, creating a contingency table that comprises I-row and J-column. In this study, the transport mode cluster variable has six categories (i.e. Cluster-1 to Cluster-6) whereas the shopping location cluster variable consists of nine categories. The other variables vary in their numbers of categories. For instance, *gender* is grouped into *male* and *female*, *residence location* is defined as short, medium, and long distances, etc. (see Chapter 5 for all variable categorizations). Therefore, the transport mode cluster and gender create a 6x2 contingency table. Furthermore, each cell in the table signifies the frequency of occurrence (or the observed count) of joined categories of two different variables. The overall contingency tables for the transport mode cluster and the other transport mode related variables indicated above (TM-a to TM-q) are shown in Appendix I1. Similarly, the contingency tables for the shopping location cluster and the rest of the shopping location related variables (SL-a to SL-h) are presented in Appendix I2.

There are a number of exact tests of independence for an *IxJ* table. One of the most common tests is *chi-square*, dividing the square of the difference between the observed and expected counts by the expected count. Chi-square statistics is calculated with the following formula:

$$X^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(x_{ij} - e_{ij})^2}{e_{ij}} = \sum_{allcells} \frac{(observed - \text{expected})^2}{\text{expected}}$$

$$\text{expected} = \frac{(row\_total) \times (column\_total)}{grand\_total}$$

A large chi-square value (i.e. low *p-value*) allows us to reject the null hypothesis of independent variables. A critical *p-value* of 0.05 is often used as a threshold. Thus p-value below 0.05 indicates that the null hypothesis can be rejected. Additionally, the calculated chi-square value is compared to the percentiles of chi-square distribution, indexed by its degrees of freedom:

df=(the number of rows-1)x(the number of columns-1)

However, chi-square statistics works based on large sample theory. Thus, conservatively it is suggested to use the test when at least 80% of all expected counts are at least 5 and no expected count is less than 1. Detailed discussion can be found for instance in Everitt (1992); Hays (1994); and Kendall & Stuart

(1979). The expected counts of this study are presented in the contingency tables in Appendix I. They are calculated using SPSS PASW Statistics 17.0 software. However, the chi-square test results (in Appendix J) show that in many cases, the basic assumption of chi-square statistics is not fulfilled, leading us to consider Fisher's test to examine the association between two variables.

6.5.2 Fisher's exact test

Fisher's test works based on a probability distribution known as *the hypergeometric distribution*. An example of how to calculate Fisher's statistics for a 2x2 contingency table is explained in the following example (Table 6.5): imagine two variables, A and B, each having two categories; i.e. A1, A2, B1, and B2 (as shown in the table).

Table 6.5 An example of a 2x2 contingency table

		A		*Total*
		A1	*A2*	
B	B1	*v*	*w*	*v+w*
	B2	*x*	*y*	*x+y*
	Total	*v+x*	*w+y*	*N*

Fisher's probability to obtain any set of values is given by the following formula:

$$p = \binom{v+w}{v}\binom{x+y}{x} \Big/ \binom{n}{v+x}$$

$$p = \frac{(v+w)!\,(x+y)!\,(v+x)!\,(w+y)!}{v!\,w!\,x!\,y!\,n!}$$

; Where p is Fisher's p-value; v, w, x, y are the numbers of observation for the combinations of Variable A and B.

Detailed statistical explanations of Fisher's statistics can be read in Fisher (1922). In this study, Fisher's p-values are obtained by using R statistical software (R Project, n.d.), using the following command under the *epitools* package: *fisher.test(…,simulate.p.value=TRUE,B=10000)*. The results are summarized in Table 6.6 and Table 6.8.

6.5.3 The results of Fisher's exact test

The results of Fisher's p-value are presented in Table 6.6, for the combinations of the transport mode cluster variable and each of the participants' characteristics (listed in the "*Variable B*" column in the table). The results indicate that some variables are statistically associated with the transport mode cluster variable; i.e. *education categories*, *car ownership*, *busabonnement card*, *parking*, *transport mode habits*, *going to Hasselt by car*, and *by bike*. These results are used later on to conclude and discuss the clusters (i.e. in Section 6.6).

Table 6.6 Fisher's p-values of the transport mode cluster and other variables

Variable A	*Variable B*	*Fisher's p-value*
Transport mode cluster	Gender (a)	0.7136
Transport mode cluster	Age categories (b)	0.05449
Transport mode cluster	Education categories (c)	0.04030*
Transport mode cluster	Income categories (d)	0.146
Transport mode cluster	Residence location categories (e)	0.6536
Transport mode cluster	Car ownership (f)	0.00030*
Transport mode cluster	Bike ownership (g)	0.2001
Transport mode cluster	Moped ownership (h)	0.7463
Transport mode cluster	Motorbike ownership (i)	0.7874
Transport mode cluster	Busabonnement card (j)	0.02670*
Transport mode cluster	Bus reduced ticket (k)	0.0973
Transport mode cluster	Parking (l)	2e-04*
Transport mode cluster	Yearly kilometres of travel by car (m)	0.05239
Transport mode cluster	Habits (n)	1e-04*
Transport mode cluster	Going to Hasselt by car (o)	0.0409*
Transport mode cluster	Going to Hasselt by bus (p)	0.4989
Transport mode cluster	Going to Hasselt by bike (q)	0.002000*

* The calculated p-value is below the critical value of 0.05, thus the null hypothesis of independent variables is rejected

The results of the contingency tables for all combinations of the transport mode cluster variable and the other variables are presented in Appendix I1. However, the contingency tables of the significantly dependent variables can also be seen in Table 6.7. These associations are used in Section 6.6 to draw conclusions about the differences among clusters, highlighting the categories with the expected counts significantly above the observed counts (i.e. shown by the highlighted cells in Table 6.7).

Table 6.7 Contingency tables of the transport mode cluster and other associated variables

			Cluster number						Total
			1	*2*	*3*	*4*	*5*	*6*	
Education categories	Low education	C[1]	21	20	10	13	6	13	83
		EC[2]	27.4	19.2	10.1	6.8	7.1	12.4	83
	High education	C	52	31	17	5	13	20	138
		EC	45.6	31.8	16.9	11.2	11.9	20.6	138
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Car ownership	No cars	C	0	0	0	0	1	0	1
		EC	.3	.2	.1	.1	.1	.1	1
	1	C	26	35	7	14	9	14	105
		EC	34.7	24.2	12.8	8.6	9.0	15.7	105
	2	C	33	16	17	4	8	13	91
		EC	30.1	21.0	11.1	7.4	7.8	13.6	91
	3	C	12	0	2	0	1	4	19
		EC	6.3	4.4	2.3	1.5	1.6	2.8	19
	More than 3	C	2	0	1	0	0	2	5
		EC	1.7	1.2	.6	.4	.4	.7	5
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Bus card	No	C	68	47	26	12	18	32	203
		EC	67.1	46.8	24.8	16.5	17.5	30.3	203
	Yes	C	5	4	1	6	1	1	18
		EC	5.9	4.2	2.2	1.5	1.5	2.7	18
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Parking	No parking	C	3	17	2	6	0	4	32
		EC	10.6	7.4	3.9	2.6	2.8	4.8	32
	Free parking	C	60	31	23	11	17	27	169
		EC	55.8	39.0	20.6	13.8	14.5	25.2	169
	Paid parking	C	10	3	2	1	2	2	20
		EC	6.6	4.6	2.4	1.6	1.7	3.0	20
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221

[1] C: Count
[2] EC: Expected Count

			Cluster number						Total
			1	2	3	4	5	6	
Habits	No habits	C	1	2	2	0	2	0	7
		EC	2.3	1.6	.9	.6	.6	1.0	7
	Car	C	53	18	15	5	6	12	109
		EC	36.0	25.2	13.3	8.9	9.4	16.3	109
	Bike	C	10	25	4	3	8	15	65
		EC	21.5	15.0	7.9	5.3	5.6	9.7	65
	Bus	C	9	6	6	10	3	6	40
		EC	13.2	9.2	4.9	3.3	3.4	6.0	40
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Going to Hasselt by car	Not frequent[3]	C	30	32	17	12	11	20	122
		EC	40.3	28.2	14.9	9.9	10.5	18.2	122
	Semi-frequent[4]	C	24	12	6	3	4	8	57
		EC	18.8	13.2	7.0	4.6	4.9	8.5	57
	Frequent[5]	C	19	7	4	3	4	5	42
		EC	13.9	9.7	5.1	3.4	3.6	6.3	42
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Going to Hasselt by bike	Not frequent	C	60	26	22	11	10	18	147
		EC	48.6	33.9	18.0	12.0	12.6	22.0	147
	Semi-frequent	C	4	9	3	4	3	10	33
		EC	10.9	7.6	4.0	2.7	2.8	4.9	33
	Frequent	C	9	16	2	3	6	5	41
		EC	13.5	9.5	5.0	3.3	3.5	6.1	41
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221

[3] Not frequent: occasionally (almost monthly) to never
[4] Semi-frequent: almost weekly
[5] Frequent: almost daily & several times per week

With regard to the shopping location decision, the results of Fisher's test are presented in Table 6.8. These results indicate that all associations between the shopping location cluster and other variables (listed in the "*Variable B*" column in Table 6.8) are not statistically significant, implying that the shopping location clusters and the other variables are independent. Thus, the results point out that the differences among clusters rest solely on the content of the participants' MR.

Table 6.8 Fisher's p-values of the shopping location cluster and other variables

Variable A	*Variable B*	*Fisher's p-value*
Shopping location cluster	Gender (a)	0.6228
Shopping location cluster	Age categories (b)	0.0749
Shopping location cluster	Education categories (c)	0.09589
Shopping location cluster	Income categories (d)	0.07109
Shopping location cluster	Residence location categories (e)	0.8176
Shopping location cluster	Yearly frequency of fun-shopping (f)	0.07919
Shopping location cluster	Last time doing fun-shopping (g)	0.2213
Shopping location cluster	Habits (h)	0.613

None of the calculated p-value is below the critical value of 0.05, thus the null hypothesis of independent variables cannot be rejected

6.6 General results and discussions: The typology of fun-shopping travellers

In the beginning of this chapter, a number of clusters are learned based on the respondents' elicited MR. Moreover, the distinction among the clusters with regard to the number of cognitive subsets are retrieved. An additional analysis is employed to learn the general MR in each group. At last, the differences among these groups and other participants' characteristics are shown. Hence, these results are summarized here below, allowing us to generate the typology of fun-shopping travellers based on their deliberations on the transport mode and shopping location decisions subsequently.

6.6.1 Results: The Transport mode decision

6.6.1.1 Cluster-1: "I love my cars"

Cluster-1 is dominated by high educated respondents. In general, it is also registered as the largest group, with 73 respondents. The number of respondents (i.e. the observed count) having more than three cars is more than the expected count. Furthermore, it has the highest number of respondents whose the transport mode habit is car-use. The members of this group do not frequently go to Hasselt by bike, but they go there semi-frequently (to frequently) by car. Comparable results can be found in Dieleman, Dijst, & Burghouwt (2002), that car-use tends to be higher in households which own many cars. Additionally, they park their car in both paid and free parking spaces in Hasselt. Because of these characteristics, this group is named as "*I love my cars*".

With regard to the elicited MR, the cognitive subset of {*normally, flexibility/independency, freedom*} is significant. *Having efficiency* is also pursued, and it is linked to the instruments of *flexibility/independency*, *treatment of bags* and *travel time*. It should be noted that there are no specific contexts activated in the generalized MR of this cluster.

6.6.1.2 Cluster-2: "Freedom on two wheels"

In Cluster-2, the cognitive subset of {*normally, flexibility, freedom*} is also elicited frequently, akin to Cluster-1. The differences between Cluster-1 and Cluster-2 lay in the instruments of *easiness for parking* and *accessibility*. Even though the content of the participants' MR in this group is relatively similar to Cluster-1, the participants' characteristics are fairly different.

In general, the members of this group only have one car. However, they never (or only occasionally) use it to go to Hasselt because they prefer to use bike to go there on a frequent basis. Consequently, car parking is not needed. The members of this group also indicate that bike-use is in fact their transport mode habit. This group is referred to as "*freedom on two wheels*".

6.6.1.3 Cluster-3: "Looking for some convenience"

In Cluster-3, the contextual variable of *time availability* is elicited, besides the *normally* variable. These contexts are linked to the benefits of *having convenience* and *efficiency*. These benefits are gained through the instruments of *flexibility* and *travel time*. However, these subsets are elicited by less than 50% of the cluster members.

Furthermore, based on the contingency table (i.e. Table 6.7), there are no noticeable differences between the observed and expected counts in this group. This cluster is one of the simplest groups (after Cluster-5) concerning the size of the participants' MR, as shown in Section 6.3. On average, 19.11 subsets are elicited by the group members. Since it is the only cluster (besides Cluster-4) in which the benefit of *having convenience* is important, this grouped is named as "*looking for some convenience*".

6.6.1.4 Cluster-4: "Bus, sure"

Cluster-4 is the most complex cluster, as described in Section 6.3 and Section 6.4 (i.e. Figure 6.7). On average, its members elicit 104.8 subsets. There are many sought after benefits in this cluster, i.e. *saving money*, *feeling safe and secure*, *having assurance and certainty*, and *durability (including environmental benefit)*. These benefits are fulfilled through the instruments of *cost*, *easiness for parking*, *environmental-friendliness of the transport mode*, and *reliability*. Additionally, the contextual aspect of *parking cost* is moderately considered.

With regard to the participants' characteristics, this group has the highest share of low educated participants. Many of them have the possession of a busabonnement card. Moreover, they also indicate that bus-use is their transport mode habit. Thus, this cluster is named as "*bus, sure*".

6.6.1.5 Cluster-5: "My choice depends on the weather"

Cluster-5 highlights the importance of {*precipitation, shelter provision, comfort*} and {*number or size of goods being purchased, treatment of bags, comfort*}. In fact, it is the only cluster in which the contextual aspect of *precipitation* and the benefit of *having comfort* dominate the elicited MR.

Similar to Cluster-3, there are no notable aspects that can draw attention to its member characteristics. The contingency table (i.e. Table 6.7) shows that the expected and observed counts are alike. Hence, it can be concluded that the proportion of categories in this group fairly represents the overall sample proportion (see Table 6.7). This cluster has the simplest MR because its members on average only elicit 18.47 subsets. Considering that the contextual aspect of *precipitation* is mostly considered when deciding the transport mode choices, this group is named as "*my choice depends on the weather*".

6.6.1.6 Cluster-6: "Efficiency on two wheels"

Cluster-6 is another simple cluster, akin to Cluser-3. The cognitive subset of {*normally, easiness for parking, efficiency*} is important in this group. With regard to members' characteristics, the shares of the participants who have three cars or more are larger than expected. However, they still indicate that bike-use is their transport mode habit. Unlike Cluster-3 in which the respondents frequently (i.e. daily or several times per week) go to Hasselt by bike, the members of Cluster-6 go there with bike less frequently (i.e. almost weekly). Because bike-use habit and the benefit of *having efficiency* are pointed up, this cluster is referred to as "*efficiency on two wheels*"

6.6.2 Discussions: An old 'car-use' habit dies hard

This study gives emphasis on TDM to alter people's transport mode choices from car to bike or bus. Therefore, issues such as how to break car-use habit and to foster other "more sustainable" behaviours become its centre of attention. Based on the participants' transport mode habits, the clusters can be further categorized into three groups, as shown in Figure 6.10. Group-1 consists of Cluster-1, in which people's transport mode habit is car-use. Group-2 is particularly interesting because it consists of samples with a relatively balanced mixture of transport mode habits and other personal characteristics. Thus, this group is referred to as "*undecided*". At last, Group-3 comprises Cluster-4 (bus users), Cluster-2 (bike users), and Cluster-6 (bike users). Based on this categorization, TDM efforts should aim at people in Group-1 and Group-2. However, it is good to understand the other group MR since that is the goal to achieve for Group-1 and Group-2.

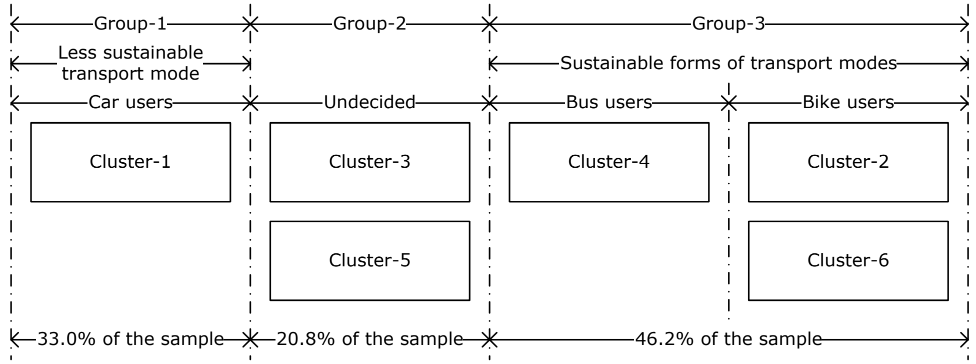


Figure 6.10 Different groups of clusters based on transport mode habits

In general, people in Group-1 and Group-2 want to gain *efficiency, freedom, convenience*, and *comfort* out of their transport mode choices. The elicited instrumental variables linked to these benefits may give some hints regarding tangible aspects of the transport mode options that can help people gain their pursued benefits. Therefore, any information at this level can be used to improve the quality of public transport systems (e.g. the bus system), or to encourage the use of another more sustainable transport mode alternative (i.e. bike). Based on the results, these instruments can be identified; namely *travel time*, *flexibility/independency*, *treatment of bags*, and *shelter provision*. However, situational or contextual factors may hinder people from achieving their goals (Gärling et al., 2002), including getting the benefits that they pursue. For people in Group-1 and Group-2, these contexts are: *normally*, *time availability*, and *the number or size of goods being purchased*.

Based on the points above, a number of TDM can be underlined. Steg & Vlek (1997) categorize TDM into policies that aim at discouraging car-use (*push measures*) and encouraging the use of other transport mode alternatives (*pull measures*). Therefore, this discussion section is split into three parts, focusing on ways to shift individuals' MR by *reducing the attractiveness of car-use* (a), and *increasing the attractiveness of bus-use* (b) and *bike-use* (c).

A number of TDM measures have been listed and categorised in other studies. For instance, Victoria Transport Institute (2010) groups a number of transport policies based on how they influence travel. The list of TDM taken from that study has been previously presented in Chapter 3, Section 3.6. In this chapter, the same list is used and represented in Table 6.9 to identify TDM that can address the three objectives above (shown by the highlighted cells in the table). The justification behind this selection is discussed in the subsequent paragraphs.

Table 6.9 The categorization of different TDM strategies (Victoria Transport Institute, 2010)

Improved transport options	*Reducing car driving*	*Managing land use & parking*	*Policy & institutional reform*
Address Security Concerns	Carbon Taxes	Bicycle Parking	Asset Management
Alternative Work Schedules	Commuter Financial Incentives	Car-Free Planning	Car-Free Planning
Bus Rapid Transit	Congestion Pricing	Strong Commercial Centres	Change Management
Cycling Improvements	Distance-Based Pricing	Connectivity	Comprehensive Market Reforms
Bike/Transit Integration	Fuel Taxes	Land Use Density and Clustering	Context Sensitive Design
Car sharing	HOV (High Occupant Vehicle) Priority	Location Efficient Development	Contingency-Based Planning
Flex-time	Multi-Modal Navigation Tools	New Urbanism	Institutional Reforms
Guaranteed Ride Home	Parking Pricing	Parking Cost, Pricing and Revenue Calculator	Least Cost Planning
Individual Actions for Efficient Transport	Pay-As-You-Drive Insurance	Parking Management	Operations and Management Programs
Light Rail Transit	Road Pricing	Comprehensive Parking Management Strategies, Evaluation and Planning	Prioritizing Transportation
Non-motorized Planning	Road Space Reallocation	Parking Pricing	Regulatory Reform

Improved transport options	*Reducing car driving*	*Managing land use & parking*	*Policy & institutional reform*
Non-motorized Facility Management	Speed Reductions	Parking Solutions	
Park & Ride	Transit Encouragement	Parking Evaluation	
Pedestrian Improvements	Vehicle Use Restrictions	Shared Parking	
Pedways	Walking And Cycling Encouragement	Smart Growth	
Public Bike Systems		Smart Growth Reforms	
Ridesharing		Comprehensive Smart Growth Reforms	
Shuttle Services		Streetscape Improvements	
Small Wheeled Transport		Transit Oriented Development (TOD)	
Transit Station Improvements		Land Use Impacts on Transport	
Taxi Service Improvements		Land Use Impacts on Transport - Comprehensive	
Telework			
Traffic Calming			
Transit Improvements			
Transit Examples			
Universal Design (Barrier Free Planning)			

a. Decreasing the attractiveness of car-use

Previous research (e.g. Jager, 2003) has indicated that breaking car-use habits may not be as easy and straightforward. For instance, individuals' intentions and attitudes usually cannot overtake habits, especially when a habitual behaviour has become strong (Verplanken & Faes, 1999). In that case, individuals do not find it necessary anymore to activate careful and deliberate decision making, because a choice has been made in the past and performed repeatedly without failing them in pursuing their goals. Consequently, individuals with strong habits are commonly unwilling to search for new information regarding other choice alternatives, as illustrated in Figure 6.11.

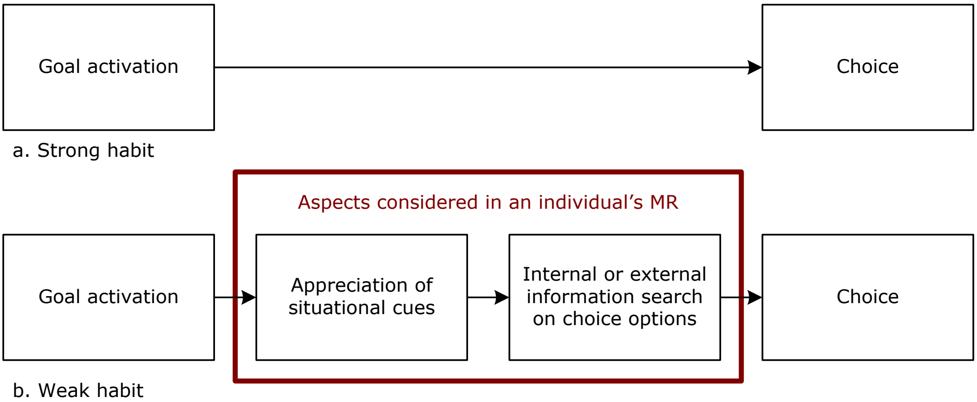


Figure 6.11 Strong (a) versus weak (b) habits (adapted from Verplanken, Aarts, & Vanknippenberg, 1997)

Hence, any public information campaign to change people's strong habitual behaviour by communicating the advantages of another behaviour being promoted may not work as expected (Gärling et al., 2002). For instance, a campaign that communicate negative impacts of excessive car-use on the environment and promote bike-use may not work effectively for people in Group-1, but it could be successful for people in Group-2. When habitual behaviours are strong enough, such a campaign may be able to alter people's attitudes and behaviours but not to the point where the old behaviour becomes habitual (Wright & Egan, 2000). It is argued that when a major change happens in someone's life (e.g. moving house to another city), an individual is forced to pay attention to new information to evaluate choice options (Gärling et al., 2002). This may eventually lead to a new habit formation. Furthermore, Fujii & Gärling (2005) find out from their research that structural temporal change (e.g. freeway closure) can also break car-use habit and make people shift to public transport-use. However, the long term effect of this behavioural change is not investigated in their study. Due to the fact that car users are unlikely to give up their car-use behaviour voluntarily, some interference that can force people to rethink about their transport mode choices should be introduced (Fujii & Gärling, 2005). It should also be noted that habitual behaviour serves *functional* and *convenient* purposes to attain goals. Therefore, TDM can be implemented for this purpose. TDM measures may hinder people with car-use habit to reach their goals (i.e. *having efficiency*, *convenience*, etc.), resulting in the alteration of this behaviour.

The generalized cognitive representations of people in Group-3 (i.e. bike and bus user groups) are further examined in order to see people' reasoning about their transport mode choices, giving insight regarding *why* bike-use or bus-use are more appealing for them than car-use. Interestingly, the instrument of *easiness for parking* appears in the generalized representations of all clusters in this group. However, that instrument does not emerge in the MR of people in Group-1 and Group-2. This raises a question whether parking measures should be implemented more strongly than in the current situation to make parking-related aspects be considered in people's decision making, especially for those who are members of Group-1 and Group-2. The fact that none of parking-related policies are thought about by people in those groups could mean that these measures are still relaxed in Hasselt. For instance, parking spaces, especially the free ones, are abundantly provided. Moreover, among all clusters of participants, only Cluster-4 considers the cost factor, i.e. especially related to the parking cost. This could indicate that parking cost may not be high enough to be considered as important in people's decision making in the other clusters, especially for car users. This could also imply that people are not aware of the (annual) cost that they spend for operating their car, and what they can actually gain from the reduction of their car-use.

Therefore, TDM to reduce parking spaces (especially the free ones) could be useful to break car-use habit, especially for people in Group-1. This TDM could be policies to increase parking fees, and implement other parking management strategies (i.e. highlighted cells in Table 6.9) that can make parking harder for people. Eventually, parking-related aspects could be considered in people's decision making. Once this happens, attitude-based influence attempts, such as campaigns, may work to give people new information concerning other transport mode options. A campaign could be conducted accordingly to communicate the negative externalities of excessive car-use to the environment, increasing their awareness and furthermore altering their behaviour towards more sustainable forms.

However, the objective of breaking car-use habit can only be optimal when it is supported by different measures. Accordingly, *parking measures* should be combined with other policies that can increase the attractiveness of public transport systems (e.g. bus) and other transport mode alternatives (e.g. bike). These policies are discussed in the following paragraphs.

b. Increasing the attractiveness of bus-use

In order to increase the attractiveness of public transport systems, especially the bus system, a number of TDM can be implemented. Based on the individuals' MR, it is shown that a number of instruments of the transport mode options are considered to help people pursue the benefits of *having efficiency, freedom, comfort,* and *convenience*. These instruments are *travel time*, *flexibility/independency*, *treatment of bags*, and *shelter provision*. Accordingly, the bus transport system can be improved by implementing policies to reduce travel time by bus, increase flexibility/independency of bus users, and improve the quality of buses and bus transits.

Hence, Bus Rapid Transit (BRT) system could be a way to reduce bus travel time and eventually make people gain more *efficiency*. This system has been previously described in Chapter 3 (i.e. Section 3.6). It works by dedicating one street lane for bus-use and/or other High Occupant Vehicles (HOV), making it possible to significantly reduce travel time. Furthermore, fast buses should also be provided, connecting major bus stops on the BRT lanes. In order to have bigger service coverage and better connectivity, a good bus feeding system (e.g. using smaller buses as feeders to go to smaller streets) should be developed as well.

Increasing bus frequency is another important measure that should be emphasized. This policy is not only going to improve the flexibility of bus users, but it is also going to reduce the overall travel time (through the reduction of waiting time). Currently, in the rush hours (in the morning and in the afternoon), buses ride more frequently (e.g. up to 4 buses per hour). However, in the off-peak hours, buses from/to Hasselt go/come every 30 minutes to every hour depending on the route that they serve. Increasing bus frequency is needed to increase the attractiveness of bus-use, especially to go to leisure locations. Moreover, the last buses to go to many destinations operate at about 8 PM from Hasselt Station. This further limits people's interests (and independencies), especially for those who want to combine their fun-shopping trips with other evening activities that may end after 8 PM (e.g. having dinner, going out to cinema, etc.). Increasing bus frequency and extending bus service hours make people gain more *freedom* and *convenience*, leading to the increase in bus ridership.

The last benefit searched by people out of their transport mode choice is *having comfort*, especially for people in Cluster-5 (i.e. Group-2). This benefit is gained through the instruments of *shelter provision* (related to *the weather conditions*) and *treatment of bags* (related to *the number and size of goods being purchased)*. Transit improvement measures can be implemented in this case. Specifically, the quality of buses and bus stops should be improved to boost passengers' comfort. More comfortable (and sheltered) bus stops should be provided, protecting people who are waiting for the bus from various weather conditions. Additionally, the comfort level inside the bus should also be enhanced, for instance by providing enough spaces or compartments above or below bus seats. This will allow passengers to temporarily store their shopping bags or other belongings, without disturbing other passengers in the bus.

c. Increasing the attractiveness of bike-use

It can be noted that *accessibility* is an important instrument considered in Cluster-2 and Cluster-6. Both clusters are dominated by people whose transport mode habit is bike-use. This could be related to the fact that Hasselt employs a car-use restriction regulation in its city centre. In some parts of the city centre, car-free zones are applied. However, all areas in the centre are accessible by bike. This could be the reason why *accessibility* is an important aspect in the consideration of bike users. Additionally, bikes can be parked anywhere, without difficulty. In some parts of the in the city centre, guarded bicycle parking areas are provided for free (at least up to 6 PM).

Even though the above measures seem to be appealing enough, other measures can still be implemented, for instance by improving bicycle paths or lanes. This can be done by building separators between the bike lanes and car lanes, making people feel more secure when biking. Additionally, a Public Bike System (PBS) can also be implemented, as previously explained in Chapter 3 (Section 3.6).

6.6.3 Results: The shopping location decision

With regard to the shopping location clusters, the results are summarized below. To begin with, there are no significant differences in the complexity of the participants' MR, implying that people in different clusters reason as much for this decision, to some extent. Furthermore, the Fisher's test results indicate that there are no correlations between the shopping location cluster variable and other participants' characteristics. This implies that all clusters have a distribution of values across different variables which represents the distribution of values of the overall sample. These results lead to a conclusion that the differences among clusters can solely be observed in the members' generalized MR. These representations have been shown in Figure 6.8 and Figure 6.9, and they are explained in Section 6.4.2.2. Some similarities can be observed between them, as shown in the figures. For instance, different clusters have the same sets of instruments linked to the same benefits. The main differences only rest on the sets of contextual variables. Thus, this section generalizes the results that have been previously presented in Section 6.4.2.2 by grouping some clusters based on the benefit variables. Further discussions concerning the clusters below from the marketing point of view can be seen in Section 6.6.4.

6.6.3.1 Group-1: "True fun shoppers"

There are two clusters in which gaining the benefit of *having fun* is important, i.e. Cluster-5 and Cluster-6. In Cluster-5, this benefit is pursued in any circumstances through the instruments of *type of store in the area* and *favourite shops*. In Cluster-6, this benefit is acquired through the instruments of *ambiance, favourite shops, price of products,* and *presence of café and restaurant*. Additionally, the contextual variable of *companion* is elicited besides the *normally* context.

6.6.3.2 Group-2: "Efficient shoppers"

There are three clusters that focus solely on the benefit of *having efficiency* (i.e. Cluster-1, Cluster-2, and Cluster-4). These clusters are alike, especially regarding the underlying instruments to achieve the benefit; i.e. *the type of stores* and *favourite shops* (in all three clusters), and *familiarity with the area* (in Cluster-2 and Cluster-4). Some varieties among these clusters can be observed at the contextual level, and in the relationships between contexts and instruments to gain *efficiency*. For instance, the contextual aspects of *interest in a specific product* and *normally* are important in Cluster-1, whereas only the context of "*normally*" is important in Cluster-2. In Cluster-4, the contextual aspects of *interest in a specific product*, *normally*, and *time availability* are of crucial important.

6.6.3.3 Group-3: "Value shoppers"

This group consists of Cluster-8 and it is slightly different than the previous groups, specifically because the benefit of *saving money* is looked for. This benefit is fulfilled by the instruments of *product price*, *product quality*, and *favourite shops* because of the contexts of *budget availability*, *interest in a specific product*, and *normally*.

6.6.3.4 Group-5: "Self-confident shoppers"

This group is made up of Cluster-7. It is somehow similar to Group-2, especially with regard to the instrumental aspects; i.e. *familiarity with the area* and *favourite shops*. The only main difference is the benefit looked for. Instead of searching to *have efficiency* (Group-2), this group emphasizes the benefit of *having assurance and certainty*.

6.6.3.5 Group-4: "Easy shoppers"

This group contains Cluster-3. Akin to Group-2 and Group-5, the instruments of *familiarity with the area* and *favourite shops* are emphasized. The basic difference is that these instruments are linked to the benefit of *having convenience*, instead of the benefit of *having efficiency* (Group-2) or *having certainty* (Group-5).

6.6.3.6 Group-6: "Desirous shoppers"

This group is composed of Cluster-9. In comparison to the other groups of clusters, this group has the biggest complexity of in terms of its members' MR. This can be seen for instance from the number of benefits being pursued and the number of instruments being considered. The following benefits are looked for: *having efficiency*, *having fun*, *having information* and *saving money*. These benefits are fulfilled by the following instruments: *favourite shops*, *customer service*, *ambiance*, *price of product*, *type of store*, *product quality*, and *familiarity of the area*. Moreover, the contextual aspects of *normally*, *interest in a specific product* and *sale season* are also considered.

6.6.4 Discussions: The underlying motivations behind the shopping location choices

It is interesting to find out form the results that there are no significant differences between the participants' MR and their personal characteristics. Other research clearly indicates the correlations among people's motivations and their socio-demographic characteristics, such as age and gender (e.g. Arnold & Reynolds, 2003).

In the marketing domain, more attention has been paid to investigate the hedonic aspects of shopping (e.g. Arnold & Reynolds, 2003; Babin, Darden, & Griffin, 1994; Langrehr, 1991; Roy, 1994), related to people's emotions. This could also be associated with people's fantasy, fun, amusement, and stimulation (Babin et al., 1994). Additionally, some studies have been previously conducted to develop shopper taxonomies based on a number of aspects, such as motivations to go shopping (Tauber, 1972), enjoyment (Bellenger & Korgaonkar, 1980), customer and retailer relationships (Reynolds & Beatty, 1999), etc. However, a study that profile shoppers based on their shopping location decision has never been done before, at least to the best of our knowledge. Accordingly, in this study, the CB-CNET interface is used to reveal people's MR when making choices concerning where to go shopping in Hasselt city centre. Moreover, the underlying benefits (or motives) behind people's location choices can be disclosed. The results of the clustering analysis can be further categorized into six groups, based on benefits that people look for: *true fun shoppers*, *efficient shoppers*, *value shoppers*, *self-confident shoppers*, *easy shoppers*, and *desirous shoppers*.

The true fun shoppers decide to go to certain shopping locations because they want to have *fun*. Therefore, *the ambiance of the shopping location* is an important shopping location attribute for this people. They tend to combine the fun-shopping experience with other leisure activities such as hang out in café or dining out, making *the availability of café and restaurant* in the shopping area important for them. They also gain enjoyment through the experience of hunting "cheap" products, even though their main intention to do that is not to save some money, but simply because of the excitement that they get from their "hunting" experiences. The other group is *the value shoppers,* borrowing terminology used by Arnold & Reynolds (2003) for a similar group of shoppers discovered in their study. Unlike *the true fun shoppers* who consider product price as a way to have some fun, *the value shoppers* consider product price because they want to save some money. In this group, *budget availability* also strongly influences people's location choices.

Another group learned in this study is *the efficient shoppers*. This type of shoppers goes shopping to a particular area because they know that they can save their time and effort, maximizing their time availability. Therefore, *the* *presence of their favourite shops* and *familiarity with shopping area* are important aspects being considered. The next group is *the self-confident shoppers* and *easy shoppers*. These types of shoppers also think *about the presence of favourite shops* and *familiarity with the shopping area* when going shopping. However, the underlying benefits behind those aspects are to gain *certainty* and *convenience* respectively. The last group of shoppers is relatively complex, chasing many benefits out of their shopping location choices, such as *having efficiency*, *having fun*, *having information* and *saving money*. Therefore, this group is named as *desirous shoppers*. They also give emphasis on the quality of customer service, implying that they may be loyal shoppers who consider sale person-customer relationships (Reynolds & Beatty, 1999).

The typology of fun-shopping travellers based on the shopping location decision clearly shows the importance of emotional variables, such as *favourite shop* and *familiarity* with shopping area. This comes in line with the results of another study by Nevin & Houston (1980). Other retailer attributes important to specific group of shoppers can also be identified, such as *product price*, supporting results of other studies by Babin, Gonzalez, & Watts (2007); Lichtenstein, Ridgway, & Netemeyer (1993); and Sinha & Prasad (2004). Additionally, *ambiance or environment* as well as *the presence of café and restaurants* are important as well. Arnold & Reynolds (2003) indicate that people consider shopping as a way to socialize with other people, i.e. social shopping. However, this study doest not find any social factors (e.g. presence of companion) as determinant aspects to decide where to go shopping.

From the retailer point of view, the results can enrich the understanding of important aspects that people consider when making their shopping location choices. They support the idea to focus on customers' shopping experiences and emotions, making people feel *fun*, *secure*, and *convenient* without sacrificing their need to gain more *efficiency*. Some information concerning instruments (or attributes) of the shopping location decision can be used to improve the attractiveness of some areas in Hasselt city centre. For instance, it is important to create a nice ambience for people to stroll around, and to provide good information by giving informative map or other types of information that can increase people's familiarity with the area. Moreover, a shopping area should allow people to do other leisure activities besides shopping, such as dining in the city centre, drinking, etc.

6.7 Conclusions

This study demonstrates how to generate the typology of fun-shopping travellers based on people's decision-making processes when making their transport mode decisions to go shopping and their location choices. To do that, Hasselt is chosen as a case study and 221 respondents are used as the sample. The CB-CNET interface is designed to capture people's thought processes and other participants' data, such as education, age, etc. A number of analyses are performed next, i.e. *hierarchical clustering analysis*, *FI*, and *Fisher's test*. The results of the transport mode and location decisions are addressed separately. The outcomes of the first decision are discussed with the main intention to identify TDM measures that can break car-use habit. The results of the latter decision are highlighted from the marketing point of view, emphasizing aspects that influence people's location choices.

The results of the transport mode decision allow us to understand the underlying considerations of people's with different transport mode habits. For instance, car users generally want to gain *efficiency, freedom, convenience*, and *comfort*. These benefits are fulfilled through car instruments of *travel time*, *flexibility/independency*, *treatment of bags*, and *shelter provision*. These instruments are *normally* considered. However, certain instruments are important in specific contexts related to *time availability* and *the number or size of goods being purchased*. Considerations of bike users are also captured. One of the main concerns of bike users is *the easiness of parking*, an instrument not considered by car users. This could happen because parking-related measures are not strict in Hasselt. This finding suggests a way to break car-use habit by limiting the number of free-parking spaces. Furthermore, parking cost should be increased and implemented strictly. TDM to increase bus-use should focus on the benefits that the car users want to gain and the instruments to achieve those benefits.

With regard to the shopping location decision, the results show that people can be grouped based on their MR. unexpectedly, no associations can be found between the shopping location decision clusters and the participants' socio-demographic characteristics. Based on people's sought after benefits, the resulted clusters can be further categorized into are six groups; namely: *true fun shoppers*, *efficient shoppers*, *value shoppers*, *self-confident shoppers*, *easy shoppers*, and *desirous shoppers*. The results reveal the importance of emotional factors. Thus, customers' shopping experiences and emotions should be emphasized to make people feel *fun*, *secure*, and *convenient* while still gaining *efficiency*. Additionally, the results indicate that, in fact, the instruments of *favourite shop* and *familiarity* with shopping area are essential. Therefore, from the city marketing point of view, the city attractiveness can be improved by creating a nice ambience for people to stroll around. Additionally, providing good information (e.g. giving informative map) can increase people's familiarity with the area, making it more attractive.

7 Performance assessments of decision tree and influence diagram

"As far as the laws of mathematics refer to reality, they are not certain, and as far as they are certain, they do not refer to reality."

Albert Einstein

7.1 Introduction

Research to model decision problems using AI techniques has been previously conducted in different fields, such as in the medical domain (e.g. Patil, Toshniwal, & Joshi, 2009), military (e.g. Howard & Matheson, 2005), education (Stevens, Ikeda, Casillas, Palacio-Cayetano, & Clyman, 1999), engineering (e.g. Bielza & Shenoy, 1999), etc. In the transportation field, decision problems are commonly represented as DT, such as in the CPM of activity-travel demand models. A well known example of these CPM models is ALBATROSS (Arentze & Timmermans, 2008), used to assess transport policy impact in the Netherlands. In ALBATROSS, a DT model consists of scheduling rules and decision heuristics. Despite its advantages, i.e. easy to understand and solve (Bielza & Shenoy, 1999), DT cannot clearly represent sequential decision making and retain interconnected aspects in cognitive subsets.

Another AI method, namely ID, can overcome the problems above and portray a complex decision process compactly using probabilistic structures (Owens, Shachter, & Nease, 1997). Arentze et al. (2008a) have underlined the importance of an integrated modelling approach to capture causal structures and parameters included in MR and decision rules. However, the performance of different modelling techniques to predict the actual travel behaviour based on people's MR has never been investigated before, at least to the best of our knowledge.

Hence, this chapter focuses on the *performance assessments* of ID and DT, highlighting the two sequential decisions of the *transportation mode* and *location* choices. The CB-CNET protocol is used to gather the MR data from 221 respondents regarding their leisure-shopping travel behaviour in Hasselt. Additional parameters (weights and utilities) are collected, allowing the data to be modelled as ID. Moreover, a total number of 2893 choice scenarios are assessed by the respondents. Each respondent evaluates up to maximum 20 scenarios depending on the personal elicited contextual aspects. Furthermore, the participant's preferred transport mode and location choices are elicited for these scenarios, enabling his model to be validated.

The analysis in this chapter highlights the accuracies of ID and DT models in predicting people's travel choices and the alteration of people's decision outcomes because of the occurrence of certain contexts. The performances of ID and DT models in predicting people's behaviours are compared. In general, the results indicate that the DT model outperforms the ID model. However, due to the specific characteristics of both techniques, the best modelling approach may rest on research questions at stake. ID is more naturally suited to explicitly model the underlying decision mechanisms of people, whereas DT gives better results as a predictive model.

An additional analysis is done to compare different methods to generate the utility weights. It has been previously described in Chapter 4 (Section 4.3.4) that two ways to calculate these weights are tested. The first method employs separate rating tasks of all the benefits, whereas the second method uses the stated preference experiment of FFD. In the analysis, the first weighting technique is employed to compute all ID models. Moreover, the second method is used to recalculate these models. The accuracies of both methods in predicting the actual choices are compared. It should be noted that the initial comparison of ID and DT on the bootstrapped datasets is done by using the first weighting method for the ID models.

Modelling individuals' MR as ID has been previously described in Chapter 2 (Section 2.4) and in Chapter 4, therefore it is not explained anymore in this chapter. The following ID model example (Figure 7.1) is presented only to give a reminder that some evidence can be entered in the network, specifically in the contextual aspect nodes. Inferring the ID model yields new utility values of all choice alternatives given the evidence (Figure 7.2).

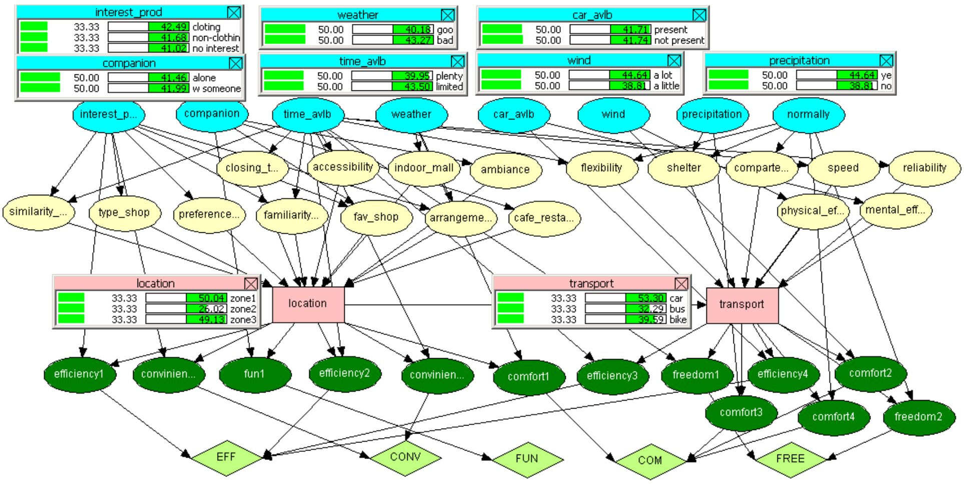


Figure 7.1 An example of the participant's influence diagram model (without evidence)

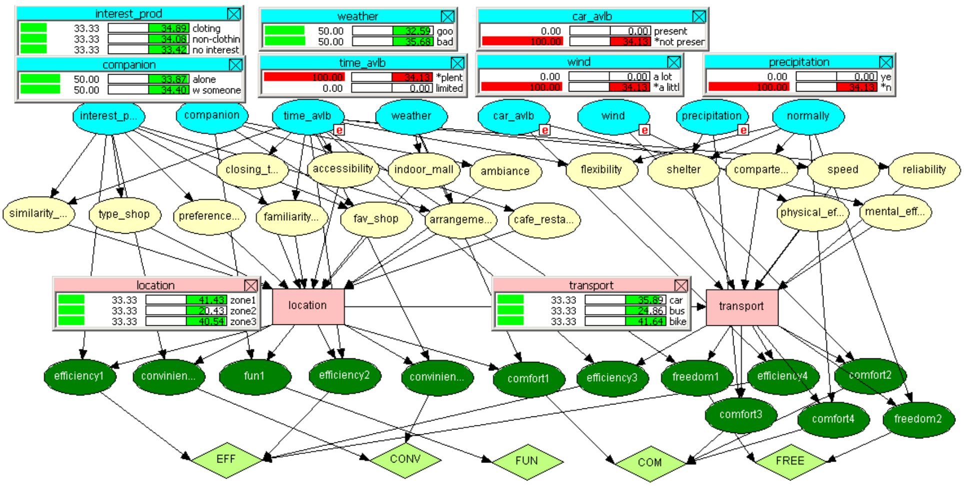


Figure 7.2 An example of the participant's influence diagram model (with evidence)

Hence, the rest of this chapter is structured as follows: modelling individuals' MR as DT is firstly explained in Section 7.2. Following that, the datasets are described in Section 7.3. Next, the analysis and results of the performance assessments are presented and discussed in Section 7.4. An additional analysis with regard to the weighting methods for ID, along with its results, is presented in Section 7.6. At last, some conclusions are drawn in Section 7.7.

7.2 Modelling individuals' fun-shopping travel decisions using the decision tree technique

DT is a technique for *discovering* hidden patterns in a dataset and *predicting* values of its attributes by means of a structural model (Rokach & Maimon, 2008). DT could be a *classifier* or *regression model.* It uses *supervised methods* to discover relationships between a target variable and its input variables. A target attribute is a variable to predict and it is referred to as a *dependent variable*, whereas input attributes are called *independent variables*. DT consists of nodes that shape a rooted tree. Its classification provides routes from the *root* to the *leafs* (Witten & Frank, 2005). A *root node*, or a *parent node*, is a node that does not have any incoming edge. *Leaf nodes* are nodes without any outgoing edge and they represent the target variable. Other nodes with one incoming and one outgoing edge are specified as *internal* or *test nodes*. The dependent variable in regression models has real (numeric) values, and in classifier models, this node uses predetermined classes.

This study employs DT as a classifier model. There are other classifier models, such as *neural networks*, *Bayesian networks*, *support vector machines*, and *instance based model* (Rokach & Maimon, 2008). However, in the transportation field, the DT classifier model is the one that is commonly used to predict people's travel behaviour. Table 7.1 illustrates a simple example of a dataset involving a decision to take *a car* or *a bike* (leaf node) given a set of contexts, i.e. *weather conditions* and *time availability*, and individuals' characteristics, i.e.

age and *gender*. *Age* is a numeric attribute. Accordingly, it is discretized into ranges so that it can be split. Figure 7.3a illustrates the resulted DT from the dataset, showing that *if* the respondent is 19 years old or younger *then* a bike is chosen; *if* the respondent is older than 19 years old and there is limited time available *then* a car is used; etc.

Table 7.1 A transport mode dataset example

Independent variables				*Dependent variable*
Age	*Gender*	*Weather*	*Time available*	*Transport mode*
15	Male	Sunny	Plenty	Bike
16	Male	Rainy	Plenty	Bike
17	Female	Sunny	Limited	Bike
18	Female	Rainy	Limited	Bike
15	Male	Sunny	Plenty	Bike
16	Male	Rainy	Plenty	Bike
18	Female	Sunny	Limited	Bike
20	Female	Rainy	Limited	Car
19	Male	Sunny	Plenty	Bike
20	Male	Rainy	Plenty	Car
21	Female	Sunny	Limited	Car
22	Female	Rainy	Limited	Car
23	Male	Sunny	Plenty	Bike
24	Male	Rainy	Plenty	Car
24	Female	Sunny	Limited	Car
23	Female	Rainy	Limited	Car
26	Male	Sunny	Plenty	Bike
27	Male	Rainy	Plenty	Car
25	Female	Sunny	Limited	Car
27	Female	Rainy	Limited	Car
28	Male	Sunny	Plenty	Bike
29	Male	Rainy	Plenty	Car
28	Female	Sunny	Limited	Car
28	Female	Rainy	Limited	Car
29	Male	Sunny	Plenty	Bike
21	Male	Rainy	Plenty	Car
22	Male	Sunny	Limited	Car
23	Male	Sunny	Limited	Car
24	Male	Sunny	Limited	Car
24	Female	Sunny	Plenty	Bike
22	Male	Sunny	Plenty	Bike
23	Female	Sunny	Plenty	Car
24	Female	Sunny	Plenty	Car

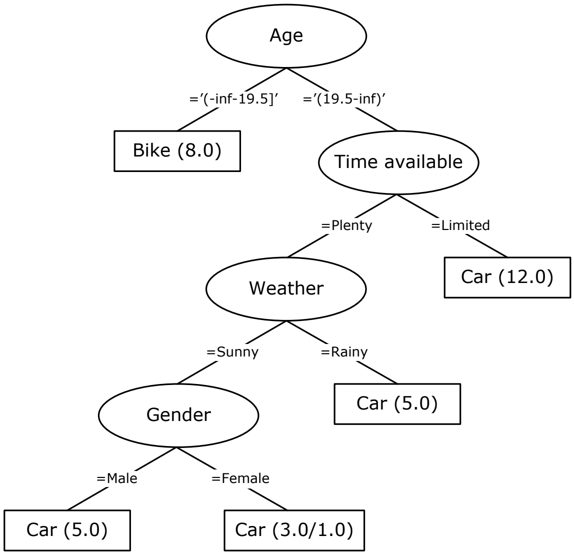


Figure 7.3 The decision tree derived from the transport mode dataset in Table 7.1

A DT model is generated by initially selecting a root node. This node should be an attribute that can split the data effectively and produce the purest child nodes with the same classification. *Information gain values* are used for this purpose to measure the degree of purity of each node in *bits*. These values are derived from the concept of *entropy* in *information theory* (Shannon & Weaver, 1998). An induction algorithm is normally used to calculate an information gain value at each attribute, assigning a node with the highest value as the root node. Details of the entropy calculations of the dataset in Table 7.1 to generate the decision tree in Figure 7.3 are shown in Appendix K2.

A DT classifier model predicts the performance of a new (*testing*) dataset based on the old database (*training*) past performance, represented by an estimated numeric *error* (or *success*) *rate*. A success rate (also referred to as *correctly classified instances*) is calculated by holding out a two-third part of a dataset for training and another one-third part for testing. Each attribute should appear proportionally in both training and testing sets to avoid over- or under-represented variables. Thus, stratified random sampling is normally used. However, when a dataset contains a relatively small number of records, it is often not sufficient to use only two-third of the data to learn the classification (Witten & Frank, 2005). The *cross-validation* technique is used to solve this problem. It equally and randomly divides a dataset into some folds, e.g. 10. Next, it runs 10 iterations, each of them uses one-fold as a testing set and the combined remaining nine-folds as a training set. The overall error rate is the average value of 10 error estimates. By doing cross-validation, every record in a dataset has been used once for testing. Accordingly, this method is suited to calculate the performance of a DT model, generated from the individuals' MR dataset, and to equally compare the result with the accuracy of individuals' ID models. Data mining software, such as Waikato Environment for Knowledge Analysis (WEKA) (University of Waikato, n.d.), can be used to automatically generate a DT classifier form a dataset (Witten & Frank, 2005).

A DT algorithm recursively splits the data until all leaf nodes are as pure as possible. This implies that the success rate of the training data is at maximum. However, perfect leafs in all cases also means that the number of rules and the tree size can be prohibitive (Han & Kamber, 2004). Moreover, it may give less effective results on a testing set. Therefore, many algorithms tend to prune their results for simplification and generalization, emphasizing on the balance between flexibility and accuracy.

A DT algorithm, such as basic J48, generates a DT using the information gain principle. J48 is WEKA implementation of the well-known C4.5 algorithm (Quinlan, 1992) and it applies some pruning methods, known as *sub-tree replacement* and *sub-tree raising* (Witten & Frank, 2005). The first technique shortens a full tree by replacing a test node with a leaf whereas the second one simplifies a tree by moving a node upwards the tree, in the direction of the root, and replacing other nodes along that path. The algorithm decides to employ the replacement or rising methods based on some factors, for instance the calculation of error rate of a full tree, the number of instances per leaf, etc.

In order to model individuals' MR using DT, all aspects that appear in people's cognitive representations should be used as input data. Personal characteristic data are also needed, allowing the tree to generate rules at a disaggregate level. Furthermore, all scenario data enable the model to predict behavioural changes of people due to certain contexts and constraints.

7.3 The datasets

This study focuses on assessing the performances of ID and DT techniques in modelling individuals' MR and also predicting people's actual travel behaviour in various scenarios. Since two different modelling approaches are investigated, the required data varies accordingly. This section describes the use of the data gathered in the CB-CNET survey for the ID and DT models. Indeed, the CB-CNET protocol is designed to capture the individuals' MR and some parameters (probabilities and utilities) for the ID modelling purpose. However, the collected data can be used for other modelling techniques as well, such as DT.

The stages of the CB-CNET elicitation protocol is summarized in Figure 7.4a. The output data and their specific use for the two tested methods are shown in Figure 7.4b. The CB-CNET stages have been previously detailed in Chapter 4 (Section 4.3). Briefly, the survey starts by asking the respondents to give their personal information, such as age, gender, housing location, etc. Additionally, the participants' transport mode behaviour to Hasselt city centre is investigated, followed by exploring their leisure-shopping behaviour. This information is used in the DT model as complementary independent variables to the cognitive subset data (Figure 7.4b), enabling a DT model to foresee all participants' travel behaviour and making it comparable to the participants' ID models.

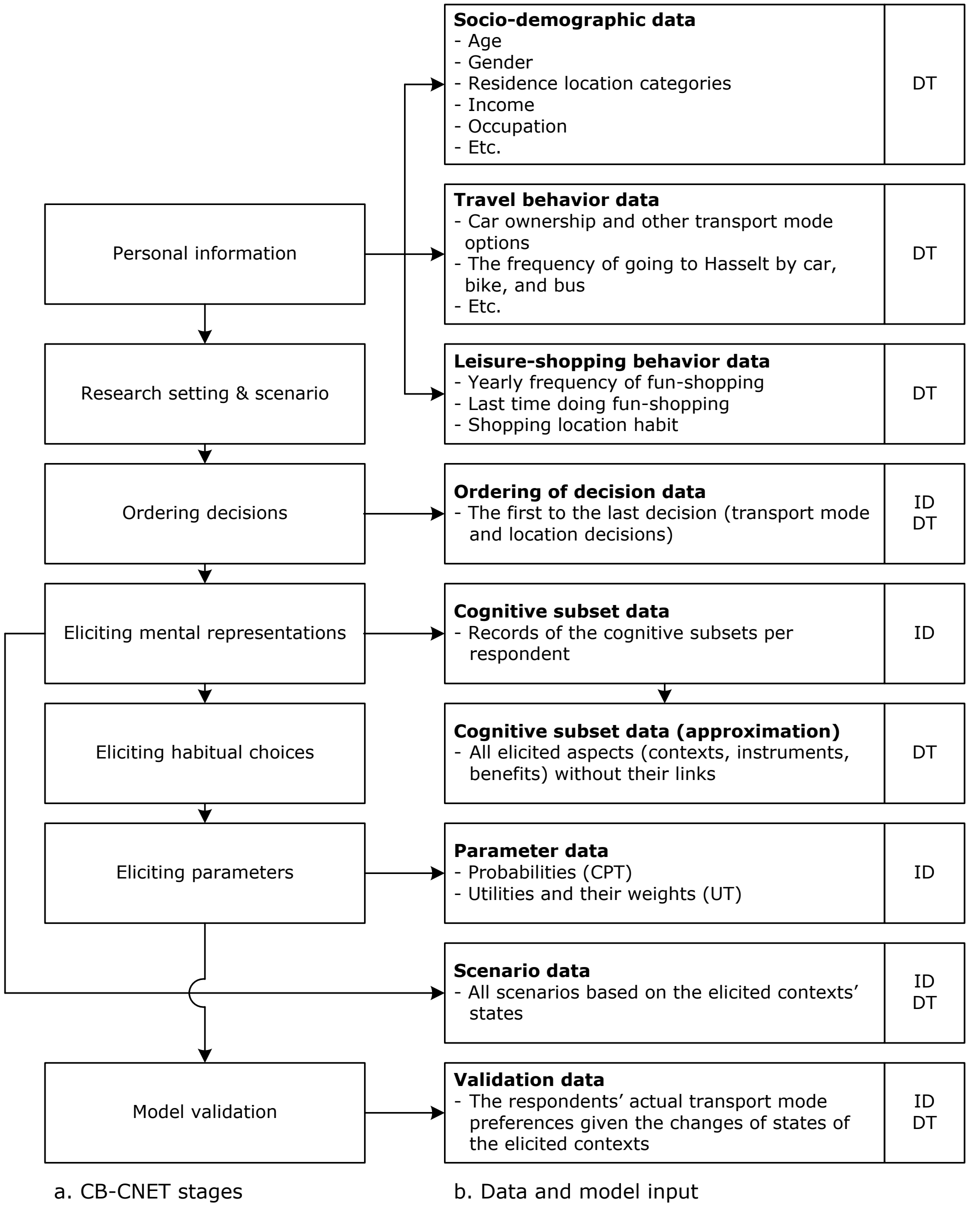


Figure 7.4 The stages in the CB-CNET protocol (a); and the derived data for the modelling input (b)

In the survey, each participant is asked to order his decision making, allowing for generating his ID model structure. Unlike ID, DT cannot clearly model sequential decision making. However, these data can still be used as one of the independent variables of the DT model. Moreover, the interface elicits every participant's MR, used to construct the graphical representation of his personalized ID model. Since DT cannot model the interconnected aspects in cognitive subsets, the approximation of these data is used as input to the DT model, using only the presence or absence of certain aspects in the respondents' MR. Subsequent parameter questions (i.e. probabilities and weights) are automatically generated based on the participants' unique networks for the purpose of ID. The last part of the survey is aimed at validating the models. In this part, the participants' actual choice preferences are elicited concerning their selected contexts. Up to 10 scenarios are generated for each respondent (per-decision), and each scenario consists of a set of contextual aspects elicited by the corresponding respondent. For instance, in the survey, a respondent selects the contextual aspect of *time availability*, *car availability*, *wind*, and *precipitation*. Accordingly, he is asked about his transport mode choice given that *there is plenty of time available, a car is not available, it is not a windy day,* and *there is no precipitation*, denoting one scenario for that respondent. A set of contextual variables stays the same for each respondent, and thus for a number of scenarios for that respondent. However, the combinations of the predetermined context states change in these scenarios (as shown in Figure 7.5).

There are 221 respondents who participate in this study. However, seven respondents' data are incomplete. Consequently, only the data from 214 participants are used for further analysis, resulting in the total number of 2893 recorded scenarios. These records are divided into two datasets, consisting of 1547 and 1346 scenarios for the transport mode and location decisions successively. Each record contains the participant's preferred transport mode or location choice, given the scenario (C1 in Figure 7.5). This can be used as a benchmark to validate the modelling results.

Respondent 1 elicits Context A {state A1, State A2, State A3}, Context B {state B1, State B2}, and Context C {state C1, state C2}					
Respondent	Scenario	Context A	Context B	Context C	C1
1	1	State A1	State B1	State C1	Car
	2	State A2	State B1	State C1	Bike
	3	State A3	State B1	State C1	Car
	4	State A1	State B2	State C1	Bus
	...	State A...	State B...	State C...	...
	10	State A3	State B2	State C2	Car

Scenario data, Randomly generated (maximum 10 scenarios per respondent, per decision) | Validation data

Respondent 2 elicits Context B {state B1, State B2}, and Context D {state D1, state D2}				
Respondent	Scenario	Context B	Context D	C1
2	1	State B1	State D1	Car
	2	State B2	State D1	Car
	3	State B1	State D2	Car
	4	State B2	State D2	Bike

Figure 7.5 The scenario and validation (raw) data of Respondent-1 and -2

7.4 The Analysis

This section starts by initially describing the DT model analysis (in Section 7.4.1). Following that, the ID model analysis is explained (in Section 7.4.2). At last, the analysis to calculate the performances of ID and DT models in predicting every decision class is shown (in Section 7.5.2).

7.4.1 The decision tree model analysis

In order to generate a DT model, the participants' socio-demographic data, travel behaviour data, etc. are used as the independent variables. Furthermore, the validation data (C1) are set as the dependent variable, as shown in Figure

7.6. The DT model is developed using WEKA Explorer, specifically by employing *J48 algorithm* and *10-fold cross-validation*. WEKA automatically calculates the accuracy value of the DT model. This accuracy is also referred to as *correctly classified estimates* or *success rate*. Details of success rate calculation are presented in Section 7.4.3. Generally, the accuracy of a DT model is very sensitive to the changes in the input data. Hence, it is never certain if an accuracy value remains approximately the same when another dataset is used or when the same experiment is repeated (Efron & Tibshirani, 1994). In order to draw a more solid conclusion regarding the performance of the DT technique, the dataset ([a] in Figure 7.6) is bootstrapped 100 times, creating 100 bootstrap datasets and 100 accuracy values. These values are recorded in another dataset ([c] in Figure 7.6).

Bootstrapping is a *re-sampling method with replacement*. By bootstrapping the original data, new datasets are generated. Each of them comes from the same distribution as the original dataset. This allows us to calculate multiple accuracies to get a better idea of the performance of DT on data generated by the same multivariate distribution as the original dataset. Further explanation of the bootstrapping technique can be read for instance in Efron & Tibshirani (1994).

Hence, the new dataset ([c] in Figure 7.6) contains 100 accuracy values that can be used to calculate one mean estimate (of the accuracy). However, it may not be sufficient to draw any conclusion about the overall accuracy of the DT model. Based on statistical theory, the true accuracy lies in an interval with a certain probability that states its confidence level (e.g. 95%). This interval is referred to as *confidence interval* (CI) and it is derived from parameter calculations over some repeated accuracy samples. Bootstrap data may help increasing certainty on the results and enabling us to calculate the CI of the bootstrapped means. Accordingly, the accuracy dataset is bootstrapped 2000 times ([f] in Figure 7.6), and the bootstrap mean and CI are calculated.

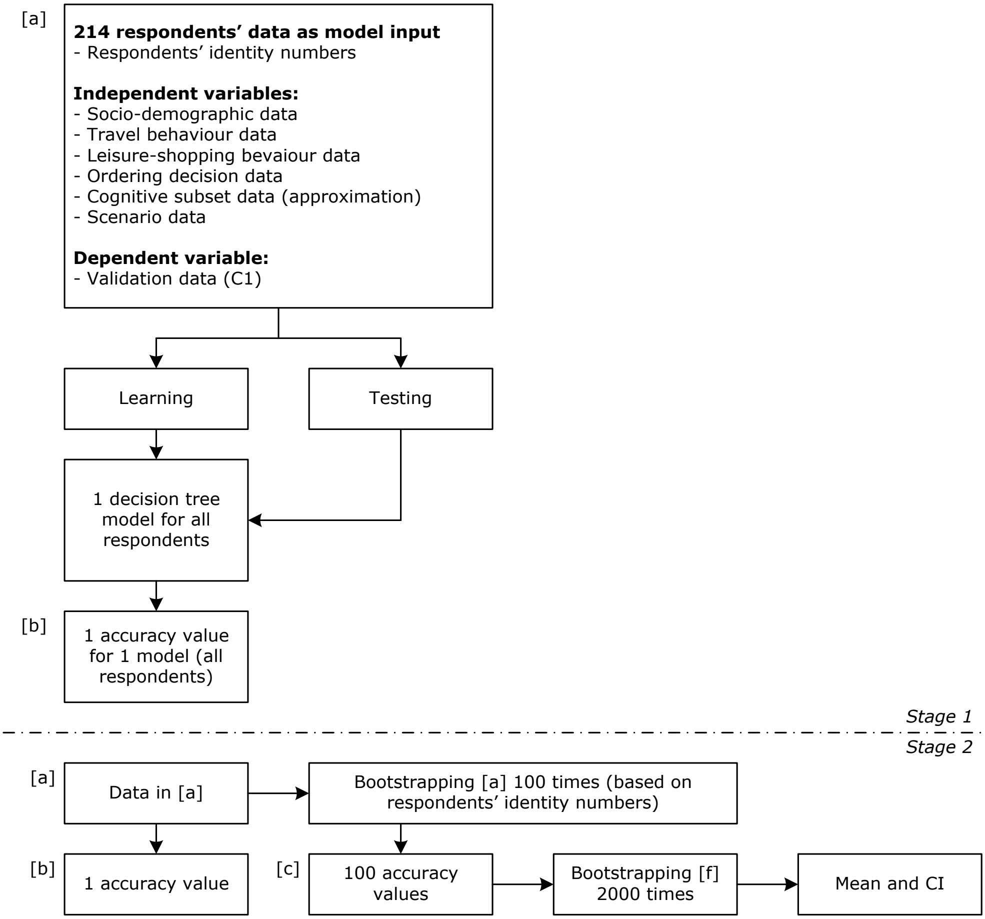


Figure 7.6 Calculating statistical estimates for the decision tree model

There are many techniques that can be used to calculate bootstrap CI. The simplest and the most popular method is *percentile bootstrap*. The 95% percentile CI is simply derived by obtaining the 2.5% and 97.5% percentile points of the bootstrap sample. However, this method works properly only on instances where the distribution of the statistic of interest is symmetrical (Efron, 1987). Otherwise, this technique tends to overestimate the CI (Schenker, 1985). Furthermore, in small sample sizes of less than 50 observations, the percentile bootstrap CI is usually too narrow (Schenker, 1985).

Another more complex method is the *bootstrap bias-corrected and accelerated* (BC_a) CI method (Efron & Tibshirani, 1994). This technique improves the percentile bootstrap, allowing for bias adjustment in the bootstrap distribution. Mathematical discussions of the BC_a bootstrap method are not present in this chapter (see Efron & Tibshirani, 1994). This study employs R statistical software (R Project, n.d.) to calculate the bootstrap mean and 95% percentile and BC_a CI. The BC_a CI is computed using *bcanon()* command from the *bootstrap package* in R. The results are shown in Section 7.5.1.

7.4.2 The influence diagram model analysis

In order to calculate the accuracy of the ID models, the stages shown in Figure 7.7 are followed. To start with, the elicited cognitive subset and parameter data of each respondent are used to develop the ID model for that respondent. Next, a set of evidence is entered in the network based on the scenario data and the network is updated in order to calculate all utility values of the choice alternatives (see Figure 7.1 and Figure 7.2 as examples). Afterwards, another set of evidence is entered and the network is recalculated. This process is repeated until all the scenarios (maximum 10 scenarios per decision) of that respondent have been used as sets of evidence in his ID model.

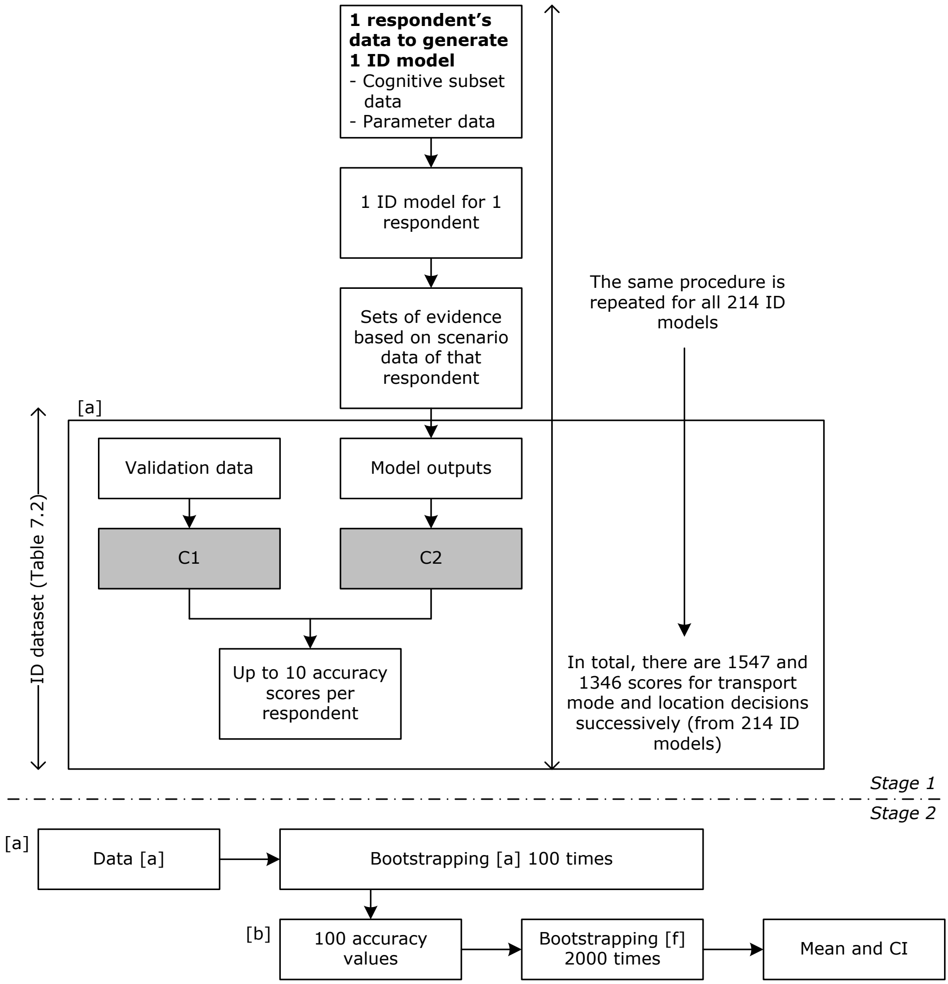


Figure 7.7 Calculating statistical estimates for the influence diagram model

The results of ID calculations are recorded in a dataset. An example of this dataset is shown in Table 7.2. This dataset also consists of the respondents' unique identity numbers (in the *Resp* column) and the scenario numbers (in the *Sc* column). The latter column only records the scenario identification numbers, whereas the associated contexts and their states are not recorded here. This happens because the contexts and their states are already taken into account in the individuals' ID models (Figure 7.7). The next columns in Table 7.2 are the *validation data*. These columns record the participants' probability estimations of choosing car, bus, and bike, given their personal evaluation on the scenarios. It is assumed here that a choice alternative with the highest probability value is assigned as the actual decision in the given scenario (the *C1* column). In this regard, some assumptions are applied, as explained in the subsequent paragraph. The ID calculated utility values of all choice options are registered in the *ID result* columns. Assuming that each respondent is a complete rational being who always chooses a choice option with the highest utility value, the predicted choice of an ID model given a scenario can be identified and recorded in the *C2* column. Here, the same assumptions used to determine the actual choice in the C1 column are also employed. An additional Java program is written to automate the generation of individuals' ID models using Hugin Researcher 7.2. Moreover, these programming codes also allow us to automatically enter sets of evidence based on the scenario data, and repeatedly infer the network. The last column of *score* signifies the matches/mismatches of the actual choices (C1) and predicted choices (C2). When the score is 1, it means that the predicted choice is the same as the respondent's actual choice, and vice versa. The score of 0 indicates that these (actual and predicted) choices do not match.

The following assumptions are used to assign the actual choices (C1) from the probability values: first, a choice alternative with the highest probability value (in the *car*, *bus* and *bike* columns) is selected as the decision outcome. This assumption is applied on 1468 and 1209 records for the transport mode and location decisions consecutively. However, when all decision alternatives have the same probability value, then the decision choice is selected randomly across these options. There are 9 and 16 records in the transport mode and location datasets successively that fall into this assumption. Similarly, if two choice alternatives have the same highest score, then the decision is assigned between these alternatives at random. This assumption is applicable to 70 records of the transport mode dataset and 121 instances of the location dataset. Such assumptions have to be made because the DT classifier model can only use a categorical variable as the dependent variable (recall that the dependent variable of the DT model is the C1 data). Hence, to have fair comparisons between ID and DT in the second analysis, these assumptions are also applied in the ID results to assign the ID choices recorded in the C2 column.

Table 7.2 An example dataset to calculate the accuracy of an influence diagram model

Resp[1]	*Sc*[2]	*Validation data*				*ID results*				*Score*
		Car	*Bus*	*Bike*	*C1*[3]	*Car*	*Bus*	*Bike*	*C2*[4]	
	…									
16_2707	15	0.75	0.5	0	Car	72.79	48.80	34.44	Car	1
16_2707	16	0.76	0.5	0	Car	70.37	50.73	34.81	Car	1
16_2707	17	0.76	0.5	0	Car	72.23	50.19	34.67	Car	1
16_2707	18	0.76	0.5	0	Car	71.93	49.54	34.44	Car	1
16_2707	19	0.73	0.49	0	Car	73.50	48.82	34.67	Car	1
16_2707	20	0.75	0.49	0	Car	73.25	48.80	34.67	Car	1
17_4107	21	0	1	0	Bus	6.81	32.25	69.63	Bike	0
17_4107	22	0	1	0	Bus	6.81	41.67	66.44	Bike	0
17_4107	23	0	0.08	0.91	Bike	6.81	29.45	80.31	Bike	1
17_4107	24	0	1	0	Bus	6.81	45.25	59.15	Bike	0
17_4107	25	0	1	0	Bus	6.81	39.09	69.88	Bike	0
17_4107	26	0	1	0	Bus	6.81	47.30	59.67	Bike	0
17_4107	27	0	1	0	Bus	6.81	33.35	69.41	Bike	0
17_4107	28	0	0.99	0	Bus	6.81	40.85	66.96	Bike	0
17_4107	29	0	1	0	Bus	6.81	48.15	59.15	Bike	0
17_4107	30	0	1	0	Bus	6.81	41.07	59.72	Bike	0
20_3951	31	0	0.49	0.48	Bus	2.33	147.67	146.17	Bus	1
20_3951	32	0	0.48	0.48	Bike	2.33	147.67	145.83	Bus	0
20_3951	33	0	0.48	0.48	Bus	2.33	148.17	147.00	Bus	1
20_3951	34	0	0.48	0.48	Bus	2.33	147.67	146.83	Bus	1
20_3951	35	0	0.48	0.48	Bus	2.33	147.67	146.83	Bus	1
…	…	…	…	…	…	…	…	…	…	…
…	1547	…	…	…	…	…	…	…	…	…
									Performance assessments	0.6716

[1] Respondent's identification number
[2] Scenario identification number
[3] Respondent's actual choice, given the scenario
[4] Respondent's ID predicted choice, given the scenario as evidence

In order to get a comparable result to the DT model accuracy (mean and CI), the dataset [a] in Figure 7.7 is bootstrapped 100 times (correspond to the DT bootstrapped data), yielding 100 accuracy values recorded as a new dataset ([b] in Figure 7.7). Similar to the procedure to generate the mean and CI of DT, the mean dataset of [b] is bootstrapped again 2000 times. The results are presented in Section 7.5.1.

7.4.3 Confusion matrix and the model accuracy in predicting every decision alternative

It has been previously explained (i.e. in Section 7.4.1 and Section 7.4.2) that this study investigates the performances of DT and ID models in predicting individuals' transport mode and location choices. Based on our observations, the data are unbalanced (or skewed), meaning that the number of samples in the predetermined classes varies considerably. Specifically, the number of cases in which *car* is selected as the transport mode choice is significantly larger than the ones in which *bike* and *bus* are chosen. A similar trend can also be seen in the shopping location dataset. The respondents prefer to go to *Zone-1* or *Zone-2* much more than to go to *Zone-3*. These unbalanced data may lead to the misinterpretation of the overall performances of DT and ID models, because accuracy values of such models may not represent their true performances. This issue is explained in the following example. Suppose that the transport mode decision variable (i.e. the dependent variable) has two classes: car-use (90 samples) and bike-use (10 samples). Even if a model predicts that all samples are car users, the accuracy of this model is still 90%. However, this model, in fact, misclassifies all bike-use samples (0% recognition rate for this class). Therefore, in order to solve this problem, a *confusion matrix* is commonly be used as a way to represent model outcomes.

In the AI field, a confusion matrix displays test results of a model in two-dimensional, as shown in Figure 7.8. Each cell in the matrix signifies the number of instances in a dataset. The actual class instances are represented in rows, whereas the predicted class instances are recorded in columns. In the matrix in Figure 7.8a, annotation *a*, *e*, and *i* represent the number of cases in which the model correctly predict (or classify) the variable classes (*X1*, *X2*, and *X3*). The other annotations (i.e. *b, c, d, f, g,* and *h*) signify the model misclassifications. An example is shown in Figure 7.8b. In this example, the overall model performance is 84.49%. This value could be a success rate of a DT model or an ID model accuracy. Furthermore, the confusion matrix shows that in fact, the model predict car-use correctly in 734 instances out of 807 cases (734+47+26), leading to 90.98% recognition rate for the car-use class. Similarly, bus-use and bike-use rates are 82.17% and 71.38% respectively. This example clarifies how a confusion matrix helps give a better idea of the performance of DT and ID models in predicting or classifying samples. Further details regarding confusion matrix can be read for instance in Witten & Frank (2005).

		Predictive			Recognition rate (accuracy)
		X1	X2	X3	
Actual	X1	**a**	b	c	a/(a+b+c)
	X2	d	**e**	f	e/(d+e+f)
	X3	g	h	**i**	i/(g+h+i)
Note: R=a+b+…+h+i S=a+e+i			Total accuracy		S/R

a. A confusion matrix

		Predictive			Recognition rate (accuracy)
		Car	Bus	Bike	
Actual	Car	**734**	47	26	90.95%
	Bus	47	**341**	27	82.17%
	Bike	53	40	**232**	71.38%
				Total accuracy	84.49%

b. An example of calculating accuracies from a confusion matrix

Figure 7.8 A confusion matrix (a) and a confusion matrix example (b)

It is explained in Section 7.4.1 that 100 DT models are created from 100 bootstrapped datasets. Hence, there are a total number of 100 confusion matrices, each of them correspond to one DT model. However, for the purpose of this study, only 50 confusion matrices are used because they are already sufficient to give an idea of the DT recognition rates of the independent variable classes. 50 DT models are randomly selected among 100 available DT models, and their correspondent matrices are used for further analysis. WEKA software is used to develop the DT models, to generate the confusion matrices, and to calculate the overall success rates of these models.

Similarly, it is explained in Section 7.4.2 that a total number of 100 ID datasets are created. Each of them consists of prediction results of 214 participants' ID models over 1547 scenarios in the transport mode decision dataset and 1346 scenarios in the shopping location dataset. It should be noted that a DT model also contains the data from 214 respondents. Therefore, it is comparable to an ID dataset. 100 confusion matrices can also be made, each of them link to every ID dataset. Comparable to the DT model analysis, 50 ID datasets are also randomly selected among 100 available datasets and used to generate 50 confusion matrices for the ID models.

In the end, 12 datasets are generated. Each dataset contains 50 accuracy records of the following items: car-use (1), bus-use (2), bike-use (3) predictions of ID models for the transport mode decision, car-use (4), bus-use (5), and bike-use (6) predictions of DT models for the transport mode decision, Zone-1 (7), Zone-2 (8), Zone-3 (9) predictions of ID models for the shopping location decision, and Zone-1 (10), Zone-2 (11), Zone-3 (12) predictions of DT models for the shopping location decision. In order to calculate bootstrapped statistical estimates (i.e. mean, 95% CI, and standard deviation), each dataset is bootstrapped 2000 times. The results of this analysis are presented in Section 7.5.2.

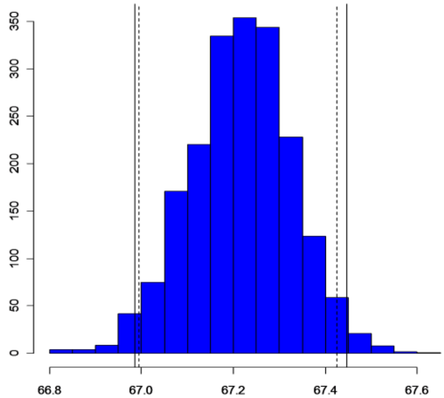
7.5 Results and discussions: Performance assessments

This section is divided into three parts. The overall results of the accuracies of DT and ID models are presented to begin with (in Section 7.5.1). Following that, the accuracies of these models in predicting each decision alternative are shown next (Section 7.5.2). At last, the results are discussed in Section 7.5.3.

7.5.1 The results of overall ID and DT performances

The results of the bootstrap mean and 95% CI are summarized in the histograms in Figure 7.9. In the figure, *axis-y* indicates the frequency whereas *axis-x* signifies the accuracy of the modelling technique. Furthermore, the dash and solid lines in the figure show the ranges of the bootstrap percentile 95% CI and the bootstrap BC_a 95% CI respectively. Additionally, the observed mean, bootstrap mean and standard deviation are also shown in the figure.

With regard to the transport mode decision, Figure 7.9 shows that the observed ID accuracy mean is the same as its bootstrap mean (i.e. 67.217%). Additionally, the bootstrap percentile (95%) CI is 66.995%-67.425% and the bootstrap BC_a CI equals 66.986%-67.446%. The bootstrap mean of DT success rate is 83.404% (percentile CI: 83.196%-83.605% and BC_a CI: 83.195%-83.624%) for the transport mode decision. For the shopping location decision, the bootstrap mean of ID accuracy is 66.967% (percentile CI: 66.744%-67.188% and BC_a CI: 66.727%-67.197%), and DT is 79.892% (percentile CI: 79.253%-80.553% and BC_a CI: 79.199%-80.560%). In both decisions, the percentile CI is approximate to the BC_a CI, with the BC_a CI is slightly larger than percentile CI. This happens because BC_a CI allows for bias estimation, making it tend to be larger than percentile (95%) CI (Efron & Tibshirani, 1994).



Observed Mean: 67.217

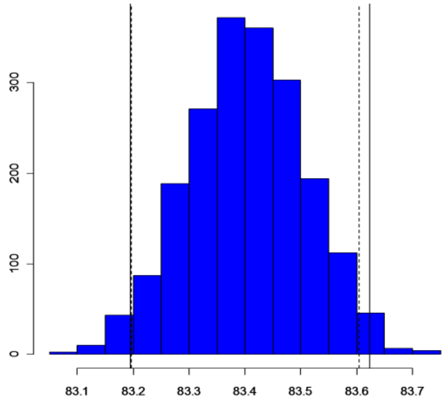
Bootstrap Mean: 67.217

Bootstrap standard deviation: 0.111

Bootstrap Percentile 95% CI: 66.995-67.425

Bootstrap BCa 95% CI: 66.986-67.446

a. Transport mode decision: Histogram of Bootstrap Mean Accuracy for ID



Observed Mean: 83.407

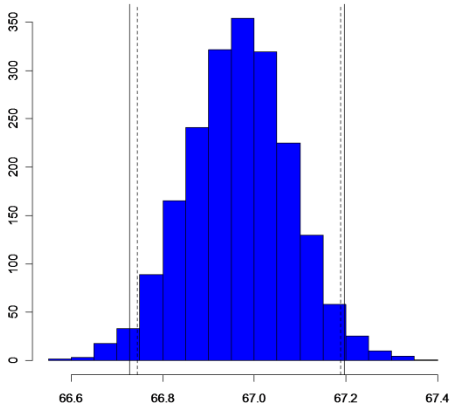
Bootstrap Mean: 83.404

Bootstrap standard deviation: 0.105

Bootstrap Percentile 95% CI: 83.196-83.605

Bootstrap BCa 95% CI: 83.195-83.624

b. Transport mode decision: Histogram of Bootstrap Mean Accuracy for DT



Observed Mean: 66.972

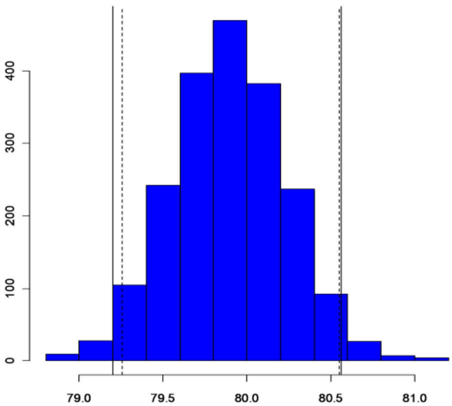
Bootstrap Mean: 66.967

Bootstrap standard deviation: 0.114

Bootstrap Percentile 95% CI: 66.744-67.188

Bootstrap BCa 95% CI: 66.727-67.197

c. Shopping location decision: Histogram of Bootstrap Mean Accuracy for ID



Observed Mean: 79.888

Bootstrap Mean: 79.892

Bootstrap standard deviation: 0.34

Bootstrap Percentile 95% CI: 79.253-80.553

Bootstrap BCa 95% CI: 79.199-80.560

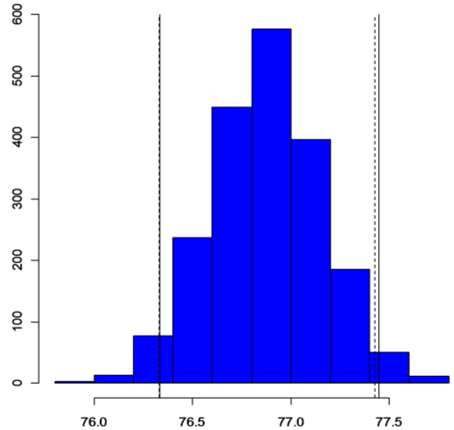
d. Shopping location decision: Histogram of Bootstrap Mean Accuracy for DT

Figure 7.9 The histograms of ID and DT overall performance

7.5.2 The results of ID and DT performances in predicting every decision alternative

7.5.2.1 The transport mode decision

The results of the ID and DT recognition rates of the transport mode decision are summarized in Figure 7.10. It can be seen in this figure that for the car-use class, the ID modelling technique bootstrap mean of accuracy is 76.873% (percentile CI: 76.329%-77.425% and BC_a CI: 76.333%-77.446%). These values are significantly lower in comparison to the DT results. The DT bootstrap mean is 90.464% (percentile CI: 90.152%-90.770% and BC_a CI: 90.124%-90.768%). With regard to the bus-use class, the ID bootstrap mean of accuracy is 69.353% (percentile CI: 68.128%-70.400% and BC_a CI: 68.070%-70.333%), whereas the DT bootstrap mean equals 78.933% (percentile CI: 78.181%-79.682% and BC_a CI: 78.206%-79.704%). At last, the ID bootstrap mean of the bike-use class is 51.784% (percentile CI: 51.081%-52.502% and BC_a CI: 51.011%-52.487%), and the DT bootstrap mean of this class is 72.989% (percentile CI: 72.097%-73.842% and BC_a CI: 72.160%-73.882%).



Observed Mean: 76.882

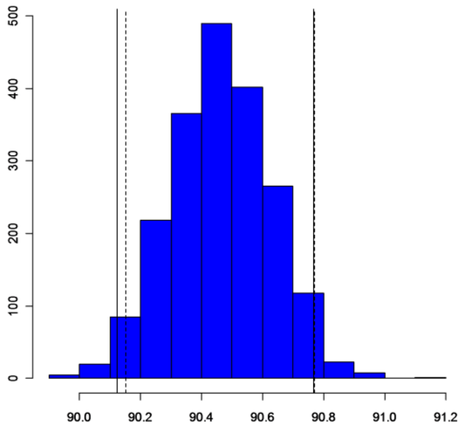
Bootstrap Mean: 76.873

Bootstrap standard deviation: 0.281

Bootstrap Percentile 95% CI: 76.329-77.425

Bootstrap BCa 95% CI: 76.333-77.446

a. Car-use: Histogram of Bootstrap Mean Accuracy for ID



Observed Mean: 90.469

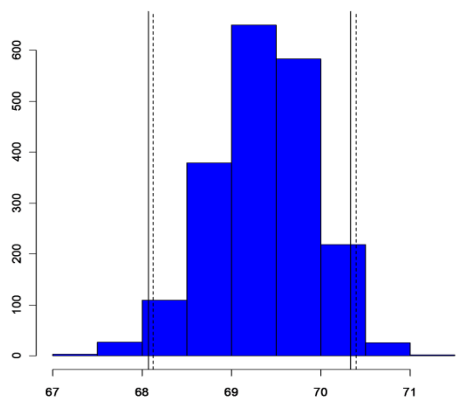
Bootstrap Mean: 90.464

Bootstrap standard deviation: 0.162

Bootstrap Percentile 95% CI: 90.152-90.770

Bootstrap BCa 95% CI: 90.124-90.768

b. Car-use: Histogram of Bootstrap Mean Accuracy for DT



Observed Mean: 69.359

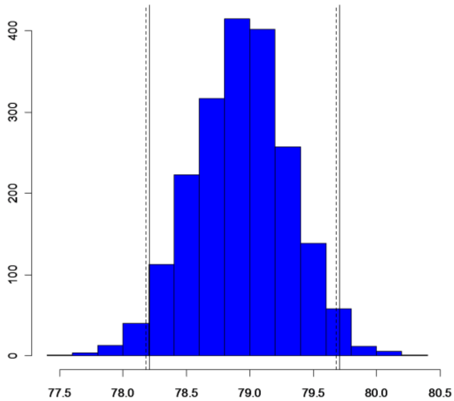
Bootstrap Mean: 69.353

Bootstrap standard deviation: 0.569

Bootstrap Percentile 95% CI: 68.128-70.400

Bootstrap BCa 95% CI: 68.070-70.333

c. Bus-use: Histogram of Bootstrap Mean Accuracy for ID



Observed Mean: 78.947

Bootstrap Mean: 78.933

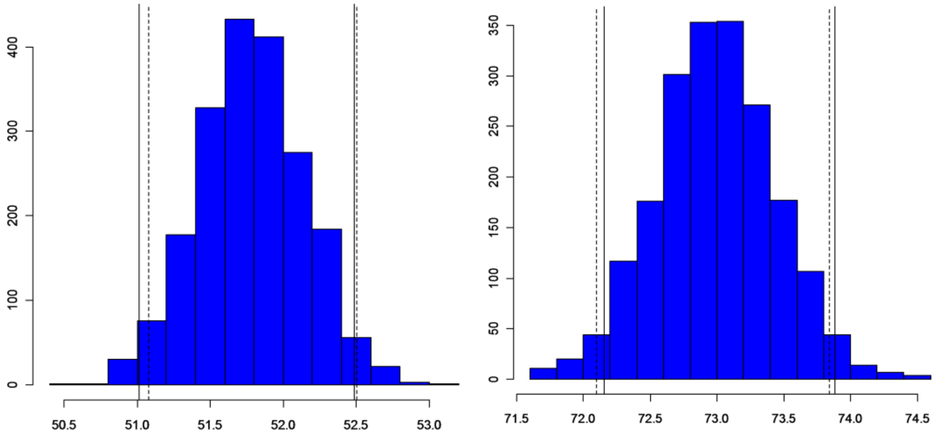
Bootstrap standard deviation: 0.384

Bootstrap Percentile 95% CI: 78.181-79.682

Bootstrap BCa 95% CI: 78.206-79.704

d. Bus-use: Histogram of Bootstrap Mean Accuracy for DT

Figure 7.10 The histograms of ID and DT performance in predicting transport mode decision alternatives



Observed Mean: 51.778

Bootstrap Mean: 51.784

Bootstrap standard deviation: 0.363

Bootstrap Percentile 95% CI: 51.081-52.502

Bootstrap BCa 95% CI: 51.011-52.487

e. Bike-use: Histogram of Bootstrap Mean Accuracy for ID

Observed Mean: 72.993

Bootstrap Mean: 72.989

Bootstrap standard deviation: 0.447

Bootstrap Percentile 95% CI: 72.097-73.842

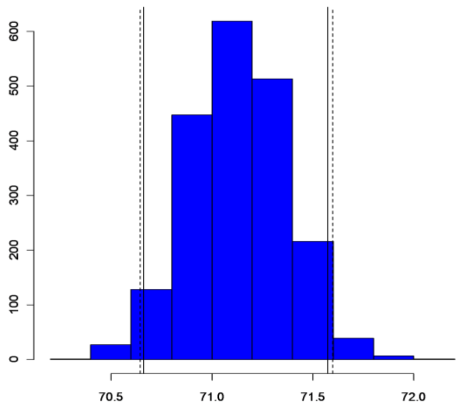
Bootstrap BCa 95% CI: 72.160-73.882

f. Bike-use: Histogram of Bootstrap Mean Accuracy for DT

Figure 7.10 (Continue) The histograms of ID and DT performance in predicting transport mode decision alternatives

7.5.2.2 The shopping location decision

The shopping location decision results of the ID and DT recognition rates are shown in Figure 7.11. The results of the Zone-1 class indicate that the ID bootstrap mean is 71.131% (percentile CI: 70.646%-71.595% and BC_a CI: 70.660%-71.574%), whereas the DT bootstrap mean is 81.847% (percentile CI: 81.365%-82.301% and BC_a CI: 81.352%-82.300%). Concerning the Zone-2 class, the ID bootstrap mean of is 64.422% (percentile CI: 63.850%-65.016% and BC_a CI: 63.777%-64.996%), and the DT bootstrap mean of this class is 73.897% (percentile CI: 73.266%-74.543% and BC_a CI: 73.195%-74.561%). Additionally, with regard to the Zone-3 class, the ID bootstrap mean is 60.528% (percentile CI: 59.181%-61.915% and BC_a CI: 59.100%-61.795%), while the DT bootstrap mean equals 65.955% (percentile CI: 64.854%-67.102% and BC_a CI: 64.823%-67.102%).



Observed Mean: 71.13

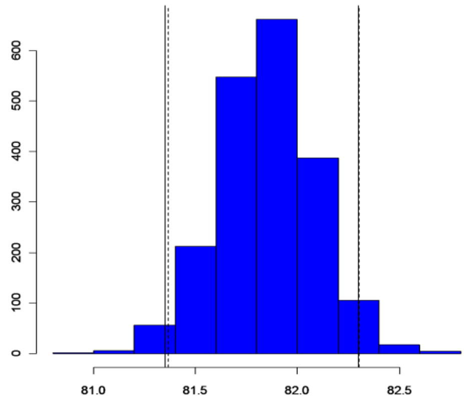
Bootstrap Mean: 71.131

Bootstrap standard deviation: 0.241

Bootstrap Percentile 95% CI: 70.646-71.595

Bootstrap BCa 95% CI: 70.660-71.574

a. Zone-1: Histogram of Bootstrap Mean Accuracy for ID



Observed Mean: 81.852

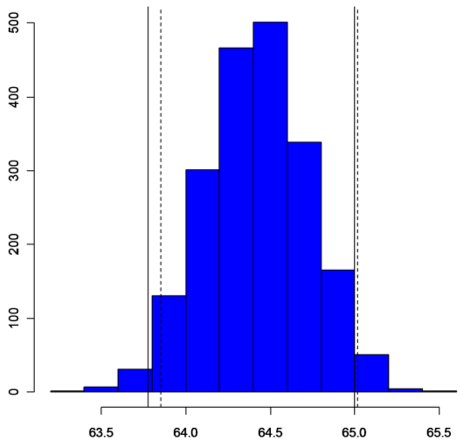
Bootstrap Mean: 81.847

Bootstrap standard deviation: 0.234

Bootstrap Percentile 95% CI: 81.365-82.301

Bootstrap BCa 95% CI: 81.352-82.300

b. Zone-1: Histogram of Bootstrap Mean Accuracy for DT



Observed Mean: 64.418

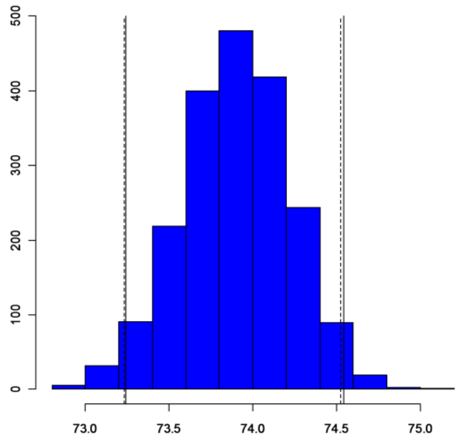
Bootstrap Mean: 64.422

Bootstrap standard deviation: 0.306

Bootstrap Percentile 95% CI: 63.850-65.016

Bootstrap BCa 95% CI: 63.777-64.996

c. Zone-2: Histogram of Bootstrap Mean Accuracy for ID



Observed Mean: 73.901

Bootstrap Mean: 73.897

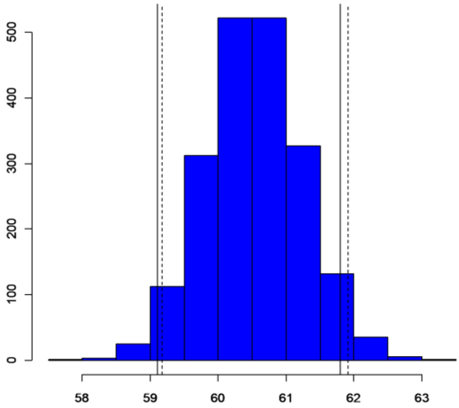
Bootstrap standard deviation: 0.328

Bootstrap Percentile 95% CI: 73.266-74.543

Bootstrap BCa 95% CI: 73.195-74.561

d. Zone-2: Histogram of Bootstrap Mean Accuracy for DT

Figure 7.11 The histograms of ID and DT performance in predicting shopping location decision alternatives



Observed Mean: 60.516

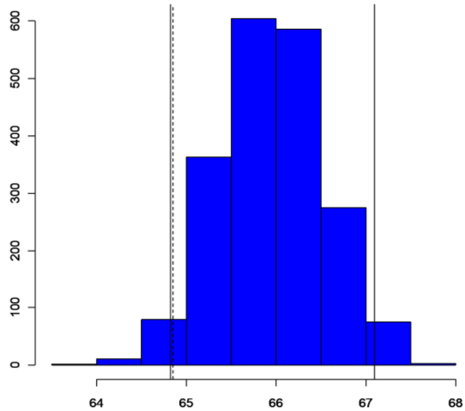
Bootstrap Mean: 60.528

Bootstrap standard deviation: 0.703

Bootstrap Percentile 95% CI: 59.181-61.915

Bootstrap BCa 95% CI: 59.100-61.795

e. Zone-3: Histogram of Bootstrap Mean Accuracy for ID



Observed Mean: 65.926

Bootstrap Mean: 65.955

Bootstrap standard deviation: 0.577

Bootstrap Percentile 95% CI: 64.854-67.102

Bootstrap BCa 95% CI: 64.823-67.102

f. Zone-3: Histogram of Bootstrap Mean Accuracy for DT

Figure 7.11 (Continue) The histograms of ID and DT performance in predicting shopping location decision alternatives

7.5.3 Discussions

The results of the overall performances of ID and DT models shown in Figure 7.9 clearly indicate that the ID accuracy is significantly lower than DT for both transport mode and location decisions. A better performance of DT over ID can also be observed in the results presented in Figure 7.10 and Figure 7.11. In these figures, the recognition rates are assessed for the transport mode and shopping location decision options. With regard to the transport mode choice (Figure 7.10), the ID and DT models best predict car-use class, followed by bus-use class, and bike-use class. The ID performance in predicting bike-use class is significantly lower than the DT model. The differences between the DT performance in predicting bus-use and bike-use are relatively small. Concerning the shopping location decision (Figure 7.11), the results show that both ID and DT models can best predict Zone-1 class, followed by Zone-2 class and Zone-3 class. It can generally be observed from the results that the ID performance in predicting the shopping location classes is more stable than in predicting the transport mode classes. Furthermore, the differences between the bootstrap means of the ID and DT models for Zone-3 class are relatively small. These results allow us to conclude that DT models outperform ID models. However, a similar trend can be observed in the ranking of the class recognition rates in both models.

It should be noted that conducting a fair comparison between DT and ID is not a straightforward process. Both methods have their particular features, yielding their own strength and weakness. For instance, DT cannot clearly model sequential decision making. Thus, the transport mode and location decisions have to be modelled as two independent DT models, whereas these decisions are modelled together in a complex ID model. Moreover, DT cannot model a MR individually because the number of observations (i.e. scenarios) per respondent is too small for proper training and testing. Accordingly, only one DT representation is generated for all the participants. In order to make the DT model as representative as possible for each individual's ID, additional socio-demographic, transport and shopping behaviour data have to be added in the model.

Next, DT classifier can only use a categorical variable as the dependent variable to predict, implying that the participants' choices have to fall into one of these categories. However, some choice options can equally be considered in particular situations, such as using car and bike to go to the city when the weather is nice and a companion joins the trip. Yet, the actual choice outcome may simply be picked randomly among these options. The survey data show that there are some cases where the participants consider two or even three choice alternatives equally as the choice outcomes, making DT unsuited to model this data type. On the other hand, inferring ID yields the expected utility values of all decision alternatives simultaneously, making it appropriate for this situation.

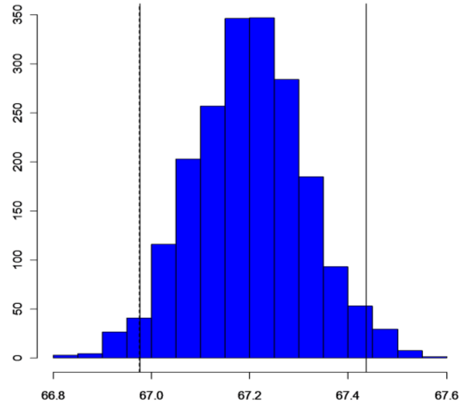
Furthermore, DT derives a general representation of a dataset. This does not necessarily correspond to people's thought processes even though MR data is used as an input. DT cannot retain the links in cognitive subsets of MR, as it only classifies all input data based on the dependent variable. Therefore, it cannot provide complete explanations regarding why certain choices are made.

Additionally, DT uses all survey scenario data. These data are divided into 10-folds and the DT algorithm runs 10 iterations, each using 9-folds of the data as training set. Thus, the DT has a chance to learn from the dataset, reducing its bias. The ID on the other hand, uses all probabilities and utilities from every individual's subjective estimation without any filtration. It is well known that human beings usually count on heuristic principles to solve complex problems, such as predicting values and assessing probabilities (O'Hagan et al., 2006). Even though heuristics are fairly useful, they may bring about serious and systematic errors (Tversky & Kahneman, 1974). This argument is supported by other research (i.e. Hogarth, 1975 p. 273) that states: *"man is a selective, stepwise information-processing system with limited capacity, …ill-suited for assessing probability distributions."* Thus, any probabilistic error is taken into the ID model, decreasing its performance.

7.6 Weighting method evaluation for the influence diagram modelling technique

It has been previously explained in Chapter 4 (Section 4.3.4) that two methods to generate the utility weights are tested, namely the rating tasks of single benefit variable and the joined benefits using FFD. In order to draw a conclusion regarding which weighting method is better suited for the ID modelling purpose, the accuracy of ID models is calculated using both weighting techniques. It should be noted that the comparison between ID and DT above is done using the first weighting method for the ID models. Similarly, the accuracy of the ID models using the second weighting method is calculated.

In order to compare the weighting methods, the dataset [b] in Figure 7.7 is used. Likewise, the same dataset is generated based on the ID model calculations using the second weighting method. For the purpose of this comparison, a similar analysis is performed on the bootstrap data, as previously explained in Section 7.4.2. The resulted histograms of ID model accuracies calculated using weighting method-1 (W1) and weighting method-2 (W2) are shown in Figure 7.12. The results of the transport mode decision indicate that the bootstrap mean calculated with W1 is 67.2% (percentile CI: 66.975%-67.436% and BC_a CI: 66.977%-67.436%), whereas the W2 bootstrap mean is 66.326% (percentile CI: 66.100%-66.546 % and BC_a CI: 66.092%-66.566%). Regarding the shopping location decision, the W1 bootstrap mean is 66.938% (percentile CI: 66.711%-67.172% and BC_a CI: 66.708%%-67.177%), while the W2 bootstrap mean equals 66.998% (percentile CI: 66.740%-67.255% and BCa CI: 66.726%-67.266%). These results clearly show that in fact there are no significant differences between the two weighting methods.



Observed Mean: 67.198

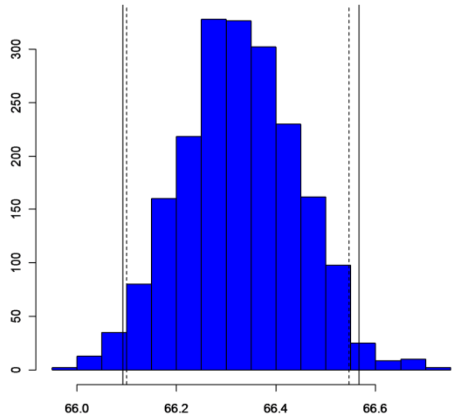
Bootstrap Mean: 67.2

Bootstrap standard deviation: 0.115

Bootstrap Percentile 95% CI: 66.975-67.436

Bootstrap BCa 95% CI: 66.977-67.436

a. Transport mode decision: Histogram of Bootstrap Mean Accuracy for ID W1



Observed Mean: 66.323

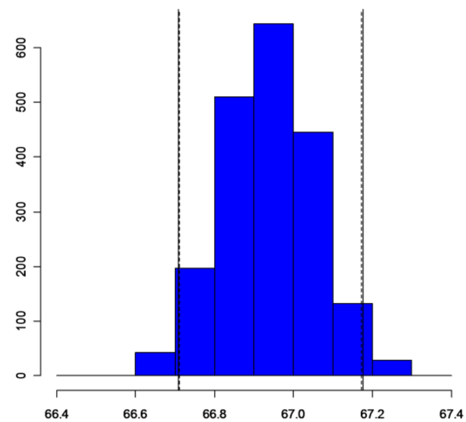
Bootstrap Mean: 66.326

Bootstrap standard deviation: 0.117

Bootstrap Percentile 95% CI: 66.100-66.546

Bootstrap BCa 95% CI: 66.092-66.566

b. Transport mode decision: Histogram of Bootstrap Mean Accuracy for ID W2



Observed Mean: 66.938

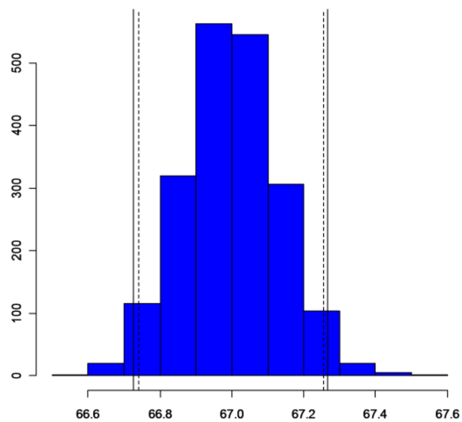
Bootstrap Mean: 66.938

Bootstrap standard deviation: 0.117

Bootstrap Percentile 95% CI: 66.711-67.172

Bootstrap BCa 95% CI: 66.708-67.177

c. Shopping location decision: Histogram of Bootstrap Mean Accuracy for ID W1



Observed Mean: 66.996

Bootstrap Mean: 66.998

Bootstrap standard deviation: 0.133

Bootstrap Percentile 95% CI: 66.740-67.255

Bootstrap BCa 95% CI: 66.726-67.266

d. Shopping location decision: Histogram of Bootstrap Mean Accuracy for ID W2

Figure 7.12 The histograms of ID models with weighting method-1 (W1) and -2 (W2)

7.7 Conclusions

This chapter reports on the performance comparisons between two advanced modelling techniques to predict individuals' travel behaviour, namely DT and ID, using individuals' MR of leisure-shopping decision problems as input data. An experiment is conducted using the computerized CB-CNET interface, involving 221 participants. The interface enables us to capture not only the participants' temporary MR, but also to gather subsequent data for the DT and ID modelling purposes. DT is a data mining technique that learns a classification from a training set and uses that classification to predict outcomes of a testing set. ID is an AI technique that uses decision nodes, probabilities and utilities to calculate the expected utility values of all decision alternatives.

For the purpose of this study, a dataset is formed, consisting of the participants' socio-demographic characteristics (e.g. age, gender, occupation, residence location, etc.), their transport mode and shopping behaviours (e.g. how often car is used to the centre, how frequent fun-shopping activities are executed in a year, etc.), and other data. Comparing the performances of DT and ID is done by bootstrapping the data twice. These bootstrapped datasets are used as input to WEKA software to generate the DT models and to calculate their accuracies. The corresponding data are used to generate the structure of the ID models, to give input to the models, and furthermore to calculate the model accuracies. The bootstrap means and 95% *percentile bootstrap* and BC_a CI of DT and ID are recorded.

The results show that the DT model performs better than the ID model in predicting people's travel behaviour. However, this model loses the ability to describe the underlying decision process that precedes the observed travel outcomes. Moreover, it cannot predict the decision process that involves many consequent decisions, usually present in travel-related decision making. Low ID performance could be caused by the use of the participants' subjective probability evaluations of certain benefits based on the elicited contexts and decision options. Hence, errors in probability judgments may reduce the ID accuracy. The results also reveal that both modelling techniques predict bike-use less accurately in comparison to car-use and bus-use.

Ultimately, considering the advantages and disadvantages of both techniques, the method to use depends on particular research goals at stake. If the purpose of the study is purely to predict people's behaviour, then the DT model should be used. However, if the main purpose is to investigate the impact of different contexts on individuals' actual choices and to understand the links between aspects in their MR, then ID should be considered. Clustering analysis can be applied in other research in this line, to categorize aspects that appear in the individuals' MR. These results can be used as input variables for the DT model. Moreover, research to learn better probability distribution from respondents' answers should be addressed to improve the ID model accuracy.

In addition, two different weighting methods are tested. The ID model accuracy is calculated using both methods. The results can be used to give feedback to the CB-CNET interface. Since the first weighting method is considered easier by most of the respondents, further development of the interface should give emphasis on this weighting method and omit the second method. This can reduce the respondents' burden in the survey.

This chapter has illustrates the performance of two advanced modelling techniques that uses individuals' MR as their input data. However, future study is needed to investigate the actual added value of using behavioural data (such as MR data) in the predictive models. For instance, discrete choice models or other derivative forms of regression models are often used in the transportation field as models to predict individuals' travel behaviour, using socio-demographic characteristics and other (usually) quantitative data. The performance of these models can be compared to the performance of ID or DT models that uses qualitative data as their input.

8 Final conclusions

"In my end is my beginning."
T.S. Eliot

This section aims at concluding the PhD research project. In this chapter, the main conclusions are summarized to start with (Section 8.1). Next, the research limitations are discussed (Section 8.2). At last, the direction for similar further research is presented (Section 8.3).

8.1 Conclusions

The PhD research objectives evolve around individuals' travel-related decision making processes, focusing on a number of decisions that people usually make when carrying out leisure-shopping activities in a city centre, such as *when to schedule fun-shopping*, *where exactly to go to*, and *how to get there*. In this research, Hasselt in Belgium is selected as a case study. In order to understand the decision making processes, individuals' MR is emphasized. Such a representation consists of a number of aspects connected to each other, referred to as *cognitive subsets*. These interconnected considerations in a cognitive subset contribute to the complexity of the decision making. Rational decision making theory argues that different choice options are evaluated based on their characteristics (or *instruments*), because of the *benefits* that a decision maker wants to gain in *specific contexts* or in *any normal circumstances*. Thus, {*context, instrument, benefit*} and {*normally, instrument, benefit*} are registered as cognitive subset type-1 and type-2 respectively.

In general, knowledge regarding people's travel behaviour is needed to give behavioural feedback on assumptions in AB models, such as FEATHERS. Additionally, comprehensive knowledge about aspects taken into account in people's MR is needed to develop high impact policy measures that can alter people's unsustainable car-use behaviour towards more sustainable forms, such as bike-use or bus-use. In line with this, the differences among people based on their elicited representations are used to generate the typology of fun-shopping travellers. As a result, TDM policies in line with the needs of specific target groups of people are highlighted. In order to enrich our understanding regarding the complexity of individuals' MR in different scenarios, time availability related scenarios are tested. The differences in the individuals' MR when performing leisure-shopping with and without time constraints are underlined accordingly.

Besides, modelling individuals' thought processes based on their MR is also emphasized. The ID modelling approach is used for this purpose to generate individuals' mental-level models that work at a disaggregate level. ID is chosen because of its ability to model sequential decision making and retain the interconnected aspects of subsets in every MR, making it suited to represent people's thought processes. Modelling these representations using DT is also examined. DT is one of the most common knowledge representations, widely used in many different domains. Its implementation in the transportation research field can be seen for instance in travel demand models such as FEATHERS and ALBATROSS. In both models, CHAID algorithm is used to learn DT form a number of input data. In this study, the performance of ID models is compared to the accuracy of DT models. The results allow us to conclude which approach is better suited to model people's decision making and to predict behavioural changes of people given some variations in their decision environment.

However, in order to achieve the objectives above, the methodology to elicit individuals' MR should initially be established. In this research, the application of the existing qualitative CNET interview method (Arentze et al., 2008a) is used after adapting it to a leisure-shopping activity context. Additionally, the CNET card game technique is developed. Unlike the CNET interview method that asks the respondents to reveal aspects considered in their decision making spontaneously, the CNET card game protocol requires the respondents to recognize variables that appear in their decision processes by showing series of cards in structured face-to-face interviews. These cards resemble the predefined lists of contextual, instrumental and benefit variables used to code participants' open answers in the CNET interviews. An experiment is conducted in which both methods are used to interview a small sample group of 26 young adults, focusing on three travel decisions of *activity-scheduling*, *transport mode* and *location decisions*. Afterwards, the respondents are asked to report their experiences on being interviewed using both techniques. Moreover, since the CNET interview method is a relatively new elicitation technique, its reliability should also be investigated.

However, using any of the CNET qualitative interview methods on large samples to gather behavioural data of people could be cumbersome, especially when the research purpose is also to model people's MR. This happens because additional parameter data have to be gathered individually after eliciting the participants' MR, enabling their models to work as predictive models. For instance, for an ID model, conditional probability and utility information is needed. The DT model requires socio-demographic and other data as well. This adds up considerable time and effort for data collection, emphasizing the need to develop a computer-based elicitation method, referred to as CB-CNET.

The results of the first experiment, along with the participants' feedback on the CNET interview and card game methods, are used to develop the CB-CNET interface. It is used in the second experiment, involving 221 people. This study is also conducted in Hasselt, akin to the first experiment, and it focuses on individuals' travel decisions when carrying out leisure-shopping activities. However, only two travel decisions are underlined in this case; i.e. *the transport mode* and *location choices*. In the survey, the participants' socio-demographic, travel behaviour, and fun-shopping behaviour data are collected to start with. Furthermore, the interface elicits individuals' MR based on their decision making styles, i.e. habitual or rational decisions, revealing all considered cognitive subsets. Next, it automatically generates subsequent questions according to the participants' initial variable selections and their interconnections. As part of the parameter data collection, two methods to generate utility weights are tested. The first weighting method requires the respondents to rate all single-benefits, whereas the second method asks them to rate joined-benefits in a FFD experiment. At last, individuals' actual transport mode and shopping location preferences are questioned based on the states of every individual's chosen contextual aspects, allowing us to validate each individual's mental-level model. This part is used further to check the performance of ID and DT modelling approaches.

Hence, the conclusions of this PhD research are structured along the above research objectives, summarized from Chapter 1 (Section 1.2). The conclusions are formulated for each research goal, focusing only on the most interesting findings. To begin with, different methods to elicit people's MR are addressed (Section 8.1.1). Next, the content of the participants' MR are indicated (Section 8.1.2). In this section, some conclusions regarding the use of MR data to give feedback to AB models and to highlight high impact TDM measures are presented. Following that, conclusions concerning people's MR in time pressure related scenarios are stressed (Section 8.1.3). In Section 8.1.4, a number of ways to break car-use habit based on the typology of fun-shopping travellers are focused on. At last, modelling individuals' MR using ID and DT techniques are emphasized (Section 8.1.5). In this part, the findings of different weighting methods are also reported.

8.1.1 Eliciting individuals' mental representations

The first PhD research objective is: "*to develop a method to elicit people's MR and other data for the modelling purpose (focusing on the influence diagram and decision tree modelling techniques).*" This objective is addressed in Chapter 2 and Chapter 4. Two experiments are conducted. In the first experiment, the CNET interview is applied to investigate individuals' leisure-shopping travel decisions in Hasselt and the CNET card game protocol is developed for the same purpose. Both techniques are tested on the same sample of 26 young adults.

From the methodological point of view, this study shows the influence of elicitation method selection on research outcomes, supporting the results of another similar study using the laddering technique (i.e. Russell et al., 2004). For instance, in the CNET interviews, the participants elicit a fewer number of variables than in the card game interviews, yielding less complex MR. Smaller MR elicited using the CNET interview protocol could be caused by additional thoughts that the respondents have due to the presentation of the pre-defined variables during the card game interviews. Showing a priori aspects to the respondents could be a good thing, since it may give them some cues to important variables forgotten in the open-ended interview format. However, there is a danger of imposing new variables, unrelated to people's actual MR. This issue is acknowledged, even though we do not know for sure which one of the two cases is relevant to this research. According to the respondents, there are many forgotten aspects in their decision making during the CNET interviews, giving an indication of their simpler representations. This could happen because travel-related decisions, in particular when performing leisure-shopping, may not be that significant. Because of that, many aspects are overlooked. Besides, it is also possible that the fun-shopping activity has been executed frequently, making people not bother to rationally think about their choices anymore and resulting in many forgotten aspects. This could give an explanation of why the respondents still argue that the card game is easier, more pleasant and more comprehensive in comparison to the CNET interview, even though the elicitation process using the card game is on average longer than its counterpart. Besides, the bilingual presentation of the variables on the cards could also contribute to the participants' preferences over the card game method.

Based on the experience of applying different elicitation methods and the results of the first experiment, the CB-CNET interface is developed. This interface is used to elicit 221 participants' MR and other data of parameters. In this experiment, people's travel-related habitual and rational behaviours are investigated by letting the respondents to initially indicate their decision making style. Based on their selection, different elicitation paths are followed. The outcomes of this experiment show a strong resemblance between the results of the card game interviews and the CB-CNET survey. This could happen because both elicitation techniques have a similar nature: using variable recognition instead of self recall on influencing variables.

This PhD research has shown the implication of using different elicitation methods. However, a question regarding the method that can best elicit MR of people remains unknown. Based on the results of the first experiment, the participants indicate that the card game method can generate better representations of their decision making processes, and presumably also the CB-CNET protocol. Yet, future study should still be done to elucidate this issue.

With regard to *intercoder reliability* of the CNET interview method, the CNET interview audio-records from the first experiment are used as the data. *Intercoder reliability* aims at investigating the reliability of coders' interpretations on the participants' open answers in the interviews. For this purpose, *percentage agreement* and *Krippnedorff's alpha* indices are employed. The results show high agreement between the two coders, confirming the reliability of the research (in particular) and CNET interview method (in general). This leads to the possibility to transfer this technique for other purposes, such as other sample, other decision types, etc.

8.1.2 Having insight into important constructs in mental representations

The second research objective is: *"to gain insight into aspects considered in individuals' MR when making fun-shopping trips".* This issue is dealt with in Chapter 3 and Chapter 5.

To start with, the results of the first experiment allow us to register the number of respondents who elicit every decision variable using the CNET interview and card game. By comparing these results, the differences of the numbers of respondents who elicit every variable are calculated. These differences may indicate variables often overlooked by people. However, they could also signify aspects induced by the card game method due to presenting the predefined variables to the respondents during the interviews. These variables are identified and they are commonly related to contextual variables. For instance, the transport mode contextual variable of *time availability* is elicited by 19.2% of the participants with the CNET interview protocol and 88.5% of the respondents with the CNET card game protocol. This indicates that, in fact, there are 69.3% of the respondents who miss this variable during the elicitation process using the CNET interview protocol. Similar cases can be found in other variables as well, such as the shopping location contextual variable of *an interest in a specific product* (73%) and the instrumental variable of *individuals' habitual transport mode and shopping location choices* (77% and 73% respectively). This result is reasonable, especially because a habitual behaviour is commonly considered unconsciously, making it often be forgotten by people or simply be neglected and regarded as irrelevant to be mentioned during the CNET interviews. Interestingly, the results of both techniques indicate that the respondents are more consistent in the elicitation of benefit variables, even though they argue that benefits are the hardest variable type to recall spontaneously. This may be caused by a fewer number of benefit variables in the predefined coding scheme, in comparison to the number of contextual and instrumental variables.

Next, the results of the CNET interviews are used to highlight the differences between factors considered in people's MR and aspects taken into account in the decision trees of FEATHERS. Similarly, high impact transport policies are identified based on the results of the CNET card game. At last, the results of the CB-CNET survey are compared to the results of the CNET interview and card game. The conclusions regarding these subjects are shown in Section 8.1.2.1 Section 8.1.2.2, and Section 8.1.2.3 respectively.

8.1.2.1 Feedback to activity-based models

One of the assumptions in FEATHERS concerns the sequence of decision making in activity-travel scheduling, assuming that the following decision sequence holds: *a specific type of activity to perform*, *its starting time*, *duration*, *likely trip-chaining*, *location*, and (if necessary) *transport mode choice*. The results of this study indicate that indeed the activity-planning is fixed prior to making location and transport mode choices. However, the results of the first experiment cannot confirm that the transport mode choice is made after the location decision. A conclusion can be drawn only after conducting the second experiment using the CB-CNET interface: that in fact the transport mode decision is made before the location choice. Despite this outcome, it should be noted that the location alternatives in both experiments are limited to a small city centre boundary, whereas in the FEATHERS system the location choices involve a larger geographical space (i.e. Region of Flanders). This limits the use of the results of this study.

In Chapter 2, the differences among aspects considered important by people and determinant factors in decision trees of FEATHERS are highlighted. AB modellers may argue that variables are only important to develop decision tree with a good model fit, therefore they do not necessarily have to represent people’s decision making considerations. However, behavioural researchers contend that aspects in people’s decision making should at least be accounted in activity-travel diaries. An example of this aspect is *weather conditions*. None of the activity-diaries to date records people’s activity-scheduling and transport mode decisions related to that variable, at least to the best of our knowledge.

The results also emphasize the importance of *companion* in determining the transport mode and activity-scheduling decisions. This supports Hägerstrand's idea of coupling constraint. Additionally, *crowdedness in the location destination* also determines individuals’ choices of day to perform leisure-shopping activities. This relates to the benefits of *having efficiency* and *fun* that people generally want to gain out of their shopping activities. Future study is needed to investigate ways to incorporate people’s personal values and preferences in activity-travel diaries.

8.1.2.2 Feedback concerning high impact TDM measures

The results of the AR analysis on the card game data are further used to give feedback to policy makers concerning TDM in line with the way people make their travel decisions. By doing so, TDM policies that give high impact on people's choices could be analysed and accordingly implemented. The results of AR analysis allows us to understand the benefits that people look for when making decisions, the contexts in which these benefits are desired, and the instruments of the decision alternatives that can help people pursue the benefits (given the contexts). For instance, based on the card game results, people want to *be sociable*, *save money,* and *gain comfort*, *efficiency*, and *convenience*. The benefit of *having efficiency* is strongly linked to the instrument of *travel time*. Therefore, some policies that can reduce travel time by bus should be given more emphasis. Specifically, this can be done by implementing the BRT system. Besides, since the cognitive subset of {*(context/normally), cost, saving money*} is also frequently elicited by the respondents, other pricing policies may also be effective, such as carbon taxes, congestion pricing, distance-based pricing, fuel taxes, parking pricing, pay-as-you-drive insurance, and road pricing. At last, bike sharing may also increase bicycle-use.

8.1.2.3 The CB-CNET survey results

Using the CB-CNET interface, rich behavioural data are gathered. In the beginning of the analysis, the developed behavioural database is used to deepen our understanding of the complexity of individuals' MR and to learn about important cognitive subsets of the participants. Some descriptive statistics is used and it can be concluded that people consider more aspects when making transport mode decisions rather than when deciding where exactly to go to. This can be caused by the research specific case study, limited to Hasselt city centre, making people consider a fewer number of aspects.

The FI analysis, as part of the AR technique, is employed next to learn about the frequently elicited cognitive subsets in the CB-CNET database. The results show that the variables taken into account in the CB-CNET dataset are to some extent similar to the ones revealed in the CNET card game data. For instance, the cognitive subset of {*precipitation, shelter provision, physical comfort*} is frequently elicited with both techniques, underlining the importance of *weather conditions* in people's transport mode decisions. The cognitive subset of {*time availability, travel time, efficiency*} is also important according to both datasets.

The CB-CNET results confirm previous discussions in Section 8.1.2.1, to incorporate *weather condition* variable in activity-travel diaries. It further validates the conclusion in Section 8.1.2.2, to increase the efficiency of public transport systems, particularly bus.

8.1.3 The shift of individuals' mental representations in time pressure scenarios

The next research objective is: *"to capture the shift of individuals' MR in time constraint related scenarios; i.e. shopping with and without time pressures."* This is done in order to examine different complexity levels of the elicited MR under these scenarios. For this purpose, the CB-CNET protocol is used. The results indicate that statistically there are no significant differences in the numbers of aspects considered in both scenarios, implying that people reason as much in these settings. This result is unexpected. It was assumed that people have less consideration when planning an activity that has to be carried out under time pressure. This research objective is addressed in Chapter 5.

The content of individuals' MR in these scenarios is investigated next, focusing only on the frequently elicited cognitive subsets. The results reveal that the number of aspects frequently considered under time pressure scenario is more than the one without the time constraint scenario. This may happen because individual decision makers activate their knowledge structure of the problem at hand, comprising all important subsets that may help them to attain their goals (i.e. going shopping) under the time restriction, and given the uncertainty in the decision environment (i.e. other possible arisen contexts also important for them). Therefore, the results indicate that people think more when facing unfavourable condition (i.e. shopping with time constraint). However, it is assumed that when they are in the actual situation and forced to make a fast decision, their deliberations would most likely be simpler. Unfortunately, this issue cannot be answered in the current study. A future study is certainly needed to mimic the real condition of having pressure and investigate people's

MR accordingly, for instance by imposing time restriction in completing the survey, etc.

8.1.4 The typology of fun-shopping travellers: Breaking a bad "car-use" habit

This PhD research also aims at "*learning the typology of fun-shopping travellers in order to analyse TDM measures to break a car-use habit*." For this purpose, clustering and other statistical analyses are applied on the CB-CNET data to examine different groups of participants based on their MR. This objective is addressed in Chapter 6.

The results highlight the differences among groups of people and aspects that are important to them. In general, the participant clusters can be grouped into people whose transport mode habits are car-use, bus-use, bike-use, and a combination of these habitual behaviours. Accordingly, people's cognitive representations associated with habitual car-use, bike-use, and bus-use are concluded. The differences among the groups' representations are highlighted and used to identify TDM measures that can break people's car-use habit and develop new, more sustainable, habitual travel behaviours, such as bike-use and bus-use. Some policies to discourage car-use can be concluded, namely *reducing the number of (free) parking spaces*, *increasing the parking cost*, and other parking-related policies. Besides, TDM measures to boost the attractiveness of bus-use are also underlined, such as *applying BRT system to reduce bus travel time*, *increasing bus frequency*, and *expanding bus service hours*. At last, policies to enhance the attractiveness of bike-use are listed, such as *improving bike lanes* and *employing PBS*. These results support the policies highlighted in Section 8.1.2.2.

8.1.5 Modelling individuals' mental representations

The next PhD research objective is: *"to develop mental-level models that are able to predict individuals' travel behaviour, using ID and DT."* For this purpose, the CB-CNET survey data is used. Since ID technique is chosen as one of the modelling approach, the structure of the MR model should initially be decided based on the research objective. The network structure determines the link between one aspect and the others in a cognitive subset, among a number of cognitive subsets, and between subsets and decisions. This issue is elucidated in Chapter 2.

The same behavioural data are used to develop DT model. The validation part of the CB-CNET interface gathers data that can be used to check the performance of ID and DT modelling approaches in predicting people's transport mode and location choices. The discussions concerning the performance of DT and ID mental-level models are highlighted in Chapter 7. It can be concluded that the DT models perform better than the ID models. However, ID modelling technique still has its strength as it is able to record the decision making process of every individual. The lower performance of ID can be caused by the probability judgement of the respondents, as it is proven that people are not good in estimating probabilities (Hogarth, 1975; Tversky & Kahneman, 1974).

With regard to the utility weights, the results show that there are no significant differences between the results of ID models calculated using rating of single-benefits and rating of joined FFD benefits. This shows that in fact, only the first weighting method should be used in other similar research. The results indicate that there is no real added value of using a more complicated and demanding FFD method, at least for the purpose of this study.

8.2 Research limitations

In general, the limitations of this research can be grouped into three parts. The first part discusses the limitations of the elicitation methods. The second one highlights the limitation of the research setting and the respondents. The third one concerns the DT and ID model limitations. These groups are discussed below subsequently in Section 8.2.1, Section 8.2.2, and Section 8.2.3.

8.2.1 Limitations of the elicitation methods

In general, the research limitations concerning the data gathering methods are discussed here below. In the first experiment, the CNET interviews are carried out in English, whereas the native language of the participants is Dutch. Accordingly, there are possibilities that the respondent may face some difficulties in expressing their considerations in English. However, it should be noted that all respondents in the first experiment are Master's students. Accordingly, they have taken English language classes in their early years, allowing us to assume that they are able to express their ideas in English.

The language barrier issue is overcome in the card game interviews with *back translation method* (Brislin, 1970), as previously explained in Section 2.3.2. In the CB-CNET survey, the interface is designed in English. However, it is translated to Dutch in order to ensure that all participants are able to follow the survey, especially because of the heterogeneous sample group in the second experiment.

Additionally, in the CB-CNET survey, the activity-scheduling decision becomes part of the scenario. This means that the participants cannot decide not to go for leisure-shopping. This may also influence the elicited MR of people that do not have any interest to perform the activity given the scenario. However, it is believed that the number of respondents who do not want to perform fun-shopping in that case (if any) only accounts for an insignificant number of people in the sample.

Another limitation of the methods is the extensive demand and length of the data gathering process, for both the researcher and the respondents. For instance, to elicit one participant's MR, the CNET interview takes about 1 hour (on average) whereas the CNET card game lasts for about 1.5 hours. Additional time of 1-2 hours is needed for the respondents to fill in the post-questionnaire concerning the data of parameters. For the researcher, the data gathering effort is even more extensive, because the post-questionnaire has to be designed for every participant separately, every individual's network has to be drawn, and each individual's parameter data have to be inputted manually. These problems are solved in the CB-CNET interface because of its capability to generate parameter questions automatically based on every respondent's variable selections. However, the survey is still demanding for the respondents. For instance, it takes them about 2 hours to complete the survey. This may lead to survey fatigue. In other type of studies, such as in online survey, survey fatigue causes low response rate. In our case, survey fatigue may make the respondent selects the minimum number of variables in order to finish the survey as soon as possible. It is also possible that the respondents are tired or confused and select variables that appear in the screen randomly.

8.2.2 Limitations of the research setting

It should be noted that this research focuses only on leisure-shopping activity in the city centre. For this purpose, Hasselt city centre is selected as the case study. The respondents are limited to people who actually live in the neighbourhood of Hasselt, in an area located 3-10 kilometres away from the city centre. Therefore, the application of the research outcomes is applied only for this population. Additionally, the location choices are set within the boundary of Hasselt city centre. This makes it hard to generate conclusions to give feedback to FEATHERS model for this decision type. Further study should be done to check if similar results can also be obtained when the experiment is carried out in other cities, longer distances, other activity types, etc.

In the first experiment, the number of respondents is relatively small (i.e. 26 people) and they all fall in the same age category of 22-23 years old. Additionally, they are high educated people with a Bachelor's degree. This limits the applicability of the research outcomes to a specific group in the population.

In the second experiment, a larger sample with more heterogeneous characteristics is used. However, due to the high demand of the survey and specific requirement of the respondents (i.e. living in Hasselt outskirts and having driving license), specific sample taking methods are used. These techniques include snowballing method, and giving announcement through flyers and in local newspapers. These make it difficult to control the balance in the proportion of different participants' characteristics. Consequently, the high educated people are still overrepresented in the sample of the second experiment (i.e. 62%), even though the proportion of the low educated people is still acceptable (38%).

8.2.3 Limitations of the modelling approaches

With regard to modelling individuals' MR using ID technique, the minimum and maximum utility values in a utility table have to be set based on a number of partial benefits that are linked to that utility node. In order to reduce respondents' burden to evaluate these values in the CB-CNET survey, it is assumed that the maximum total utility that someone can gain is 100 (times by the weight of utility), and the minimum utility is set at 0. Thus, having negative utility values are not considered in the model. This could probably give an influence to the performance of ID models, and should be investigated in future research.

Additionally, in the ID model structure, interaction effects among various contexts that lead to the same benefit are not taken into account. This is also done in order to reduce respondents' burden in the survey. For instance, there could be some interactions between the contexts of *weather* and *wind conditions* in determining an individual's benefit of *having comfort*. However, the impact of these contextual aspects on the individual's pursued benefit of *having comfort* is assessed separately. At last, the design of experiment is employed by using the fixed seven-utility design. Even though the decision to use seven benefits is made based on the results of the first experiment using the CNET interview and card game, it is aware that this could give some impact on the calculated weights, particularly for the weighting method-2.

With regard to the DT model, indeed the performance of DT is better than ID. However, it should be noted that DT cannot be used to understand the process (in this case, the decision making process). The model can take any kind of variables as input and the algorithm will generate a tree with the best model fit. Therefore, the links between aspects in the MR cannot be taken into account. This is not an issue when the purpose of the study is simply to make predictions. However, if the aim is also to understand people's behaviour, particularly related to how changes in the contextual variables influence people's choices, the ID model is better suited.

8.3 Directions for research along the lines

In the previous section (i.e. Section 8.1), the research conclusions are drawn. Furthermore, the research limitations are discussed in Section 8.2. In this section, the directions for other future research along the lines are presented. This section is organized into two parts. In the beginning, the directions of other similar behavioural studies are proposed. Following that, the directions of other research to generate individuals' mental-level models are explained.

8.3.1 Behavioural research

This research particularly focuses on individuals' travel decisions when performing leisure-shopping activities in Hasselt. Similar types of studies should also be conducted for other cities and other types of activities, yielding a better understanding of individuals' travel decisions. Additionally, results of such behavioural studies should be used to improve activity-travel diaries.

It has been previously discussed (i.e. in Chapter 2) that assumptions in AB models are often questioned due to the lack of an actual behavioural foundation.

Therefore, other studies should be done to integrate the results of different behavioural studies to ground assumptions in AB models. Another possibility is also to carry out research that can integrate the outcomes of behavioural studies to improve activity-travel diaries, such as regarding how to transfer important aspects (such as benefits) that appear in the individuals' MR into factors being recorded in the diary.

Many studies have shown a strong influence of habitual decision making in daily travel decisions, focusing on habitual transport mode choices (e.g. Gärling et al., 2001; Jager, 2003; Verplanken et al., 1997; etc.). However, more studies should be done to investigate other decisions as well, such as activity duration, trip chaining, etc. Results of such studies can be further used as feedback to activity-based travel demand models.

Based on the experience of developing and implementing different elicitation methods, the research shows that it is important to make respondents really feel the actual scenario under investigation. For instance, any behavioural study that wants to investigate people's behaviour under time pressure should make the respondents feel the actual time pressure, or introducing other types of stress to the respondents when answering the survey.

At last, this PhD research shows the real influence of method selection on the gathered behavioural information. However, the method that can best elicit individuals' MR should still be investigated. More studies should be done in this field, finding the most representative ways to represent people's MR, for different activity types, sample, case study, etc.

8.3.2 Modelling research

From the modelling perspective using ID, future research should be done to learn probability distribution from the data. This would possibly reduce the participants' error in estimating probabilities. This could be done for instance by generating different clusters of people and generate one model for each cluster.

Accordingly, probability distribution can be learnt from the dataset to build the model. Moreover, some data can be used for testing the performance of each model. The most optimal probability distribution can be found for each model. This could lead to a better predictive accuracy of the ID model.

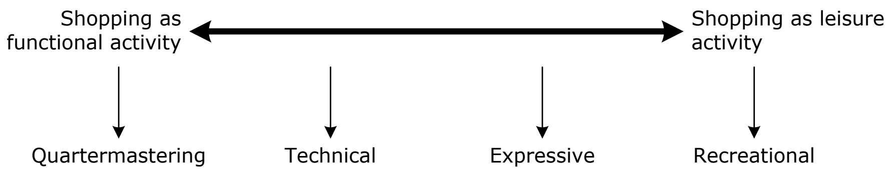
Further research should be done to examine different model structures of ID, in order to find the structure that can best represent the thought process. Furthermore, other modelling approaches to model individuals' MR should also be tested, such as using *fuzzy cognitive map*, *neural network*, or other AI techniques. In order to find the most suited modelling approach that can more accurately predict individuals' travel behaviour, results of studies using other AI approaches can be compared with the results of the ID model (e.g. Hannes, et al., 2010).

At last, in order to examine the added value of using behavioural data as a modelling input, future research should be conducted to compare the performance of ID models with the accuracy of a more common predictive model that do not use MR data as its input. One of these well known methods is *discrete choice model*, using socio-demographic characteristics and other quantitative data as input.

A future study can also be done to investigate the influence of different TDM measures that appear in people's ID models. This can be done, for instance by setting some policy scenarios, such as very frequent bus service, very high parking cost, etc. These scenarios are used as evidence in every individual's network. By doing that, behavioural changes of people due to certain TDM measures can be investigated. However, there are a few issues that should be taken into account in this exercise. For instance, the accuracy of individuals' ID models in predicting people's behaviours should be relatively good to start with. Next, there are some possibilities that an individual does into take into account a certain measure based on the current condition. For instance, an individual decision maker may think that the current parking fee per hour is still acceptable. Accordingly, this aspect is not considered in his decision making process. However, the increase of this fee (e.g. more than 2 Euro per hour) may make this factor being considered by the decision maker, despite the fact that it is not present in that individual's MR. A future study should find ways to assess behavioural changes of people, taken into account the limitation of the modelling approaches.

Appendix A Fun-shopping activity

In the past years, shopping was mostly seen as a mandatory activity, as a way to survive. However, this paradigm has shifted towards shopping as a free-time leisure activity in which some enjoyment can be obtained. However, a clear-cut to categorize shopping as purely utilitarian or as entirely recreational pursuit is often hard to make. It is believed that such an activity contains a combination of both aspects.



Shopping continuum (Carr, 1990)

Shopping is a complex and unique phenomenon. Carr (1990) proposes a functional-leisure continuum, in which shopping is ranging from completely functional to purely leisure based on various degrees of functionality. When shopping is done solely as a routine-based functional activity to serve the necessities, then it is called *quartermastering shopping*, such as (pure) grocery shopping. Next, *technical shopping* is seen as buying mechanical items, such as cars, computers, etc. Therefore, it usually requires information seeking and careful considerations prior to the actual buying of the items. *Expressive shopping* is done when people buy goods to portray their images. Examples of it are buying clothes, jewellery, etc. Thus, this type of shopping contains more elements of leisure than the two previous ones. At last, *recreational shopping* is done purely for leisure. Due to these contrasted differences between utilitarian and recreational shopping, shopping as a pastime should be better understood, especially regarding its impact on individuals' travel behaviour.

In scientific literature, shopping as a free-time activity is referred to in different ways such as *recreational-shopping* (Guiry, Mägi, & Lutz, 2006; Westbrook &

Black, 1985), *active-shopping* (Lesser & Hughes, 1986), *new-type shopping* (Boedeker, 1995), *leisure-shopping* (Newby, 1993; Timothy, 2003), and *fun-shopping* (Sinha & Prasad, 2004). Despite this varying terminology, most of them emphasize shopping as part of recreational activities from which people can draw enjoyment and pleasure. Table below summarizes the characteristics of leisure-shopping based on a number of existing studies.

Characteristics of leisure shoppers

Characteristics of leisure-shoppers	*1*	*2*	*3*	*4*	*5*	*6*	*7*
Attracted by images, using shopping as media of expression and their search for values	■	■					
Shopping as recreational, enjoyable, entertaining leisure activity	■	■		■	■		■
Going shopping without a pre-planned purchase in mind (purchase is made impulsively)					■	■	
Shopping to find information					■	■	■
Motivated by both functional and instrumental concerns			■				
High involvement in virtually all aspects of shopping processes. Getting enjoyment from the shopping process rather than from the searched merchandise			■				
Having demanding life-styles		■					
Engaging in all forms of outdoor activities usually do-it-yourself-ers		■					
Tough shoppers		■					■
Price and product quality are major considerations		■					■

[1] New-type shopper (Boedeker, 1995)
[2] Active-shopper (Lesser & Hughes, 1986)
[3] Recreational-shopper (Westbrook & Black, 1985)
[4] Recreational-shopper (Guiry et al., 2006)
[5] Recreational-shopper (Bellenger & Korgaonkar, 1980)
[6] Recreational-shopper (Barnes, 1984)
[7] Fun-shopper (Sinha, 2003)

Hence, with regard to its meaning, shopping has to be differentiated from buying, in which specific items are acquired from a seller. Shopping is not necessarily to actually buying some goods. The main shoppers' intention can simply be the enjoyment of walking around the town (Dellaert et al., 1995) and meeting other people (Bromley & Thomas, 1993), or browsing, checking and collecting some information to find the balance between price and quality in the individual's search for values (Lesser & Hughes, 1986).

Appendix B The CNET interview & card game lists of variables

1. Contextual variables and their definitions for the activity-scheduling decision

Contextual variable	*Definition*
Being forced by someone	Consideration to decide going fun-shopping on a certain day in a week because you are being forced to do that (e.g. by your mother, friends, etc.).
Existing plan of other activities	Consideration to decide going fun-shopping on a certain day in a week because you have made other plans of activities to do.
Happening/events	Consideration to decide going fun-shopping on a certain day in a week because there is happening/event that you wants to attend.
Mood	Consideration to decide going fun-shopping on a certain day in a week because of your mood (good or bad).
Physical condition	Consideration to decide going fun-shopping on a certain day in a week because of your physical condition (fit or unfit).
Pre-planned purchase	Consideration to decide going fun-shopping on a certain day in a week because of a pre-purchasing plan that you have in mind.
Sale season	Consideration to decide going fun-shopping on a certain day in a week because of sale season.
Weather	Consideration to decide going fun-shopping on a certain day in a week because of the weather (good or bad).

2. Instrumental variables and their definitions for the activity-scheduling decision

Instrumental variable	*Definition*
Budget availability	Consideration to decide going fun-shopping on a certain day in a week because of budget availability on that day.
Closing time	Consideration to decide going fun-shopping on a certain day in a week because of the shop closing time on that day.
Companion	Consideration to decide going fun-shopping on a certain day in a week because of your companion.
Crowdedness in Hasselt	Consideration to decide (or avoid) going fun-shopping on a certain day in a week because of the crowdedness (or quietness) in Hasselt on that day.
Duration of shopping	Consideration to decide going fun-shopping on a certain day in a week because of the time duration of fun-shopping on that day.
Environment of day	Consideration to decide going fun-shopping on a certain day in a week because you like (or dislike) the environment of a certain day in a week.
Last time fun-shop	Consideration to decide going fun-shopping on a certain day in a week because you have not performed the activity for a while.
Opening time	Consideration to decide going fun-shopping on a certain day in a week because of the shop opening time on that day.
Preference of day	Consideration to decide going fun-shopping on a certain day in a week because you prefer it.
Scheduling effort	Consideration to decide going fun-shopping on a certain day in a week because you want to avoid rescheduling your existing plans of activities.
Time availability	Consideration to decide going fun-shopping on a certain day in a week because of time availability on that day.
Time of day	Consideration to decide going fun-shopping on a certain day in a week because of the time of day in which the activity can be performed on that day.
Urgency of shopping	Consideration to decide going fun-shopping on a certain day in a week because of the urgency of fun-shopping.

3. Contextual variables and their definitions for the transport mode decision

Contextual variable	*Definition*
Arrival time at home	Consideration to decide (or avoid) using a certain mode of transport because of your arrival time at home.
Availability of parking space	Consideration to decide (or avoid) using a certain mode of transport because of the availability of parking space.
Companion	Consideration to decide (or avoid) using a certain mode of transport because of your companion.
Crowdedness in bus	Consideration to decide (or avoid) using a bus because of the crowdedness inside it.
Existing plan of other activities	Consideration to decide (or avoid) using a certain mode of transport because of other plans of activities that you have made beforehand.
Mood	Consideration to decide (or avoid) using a certain mode of transport because of your mood (good or bad).
Number or size of goods being purchased	Consideration to decide (or avoid) using a certain mode of transport because of the number (or size) of goods that you have to carry back home.
Physical condition	Consideration to decide (or avoid) using a certain mode of transport because of you physical condition (fit or unfit)
Possession of busabonnement card	Consideration to decide (or avoid) using a bus because you own (do not own) a busabonnement card.
Precipitation	Consideration to decide (or avoid) using a certain mode of transport because of weather conditions (good or bad).
Pre-planned purchase	Consideration to decide (or avoid) using a certain mode of transport because of the pre-purchasing plan that you have in mind.
Sale season	Consideration to decide (or avoid) using a certain mode of transport because of sale season.
Tax & insurance	Consideration to decide (or avoid) using a car because you have (or have not) paid the tax and insurance for the car.
Temperature	Consideration to decide (or avoid) using a certain mode of transport because of the temperature in the year (spring/autumn temperature, summer temperature, or winter temperature).
Time availability	Consideration to decide (or avoid) using a certain mode of transport because of time availability to perform the fun-shopping activity.

Contextual variable	*Definition*
Time of day	Consideration to decide (or avoid) using a certain mode of transport because of time of day to perform the fun-shopping activity.
Unusual things	Consideration to decide (or avoid) using a certain mode of transport because of the unusual things that may happen during the trip.

4. Instrumental variables and their definitions for the transport mode decision

Instrumental variable	*Definition*
Accident & damage	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different levels of protection in case of accident and damage.
Adjustment in transport mode	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different possibilities to make some adjustments inside.
Availability of seat	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different possibilities to have an available seat.
Bus frequency	Consideration to decide (or avoid) using a bus because of its frequency.
Capacity of vehicle	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different capacities of passengers.
Cost	Consideration to decide (or avoid) using a certain mode of transport because of the cost that you have to spend.
Direct travel	Consideration to decide (or avoid) using a certain mode of transport because some transport modes offer a possibility to have direct travel (e.g. car and bike) while others (e.g. bus) make you experience a detour.
Easiness for parking	Consideration to decide (or avoid) using a certain mode of transport because some transport modes (e.g. bike) can be parked easily, and some others (e.g. bus) do not need parking.
Environment inside bus & car or around bike	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different environment inside.
Environment-friendliness of the transport mode	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different levels of emission, for the environmental reasons.
Flexibility/independency	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different levels of flexibility and independency.
Getting fine	Consideration to avoid using a car because to avoid getting a fine.
Habit	Consideration to decide (or avoid) using a certain mode of transport because it is your habit.

Instrumental variable	*Definition*
Infrastructure availability	Consideration to decide (or avoid) using a certain mode of transport because of the availability of infrastructure for it.
Mental effort & ease	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different levels of (mental) ease.
Physical effort	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different requirements of (physical) effort.
Possibility to be stolen	Consideration to decide (or avoid) using a certain mode of transport because some transport modes are safer than others.
Possibility to consume alcohol	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different possibilities to consume alcohol.
Preference of transport mode	Consideration to decide (or avoid) using a certain mode of transport because you prefer it.
Reliability	Consideration to decide (or avoid) using a certain mode of transport because some transport modes are more reliable than others.
Sensation of speed	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different sensation of speed.
Shelter provision (staying dry)	Consideration to decide (or avoid) using a certain mode of transport because of shelter provision in it.
Transport mode availability	Consideration to decide (or avoid) using a certain mode of transport because of its availability.
Travel flow	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different travel flows (e.g. bus stops in almost every bus stops).
Travel time	Consideration to decide (or avoid) using a certain mode of transport because of its travel time.
Treatment of bags	Consideration to decide (or avoid) using a certain mode of transport because different transport modes offer different levels of easiness to treat your (shopping) bags.

5. Contextual variables and their definitions for the shopping location decision

Contextual variable	*Definition*
Budget availability	Consideration to decide (or avoid) going to a certain shopping location because of your budget availability.
Companion	Consideration to decide (or avoid) going to a certain shopping location because of your companion.
Crowdedness in Hasselt	Consideration to decide (or avoid) going to a certain shopping location because of the crowdedness (or quietness) in Hasselt.
Eating a snack	Consideration to decide (or avoid) going to a certain shopping location because of the possibility to eat a snack.
Existing plan of other activities	Consideration to decide (or avoid) going to a certain shopping location because of other plans of activities that you have made beforehand.
Information from others	Consideration to decide (or avoid) going to a certain shopping location because of some information that you get from others.
Interest in a specific product	Consideration to decide (or avoid) going to a certain shopping location because of your interest in a specific product.
Mood	Consideration to decide (or avoid) going to a certain shopping location because of your mood.
Number or size of goods being purchased	Consideration to decide (or avoid) going to a certain shopping location because of the number (or size) of goods that you buy.
Physical condition	Consideration to decide (or avoid) going to a certain shopping location because of your physical condition (fit or unfit).
Pre-planned purchase	Consideration to decide (or avoid) going to a certain shopping location because of the pre-purchasing plan that you have in mind.
Sale season	Consideration to decide (or avoid) going to a certain shopping location because of sale season.
Temperature	Consideration to decide (or avoid) going to a certain shopping location because of the temperature in a year.
Time availability	Consideration to decide (or avoid) going to a certain shopping location because of your time availability.
Weather	Consideration to decide (or avoid) going to a certain shopping location because of weather conditions (good or bad)

6. Instrumental variables and their definitions for the shopping location decision

Instrumental variable	*Definition*
Accessibility for bike	Consideration to decide (or avoid) going to a certain shopping location because different shopping locations offer different accessibility for bike.
Accessibility for bus	Consideration to decide (or avoid) going to a certain shopping location because different shopping locations offer different accessibility for bus.
Accessibility for car	Consideration to decide (or avoid) going to a certain shopping location because different shopping locations offer different accessibility for car.
Ambiance/environment	Consideration to decide (or avoid) going to a certain shopping location because different shopping locations offer different ambiance/environment.
Café & restaurant	Consideration to decide (or avoid) going to a certain shopping location because of the presence of cafés & restaurants in it.
Chance to meet someone you know	Consideration to decide (or avoid) going to a certain shopping location because of the chance to meet someone you know.
Customer service	Consideration to decide (or avoid) going to a certain shopping location because of the customer service in the area.
Familiarity with the area	Consideration to decide (or avoid) going to a certain shopping location because of your familiarity with the area.
Habit	Consideration to decide (or avoid) going to a certain shopping location because of your habit.
Image of shops	Consideration to decide (or avoid) going to a certain shopping location because of the image of shops in the area.
Indoor shopping mall	Consideration to decide (or avoid) going to a certain shopping location because of the presence of indoor shopping mall in the area.
Other activities in the area	Consideration to decide (or avoid) going to a certain shopping location because of other (non-shopping) activities that you can do in the area.
Presence of favourite shop	Consideration to decide (or avoid) going to a certain shopping location because of the presence of your favourite shop in the area.
Product price	Consideration to decide (or avoid) going to a certain shopping location because of the product price in the area.

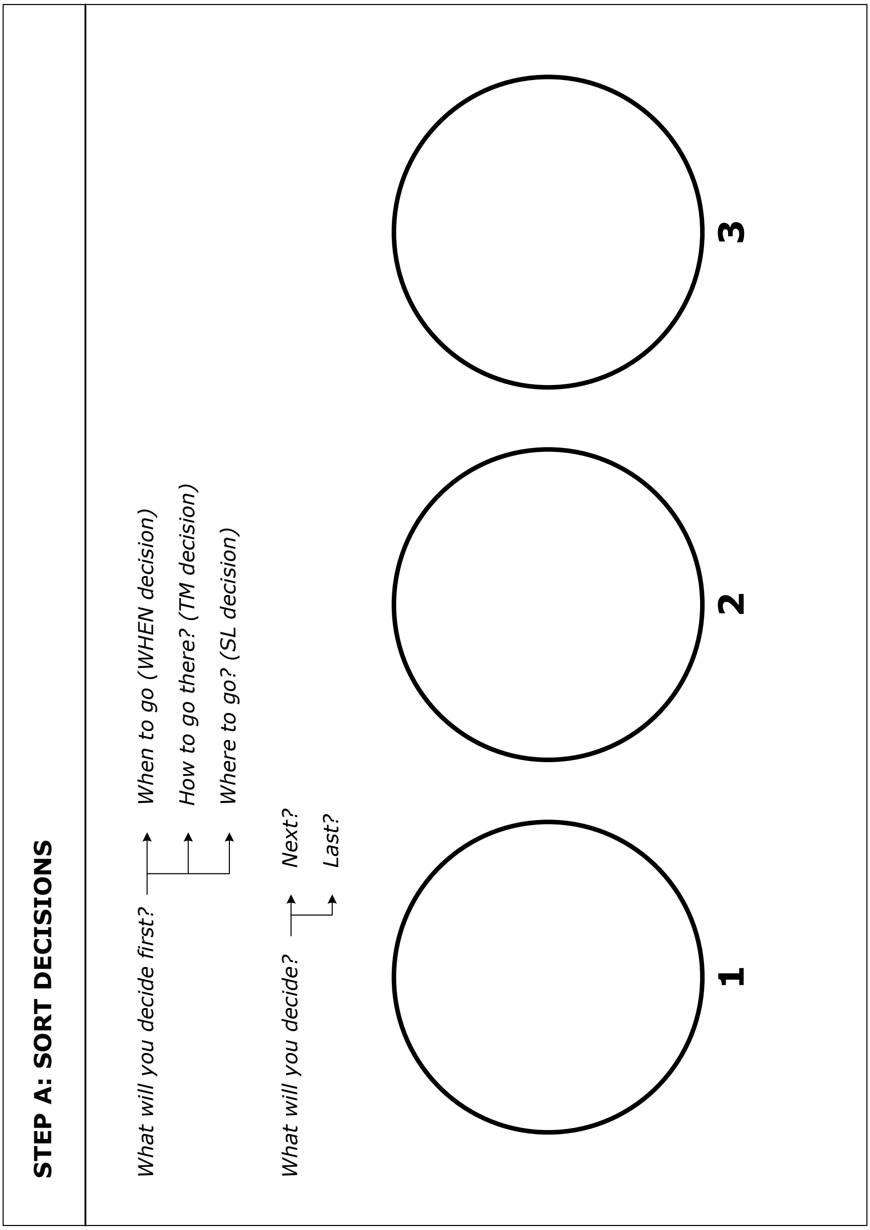
Instrumental variable	*Definition*
Product quality	Consideration to decide (or avoid) going to a certain shopping location because of the product quality in the area.
Routing	Consideration to decide (or avoid) going to a certain shopping location because of the route that you take to get there.
Shop arrangement	Consideration to decide (or avoid) going to a certain shopping location because of the shop arrangement in the area.
Shopping location preference	Consideration to decide (or avoid) going to a certain shopping location because you prefer it.
Similarity of product	Consideration to decide (or avoid) going to a certain shopping location because of the similarity of products being sold in the area.
Size of shopping location	Consideration to decide (or avoid) going to a certain shopping location because of the size of shopping location.
Size of shops	Consideration to decide (or avoid) going to a certain shopping location because of the size of shops in the area.
Social status	Consideration to decide (or avoid) going to a certain shopping location because of the social status it may give you.
Type of store	Consideration to decide (or avoid) going to a certain shopping location because of the type of store in the area.

7. Benefit variables and their definitions for all decisions

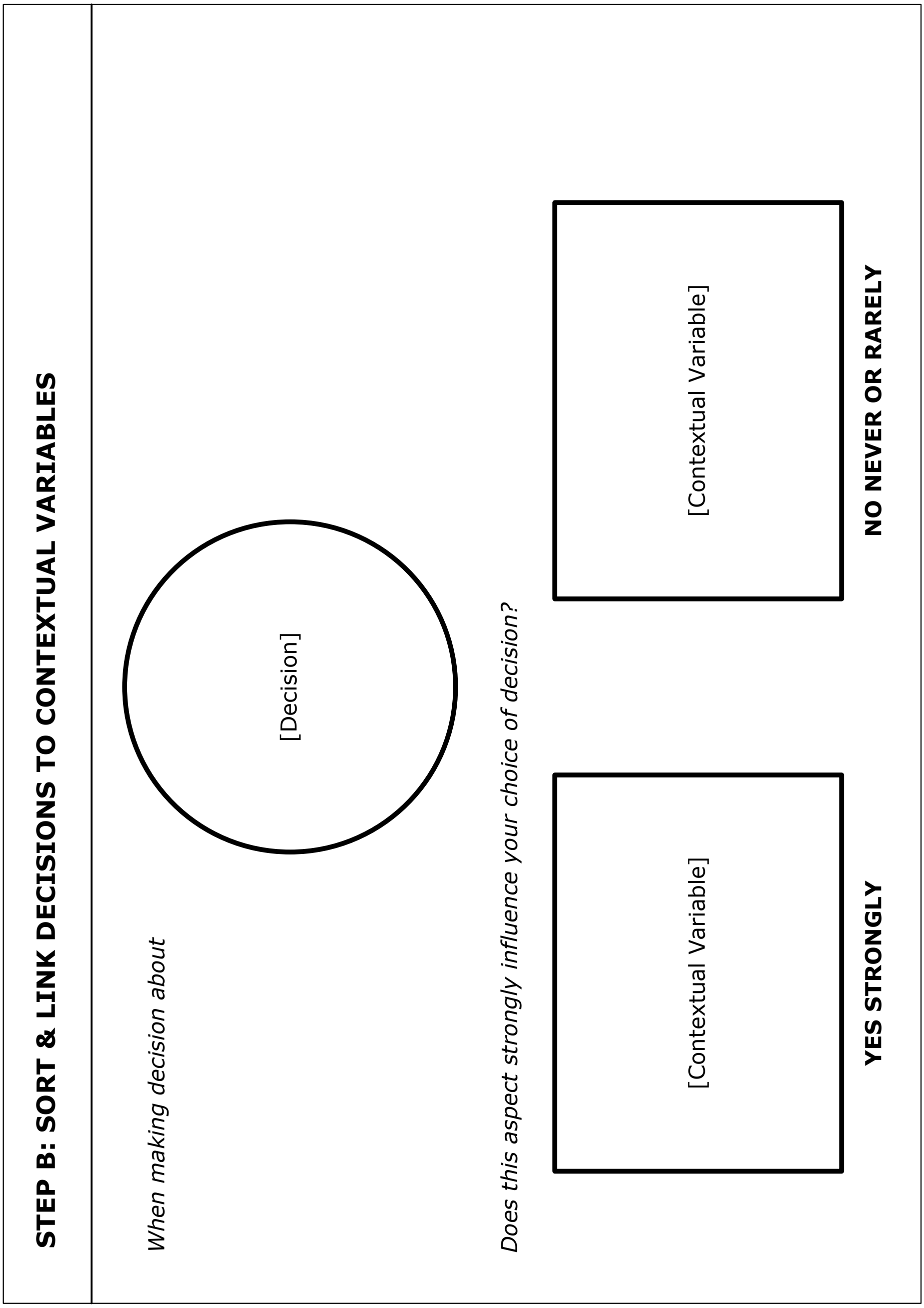
Benefit variable	*Definition*
Assurance/certainty	Full of confidence and freedom from doubt.
Being healthy	Possession or enjoying good health.
Being sociable	Friendly or agreeable in company. Companionable. Pleasant.
Convenient	Suited or favourable to one's purpose or needs. Easy to reach. Accessible. Mental well being.
Durability	Well lasting and endurance.
Efficiency (time & effort)	Accomplishment of a job with a minimum expenditure of time and effort.
Environment benefit	Reducing the effect on environmental resources or value resulting from human activities.
Freedom	A state of being free and not under any restraints.
Fun (e.g. happiness, enjoyment, pleasure, satisfaction)	Happiness, enjoyment, pleasure, satisfaction
Get the best use	The state of getting the best use out of something owned.
Having information	The state of having information (about price, products, quality, etc.).
Having privacy	A state of being free from disturbance in one's private life.
Luxury & prestige	A material object or service conducive for fine living (a delicacy, elegance, refinement) instead of necessity.
Physical comfort	Physical well being provided by a person or thing.
Reducing stress	The state of not having stress. Reducing the stress because you have your things done.
Safety & security	Condition of being safe from danger, risk, or injury. Something that secures (gives protection or defence).
Saving money	Reducing an outlay or expenditure of money spent for doing such an activity.

Appendix C The CNET card game boards

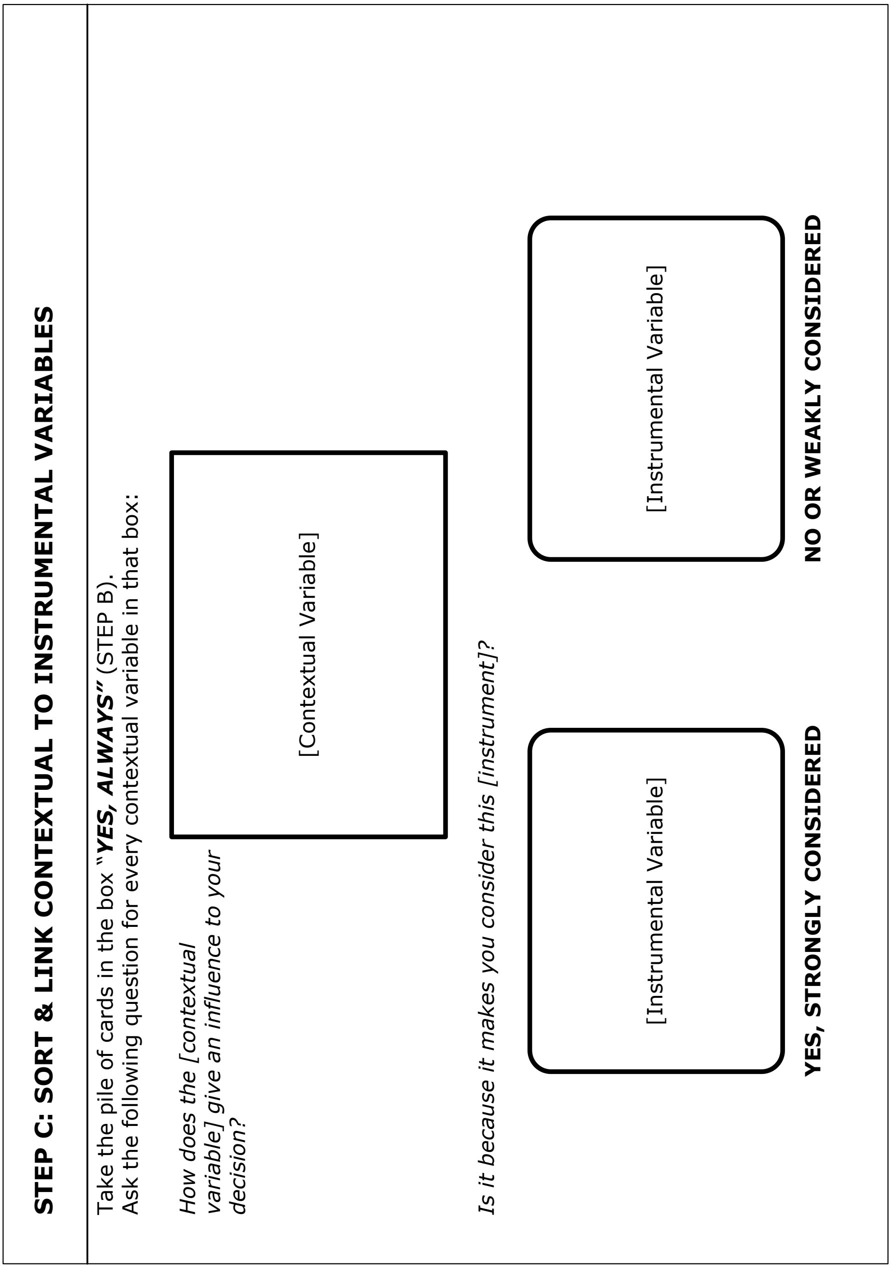
1. Step A Sort decisions



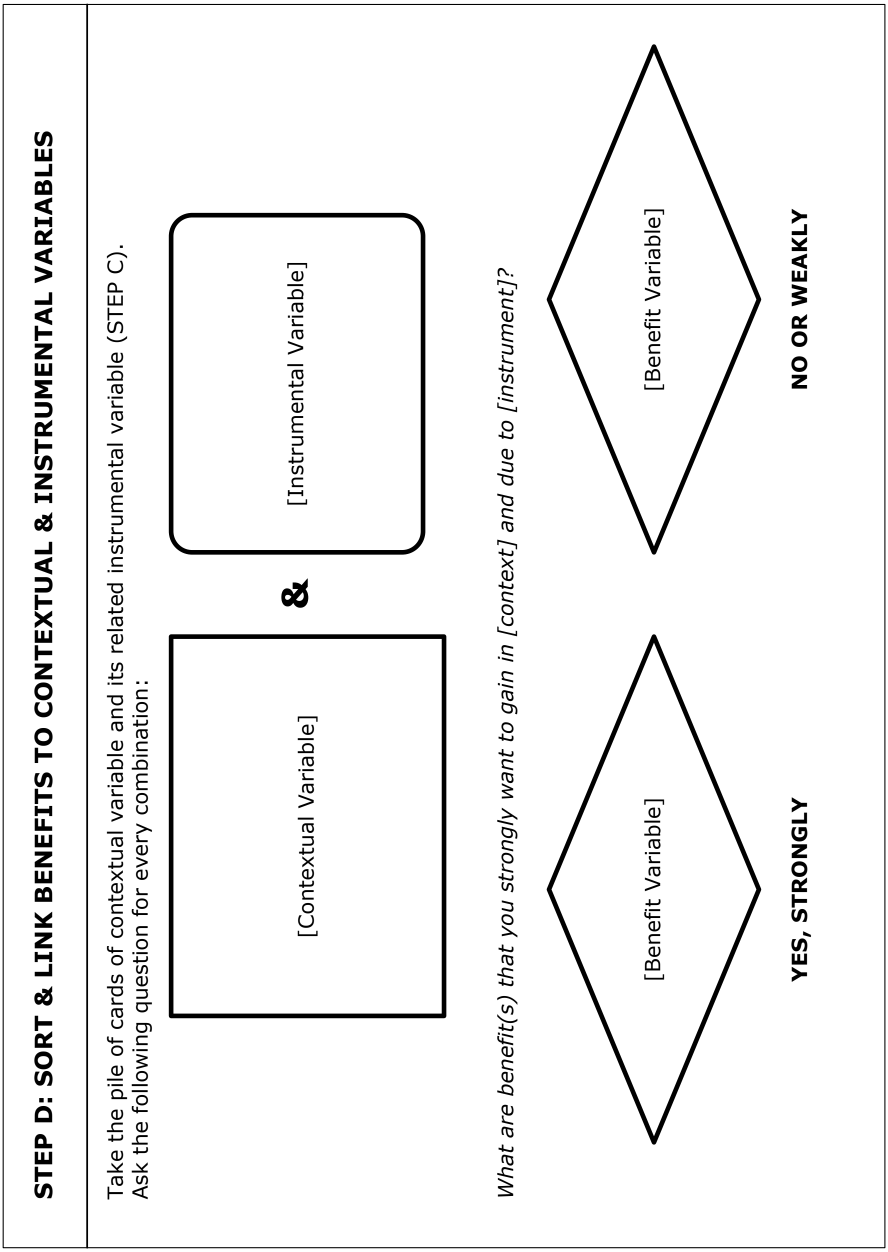
2. Step B Sort & link decisions to contextual variables



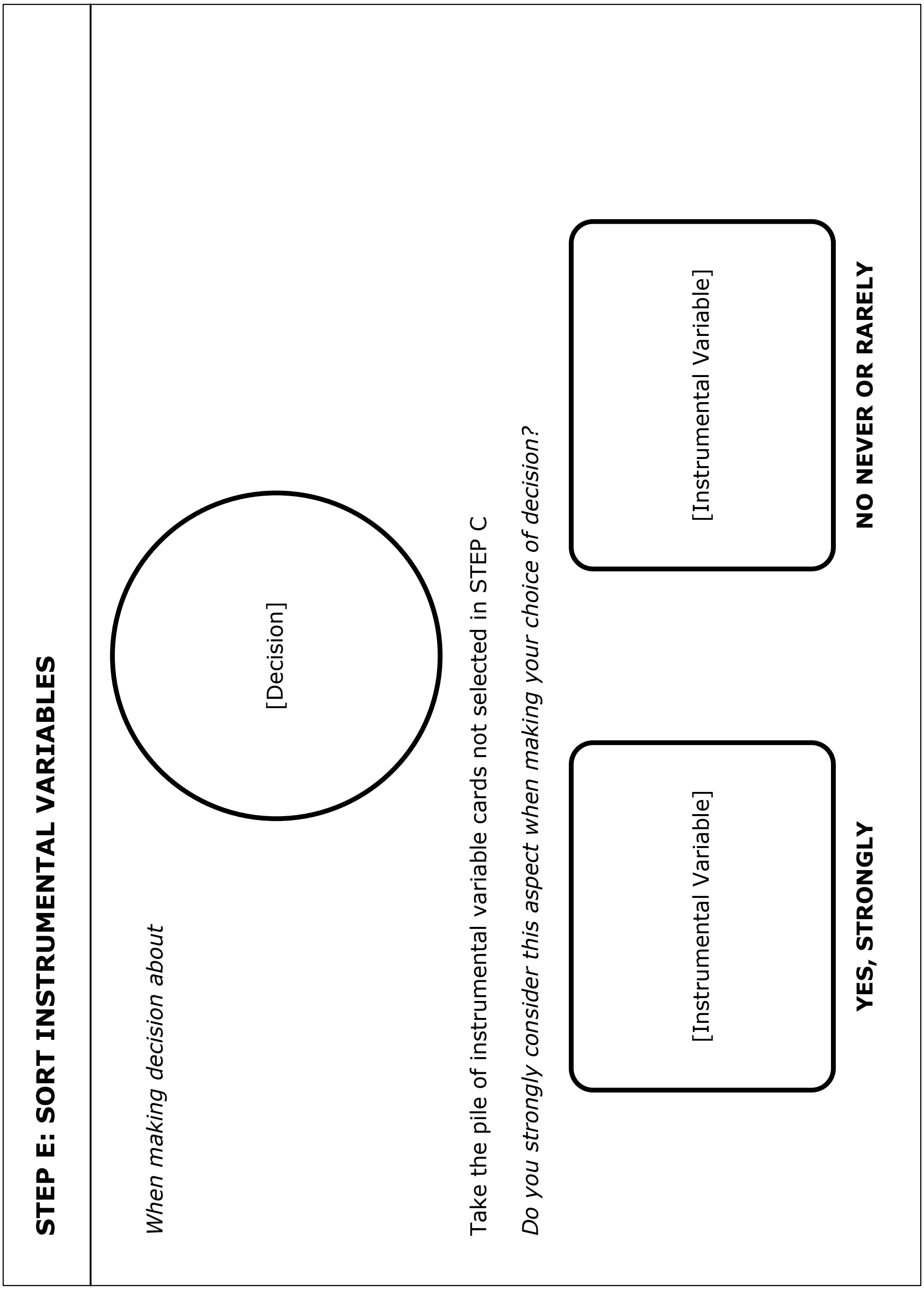
3. Step C Sort & link contextual & instrumental variables



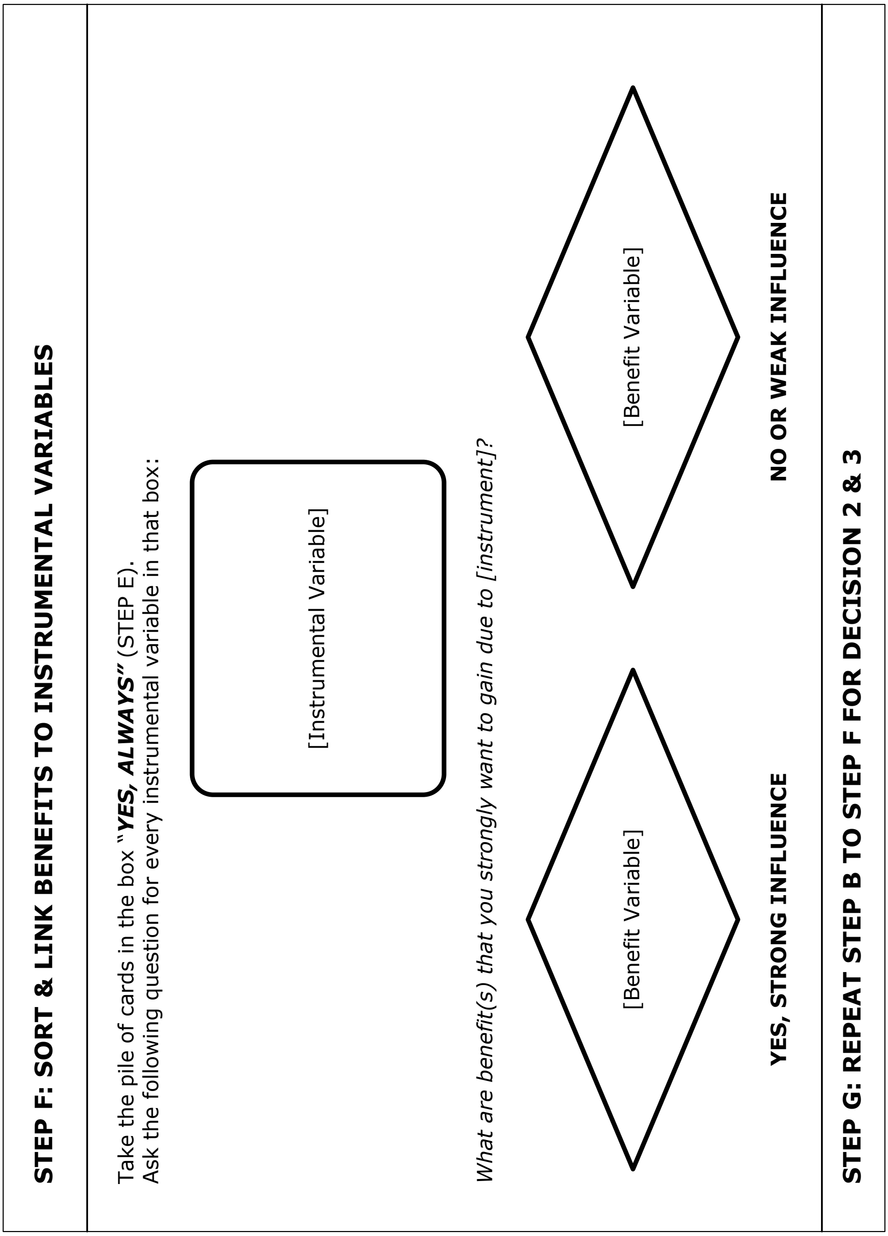
4. Step D Sort & link benefits to contextual & instrumental variables



5. Step E Sort instrumental variables



6. Step E Sort & link benefits to instrumental variables



Appendix D The association rules results of the CNET card game data

1. The transport mode decision

Antecedent	*Consequent*	*SV*[1]	*CV*[2]	*Lift*
Travel time (I[3])	Efficiency (B[4])	9.19%	94.59%	3.08
Time availability (C[5])	Efficiency (B)	7.61%	78.38%	2.55
Weather (C)	Shelter (I)	6.04%	76.67%	12.70
Shelter (I)	Weather (C)	6.04%	100.00%	12.70
Weather (C)	Comfort (B)	5.77%	73.33%	3.88
Shelter (I)	Comfort (B)	5.51%	91.30%	4.83
Weather (C), Comfort (B)	Shelter (I)	5.51%	95.45%	15.81
Shelter (I), Comfort (B)	Weather (C)	5.51%	100.00%	12.70
Shelter (I), Weather (C)	Comfort (B)	5.51%	91.30%	4.83
Weather (C)	Shelter (I), Comfort (B)	5.51%	70.00%	12.70
Shelter (I)	Weather (C), Comfort (B)	5.51%	91.30%	15.81
Parking space (C)	Easiness for parking (I)	4.46%	58.62%	9.31
Easiness for parking (I)	Parking space (C)	4.46%	70.83%	9.31
Time availability (C), Efficiency (B)	Travel time (I)	3.94%	51.72%	5.33
Travel time (I), Time availability (C)	Efficiency (B)	3.94%	93.75%	3.05
Crowdedness in bus (C)	Comfort (B)	3.94%	83.33%	4.41
Bus frequency (I)	Efficiency (B)	3.67%	63.64%	2.07
Physical effort (I)	Comfort (B)	3.67%	87.50%	4.63
Direct travel (I)	Efficiency (B)	3.15%	80.00%	2.61
Easiness for parking (I)	Efficiency (B)	3.15%	50.00%	1.63
Companion (C)	Preference of TM (I)	3.15%	66.67%	8.19

[1] Support value
[2] Confidence value
[3] Instrumental variable
[4] Benefit variable
[5] Contextual variable

Antecedent	*Consequent*	*SV*	*CV*	*Lift*
Sociable (B)	Companion (C)	3.15%	85.71%	18.14
Companion (C)	Sociable (B)	3.15%	66.67%	18.14
Availability of seat (I)	Comfort (B)	2.62%	100.00%	5.29
Environment inside TM (I)	Comfort (B)	2.62%	71.43%	3.78
Mental effort (I)	Convenient (B)	2.62%	83.33%	7.22
Companion (C), Sociable (B)	Preference of TM (I)	2.62%	83.33%	10.24
Preference of TM (I), Sociable (B)	Companion (C)	2.62%	100.00%	21.17
Preference of TM (I), Companion (C)	Sociable (B)	2.62%	83.33%	22.68
Sociable (B)	Preference of TM (I), Companion (C)	2.62%	71.43%	22.68
Companion (C)	Preference of TM (I), Sociable (B)	2.62%	55.56%	21.17
Sociable (B)	Preference of TM (I)	2.62%	71.43%	8.78
Number bags (C)	Treatment of bags (I)	2.62%	62.50%	14.01
Treatment of bags (I)	Number bags (C)	2.62%	58.82%	14.01
Saving money (B)	Cost (I)	2.36%	52.94%	18.34
Cost (I)	Saving money (B)	2.36%	81.82%	18.34

2. The shopping location decision

Antecedent	*Consequent*	*SV*[1]	*CV*[2]	*Lift*
Saving money (B[3])	Product price (I[4])	6.29%	81.48%	10.56
Product price (I)	Saving money (B)	6.29%	81.48%	10.56
Type of store (I)	Efficiency (B)	5.14%	51.43%	2.02
Time availability (C[5])	Efficiency (B)	4.86%	58.62%	2.31
Ambiance (C)	Fun (B)	3.43%	52.17%	4.94
Shop arrangement (I)	Efficiency (B)	3.14%	61.11%	2.40
Weather (C)	Comfort (B)	3.14%	84.62%	11.85
Budget availability (C)	Product price (I)	2.86%	55.56%	7.20
Crowdedness in Hasselt (C)	Ambiance (C)	2.57%	81.82%	12.45
Shop arrangement (I)	Time availability (C)	2.57%	50.00%	6.03
Budget availability (C)	Saving money (B)	2.57%	50.00%	6.48
Existing plan of other activities (C)	Efficiency (B)	2.57%	100.00%	3.93

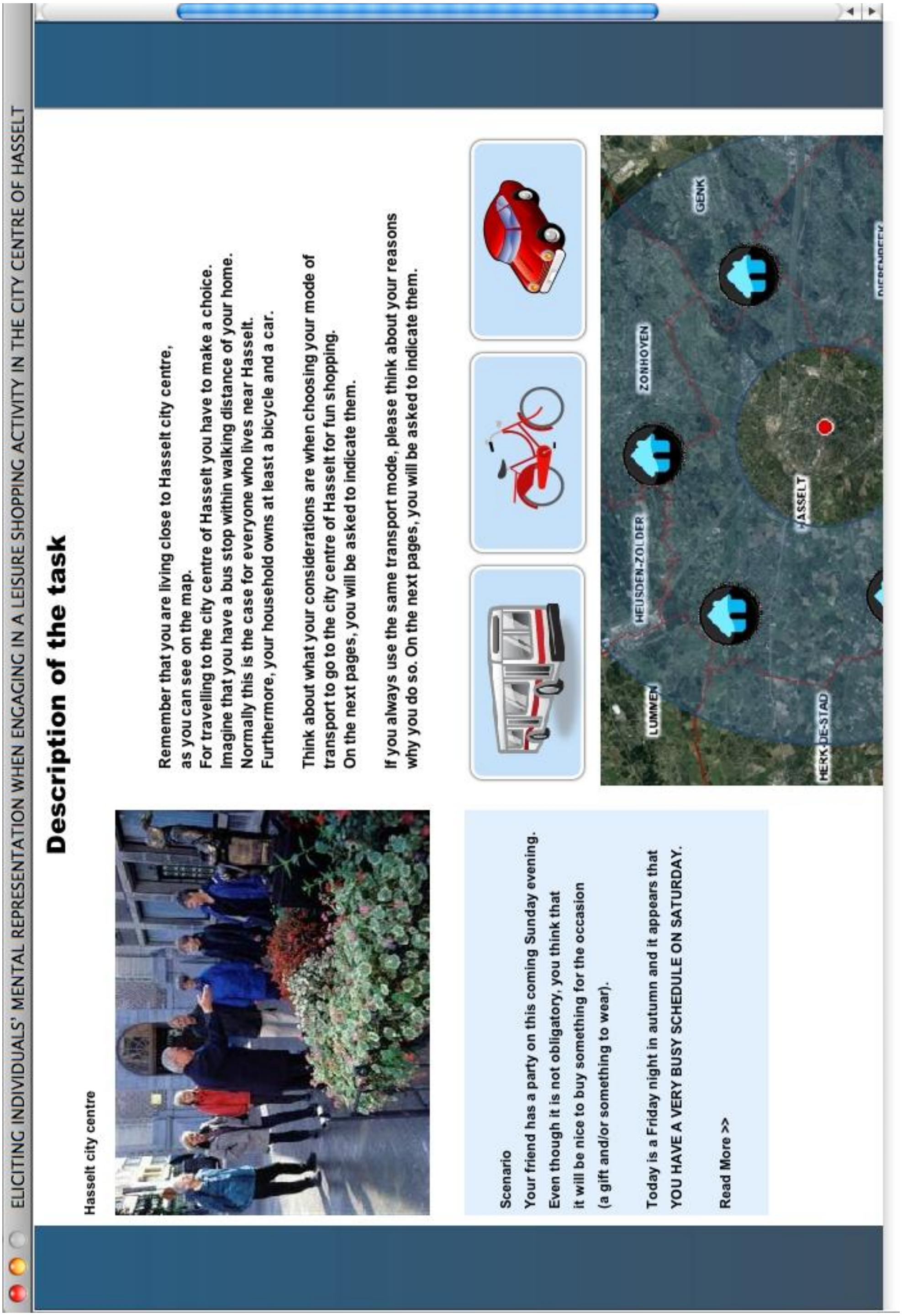
[1] Support value
[2] Confidence value
[3] Benefit variable
[4] Instrumental variable
[5] Contextual variable

3. The activity-scheduling decision

Antecedent	*Consequent*	*SV*[1]	*CV*[2]	*Lift*
Scheduling effort (I[3])	Efficiency (B[4])	7.60%	65.00%	2.58
Comfort (B)	Weather (C[5])	7.02%	85.71%	5.86
Sociable (B)	Companion (C)	6.43%	78.57%	6.72
Companion (C)	Sociable (B)	6.43%	55.00%	6.72
Mood (C)	Fun (B)	5.26%	75.00%	3.56
Pre-planned purchase (C)	Efficiency (B)	5.26%	52.94%	2.11

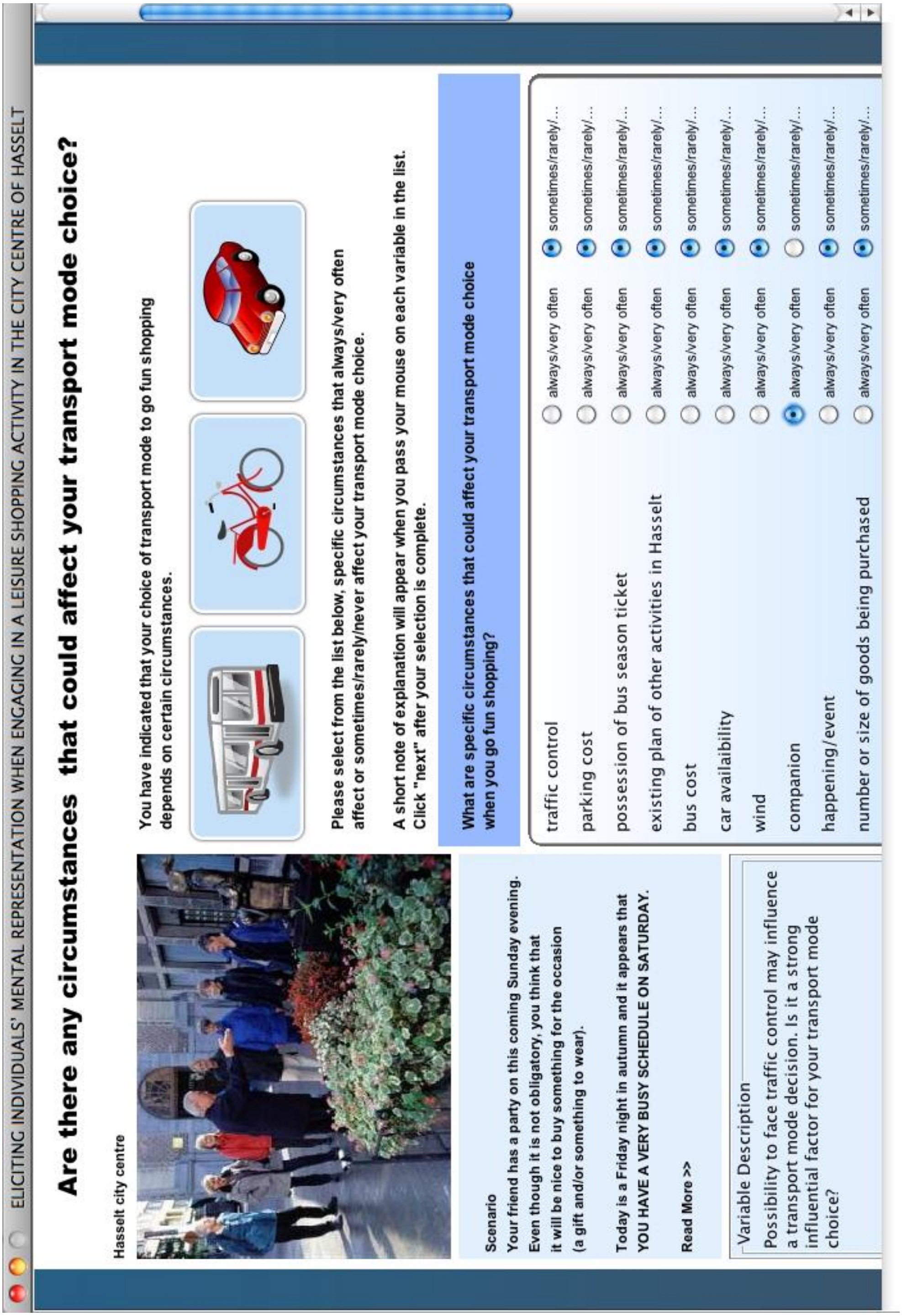
[1] Support value
[2] Confidence value
[3] Instrumental variable
[4] Benefit variable
[5] Contextual variable

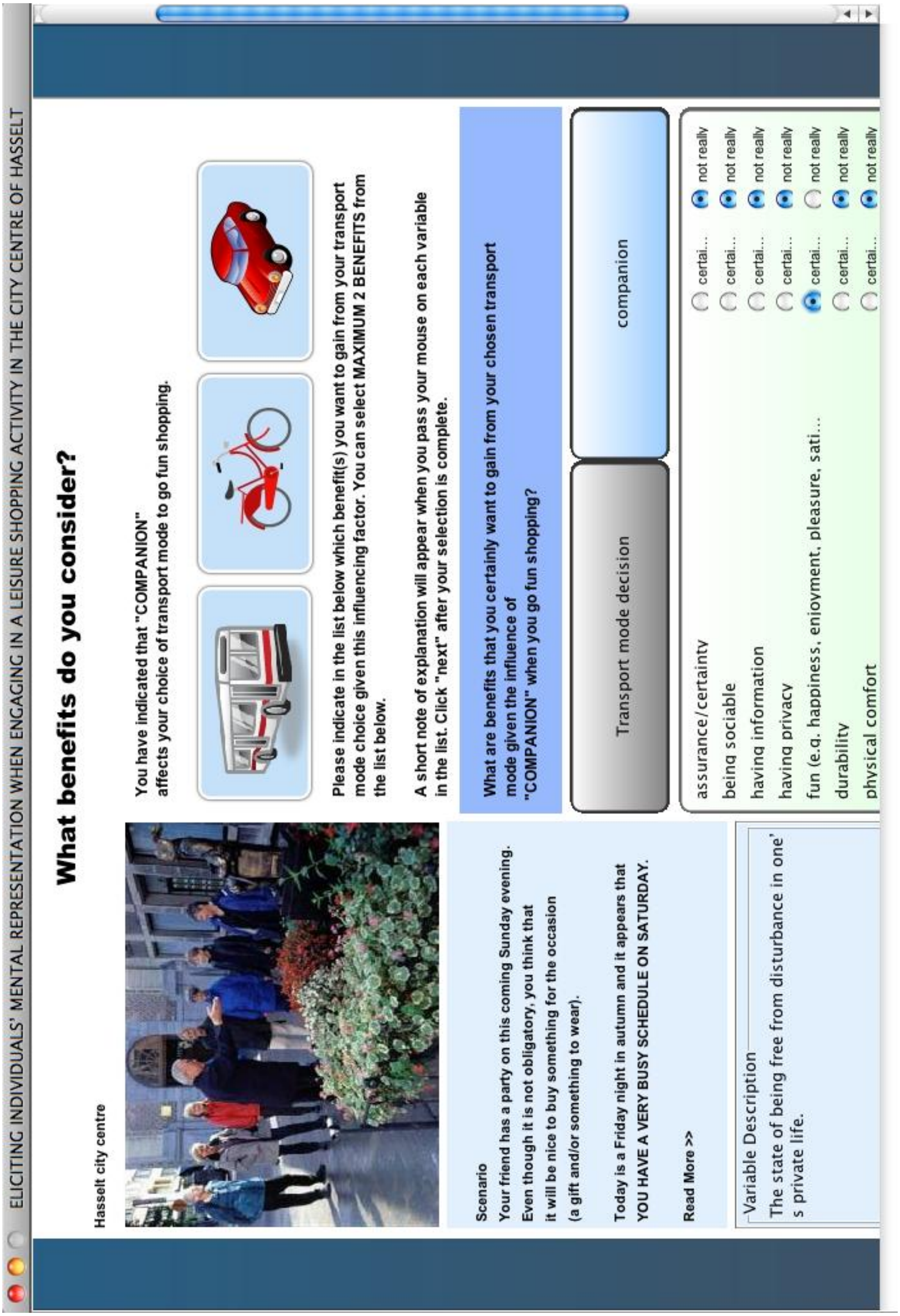
Appendix E Some screenshots of the CB-CNET interface

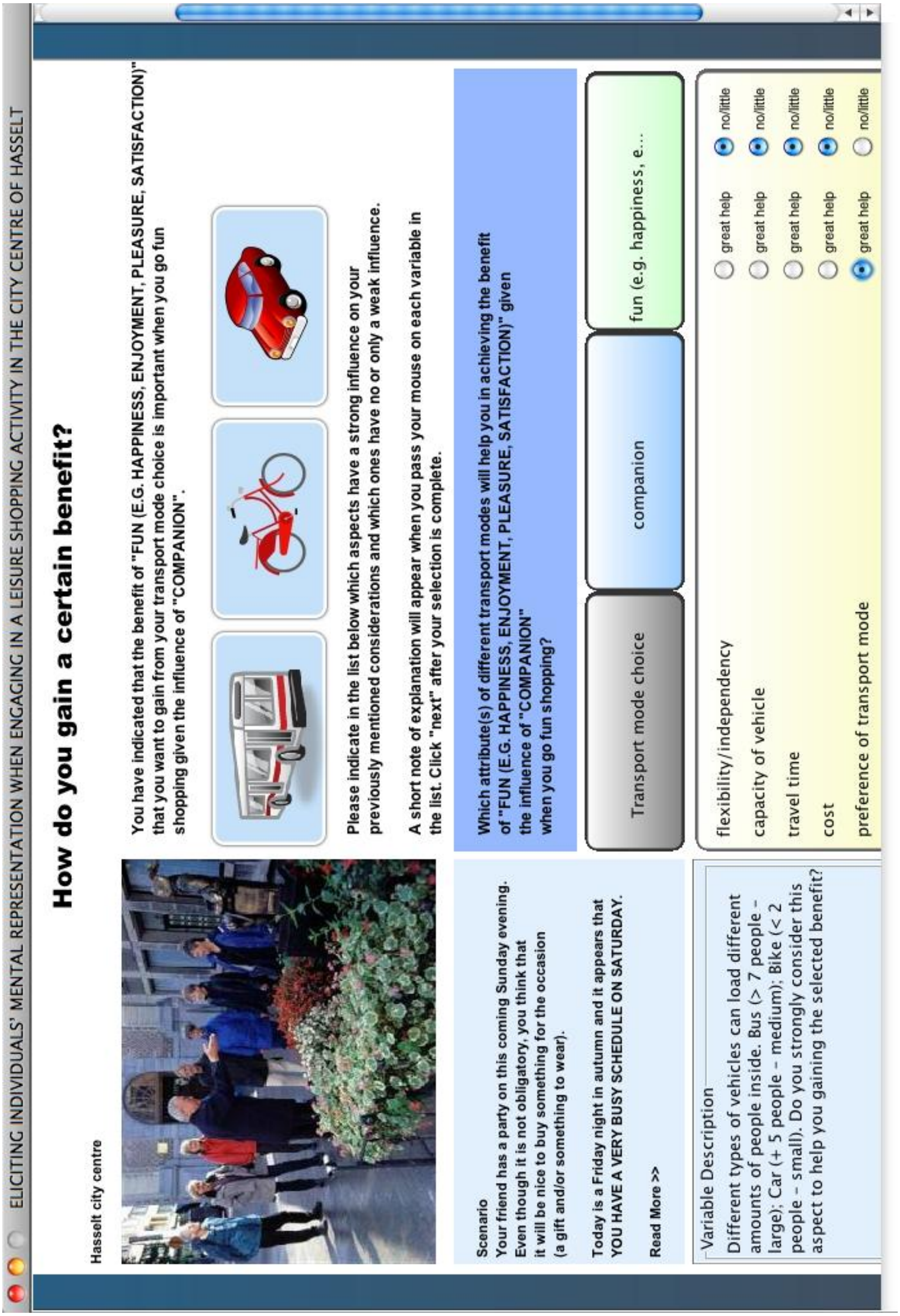

ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
Description of the task
Hasselt city centre
Remember that you are living close to Hasselt city centre,
as you can see on the map.
For travelling to the city centre of Hasselt you have to make a choice.
Imagine that you have a bus stop within walking distance of your home.
Normally this is the case for everyone who lives near Hasselt.
Furthermore, your household owns at least a bicycle and a car.
Think about what your considerations are when choosing your mode of
transport to go to the city centre of Hasselt for fun shopping.
On the next pages, you will be asked to indicate them.
If you always use the same transport mode, please think about your reasons
why you do so. On the next pages, you will be asked to indicate them.
Scenario
Your friend has a party on this coming Sunday evening.
Even though it is not obligatory, you think that
it will be nice to buy something for the occasion
(a gift and/or something to wear).
Today is a Friday night in autumn and it appears that
YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>
LUMMEN
HEUSDEN-ZOLDER
ZONHOVEN
GENK
HASSELT
HERK-DE-STAD

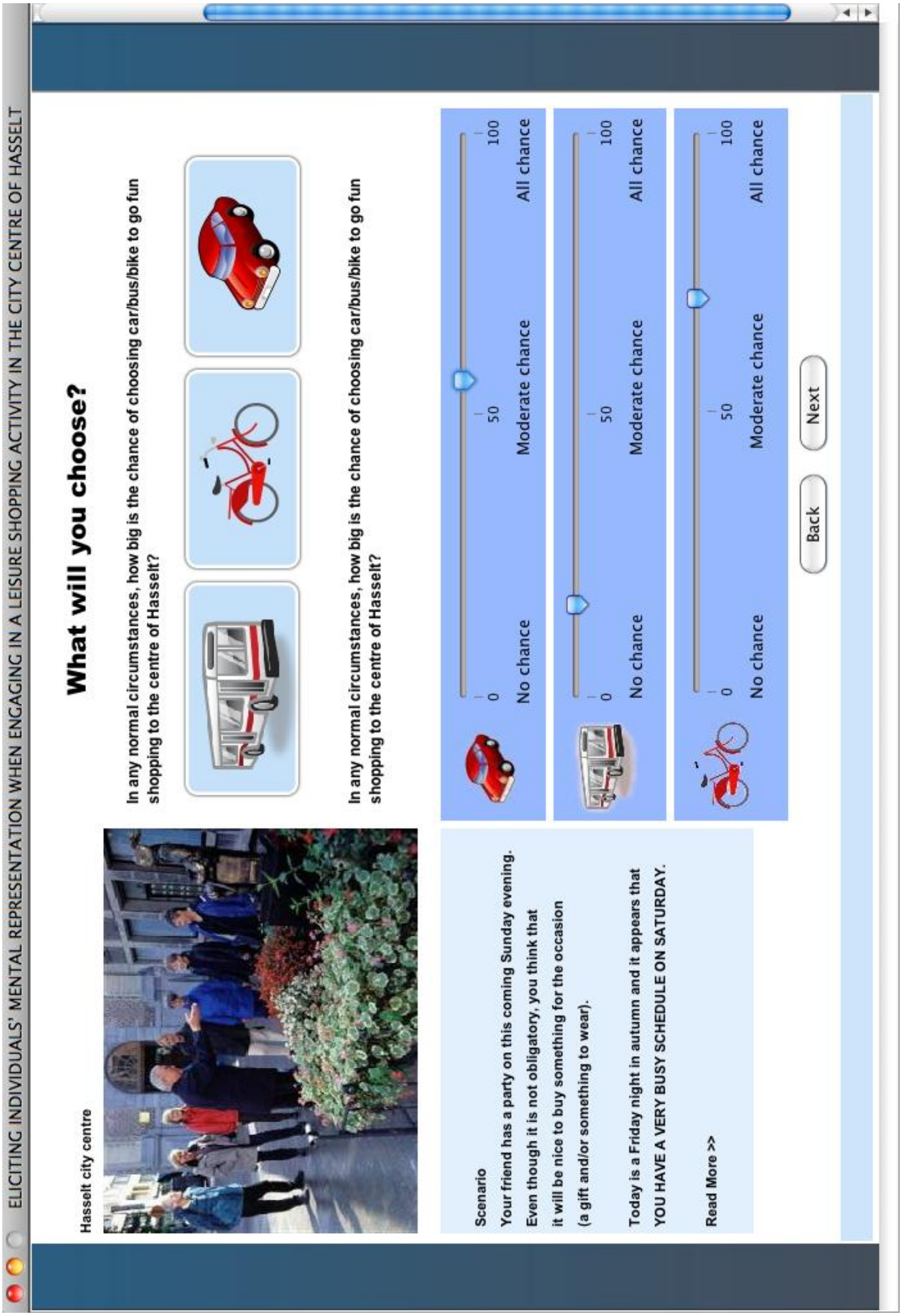

ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
FUN-SHOPPING in Hasselt
STEDELIJK MUSEUM
WAERDENHOF
Which decision will you take first?
Hasselt city centre
Based on the task, there are two decisions you can take; namely WHERE TO GO in the city centre of Hasselt and HOW TO GO THERE. It is up to you to select which decisions to take first and second.
Please indicate below in which order you would take the decisions.
First decision to take
What mode of transport to take?
Second decision to take
Where to go in the city centre of Hasselt?
Back
Next
Scenario
Your friend has a party on this coming Sunday evening.
Even though it is not obligatory, you think that
it will be nice to buy something for the occasion
(a gift and/or something to wear).
Today is a Friday night in autumn and it appears that
YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.

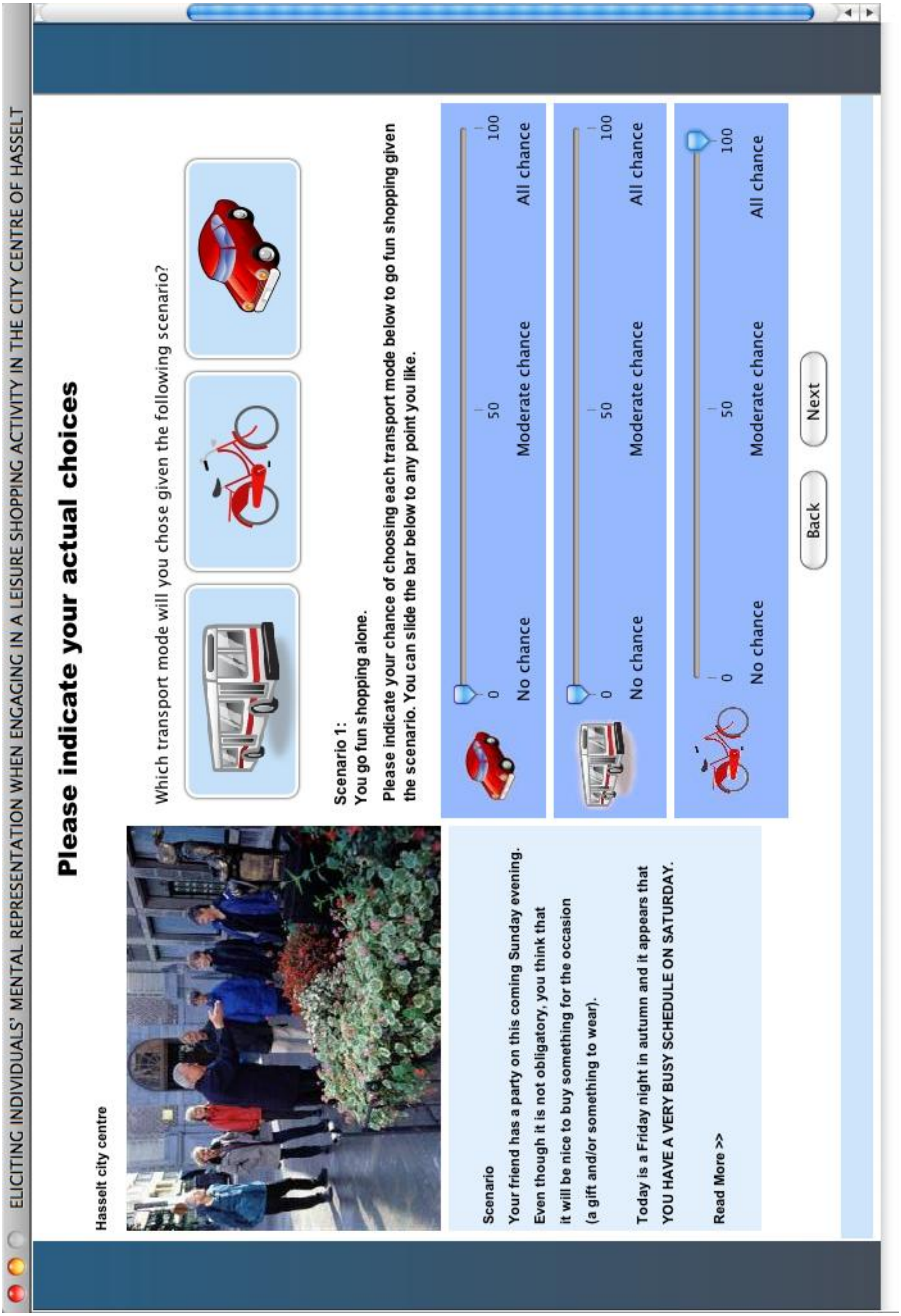

ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
FUN-SHOPPING in Hasselt
STEDELIJK MUSEUM
How do you make your choice?
Hasselt city centre
You have indicated that when you go fun shopping in Hasselt, you will make the transport mode decision first.
Which of the following statements represents the way you make your choice out of different transport mode options (bus, bike and car)?
I would directly choose t...
My transport mode choice depends on certain circumstances
Back
Next
Scenario
Your friend has a party on this coming Sunday evening. Even though it is not obligatory, you think that it will be nice to buy something for the occasion (a gift and/or something to wear).
Today is a Friday night in autumn and it appears that YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>

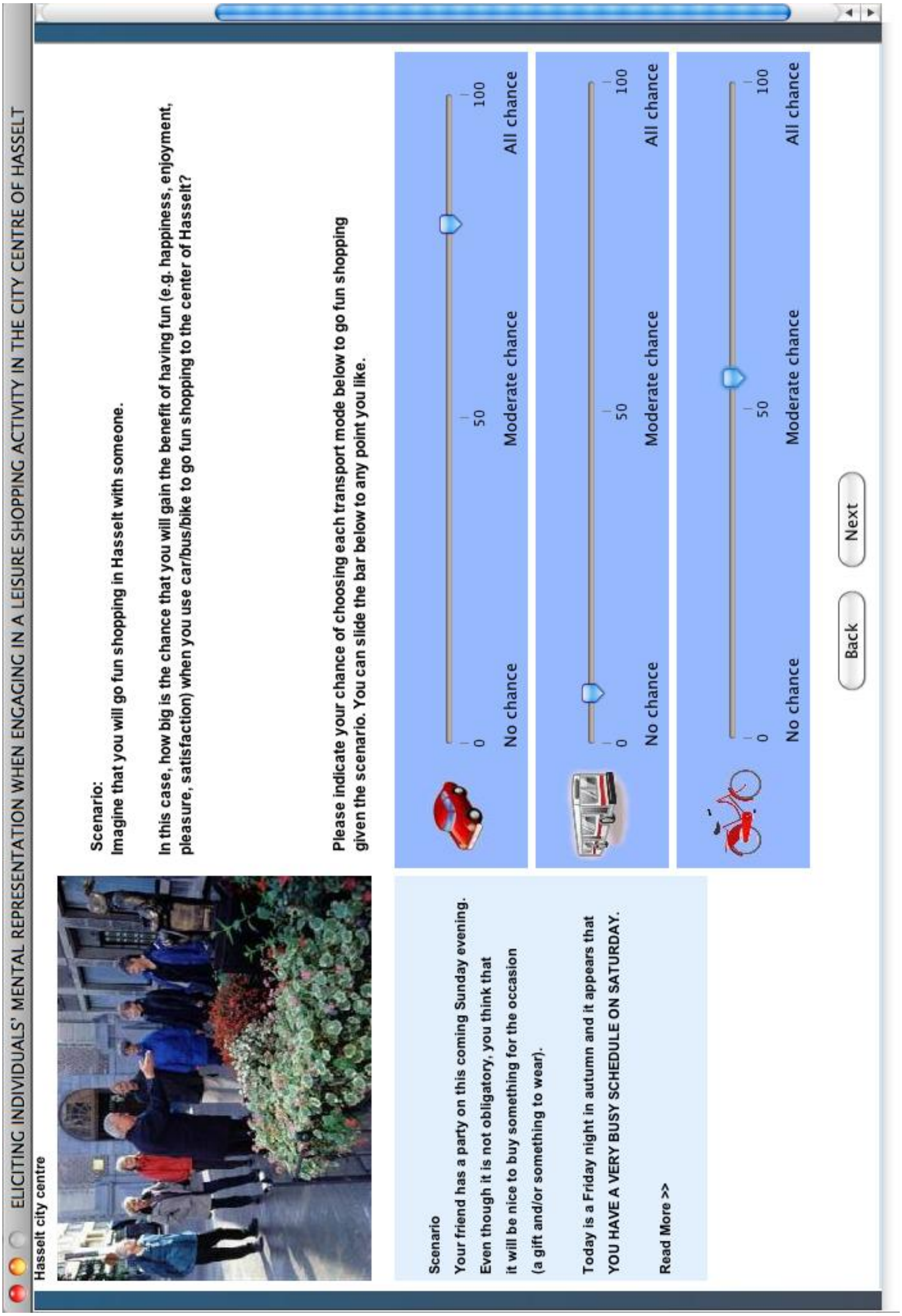

ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
Are there any circumstances that could affect your transport mode choice?
Hasselt city centre
You have indicated that your choice of transport mode to go fun shopping depends on certain circumstances.
Please select from the list below, specific circumstances that always/very often affect or sometimes/rarely/never affect your transport mode choice.
A short note of explanation will appear when you pass your mouse on each variable in the list. Click "next" after your selection is complete.
What are specific circumstances that could affect your transport mode choice when you go fun shopping?
Scenario
Your friend has a party on this coming Sunday evening. Even though it is not obligatory, you think that it will be nice to buy something for the occasion (a gift and/or something to wear).
Today is a Friday night in autumn and it appears that YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>
Variable Description
Possibility to face traffic control may influence a transport mode decision. Is it a strong influential factor for your transport mode choice?
traffic control always/very often sometimes/rarely/...
parking cost always/very often sometimes/rarely/...
possession of bus season ticket always/very often sometimes/rarely/...
existing plan of other activities in Hasselt always/very often sometimes/rarely/...
bus cost always/very often sometimes/rarely/...
car availaibility always/very often sometimes/rarely/...
wind always/very often sometimes/rarely/...
companion always/very often sometimes/rarely/...
happening/event always/very often sometimes/rarely/...
number or size of goods being purchased always/very often sometimes/rarely/...


ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
What benefits do you consider?
Hasselt city centre
You have indicated that "COMPANION"
affects your choice of transport mode to go fun shopping.
Please indicate in the list below which benefit(s) you want to gain from your transport mode choice given this influencing factor. You can select MAXIMUM 2 BENEFITS from the list below.
A short note of explanation will appear when you pass your mouse on each variable in the list. Click "next" after your selection is complete.
Scenario
Your friend has a party on this coming Sunday evening.
Even though it is not obligatory, you think that
it will be nice to buy something for the occasion
(a gift and/or something to wear).
Today is a Friday night in autumn and it appears that
YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>
What are benefits that you certainly want to gain from your chosen transport mode given the influence of "COMPANION" when you go fun shopping?
Transport mode decision
companion
assurance/certainty
being sociable
having information
having privacy
fun (e.g. happiness, enjoyment, pleasure, sati...
durability
physical comfort
certai...
not really
Variable Description
The state of being free from disturbance in one's private life.

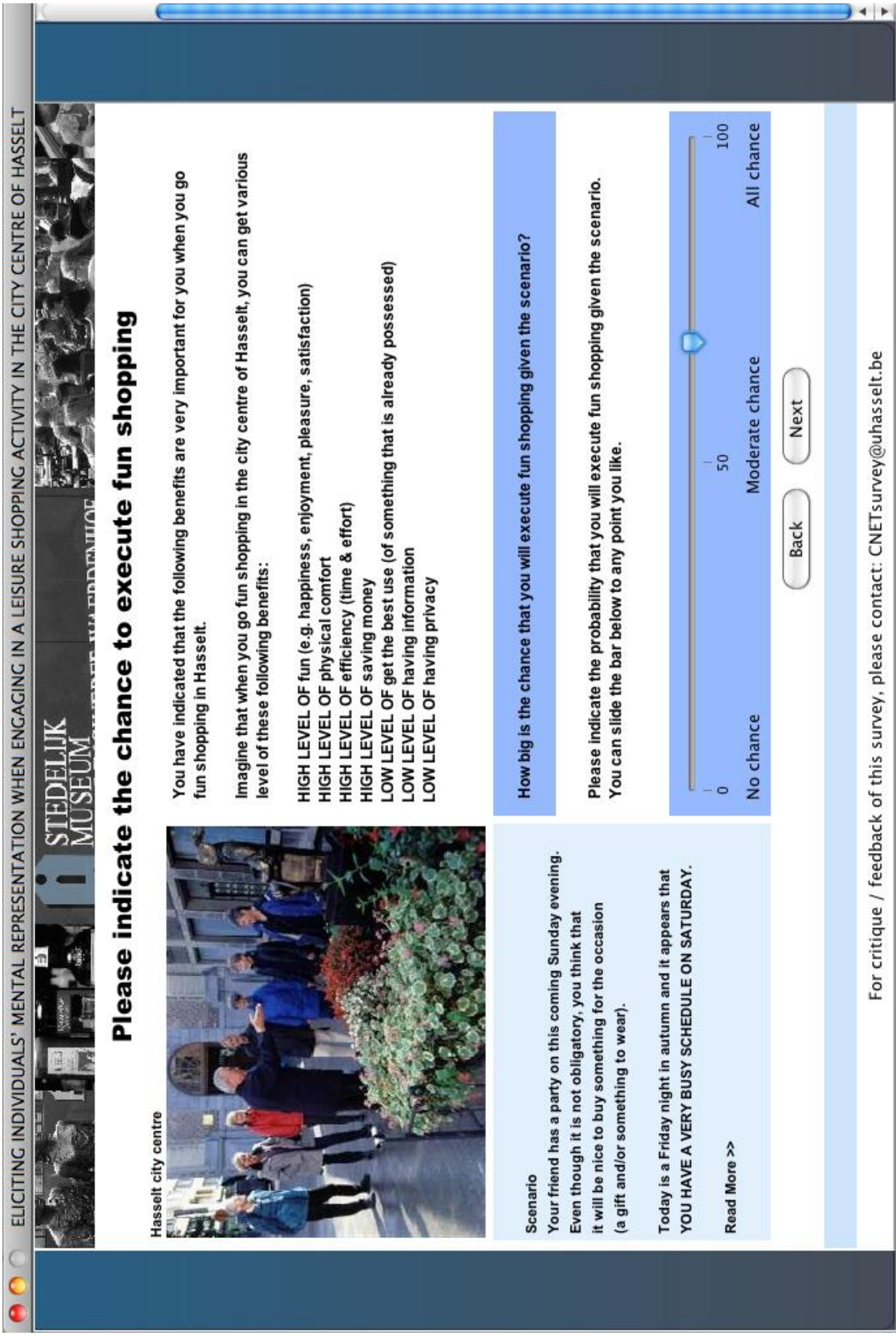

ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
Hasselt city centre
How do you gain a certain benefit?
You have indicated that the benefit of "FUN (E.G. HAPPINESS, ENJOYMENT, PLEASURE, SATISFACTION)" that you want to gain from your transport mode choice is important when you go fun shopping given the influence of "COMPANION".
Please indicate in the list below which aspects have a strong influence on your previously mentioned considerations and which ones have no or only a weak influence.
A short note of explanation will appear when you pass your mouse on each variable in the list. Click "next" after your selection is complete.
Scenario
Your friend has a party on this coming Sunday evening. Even though it is not obligatory, you think that it will be nice to buy something for the occasion (a gift and/or something to wear).
Today is a Friday night in autumn and it appears that YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>
Which attribute(s) of different transport modes will help you in achieving the benefit of "FUN (E.G. HAPPINESS, ENJOYMENT, PLEASURE, SATISFACTION)" given the influence of "COMPANION" when you go fun shopping?
Transport mode choice
companion
fun (e.g. happiness, e...
flexibility/independency
great help
no/little
capacity of vehicle
great help
no/little
travel time
great help
no/little
cost
great help
no/little
preference of transport mode
great help
no/little
Variable Description
Different types of vehicles can load different amounts of people inside. Bus (> 7 people – large); Car (+ 5 people – medium); Bike (< 2 people – small). Do you strongly consider this aspect to help you gaining the selected benefit?


ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
Hasselt city centre
What will you choose?
In any normal circumstances, how big is the chance of choosing car/bus/bike to go fun shopping to the centre of Hasselt?
Scenario
Your friend has a party on this coming Sunday evening.
Even though it is not obligatory, you think that
it will be nice to buy something for the occasion
(a gift and/or something to wear).
Today is a Friday night in autumn and it appears that
YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>
In any normal circumstances, how big is the chance of choosing car/bus/bike to go fun shopping to the centre of Hasselt?
0
50
100
No chance
Moderate chance
All chance
0
50
100
No chance
Moderate chance
All chance
0
50
100
No chance
Moderate chance
All chance
Back
Next


ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
Please indicate your actual choices
Hasselt city centre
Which transport mode will you chose given the following scenario?
Scenario 1:
You go fun shopping alone.
Please indicate your chance of choosing each transport mode below to go fun shopping given the scenario. You can slide the bar below to any point you like.
0
50
100
No chance
Moderate chance
All chance
0
50
100
No chance
Moderate chance
All chance
0
50
100
No chance
Moderate chance
All chance
Scenario
Your friend has a party on this coming Sunday evening.
Even though it is not obligatory, you think that
it will be nice to buy something for the occasion
(a gift and/or something to wear).
Today is a Friday night in autumn and it appears that
YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>
Back
Next


ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
Hasselt city centre
Scenario:
Imagine that you will go fun shopping in Hasselt with someone.
In this case, how big is the chance that you will gain the benefit of having fun (e.g. happiness, enjoyment, pleasure, satisfaction) when you use car/bus/bike to go fun shopping to the center of Hasselt?
Please indicate your chance of choosing each transport mode below to go fun shopping given the scenario. You can slide the bar below to any point you like.
Scenario
Your friend has a party on this coming Sunday evening.
Even though it is not obligatory, you think that
it will be nice to buy something for the occasion
(a gift and/or something to wear).
Today is a Friday night in autumn and it appears that
YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>
0
50
100
No chance
Moderate chance
All chance
0
50
100
No chance
Moderate chance
All chance
0
50
100
No chance
Moderate chance
All chance
Back
Next


ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
Please indicate how important these benefits are in your decisions
sselt city centre
cenario
our friend has a party on this coming Sunday evening.
ven though it is not obligatory, you think that
will be nice to buy something for the occasion
gift and/or something to wear).
oday is a Friday night in autumn and it appears that
OU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
ead More >>
Please indicate in the list below for EACH BENEFIT how important it is to gain that
benefit from your TRANSPORT MODE and LOCATION DECISIONS when you go FUN SHOPPING.
Assurance/certainty
Being healthy
Being sociable
Convenient
Durability
Efficiency (time & effort)
0
50
100
Not Important
Moderate Important
Extremely Important


ELICITING INDIVIDUALS' MENTAL REPRESENTATION WHEN ENGAGING IN A LEISURE SHOPPING ACTIVITY IN THE CITY CENTRE OF HASSELT
STEDELIJK MUSEUM
Please indicate the chance to execute fun shopping
Hasselt city centre
You have indicated that the following benefits are very important for you when you go fun shopping in Hasselt.
Imagine that when you go fun shopping in the city centre of Hasselt, you can get various level of these following benefits:
HIGH LEVEL OF fun (e.g. happiness, enjoyment, pleasure, satisfaction)
HIGH LEVEL OF physical comfort
HIGH LEVEL OF efficiency (time & effort)
HIGH LEVEL OF saving money
LOW LEVEL OF get the best use (of something that is already possessed)
LOW LEVEL OF having information
LOW LEVEL OF having privacy
Scenario
Your friend has a party on this coming Sunday evening.
Even though it is not obligatory, you think that
it will be nice to buy something for the occasion
(a gift and/or something to wear).
Today is a Friday night in autumn and it appears that
YOU HAVE A VERY BUSY SCHEDULE ON SATURDAY.
Read More >>
How big is the chance that you will execute fun shopping given the scenario?
Please indicate the probability that you will execute fun shopping given the scenario.
You can slide the bar below to any point you like.
0
50
100
No chance
Moderate chance
All chance
Back
Next
For critique / feedback of this survey, please contact: CNETsurvey@uhasselt.be

Appendix F The CB-CNET lists of variables

1. The full list of contextual variables and their definitions for the transport mode decision

Contextual variable	*Definition*
Arrival time at home	Consideration to decide (or avoid) using a certain vehicle because you will reach your house at a certain time. In general, someone's arrival time at home (late at night after 8pm or early before 8pm) may influence the transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Availability of parking space	Consideration to decide (or avoid) using a certain vehicle because of the availability of parking space. In general, parking space availability may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Bike infrastructure availability	Consideration to decide (or avoid) using a certain vehicle because of the presence of bike infrastructure (i.e. sufficient present or not). In general, bike infrastructure availability (whether it is sufficiently available or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Bus ticket price	Consideration to decide (or avoid) using a certain vehicle because of the bus cost. In general, bus ticket price (i.e. free or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Bus frequency	Consideration to decide (or avoid) using a certain vehicle because of the frequency of the bus (to or from the city centre). In general, bus frequency (whether it is frequent or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?

Contextual variable	*Definition*
Car availability	Consideration to decide (or avoid) using a car because of its availability (i.e. when you share your car with other household members). In general, car availability (whether a car is available or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Companion	Consideration to decide (or avoid) using a certain vehicle because of companion. In general, having companion (e.g. his/her transport mode preference) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Crowdedness in bus	Consideration to decide (or avoid) using bus because of the crowdedness that you have to face inside it (e.g. during peak hour). In general, different levels of the crowdedness inside a bus may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Crowdedness in the centre	Consideration to decide (or avoid) using a certain vehicle because of the crowdedness in the city centre (e.g. in sale season). In general, crowdedness in the city centre (whether it is crowded or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Departure time from home	Consideration to decide (or avoid) using a certain vehicle because of departure time from home. In general, someone's departure time from home (early in the morning before 9am or after 9am) may influence the transport mode decision. Is it a strong influential factor for in your fun-shopping transport mode decision?
Existing plan of other activities elsewhere but Hasselt	Consideration to decide (or avoid) using a certain vehicle because of other plans of activities in other place (but Hasselt) that you have made in advance. In general, having existing plans of other activities elsewhere but Hasselt or not may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?

Contextual variable	*Definition*
Existing plan of other activities in Hasselt	Consideration to decide (or avoid) using a certain vehicle because of other plans of activities in Hasselt that you have made in advance. In general, having existing plans of other activities in Hasselt or not may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Fuel cost	Consideration to decide (avoid) using a certain vehicle because of the fuel cost. In general, fuel cost (whether it is cheap or expensive) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Happening/event	Consideration to decide (or avoid) using a certain vehicle because there is a happening / event during that day (e.g. open market, concert, etc.) In general, a happening (or an event) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Having a lift by someone	Consideration to decide using a certain vehicle because you have some one to take you to the centre of Hasselt (e.g. your family member). In general, having a lift by someone else may influence the transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Mood	Consideration to decide (or avoid) using a certain transport mode because you are in a good or bad mood. In general, mood (good or bad) may influence the transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Number or size of goods being purchased	Consideration to decide (or avoid) using a certain vehicle because of the number or size of goods being purchased. In general, the number or size of goods being purchased may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Parking cost	Consideration to decide (or avoid) using a certain vehicle because of the parking cost. In general, parking cost (whether it is free or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?

Contextual variable	*Definition*
Physical condition	Consideration to decide (or avoid) using a certain vehicle because of the physical condition (i.e. whether you are fit or not). In general, physical condition (whether someone is fit or not) may influence the transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Possession of busabonnement card	Consideration to decide (or avoid) using a certain vehicle because of the possession of a busabonnement card (i.e. buzzy pass, omnipas, or omnipas 65+). In general, busabonnement card (whether someone already owns it or not) may influence the transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Precipitation	Consideration to decide (or avoid) using a certain vehicle because of the precipitation (e.g. raining or not raining). In general, precipitation (whether it is raining or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Tax & insurance	Consideration to decide (or avoid) using a certain vehicle (car) because you have (or have not) paid tax & insurance. In general, tax & insurance (whether it has been paid or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Temperature	Consideration to decide (or avoid) using a certain vehicle because of the outdoor temperature. In general, outdoor temperature (whether it is pleasant or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Time availability	Consideration to decide (or avoid) using a certain vehicle because of the time availability to perform the whole fun-shopping activity. In general, time availability (whether someone has plenty or limited time) may influence the transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?

Contextual variable	*Definition*
Traffic control	Consideration to decide (or avoid) using a certain vehicle because of the risk of facing traffic control (e.g. speed control, alcohol testing, etc.). In general, having possibility to face traffic control may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Unusual things	Consideration to decide (or avoid) using a certain vehicle because there may happen unusual things that can delay the trip. In general, whether someone expects something unusual or not (e.g. bus strike, etc.) may influence the transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?
Wind	Consideration to decide (or avoid) using a certain vehicle because of wind conditions. In general, wind (whether it is a windy day or not) may influence someone's transport mode decision. Is it a strong influential factor in your fun-shopping transport mode decision?

2. The full list of instrumental variables and their definitions for the transport mode decision

Instrumental variable	*Definition*
Accessibility	The accessibility concern. For instance, a certain area is more accessible with bike, car, or bus. Do you strongly consider this aspect to help you gaining the selected benefit?
Accident & damage	Various vehicle types give different consequences to the user(s) in case of an accident. Do you strongly consider this aspect to help you gaining the selected benefit?
Adjustment in transport mode	Various vehicle types give some possibilities to make some adjustments inside. For instance, you can hear music in car, adjust the position of your seat, adjust the air condition, etc. Do you strongly consider this aspect to help you gaining the selected benefit?
Availability of seat	The seat may not always be available for you in a certain vehicle (e.g. bus during peak hour) whereas it is always available in the others (e.g. car). Do you strongly consider this aspect to help you gaining the selected benefit?
Capacity of vehicle	Various vehicle types have different passenger capacities. For instance, bus can load more than 7 people; car can carry up to 6 people; and bike has a maximum number of 2 passengers. Do you strongly consider this aspect to help you gaining the selected benefit?
Cost	The cost consideration of the transport modes. Do you strongly consider this aspect to help you gaining the selected benefit?
Decreasing value (because of use)	The reduction of a vehicle value because of its frequent use (i.e. car). Do you strongly consider this aspect to help you gaining the selected benefit?
Direct travel	The use of a certain vehicle because of its directness. For instance, you may have to change bus several times; or it can be that you have to change from bike to bus, etc. Do you strongly consider this aspect to help you gaining the selected benefit?
Easiness for parking	Various vehicle types have different needs for parking. For instance, you can park your bicycle anywhere in the centre of Hasselt. However, that is not the case for you car. Additionally, the availability of car parking space can be very limited especially on Saturday. Do you strongly consider this aspect to help you gaining the selected benefit?

Instrumental variable	*Definition*
Environment inside bus & car or around bike	Various vehicle types have different environment inside (it can be hot or cold, noisy or silent; you can socialize or not; being in open air or not; etc). It can be generalized that the environment inside car and bus (or around bike) can be favourable to you or not. Do you strongly consider this aspect to help you gaining the selected benefit?
Environment-friendliness of the transport mode	Various vehicle types produce different levels of emission, noise, and fuel consumption. In general, bike is the most environmental friendly transport mode, and bus is more environmental friendly than car. Do you strongly consider this aspect to help you gaining the selected benefit?
Getting fine	The risk of getting a fine. For instance, you can get a fine when your car is not parked properly, if you stay longer than the time written in your parking ticket, etc. Do you strongly consider this aspect to help you gaining the selected benefit?
Flexibility/independency	Various vehicle types offer you distinct flexibility due to the control that you have over them. For instance, flexibility offered by car & bike is bigger than bus. Do you strongly consider this aspect to help you gaining the selected benefit?
Maintenance	The need for maintenance. For instance, the more frequent you use your car, the more maintenance you have to do. Do you strongly consider this aspect to help you gaining the selected benefit?
Mental effort & ease	Some vehicles give easiness to you (mentally), whereas others require more mental effort. For instance, you have to check for bus schedule and make sure that there is bus that can take you back home; you have to think where to park your car, etc. Do you strongly consider this aspect to help you gaining the selected benefit?
Physical effort	Various vehicle types require different levels of physical effort. For instance, bike demands more physical effort in comparison to the other transport modes. Do you strongly consider this aspect to help you gaining the selected benefit?
Possibility to consume alcohol	The use of some vehicles is restricted by the alcohol consumption of the driver (e.g. car). Do you strongly consider this aspect to help you gaining the selected benefit?

Instrumental variable	*Definition*
Possibility to be stolen	A certain vehicle type (i.e. bike) has a locking system that makes it more vulnerable for stealing. Do you strongly consider this aspect to help you gaining the selected benefit?
Preference of transport mode	The use of a certain vehicle because of user's preference. Do you strongly consider this aspect to help you gaining the selected benefit?
Reliability	The reliability of different vehicle types. A certain type of vehicle can be unreliable (undependable, questionable, or deceitful). For instance, a bus can be late, or leave earlier than what it should, etc. Do you strongly consider this aspect to help you gaining the selected benefit?
Route	The use of a certain vehicle because of its routing (e.g. direct route, d-tour, etc). Do you strongly consider this aspect to help you gaining the selected benefit?
Sensation of speed	The sensation of speed of various vehicle types. Do you strongly consider this aspect to help you gaining the selected benefit?
Shelter provision (staying dry)	Various vehicle types offer district protection to you against bad weather (raining, wind, cold) due to the presence of shelter. For instance, car & bus offer a bigger chance to stay dry than bike when it is raining. Do you strongly consider this aspect to help you gaining the selected benefit?
Travel time	Various vehicle types offer different probabilities of having a short, medium, or long travel time. For instance, car can have medium travel time because you still have to find parking. Do you strongly consider this aspect to help you gaining the selected benefit?
Treatment of bags	Various vehicle types offer different possibilities to store your belongings (e.g. your shopping bags), making you able to easily treat your bags or not. Do you strongly consider this aspect to help you gaining the selected benefit?

3. The short lists of instrumental variables and their correlation to each contextual aspect for the transport mode decision

Contextual variable	*Instrumental variable*
Arrival time at home	Direct travel Flexibility / independency Mental effort & ease Physical effort Possibility to be stolen Possibility to consume alcohol Preference of transport mode Reliability Route Travel time
Availability of parking space	Accessibility Accident & damage Cost Easiness for parking Environment-friendliness of the transport mode Getting fine Physical effort Preference of transport mode Reliability Travel time
Bike infrastructure availability	Accessibility Mental effort & ease Physical effort Preference of transport mode
Bus ticket price	Cost Flexibility / independency Getting fine Preference of transport mode
Bus frequency	Accessibility Flexibility / independency Mental effort & ease Physical effort Preference of transport mode Reliability Travel time

Contextual variable	*Instrumental variable*
Car availability	Flexibility / independency Mental effort & ease Physical effort Preference of transport mode Reliability Sensation of speed Travel time Treatment of bags
Companion	Accessibility Availability of seat Capacity of vehicle Cost Flexibility / independency Preference of transport mode Travel time
Crowdedness in bus	Availability of seat Environment inside bus & car / around bike Physical effort Preference of transport mode Reliability Treatment of bags
Crowdedness in the centre	Accessibility Accident & damage Availability of seat Cost Easiness for parking Possibility to be stolen Preference of transport mode Sensation of speed Travel time Treatment of bags
Departure time from home	Direct travel Flexibility / independency Mental effort & ease Physical effort Preference of transport mode Reliability Route Travel time

Contextual variable	*Instrumental variable*
Existing plan of other activities elsewhere but Hasselt	Cost Direct travel Easiness for parking Flexibility / independency Mental effort & ease Physical effort Possibility to be stolen Possibility to consume alcohol Preference of transport mode Reliability Route Sensation of speed Travel time Treatment of bags
Existing plan of other activities in Hasselt	Cost Direct travel Easiness for parking Flexibility / independency Mental effort & ease Physical effort Possibility to be stolen Possibility to consume alcohol Preference of transport mode Reliability Route Sensation of speed Travel time Treatment of bags
Fuel cost	Cost Mental effort & ease Preference of transport mode Sensation of speed Travel time
Happening/event	Accessibility Availability of seat Easiness for parking Flexibility / independency Mental effort & ease Physical effort Possibility to consume alcohol Preference of transport mode Reliability Travel time Treatment of bags

Contextual variable	*Instrumental variable*
Having a lift by someone	Accessibility Cost Environment-friendliness of the transport mode Flexibility / independency Mental effort & ease Possibility to be stolen Possibility to consume alcohol Preference of transport mode Reliability Travel time Treatment of bags
Mood	Adjustment in transport mode Cost Decreasing value (because of use) Environment inside bus & car / around bike Environment-friendliness of the transport mode Maintenance Mental effort & ease Physical effort Possibility to consume alcohol Preference of transport mode
Number or size of goods being purchased	Accessibility Accident & damage Adjustment in transport mode Mental effort & ease Physical effort Treatment of bags
Parking cost	Cost Easiness for parking Getting fine Mental effort & ease Possibility to be stolen Preference of transport mode Travel time
Physical condition	Accessibility Accident & damage Availability of seat Direct travel Easiness for parking Environment inside car & bus / around bike Flexibility / independency Physical effort Preference of transport mode Shelter provision (staying dry) Travel time

Contextual variable	*Instrumental variable*
Possession of busabonnement card	Cost Flexibility / independency Mental effort & ease Preference of transport mode
Precipitation	Accessibility Accident & damage Availability of seat Direct travel Easiness for parking Environment inside car & bus / around bike Maintenance Possibility to consume alcohol Preference of transport mode Reliability Route Sensation of speed Shelter provision (staying dry) Travel time Treatment of bags
Tax & insurance	Flexibility / independency Mental effort & ease Preference of transport mode
Temperature	Adjustment in transport mode Availability of seat Environment inside car & bus / around bike Environment-friendliness of the transport mode Maintenance Preference of transport mode Shelter provision (staying dry)
Time availability	Accessibility Cost Direct travel Easiness for parking Flexibility / independency Preference of transport mode Reliability Route Sensation of speed Travel time

Contextual variable	*Instrumental variable*
Traffic control	Cost Getting fine Mental effort & ease Physical effort Possibility to be stolen Possibility to consume alcohol Preference of transport mode Route Sensation of speed Travel time
Unusual things	Accessibility Accident & damage Flexibility / independency Mental effort & ease Physical effort Preference of transport mode Reliability Travel time
Wind	Accident & damage Availability of seat Direct travel Easiness for parking Environment inside car & bus / around bike Physical effort Preference of transport mode Reliability Route Sensation of speed Shelter provision (staying dry) Travel time Treatment of bags

4. The full list of contextual variables and their definitions for the shopping location decision

Contextual variable	*Definition*
Availability of parking space in/near the area	Consideration to decide going to a certain shopping location because of the availability of parking space in / near the area. In general, parking space availability in or near a shopping location may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Budget availability	Consideration to decide (or avoid) going to a certain shopping location because of your budget availability. In general, budget availability (whether you have plenty or limited budget) may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Companion	Consideration to decide (or avoid) going to a certain shopping location because of companion. In general, having companion may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Crowdedness in Hasselt	Consideration to decide (or avoid) going to a certain shopping location because of the crowdedness of the area. In general, the crowdedness in the city centre may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Eating a snack	Consideration to decide going to a certain shopping location because you feel/feel not like having a snack (e.g. waffle / ice cream). In general, whether someone feels more welcome to eat snack in a shopping location may influence the shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?

Contextual variable	*Definition*
Existing plan of other activities elsewhere but Hasselt	Consideration to decide (or avoid) going to a certain shopping location because of other plans of activities in other place (but Hasselt) that you have made in advance. In general, having existing plans of other activities elsewhere but Hasselt may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Existing plan of other activities in Hasselt	Consideration to decide (or avoid) going to a certain shopping location because of other plans of activities in Hasselt that you have made in advance. For instance, to reduce the distance between shopping location and place of other activity. In general, having existing plans of other activities in Hasselt may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Information from others	Consideration to decide (or avoid) going to a certain location because of the information that you get from others (friends, family, etc.). This information can be about the quality of the shops in the area, the style of products in a particular shop in the area, etc. In general, having information from others (e.g. positive/negative advice about a specific location) may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Interest in a specific product	Consideration regarding your interest in a specific product. For instance, you have an interest towards electronic equipments / music instruments / clothes, etc. In general, having an interest in specific product (e.g. clothing or non-clothing) may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Mood	Consideration to decide (or avoid) going to a certain shopping location because you are in a good/bad mood. In general, mood (whether good or bad mood) may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?

Contextual variable	*Definition*
Number or size of goods being purchased	Consideration to decide (or avoid) going to a certain shopping location because of the amount (or size) of luggage that you have to carry back home. In general, the number or size of goods being purchased may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Physical condition	Consideration to decide (or avoid) going to a certain shopping location because of your physical condition (whether you are fit or not). In general, physical condition (fit or unfit) may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Sale season	Consideration to decide going to a certain shopping location because of sale season. In general, sale season (whether there is sale or not) may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Time availability	Consideration to decide (or avoid) going to a certain shopping location because of the time availability to perform the whole fun-shopping activity. In general, time availability (whether you have plenty or limited time) may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?
Weather	Consideration to decide going to a certain shopping location because of the weather (raining or not raining). In general, weather conditions (e.g. good or bad) may influence someone's shopping location decision. Is it a strong influential factor in your shopping location decision (particularly the location where you want to fun-shop first)?

5. The full list of instrumental variables and their definitions for the shopping location decision

Instrumental variable	*Definition*
Accessibility of the area	Various shopping areas have different accessibility. Accessibility to a certain area can be good whilst to the others are bad. Or it can also be that you go to a certain shopping location because it is on your route. Do you strongly consider this aspect to help you gaining the selected benefit?
Ambiance / environment	Various shopping areas have different environment (ambiance). Environment in a certain shopping location can be favourable to you or not. Do you strongly consider this aspect to help you gaining the selected benefit?
Cafe & restaurant	Various shopping areas have different characteristics regarding the presence of café & restaurant. Do you strongly consider this aspect to help you gaining the selected benefit?
Chance to meet someone you know	The chance to meet your friend(s) or other people that you know can be bigger in a certain shopping area. Do you strongly consider this aspect to help you gaining the selected benefit?
Closing time	The shop closing time in the area. Do you strongly consider this aspect to help you gaining the selected benefit?
Customer service	Various shopping areas have different levels of customer service (it can be good or bad). Do you strongly consider this aspect to help you gaining the selected benefit?
Familiarity with the area	You familiarity with a certain shopping area and unfamiliar with the other areas. Do you strongly consider this aspect to help you gaining the selected benefit?
Image of shops	The image that you want to get from a certain shopping area. For instance, there is an image that the gallery sells cheaper products, or an image that boutique has better quality products, etc. Do you strongly consider this aspect to help you gaining the selected benefit?
Indoor shopping mall	The presence of mall in the area. For instance in the gallery area. Do you strongly consider this aspect to help you gaining the selected benefit?

Instrumental variable	*Definition*
Opening time	The shop opening time in the area. Do you strongly consider this aspect to help you gaining the selected benefit?
Other activities in the area	Various activities in the area (besides café & restaurant), such as museums, parks, etc. Do you strongly consider this aspect to help you gaining the selected benefit?
Presence of favourite shops	The presence of your favourite shop(s) in a certain area. Do you strongly consider this aspect to help you gaining the selected benefit?
Presence of infrastructure	Various shopping areas provide you with different infrastructures (e.g. presence of parking for your car & bike and bus stop in the area). Do you strongly consider this aspect to help you gaining the selected benefit?
Product price	Various shopping areas have different product prices. Do you strongly consider this aspect to help you gaining the selected benefit?
Product quality	Various shopping areas have different product qualities. Do you strongly consider this aspect to help you gaining the selected benefit?
Shop arrangement	Various shopping areas have different arrangements of the shops (whether the shops in the area located close to each other or not). For instance, in the gallery area, the shops are located closer to each others, in comparison with the boutique area (because there are churches, parks, etc.). Do you strongly consider this aspect to help you gaining the selected benefit?
Shopping location preference	Going to a certain shopping location because you like it. Do you strongly consider this aspect to help you gaining the selected benefit?
Similarity of product	The similarity (mostly clothing product or mostly non-clothing product) or diversity of the product type being sold in the area. Do you strongly consider this aspect to help you gaining the selected benefit?
Size of shops	The size of the shops in the area (how big they are). Do you strongly consider this aspect to help you gaining the selected benefit?
Size of shopping location	The size of the shopping area. Do you strongly consider this aspect to help you gaining the selected benefit?
Social status	Various shopping areas give different images to your social status. For instance, if you go shopping in the boutique area, people may think that you have a high social status. Do you strongly consider this aspect to help you gaining the selected benefit?

Instrumental variable	*Definition*
Type of store	Different types of products being sold. The types of products can be generalized into two groups; namely clothing (clothes and accessories, shoes, cosmetics & perfume), or non-clothing (CD, electronics, toys, home appliances shops & food). Do you strongly consider this aspect to help you gaining the selected benefit?

6. The short lists of instrumental variables and their correlation to each contextual aspect for the shopping location decision

Contextual variable	*Instrumental variable*
Availability of parking space in/near the area	Accessibility of the area Shopping location preference Size of shopping location Presence of infrastructure
Budget availability	Café & restaurant Customer service Image of shops Presence of favourite shops Product price Product quality Social status Shopping location preference Type of store
Companion	Ambiance / environment Café & restaurant Chance to meet someone you know Familiarity with the are Image of shops Other activities in the area Presence of favourite shops Shopping location preference Type of store
Crowdedness in Hasselt	Accessibility of the area Ambiance / environment Chance to meet someone you know Customer service Presence of favourite shops Shop arrangement Shopping location preference Size of shops
Eating a snack	Ambiance / environment Cafe & restaurant Product price Product quality Shop arrangement Shopping location preference

Contextual variable	*Instrumental variable*
Existing plan of other activities elsewhere but Hasselt	Accessibility of the area Café & restaurant Closing time Customer service Familiarity with the area Opening time Other activities in the area Presence of infrastructure Shop arrangement Size of shopping location Size of shops
Existing plan of other activities in Hasselt	Accessibility of the area Café & restaurant Closing time Customer service Familiarity with the area Opening time Other activities in the area Presence of infrastructure Shop arrangement Size of shopping location Size of shops
Information from others	Accessibility of the area Ambiance / environment Café & restaurant Chance to meet someone you know Closing time Customer service Familiarity with the area Image of shops Indoor shopping mall Opening time Other activities in the area Presence of favourite shops Presence of infrastructure Product price Product quality Shop arrangement Shopping location preference Similarity of product Size of shops Size of shopping location Social status Type of store

Contextual variable	*Instrumental variable*
Interest in a specific product	Ambiance / environment Customer service Familiarity with the area Image of shops Presence of favourite shops Product price Product quality Shop arrangement Shopping location preference Similarity of product Size of shops Size of shopping location Social status Type of store
Mood	Accessibility of the area Ambiance / environment Café & restaurant Chance to meet someone you know Other activities in the area Presence of favourite shops Shop arrangement Shopping location preference
Number or size of goods being purchased	Accessibility of the area Presence of infrastructure Shopping location preference Size of shopping location
Physical condition	Accessibility of the area Customer service Presence of favourite shops Presence of infrastructure Shop arrangement Shopping location preference Similarity of product Size of shops Size of shopping location Type of store

Contextual variable	*Instrumental variable*
Sale season	Ambiance / environment
	Customer service
	Image of shops
	Presence of favourite shops
	Product price
	Product quality
	Shopping location preference
	Size of shops
	Size of shopping location
	Social status
	Type of store
Time availability	Accessibility of the area
	Ambiance / environment
	Chance to meet someone you know
	Closing time
	Customer service
	Familiarity with the area
	Opening time
	Other activities in the area
	Presence of favourite shops
	Presence of infrastructure
	Product quality
	Shop arrangement
	Shopping location preference
	Similarity of product
	Size of shops
	Size of shopping location
Weather	Accessibility of the area
	Café & restaurant
	Indoor shopping mall
	Other activities in the area
	Presence of favourite shops
	Presence of infrastructure
	Shop arrangement
	Size of shops

7. The full list of benefit variables and their definitions for the transport mode and shopping location decisions

Benefit variable	*Definition*
Assurance / certainty	Full confidence & freedom from doubt, being sure of something.
Being healthy	Possessing or enjoying good health; thinking about your health.
Being sociable	Being friendly, sociable; enjoying presence of others; companionable
Convenient	Having the benefit not having to think too much about something; suited or favourable to one's purpose or needs, easy to reach, accessible.
Durability	Well lasting and endurance, environment friendly.
Efficiency (time & effort)	Accomplishment of a job with a minimum expenditure of time & effort.
Fun (e.g. happiness, enjoyment, pleasure, satisfaction)	Including happiness, enjoyment, pleasure, satisfaction.
Freedom	The state of being free and not under any restraints.
Get the best use (of something that is already possessed)	The state of getting the best use out of something owned (e.g. bus yearly card, leasing car; always getting a special discount in a certain store, etc.).
Having information	The state of having information (about price, products, quality, etc.).
Having privacy	The state of being free from disturbance in one's private life.
Luxury & prestige	A material object or service conducive to fine living (a delicacy, elegance, refinement) instead of necessity.
Physical comfort	Physical well being provided by a person or thing.
Safety & security	Condition of being safe from danger, risk or injury. Something that secures (makes safe, protection or defence).
Saving money	Reducing an outlay or expenditure of money spent for doing such an activity.

Appendix G Influence diagram states

1. Contextual variables and their states for the transport mode decision

Contextual variable	*States*
Arrival time at home	{before 8pm, after 8pm}
Availability of parking space	{available, unavailable}
Bike infrastructure availability	{absent, present}
Bus ticket price	{free, 1 Euro/trip or less, >1 Euro/trip}
Bus frequency	{1 bus/hour (low), 2-4 buses/hour (medium), >4 buses/hour (high)}
Car availability	{ absent, present}
Companion	{alone, with someone}
Crowdedness in bus	{not crowded, crowded}
Crowdedness in the centre	{not crowded, crowded}
Departure time from home	{before 9am, after 9am}
Existing plan of other activities elsewhere but Hasselt	{absent, present}
Existing plan of other activities in Hasselt	{absent, present}
Fuel cost	{ <1 Euro/litre, 1-1,40 Euro/litre, >1,40 Euro/litre }
Happening/event	{absent, present}
Having a lift by someone	{no lift, having a lift}
Mood	{bad, good}
Number or size of goods being purchased	{none/a little, a lot}
Parking cost	{free, <2 Euro/hour, >2 Euro/hour }
Physical condition	{bad, good}
Possession of busabonnement card	{not having the card, having the card}
Precipitation	{no precipitation, precipitation}
Tax & insurance	{unpaid, paid}
Temperature	{unpleasant, pleasant}
Time availability	{limited, plenty}
Traffic control	{not expected, expected}
Unusual things	{nothing unusual, unusual things related to car trip (e.g. traffic jam), unusual things related to bus trip (e.g. strike), unusual things related to bike trip (e.g. storm)}
Wind	{none/a little, a lot}

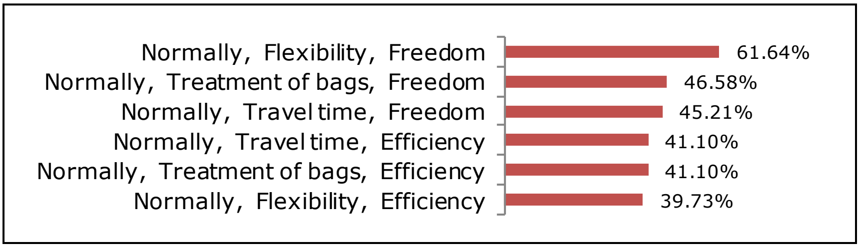
2. Contextual variables and their states for the shopping location decision

Contextual variable	*States*
Availability of parking space in/near the area	{available, unavailable}
Budget availability	{limited, plenty}
Companion	{alone, with someone}
Crowdedness in Hasselt	{not crowded, crowded}
Eating a snack	{not feeling like eating, feeling like eating}
Existing plan of other activities elsewhere but Hasselt	{absent, present}
Existing plan of other activities in Hasselt	{absent, present}
Information from others	{no advice, positive advice for area 1, negative advice for area 1, + area 2, - area 2, + area 3, - area 3}
Interest in specific product	{no interest, interest in clothing related products, interest in non-clothing related products}
Mood	{bad, good}
Number or size of goods being purchased	{none/a little, a lot}
Physical condition	{bad, good}
Sale season	{not a sale season, a sale season}
Time availability	{limited, plenty}
Weather	{bad, good}

Appendix H Frequent itemset results of the CB-CNET data

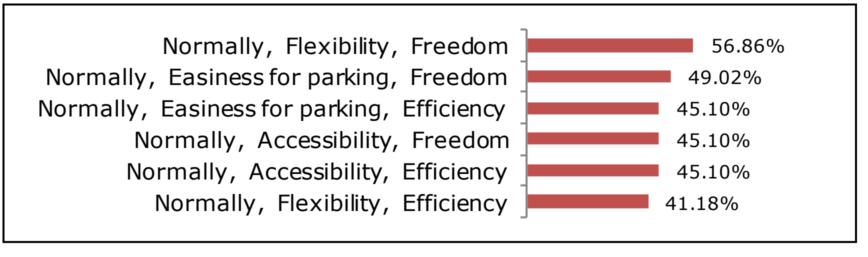
1. The transport mode decision

a. Cluster-1

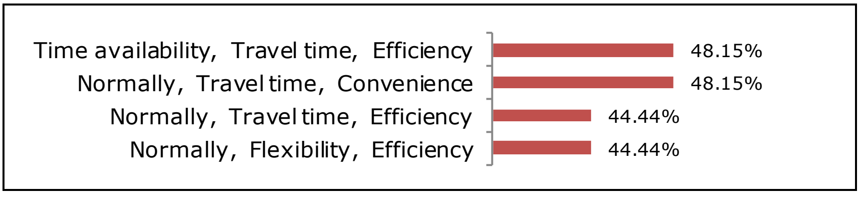


Note: the left-hand side of the figure above indicates the list of cognitive subsets and the right-hand side of the figure signifies the number of respondents who elicit the subsets (in percentage).

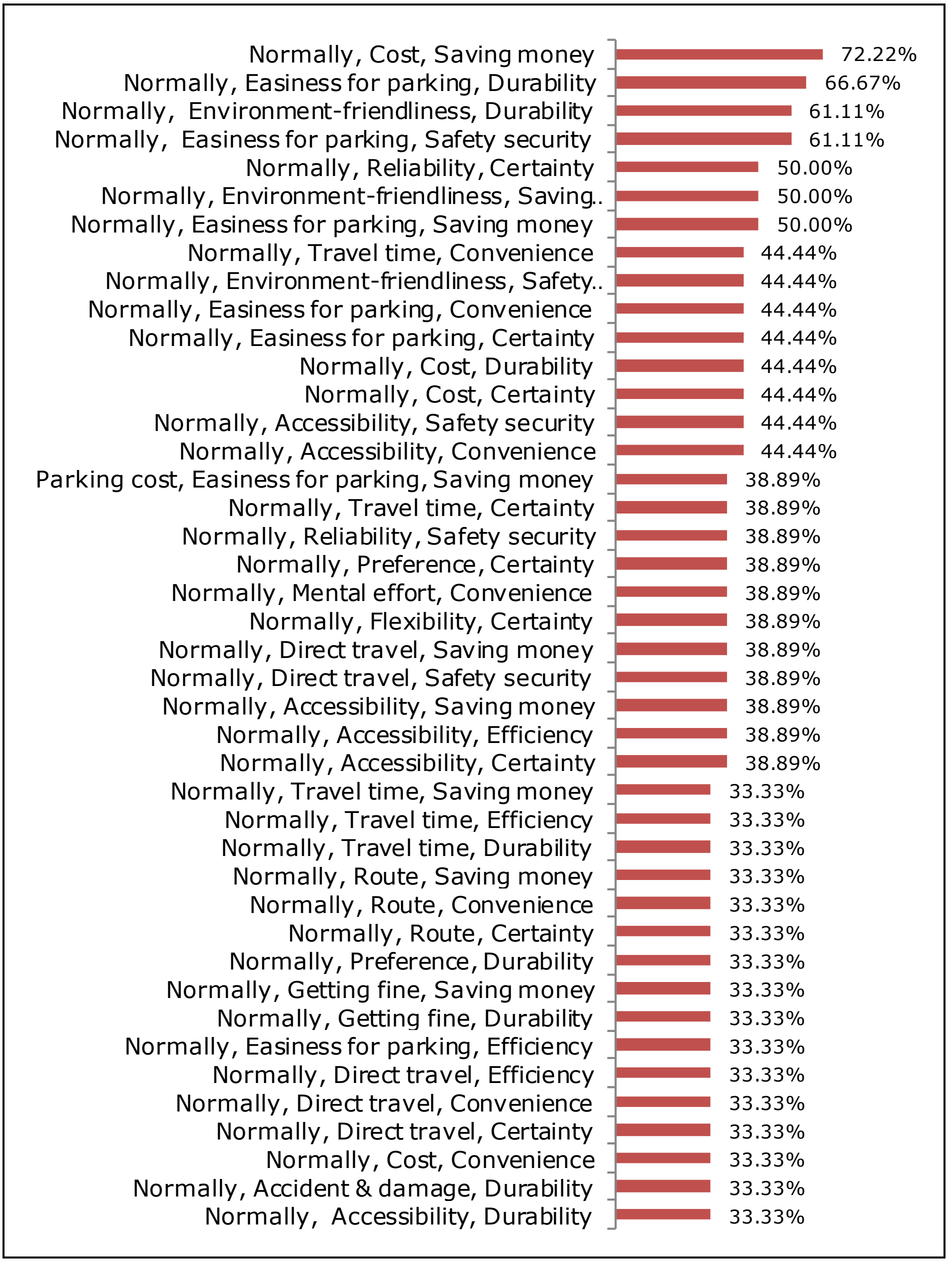
b. Cluster-2



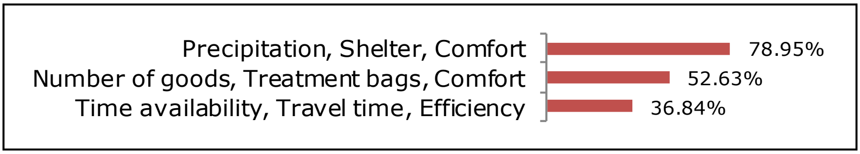
c. Cluster-3



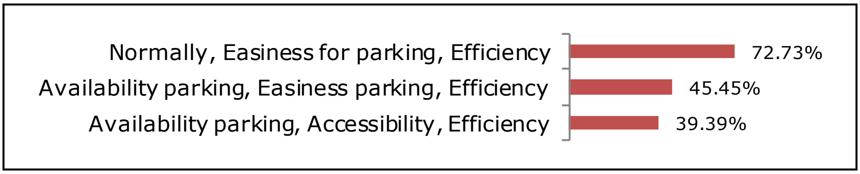
d. Cluster-4


Normally, Cost, Saving money 72.22%
Normally, Easiness for parking, Durability 66.67%
Normally, Environment-friendliness, Durability 61.11%
Normally, Easiness for parking, Safety security 61.11%
Normally, Reliability, Certainty 50.00%
Normally, Environment-friendliness, Saving.. 50.00%
Normally, Easiness for parking, Saving money 50.00%
Normally, Travel time, Convenience 44.44%
Normally, Environment-friendliness, Safety.. 44.44%
Normally, Easiness for parking, Convenience 44.44%
Normally, Easiness for parking, Certainty 44.44%
Normally, Cost, Durability 44.44%
Normally, Cost, Certainty 44.44%
Normally, Accessibility, Safety security 44.44%
Normally, Accessibility, Convenience 44.44%
Parking cost, Easiness for parking, Saving money 38.89%
Normally, Travel time, Certainty 38.89%
Normally, Reliability, Safety security 38.89%
Normally, Preference, Certainty 38.89%
Normally, Mental effort, Convenience 38.89%
Normally, Flexibility, Certainty 38.89%
Normally, Direct travel, Saving money 38.89%
Normally, Direct travel, Safety security 38.89%
Normally, Accessibility, Saving money 38.89%
Normally, Accessibility, Efficiency 38.89%
Normally, Accessibility, Certainty 38.89%
Normally, Travel time, Saving money 33.33%
Normally, Travel time, Efficiency 33.33%
Normally, Travel time, Durability 33.33%
Normally, Route, Saving money 33.33%
Normally, Route, Convenience 33.33%
Normally, Route, Certainty 33.33%
Normally, Preference, Durability 33.33%
Normally, Getting fine, Saving money 33.33%
Normally, Getting fine, Durability 33.33%
Normally, Easiness for parking, Efficiency 33.33%
Normally, Direct travel, Efficiency 33.33%
Normally, Direct travel, Convenience 33.33%
Normally, Direct travel, Certainty 33.33%
Normally, Cost, Convenience 33.33%
Normally, Accident & damage, Durability 33.33%
Normally, Accessibility, Durability 33.33%

e. Cluster-5

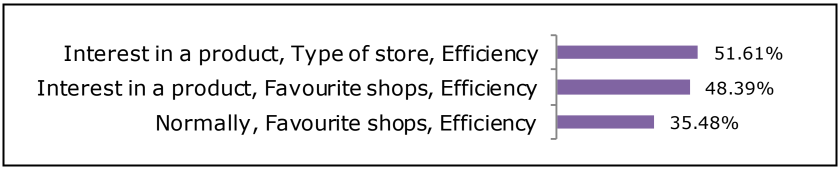


f. Cluster-6



2. The shopping location decision

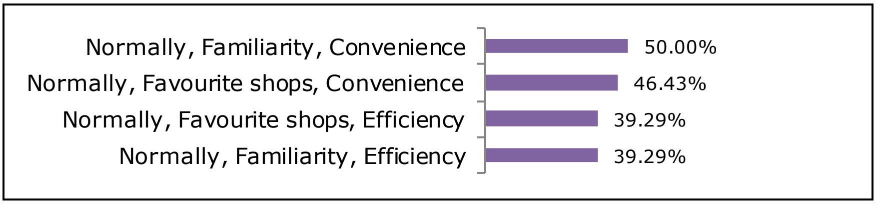
a. Cluster-1



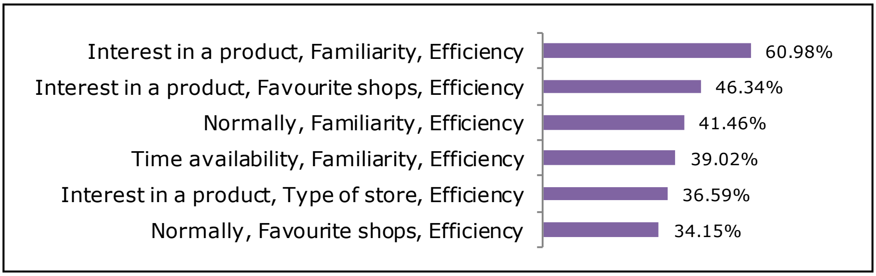
Note: the left-hand side of the figure above indicates the list of cognitive subsets and the right-hand side of the figure signifies the number of respondents who elicit the subsets (in percentage).

b. Cluster-2

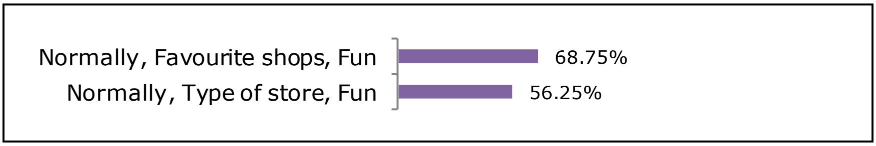
c. Cluster-3



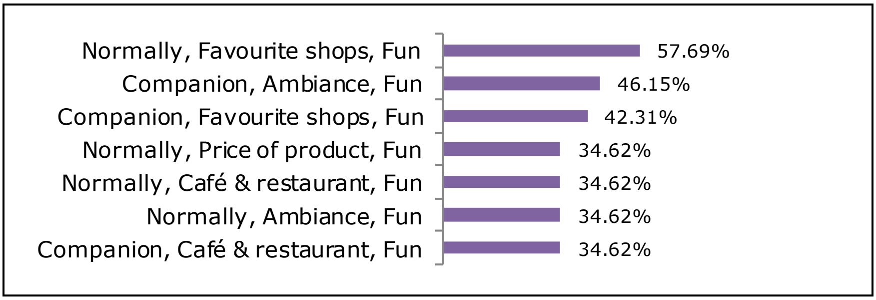
d. Cluster-4



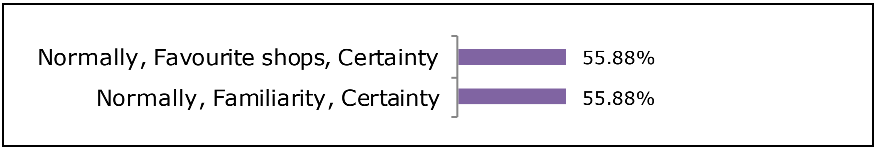
e. Cluster-5



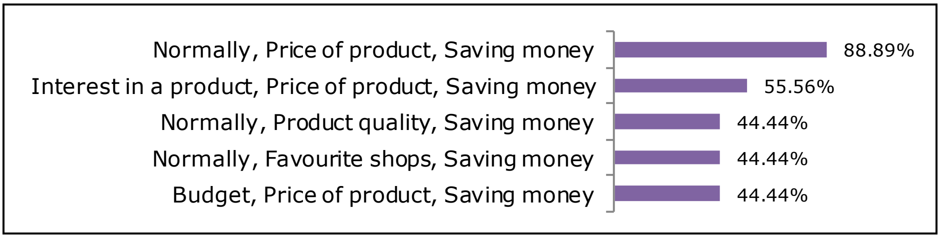
f. Cluster-6



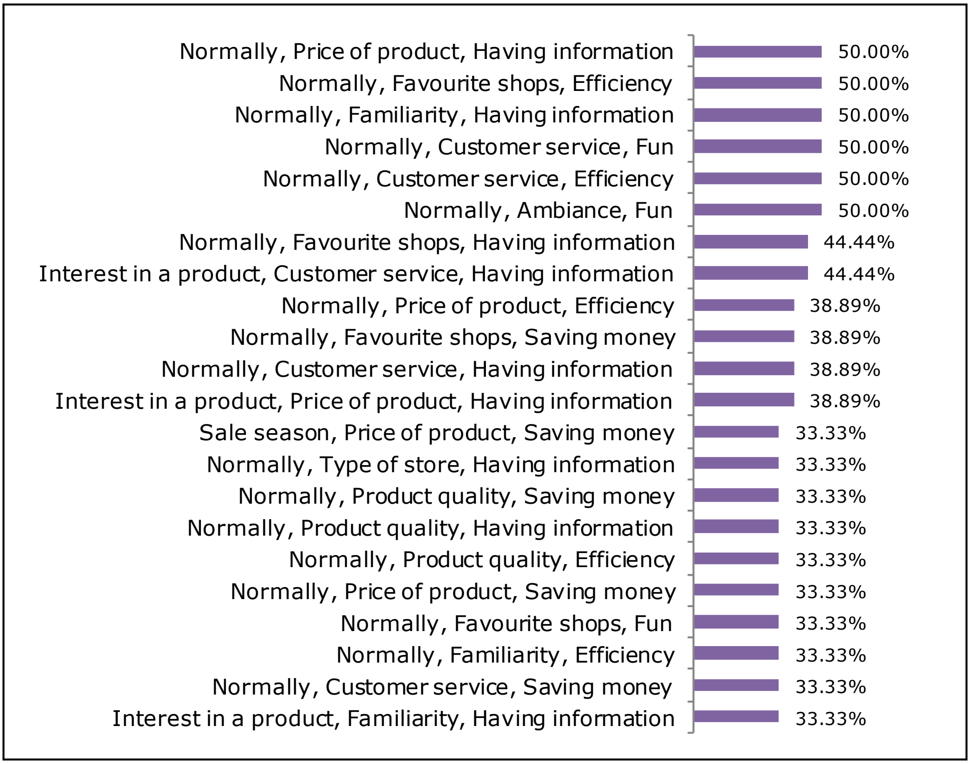
g. Cluster-7



h. Cluster-8



i. Cluster-9


Normally, Price of product, Having information 50.00%
Normally, Favourite shops, Efficiency 50.00%
Normally, Familiarity, Having information 50.00%
Normally, Customer service, Fun 50.00%
Normally, Customer service, Efficiency 50.00%
Normally, Ambiance, Fun 50.00%
Normally, Favourite shops, Having information 44.44%
Interest in a product, Customer service, Having information 44.44%
Normally, Price of product, Efficiency 38.89%
Normally, Favourite shops, Saving money 38.89%
Normally, Customer service, Having information 38.89%
Interest in a product, Price of product, Having information 38.89%
Sale season, Price of product, Saving money 33.33%
Normally, Type of store, Having information 33.33%
Normally, Product quality, Saving money 33.33%
Normally, Product quality, Having information 33.33%
Normally, Product quality, Efficiency 33.33%
Normally, Price of product, Saving money 33.33%
Normally, Favourite shops, Fun 33.33%
Normally, Familiarity, Efficiency 33.33%
Normally, Customer service, Saving money 33.33%
Interest in a product, Familiarity, Having information 33.33%

Appendix I Contingency tables of the cluster variables

1. The transport mode cluster variables

			Cluster number						*Total*
			1	*2*	*3*	*4*	*5*	*6*	
Gender (a)	Female	C[1]	39	28	17	11	9	22	126
		EC[2]	41.6	29.1	15.4	10.3	10.8	18.8	126
	Male	C	34	23	10	7	10	11	95
		EC	31.4	21.9	11.6	7.7	8.2	14.2	95
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Age categories (b)	Below 30	C	13	10	11	2	8	10	54
		EC	17.8	12.5	6.6	4.4	4.6	8.1	54
	30 to 39	C	7	6	4	3	1	4	25
		EC	8.3	5.8	3.1	2.0	2.1	3.7	25
	40 to 49	C	21	11	3	3	4	6	48
		EC	15.9	11.1	5.9	3.9	4.1	7.2	48
	50 to 59	C	19	12	6	2	6	11	56
		EC	18.5	12.9	6.8	4.6	4.8	8.4	56
	60 and above	C	13	12	3	8	0	2	38
		EC	12.6	8.8	4.6	3.1	3.3	5.7	38
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Education categories (c)	Low education	C	21	20	10	13	6	13	83
		EC	27.4	19.2	10.1	6.8	7.1	12.4	83
	High education	C	52	31	17	5	13	20	138
		EC	45.6	31.8	16.9	11.2	11.9	20.6	138
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221

[1] Count
[2] Expected Count

			Cluster number						Total
			1	2	3	4	5	6	
Income categories (d)	Not specified	C	11	3	3	2	1	4	24
		EC	7.9	5.5	2.9	2.0	2.1	3.6	24
	Low income	C	15	19	9	10	5	7	65
		EC	21.5	15.0	7.9	5.3	5.6	9.7	65
	Medium income	C	29	24	10	6	8	16	93
		EC	30.7	21.5	11.4	7.6	8.0	13.9	93
	High income	C	18	5	5	0	5	6	39
		EC	12.9	9.0	4.8	3.2	3.4	5.8	39
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Residence location categories (e)	Short	C	19	20	11	6	8	13	77
		EC	25.4	17.8	9.4	6.3	6.6	11.5	77
	Medium	C	36	16	11	7	5	13	88
		EC	29.1	20.3	10.8	7.2	7.6	13.1	88
	Long	C	18	15	5	5	6	7	56
		EC	18.5	12.9	6.8	4.6	4.8	8.4	56
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Car ownership (f)	No cars	C	0	0	0	0	1	0	1
		EC	.3	.2	.1	.1	.1	.1	1
	1	C	26	35	7	14	9	14	105
		EC	34.7	24.2	12.8	8.6	9.0	15.7	105
	2	C	33	16	17	4	8	13	91
		EC	30.1	21.0	11.1	7.4	7.8	13.6	91
	3	C	12	0	2	0	1	4	19
		EC	6.3	4.4	2.3	1.5	1.6	2.8	19
	More than 3	C	2	0	1	0	0	2	5
		EC	1.7	1.2	.6	.4	.4	.7	5
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Bike ownership (g)	No	C	8	4	2	4	0	1	19
		EC	6.3	4.4	2.3	1.5	1.6	2.8	19
	Yes	C	65	47	25	14	19	32	202
		EC	66.7	46.6	24.7	16.5	17.4	30.2	202
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Moped ownership (h)	No	C	72	49	26	18	19	33	217
		EC	71.7	50.1	26.5	17.7	18.7	32.4	217
	Yes	C	1	2	1	0	0	0	4
		EC	1.3	.9	.5	.3	.3	.6	4
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221

			Cluster number						Total
			1	2	3	4	5	6	
Motorbike ownership (i)	No	C	70	50	27	18	19	31	215
		EC	71.0	49.6	26.3	17.5	18.5	32.1	215
	Yes	C	3	1	0	0	0	2	6
		EC	2.0	1.4	.7	.5	.5	.9	6
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Bus card (j)	No	C	68	47	26	12	18	32	203
		EC	67.1	46.8	24.8	16.5	17.5	30.3	203
	Yes	C	5	4	1	6	1	1	18
		EC	5.9	4.2	2.2	1.5	1.5	2.7	18
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Bus reduced ticket (k)	No	C	67	42	26	14	14	28	191
		EC	63.1	44.1	23.3	15.6	16.4	28.5	191
	Yes	C	6	9	1	4	5	5	30
		EC	9.9	6.9	3.7	2.4	2.6	4.5	30
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Parking (l)	No parking	C	3	17	2	6	0	4	32
		EC	10.6	7.4	3.9	2.6	2.8	4.8	32
	Free parking	C	60	31	23	11	17	27	169
		EC	55.8	39.0	20.6	13.8	14.5	25.2	169
	Paid parking	C	10	3	2	1	2	2	20
		EC	6.6	4.6	2.4	1.6	1.7	3.0	20.0
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
YKT[3] (m)	No idea	C	0	0	0	2	0	0	2
		EC	.7	.5	.2	.2	.2	.3	2
	0-5000	C	16	15	6	1	8	11	57
		EC	18.8	13.2	7.0	4.6	4.9	8.5	57
	5001-15000	C	34	27	14	12	5	16	108
		EC	35.7	24.9	13.2	8.8	9.3	16.1	108
	>15000	C	23	9	7	3	6	6	54
		EC	17.8	12.5	6.6	4.4	4.6	8.1	54
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221

[3] Yearly Kilometre Travelled

			Cluster number						Total
			1	*2*	*3*	*4*	*5*	*6*	
Habits (n)	No habits	C	1	2	2	0	2	0	7
		EC	2.3	1.6	.9	.6	.6	1.0	7
	Car	C	53	18	15	5	6	12	109
		EC	36.0	25.2	13.3	8.9	9.4	16.3	109
	Bike	C	10	25	4	3	8	15	65
		EC	21.5	15.0	7.9	5.3	5.6	9.7	65
	Bus	C	9	6	6	10	3	6	40
		EC	13.2	9.2	4.9	3.3	3.4	6.0	40
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Going to	Not	C	30	32	17	12	11	20	122
Hasselt	frequent[4]	EC	40.3	28.2	14.9	9.9	10.5	18.2	122
by car (o)	Semi-	C	24	12	6	3	4	8	57
	frequent[5]	EC	18.8	13.2	7.0	4.6	4.9	8.5	57
	Frequent[6]	C	19	7	4	3	4	5	42
		EC	13.9	9.7	5.1	3.4	3.6	6.3	42
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27. 0	18.0	19.0	33.0	221
Going to	Not	C	62	44	20	9	14	29	178
Hasselt	frequent	EC	58.8	41.1	21.7	14.5	15.3	26.6	178
by bus	Semi-	C	4	3	4	5	4	3	23
(p)	frequent	EC	7.6	5.3	2.8	1.9	2.0	3.4	23
	Frequent	C	7	4	3	4	1	1	20
		EC	6.6	4.6	2.4	1.6	1.7	3.0	20
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221
Going to	Not	C	60	26	22	11	10	18	147
Hasselt	frequent	EC	48.6	33.9	18.0	12.0	12.6	22.0	147
by bike	Semi-	C	4	9	3	4	3	10	33
(q)	frequent	EC	10.9	7.6	4.0	2.7	2.8	4.9	33
	Frequent	C	9	16	2	3	6	5	41
		EC	13.5	9.5	5.0	3.3	3.5	6.1	41
	Total	C	73	51	27	18	19	33	221
		EC	73.0	51.0	27.0	18.0	19.0	33.0	221

[4] Occasionally (almost monthly) to never
[5] Almost weekly
[6] Almost daily & several times per week

2. The shopping location cluster variables

			Cluster number									T[3]
			1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	
Gender (a)	Female	C[1]	14	10	14	27	12	16	18	5	10	126
		EC[2]	17.7	10.3	16.0	23.4	9.1	14.8	19.4	5.1	10.3	126
	Male	C	17	8	14	14	4	10	16	4	8	95
		EC	13.3	7.7	12.0	17.6	6.9	11.2	14.6	3.9	7.7	95
	Total	C	31	18	28	41	16	26	34	9	18	221
		EC	31.0	18.0	28.0	41.0	16.0	26.0	34.0	9.0	18.0	221
Age (b)	Below 30	C	7	7	2	17	5	8	4	0	4	54
		EC	7.6	4.4	6.8	10.0	3.9	6.4	8.3	2.2	4.4	54
	30 to 39	C	2	3	4	4	5	3	4	0	0	25
		EC	3.5	2.0	3.2	4.6	1.8	2.9	3.8	1.0	2.0	25
	40 to 49	C	8	1	9	9	2	6	9	1	3	48
		EC	6.7	3.9	6.1	8.9	3.5	5.6	7.4	2.0	3.9	48
	50 to 59	C	8	5	6	7	3	5	9	6	7	56
		EC	7.9	4.6	7.1	10.4	4.1	6.6	8.6	2.3	4.6	56
	60 and above	C	6	2	7	4	1	4	8	2	4	38
		EC	5.3	3.1	4.8	7.0	2.8	4.5	5.8	1.5	3.1	38
	Total	C	31	18	28	41	16	26	34	9	18	221
		EC	31.0	18.0	28.0	41.0	16.0	26.0	34.0	9.0	18.0	221
Education categories (c)	Low	C	7	8	7	12	7	14	15	6	7	83
		EC	11.6	6.8	10.5	15.4	6.0	9.8	12.8	3.4	6.8	83
	High	C	24	10	21	29	9	12	19	3	11	138
		EC	19.4	11.2	17.5	25.6	10.0	16.2	21.2	5.6	11.2	138
	Total	C	31	18	28	41	16	26	34	9	18	221
		EC	31.0	18.0	28.0	41.0	16.0	26.0	34.0	9.0	18.0	221
Income categories (d)	Not specified	C	2	1	1	2	4	6	6	0	2	24
		EC	3.4	2.0	3.0	4.5	1.7	2.8	3.7	1.0	2.0	24
	Low income	C	8	5	5	16	2	7	10	4	8	65
		EC	9.1	5.3	8.2	12.1	4.7	7.6	10.0	2.6	5.3	65
	Medium income	C	11	8	17	13	10	11	14	3	6	93
		EC	13.0	7.6	11.8	17.3	6.7	10.9	14.3	3.8	7.6	93
	High income	C	10	4	5	10	0	2	4	2	2	39
		EC	5.5	3.2	4.9	7.2	2.8	4.6	6.0	1.6	3.2	39
	Total	C	31	18	28	41	16	26	34	9	18	221
		EC	31.0	18.0	28.0	41.0	16.0	26.0	34.0	9.0	18.0	221

[1] Count
[2] Expected count
[3] Total

			Cluster number									T
			1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	
Residence	Short	C	12	5	9	15	5	9	11	3	8	77
location	distance[4]	EC	10.8	6.3	9.8	14.3	5.6	9.1	11.8	3.1	6.3	77
categories	Medium	C	12	5	11	16	9	9	14	3	9	88
(e)	distance[5]	EC	12.3	7.2	11.1	16.3	6.4	10.4	13.5	3.6	7.2	88
	Long	C	7	8	8	10	2	8	9	3	1	56
	distance[6]	EC	7.9	4.6	7.1	10.4	4.1	6.6	8.6	2.3	4.6	56
	Total	C	31	18	28	41	16	26	34	9	18	221
		EC	31.0	18.0	28.0	41.0	16.0	26.0	34.0	9.0	18.0	221
Yearly	Rarely[7]	C	17	8	15	19	4	7	18	2	8	98
shopping		EC	13.7	8.0	12.4	18.2	7.1	11.5	15.1	4.0	8.0	98
frequency	Semi-	C	7	7	8	12	3	4	9	3	3	56
(f)	frequent[8]	EC	7.9	4.6	7.1	10.4	4.1	6.6	8.6	2.3	4.6	56
	Frequent[9]	C	7	3	5	10	9	15	7	4	7	67
		EC	9.4	5.5	8.5	12.4	4.9	7.9	10.3	2.7	5.5	67
	Total	C	31	18	28	41	16	26	34	9	18	221
		EC	31.0	18.0	28.0	41.0	16.0	26.0	34.0	9.0	18.0	221
Last time	>1 month	C	4	3	9	4	0	5	4	1	4	34
fun-	ago	EC	4.8	2.8	4.3	6.3	2.5	4.0	5.2	1.4	2.8	34.0
shopping	Past	C	12	6	9	18	5	4	8	3	4	69
(g)	month	EC	9.7	5.6	8.7	12.8	5.0	8.1	10.6	2.8	5.6	69.0
	Past week	C	15	9	10	19	11	17	22	5	10	118
		EC	16.6	9.6	15.0	21.9	8.5	13.9	18.2	4.8	9.6	118
	Total	C	31	18	28	41	16	26	34	9	18	221
		EC	31.0	18.0	28.0	41.0	16.0	26.0	34.0	9.0	18.0	221
Habits (h)	No habits	C	5	2	1	2	0	1	3	1	1	16
		EC	2.2	1.3	2.0	3.0	1.2	1.9	2.5	.7	1.3	16.0
	Zone-1	C	12	9	14	17	4	12	11	4	8	91
		EC	12.8	7.4	11.5	16.9	6.6	10.7	14.0	3.7	7.4	91.0
	Zone-2	C	8	6	10	18	10	7	18	3	7	87
		EC	12.2	7.1	11.0	16.1	6.3	10.2	13.4	3.5	7.1	87.0
	Zone-3	C	6	1	3	4	2	6	2	1	2	27
		EC	3.8	2.2	3.4	5.0	2.0	3.2	4.2	1.1	2.2	27.0
	Total	C	31	18	28	41	16	26	34	9	18	221
		EC	31.0	18.0	28.0	41.0	16.0	26.0	34.0	9.0	18.0	221

[4] 3-4 kilometres
[5] 4-7 kilometres
[6] 7-10 kilometres
[7] Several times per year & rarely/never
[8] Monthly or almost monthly
[9] More than 1 times per month

Appendix J Chi-square test results of the cluster variables

1. The transport mode cluster variables

Variables	*Pearson chi-square*	*df*	*Asymp. Sig. (2-sided)*	*Information regarding the test*
Gender (a)	2.966	5	.705	0 cells (.0%) have expected count less than 5. The minimum expected count is 7.74.
Age categories (b)	31.947	20	.044	13 cells (43.3%) have expected count less than 5. The minimum expected count is 2.04.
Education categories (c)	12.028	5	.034	0 cells (.0%) have expected count less than 5. The minimum expected count is 6.76.
Income categories (d)	20.132	15	.167	7 cells (29.2%) have expected count less than 5. The minimum expected count is 1.95.
Residence location categories (e)	7.520	10	.676	2 cells (11.1%) have expected count less than 5. The minimum expected count is 4.56.
Car ownership (f)	46.417	20	.001	17 cells (56.7%) have expected count less than 5. The minimum expected count is .08.
Bike ownership (g)	7.945	5	.159	5 cells (41.7%) have expected count less than 5. The minimum expected count is 1.55.
Moped ownership (h)	3.194	5	.670	6 cells (50.0%) have expected count less than 5. The minimum expected count is .33.

Variables	*Pearson chi-square*	*df*	*Asymp. Sig. (2-sided)*	*Information regarding the test*
Motorbike ownership (i)	3.832	5	.574	6 cells (50.0%) have expected count less than 5. The minimum expected count is .49.
Busabonnement card (j)	17.511	5	.004	5 cells (41.7%) have expected count less than 5. The minimum expected count is 1.47.
Bus reduced ticket (k)	8.594	5	.126	4 cells (33.3%) have expected count less than 5. The minimum expected count is 2.44.
Parking (l)	32.495	10	.000	9 cells (50.0%) have expected count less than 5. The minimum expected count is 1.63.
Yearly kilometres of travel by car (m)	36.215	15	.002	10 cells (41.7%) have expected count less than 5. The minimum expected count is .16.
Habits (n)	57.942	15	.000	9 cells (37.5%) have expected count less than 5. The minimum expected count is .57.
Going to Hasselt by car (o)	9.756	10	.462	4 cells (22.2%) have expected count less than 5. The minimum expected count is 3.42.
Going to Hasselt by bus (p)	18.798	10	.043	9 cells (50.0%) have expected count less than 5. The minimum expected count is 1.63.
Going to Hasselt by bike (q)	27.381	10	.002	6 cells (33.3%) have expected count less than 5. The minimum expected count is 2.69.

2. The shopping location cluster variables

Variables	*Pearson chi-square*	*df*	*Asymp. Sig. (2-sided)*	*Information regarding the test*
Gender (a)	6.245	8	.620	1 cell (5.6%) has expected count less than 5. The minimum expected count is 3.87.
Age categories (b)	45.156	32	.062	27 cells (60.0%) have expected count less than 5. The minimum expected count is 1.02.
Education categories (c)	13.506	8	.096	1 cell (5.6%) has expected count less than 5. The minimum expected count is 3.38.
Income categories (d)	35.379	24	.063	18 cells (50.0%) have expected count less than 5. The minimum expected count is .98.
Residence location categories (e)	10.786	16	.823	6 cells (22.2%) have expected count less than 5. The minimum expected count is 2.28.
Yearly frequency of fun-shopping (f)	25.560	16	.061	7 cells (25.9%) have expected count less than 5. The minimum expected count is 2.28.
Last time doing fun-shopping (g)	20.119	16	.215	10 cells (37.0%) have expected count less than 5. The minimum expected count is 1.38.
Habits (h)	21.995	24	.580	19 cells (52.8%) have expected count less than 5. The minimum expected count is .65.

Appendix K Calculations

1. The percentage agreement and Krippendorff's alpha values (Chapter 2)

The following example demonstrates how to calculate the percentage agreement and Krippendorff's alpha values between two coders.

The dataset example to calculate the intercoder reliability

	Case 1	*Case 2*	*Case 3*	*Case 4*	*Case 5*
Coder-1	Variable A	Variable B	Variable B	Variable C	Variable A
Coder-2	Variable A	Variable B	Variable B	Missing	Variable B

The percent agreement index is calculated by simply dividing the number of cases where there is an agreement between the coders with the total number of cases. Thus, in the example above, percent agreement equals 60% (or 3/5x100%).

In order to calculate the alpha value of the example in the example above, a coincidence matrix has to be created. This matrix records the number of times that pairs of variables are coded by Coder-1 and Coder-2, as shown in the table below. In that table, a combination of Variable A (Coder-1) and Variable A (Coder-2) is counted as one record, whereas the combination of Variable A (Coder-2) and Variable A (Coder-1) is another record, yielding the total number of two records. This counting method is applied for all combinations of variables.

An example of coincidence matrix

	Variable A	*Variable B*	*Variable C*	*Missing*	*Total*
Variable A	2	1	0	0	3
Variable B	1	4	0	0	5
Variable C	0	0	0	1	1
Missing	0	0	1	0	1
Total	3	5	1	1	10 (=n)

The coincidence matrix is used next to calculate the alpha value using the following formula:

$$\alpha = \frac{(n-1)\sum O_{cc} - \sum n_c(n_c - 1)}{n(n-1) - \sum n_c(n_c - 1)}$$

; Where α is the Krippendorf's alpha value; n is the total number of cases; O_{cc} is the total sum of the main diagonal cells; and n_c is the total value of each row c.

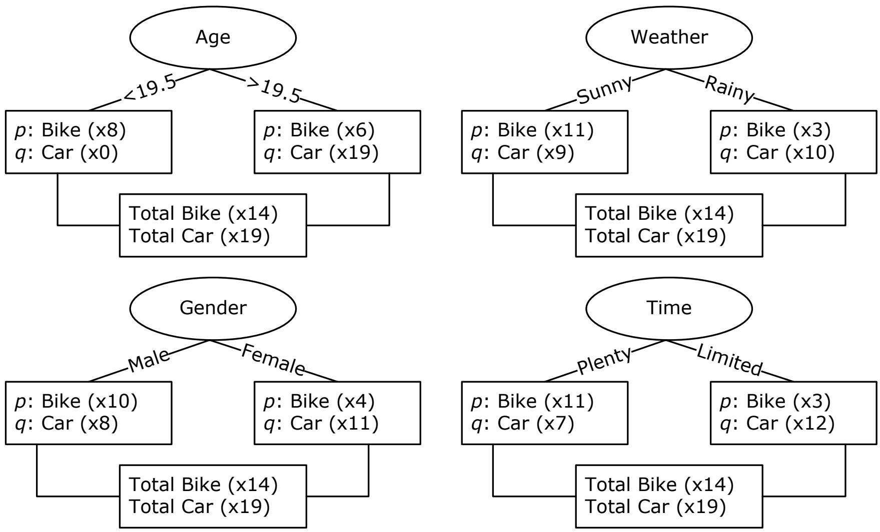
Hence, the alpha value of the example is calculated below.

$$\alpha = \frac{(10-1)(2+4+0+0) - [3(3-1)+5(5-5)+1(1-1)+1(1-1)]}{10(10-1) - [3(3-1)+5(5-5)+1(1-1)+1(1-1)]} = 43.75\%$$

The calculated alpha value of the example (43.75%) is substantially lower than the percent agreement value (60%). This could happen because the small number of cases in this example results in bigger probability of agreement by chance, yielding bigger penalty and lower alpha value.

2. The entropy of decision tree (Chapter 7)

In this part, the entropy calculation is demonstrated for the example in Table 7.1 (Chapter 7). The DT corresponds to this example is shown in Figure 7.3 (Chapter 7). In order to generate that DT, some trees related to the database are shown in the following figure.



The trees of the transport mode decision (summarized from Table 7.1)

In order to calculate the entropy, the equations below are used. Notation *p* and *q* represent a number of instances of every independent attribute in a dataset that chooses each decision value. Thus *p* (i.e. choosing bike) and *q* (i.e. choosing car) derived from the example (Figure 7.3a) are summarized in Figure 7.3b. This figure shows that there are 8 recorded cases in the data where the participants aged 19 years old or younger choose a bike and 0 cases for choosing a car, and so forth.

$$Info([p,q]) = entropy(\frac{p}{p+q}, \frac{q}{p+q})$$

$$Info([p,q]) = -\frac{p}{p+q} \times \log_2 \frac{p}{p+q} - \frac{q}{p+q} \times \log_2 \frac{q}{p+q}$$

$$Info([p,q]) = \frac{-p \times \log_2 p - q \times \log_2 q + (p+q)\log_2(p+q)}{p+q}$$

There are four possibilities to start the DT since there are four input variables; i.e. *age*, *gender*, *weather*, and *time availability.* The information gain value at the *age* attribute is calculated below. Similarly, these values for the other attributes are shown subsequently. The results show that the *age* attribute has the highest gained value. Thus, selecting it as the tree root yields the highest advantage.

Gain (Age)=Info([14,19])-Info([8,0],[6,19])

$Info([14,19])=(-14log_2 14-19log_2 19+33log_2 33)x1/33=0.983376bits$

$Info([8,0])=(-8log_2 8-0log_2 0+8log_2 8)x1/8=0bits$

$Info([6,19])=(-6log_2 6-19log_2 19+25log_2 25)x1/25=0.79504bits$

Info([8,0],[6,19])=8/33x0+25/33x0.79504=0.602303bits

Gain (Age)= 0.983376-0.602303=0.381073bits

Gain(Gender)= Info([14,19])-Info([10,8],[4,11])

Gain(Gender)=0.062498bits

Gain(Weather)= Info([14,19])-Info([11,9],[3,10])

Gain(Weather)=0.074678bits

Gain(Time)= Info([14,19])-Info([11,7],[3,12])

Gain(Time)=0.129366bits

Figure 7.3 (in Chapter 7) shows that the attribute of *age* with the branch of *<19.5 years old* is already pure since a bike is chosen in all cases. Hence, there is no need to split it further. However, the attribute's value of *>19.5 years old* is not yet pure. The next task is to discover the subsequent attribute to split by calculating the information gain values for the other remaining variables given the branch of age *>19.5 years old*. This process is carried on until all leaf nodes are pure or when the data cannot be split anymore (Han & Kamber, 2004).

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PUBLICATIONS (2007-2011)

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