

The description of individuals' cognitive subsets in fun shopping activities by making use of association rules algorithms

Case study in Hasselt, Belgium

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The Description of Individuals' Cognitive Subsets in Fun Shopping Activities by Making
Use of Association Rules Algorithms: Case Study in Hasselt, Belgium

Master thesis submitted to
obtain the degree of Master in Transportation Sciences,
specialization Mobility Management
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Preface

The document you have in your hands is my master thesis to obtain the degree of Master in Transportation Sciences, specialization Mobility Management. It contains the aim, the theoretical background, the implementation and the results of the research that has occupied me most of my graduation year at Hasselt University.

The intention of the research is to get a better idea about what elements and associations are most important to people when they make transportation-related decisions about fun shopping activities, using the CNET protocol. In my first master year, I already performed a small-scale research about the CNET protocol. Since I really enjoyed carrying out this research, my choice was made quite quickly when I was offered the opportunity to do related research for my master thesis; thought processes of people are simply fascinating. I am also convinced that understanding people's mobility behavior is the most important step towards changing it; a transportation scientist who is insufficiently able to understand people's decision making process, is not be able to realize significant changes in people's mobility behavior.

I am fortunate to have had the best guidance I could have ever hoped for. First and foremost, I am greatly indebted to my supervisor Diana Kusumastuti and to Els Hannes. Their quick and useful feedback, their help with every aspect of this research and their encouragements and their faith in me were invaluable to get to a scientifically sound and coherent thesis. Furthermore, I would also like to thank prof. dr. Davy Janssens for creating the framework in which this master thesis could take place. Maikel León Espinosa is acknowledged for his efforts in programming the survey. I am also very grateful to dr. Benoît Depaire for his help in debugging the software, for the development of the survey database and his help with the association rules analysis. And last but not least, I am grateful to my friends, my family and my girlfriend Sofie for their support, their understanding and the distraction during the course of this master thesis.

Summary

The last decades, the yearly number of vehicle kilometers has strongly increased. Both policy makers and citizens are becoming more and more aware of the negative impacts of abundant car use: traffic accidents, emissions, congestion... Abundant traffic is especially undesirable in city centers because many people are exposed to its negative influences in these areas. Furthermore, both driving and parked cars take up a lot of valuable space that can be put to better use, and they lead to a depreciation of the public space.

The rise in the yearly number of vehicle kilometers in the last few years seems to be mainly caused by leisure trips. Therefore, more attention should be paid to measures that change the travel behavior for leisure activities. One of these leisure activities is fun shopping. Fun shopping trips are particularly important because they are usually directed to the city centre.

Fun shopping is a leisure activity in which shopping information is gathered about products that are not bought every day (e.g. clothing, electronics, gifts,...). It can be related to actually buying things, but this is not necessarily the case.

A shift towards more sustainable fun shopping behavior is desirable. For this purpose, Travel Demand Management (TDM) measures that influence the demand for travel can be used. TDM measures are measures that intent to lower the demand for travel, or to redistribute it over space, over time or over the different travel modes to reduce its negative impacts. Such measures can be implemented more efficiently and effectively if they aim at contextual, evaluative and instrumental aspects that are most important in people's decision making process. Therefore, it is important to investigate how people exactly make a transport mode decision and decide to which location they go.

Literature about choice processes and decision making states that decisions are rarely made purely rational because of cognitive limitations and uncertainty. According to the heuristic decision theory, people's decision depends on a limited number of simplified heuristics. These are in fact efficient rules of thumb of the type if-then(-else), that are based on prior knowledge and experiences. They allow the decision maker to weigh the available alternatives and their characteristics quite easily, but they do not guarantee

that the optimal solution is found because the underlying reasoning can be based on incomplete, incorrect or biased information and experiences.

For new or infrequently occurring situations, it is possible that people do not have ready-made heuristics for all possible circumstances. In these situations, people activate a complex and deliberative cognitive process, in which different considerations are linked by means of causal connections to come up with the best possible solution. This way, a temporary mental representation of the decision problem is created in which the decision maker details the characteristics of the different choice alternatives and judges their attractiveness or suitability.

Furthermore, there is also habitual behavior. Habits are formed when people repeat a certain behavior in stable circumstances. As the behavior is repeated more often, the conscious decision making process recedes. Because of this, the behavior comes to be automatically triggered by certain contextual characteristics.

There is a large twilight zone between these extremes of a fully conscious and deliberate decision and a fully automated habitual response. Fun shopping related decisions also belong to this zone. Therefore, people's mental representation concerning these decisions may contain both elements of conscious deliberation and automated scripts. Scripts are fixed, context-specific rules or heuristics, in which no alternatives are perceived by the decision maker. For instance, someone may always go fun shopping by car in case it rains, which is a script, but can make a well-considered choice between the different transport modes when the weather is nice, based on the time he has available, the fact whether he goes fun shopping alone or with a companion, etc. **The aim of this thesis is to reveal the content of individuals' mental representation when making a transport mode choice and a shopping location choice for fun shopping trips.**

To reveal the mental representation of individuals' mental representation for fun shopping related decisions, the Causal Network Elicitation Technique (CNET) is used. This technique distinguishes four types of variables in the mental representation of a decision problem. Decision variables are the variables the individual has to make a decision about. Contextual variables are environmental factors that can have an influence on the decision, but that can not be controlled by the decision maker himself. The inherent characteristics of the different choice options are represented by instrumental variables.

Evaluative variables are directly related to utilities and describe the impact of instrumental and contextual variables on the physiological and psychological needs of the decision maker. The variables can be linked to so-called cognitive subsets. There are two types of cognitive subsets. The context-specific subsets are of the type "context – value – instrument". The not context-specific subsets are of the type "(in any circumstances -) value – instrument".

In this research, the CNET protocol is translated to a computer-based survey. 221 respondents are questioned in small guided group sessions. It appears that the gathered sample is quite representative. The only disturbance is the education level. There appears to be an overrepresentation of higher educated respondents.

First, the complexity of the respondents' mental representation is analyzed. For this purpose, the number of different variables respondents indicate is investigated. On average, respondents indicate 44 variables. The transport mode choice (27 variables on average) appears to be significantly more complex than the shopping location choice (17 variables on average). The individual differences in network complexity are large. The most simple network of an individual contains only 10 variables, while the most complex network consists of 104 variables. Despite these major individual differences, they show little correlation with socio-demographic characteristics. For instance, there are no differences between men and women, between different age groups, income categories... There is only a correlation with education level. Higher educated respondents (higher non-university or university degree) indicate significantly less variables than respondents with a lower education (secondary school degree or lower). So, it can be concluded that the network complexity is relatively stable over the different socio-demographic variables.

Next, the associations respondents make most often between these different variables are investigated. This analysis is performed by applying association rules algorithms to the database. This is a data mining technique that is mainly used in marketing research to reveal recurring patterns from large databases.

For the shopping location choice, the contextual variables that are mentioned most often are "interest in a specific product" and "time available". By far the most important evaluative aspect is "efficiency", but also "assurance and certainty", "convenience",

“saving money” and “fun” are quite important. The instrumental aspects that are mentioned most often are “presence of favorite shop”, “familiarity with zone” and “type of stores”.

The not context-specific associations made by most respondents in the shopping location choice are presented in the following table. The cognitive subsets that are mentioned most often are related to efficiency: “efficiency – presence of favorite shop”, “efficiency – familiarity with the zone” and “efficiency – type of stores”. Also the association “saving money – product price in zone” is very important. Furthermore, many respondents relate the evaluative variables “assurance and certainty” and “convenience” to the instrumental aspects “presence of favorite shop” and “familiarity with the zone”. The variable “fun” is often linked to the instruments “presence of favorite shop” and “ambiance environment”.

Table 1: Not context-specific associations in the shopping location choice.

<i>Value</i>	<i>Instrument</i>	<i>% of respondents</i>
efficiency	favorite shop	28,1%
efficiency	familiarity	25,8%
saving money	product price	19,5%
efficiency	type of stores	19,5%
fun	favorite shop	18,1%
certainty	favorite shop	17,6%
certainty	familiarity	17,6%
convenience	familiarity	14,5%
convenience	favorite shop	13,6%
fun	ambiance	12,7%

The most important context-specific cognitive subsets in the shopping location choice are associations related to the contextual aspects “interest in specific product” and “time available”. They are linked to the value “efficiency”, and to the instruments “presence of favorite shop”, “type of stores” and “familiarity with the zone”. Furthermore, financial aspects appear to be very important. The contextual variable “sale season” is often linked to “saving money” and “product price in zone”. “Budget availability” is also often related to “saving money” and “product price in zone”. Furthermore, respondents take the contextual variable “companion” into account, which is linked to the value “fun” and the instruments “presence of favorite shop” and “cafe and restaurant”.

Table 2: Context-specific associations in the shopping location choice.

<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>% resp.</i>
specific product	efficiency	favorite shop	20,8%
specific product	efficiency	type of stores	18,1%
time available	efficiency	favorite shop	17,2%
specific product	efficiency	familiarity	16,7%
time available	efficiency	familiarity	16,3%
sale season	saving money	product price	11,3%
companion	fun	favorite shop	11,3%
budget available	saving money	product price	10,4%
sale season	saving money	favorite shop	10,4%
companion	fun	cafe restaurant	10,0%

In the transport mode decision, the contextual variables "time available", "precipitation", "baggage" and "parking space availability" are indicated most often. The most important evaluative variables are "efficiency" and "freedom", and the instrumental variables that are indicated most often are "flexibility", "travel time", "easiness for parking", "accessibility" and "treatment of bags".

The most important not context-specific associations in the transport mode choice are interrelations between the evaluative aspects "efficiency" and "freedom", and the instrumental aspects "flexibility", "travel time", "easiness for parking", "accessibility" and "treatment of bags". The association that is made most often is "freedom – flexibility".

Table 3: Not context-specific associations in the transport mode choice.

<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
freedom	flexibility	39,8%
efficiency	flexibility	33,9%
efficiency	travel time	33,9%
efficiency	easiness parking	32,1%
freedom	travel time	26,7%
efficiency	accessibility	26,2%
freedom	accessibility	24,9%
freedom	easiness parking	23,1%
freedom	treatment bags	20,8%
convenience	travel time	19,0%

Concerning the context-specific associations in the transport mode choice, respondents attach by far the most importance to the association "precipitation – physical comfort – shelter provision". Furthermore, the contextual variable "time available" is often linked to the evaluative variable "efficiency" and the instrumental variables "travel time", "flexibility", "easiness for parking" and "direct travel". Also, the associations "baggage – physical comfort – treatment of bags / physical effort" are important. And finally, the links between the contextual variable "parking space availability", the evaluative variable "efficiency" and the instrumental variables "easiness for parking", "accessibility" and "travel time" are quite important for the transport mode choice.

Table 4: Frequent itemsets TM decision (with context).

<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
precipitation	physical comfort	shelter	21,7%
time available	efficiency	travel time	16,3%
baggage	physical comfort	treatment bags	14,9%
parking availability	efficiency	easiness parking	12,7%
time available	efficiency	flexibility	12,2%
parking availability	efficiency	accessibility	10,0%
baggage	physical comfort	physical effort	10,0%
time available	efficiency	easiness parking	9,5%
time available	efficiency	direct travel	9,5%
parking availability	efficiency	travel time	9,0%

There are also considerable differences between the different socio-demographic groups. For instance, it appears that in the transport mode choice cost aspects are more important to elderly and the low income category, and the environmental aspect is more important to men and elderly. For other socio-demographic groups, these factors only have a limited importance. The limited importance of cost and environmental aspects has two important consequences. First of all, it means that the promotion campaigns for sustainable transport modes should be reconsidered. They should focus on the aspects that are most important to people: flexibility, travel time, accessibility, shelter provision, easiness for parking and the treatment of bags. Currently, these campaigns focus mainly on environmental and price arguments, which are of a lower importance to the transport mode choice. And second, it implies that cost measures, that are often used to promote a shift towards sustainable transport modes, are possibly not the most effective means to accomplish this goal. In a fun shopping context, measures should be aimed at the transport mode characteristics that are most important to people. Parking restriction

measures seem to have the largest potential to accomplish a shift towards sustainable transport modes for several reasons. For instance, they simultaneously influence several of the most important characteristics, and they are particularly relevant for people without a transport mode habit for fun shopping trips, which is a large target group of which the behavior can be changed relatively easily.

Samenvatting

De laatste decennia is het aantal afgelegde voertuigkilometers sterk toegenomen. Beleidsmakers en burgers worden zich echter steeds meer bewust van de negatieve impact van overtollig autogebruik: verkeersongevallen, emissies, congestie... Vooral in de omgeving van stadscentra is overtollig verkeer onwenselijk omdat hier veel mensen worden blootgesteld aan de negatieve invloeden. Bovendien nemen zowel rijdende als geparkeerde wagens veel kostbare ruimte in die beter benut kan worden, en leiden ze tot een banalisering van de publieke ruimte.

De toename in het aantal voertuigkilometers blijkt de laatste jaren voornamelijk te wijten aan vrijetijdsverplaatsingen. Daarom zou meer aandacht geschonken moeten worden aan maatregelen die het verplaatsingsgedrag voor vrijetijdsactiviteiten wijzigen. Één van die vrijetijdsactiviteiten is fun shopping. Fun shopping verplaatsingen zijn extra belangrijk omdat zij meestal georiënteerd zijn op stadscentra.

Fun shopping is een vrijetijdsactiviteit waarbij winkelinformatie wordt verzameld over goederen die men niet dagelijks koopt (bv. kleding, elektronica, geschenken,...). Het kan gerelateerd zijn aan het effectief kopen van goederen, maar dit is niet noodzakelijk het geval.

Een verschuiving naar een duurzamer fun shopping gedrag is wenselijk. Travel Demand Management (TDM) maatregelen die de vraag naar vervoer beïnvloeden kunnen hiervoor gebruikt worden. TDM maatregelen zijn maatregelen die de bedoeling hebben de vraag naar vervoer te verminderen, of te herverdelen in ruimte, in tijd of over de verschillende vervoerwijzen om zo de negatieve impact te verminderen. Dergelijke maatregelen kunnen veel efficiënter en doeltreffender worden ingezet indien ze inwerken op de werkelijke contextuele, evaluatieve en instrumentele aspecten in het beslissingsproces van de mensen. Daarom is het belangrijk om te onderzoeken hoe mensen precies een vervoerwijzekeuze maken en beslissen naar welke locatie ze gaan.

De literatuur rond beslissingen en keuzeprocessen stelt dat beslissingen zelden zuiver rationeel worden genomen omwille van mentale beperkingen en onzekerheden. Volgens de Heuristische Beslissingstheorie hangt de beslissing van mensen af van een beperkt aantal vereenvoudigde heuristieken. Dit zijn in feite efficiënte vuistregels van het als-

dan(-anders) type, die gebaseerd zijn op voorgaande ervaringen en kennis. Ze zorgen ervoor dat de beslissingnemer vrij eenvoudig de verschillende alternatieven en hun kenmerken en karakteristieken kan afwegen, maar ze garanderen geen optimale oplossing omdat de onderliggende redenering gebaseerd kan zijn op onvolledige, onjuiste of bevooroordeelde informatie en ervaringen.

Voor nieuwe of ongewone situaties is het echter mogelijk dat mensen geen kant-en-klare heuristische beschikbaar hebben voor alle mogelijke omstandigheden. Het blijkt dat mensen in dergelijke situaties een complex en doelbewust cognitief proces in gang zetten, waarbij verschillende overwegingen door middel van causale verbanden aan elkaar worden gekoppeld om de best mogelijke beslissing te kunnen nemen. Op deze manier wordt een tijdelijke mentale voorstelling gemaakt van het beslissingsprobleem, waarbij de beslissingnemer de verschillende kenmerken van de keuzemogelijkheden detailleert, en de geschiktheid of aantrekkelijkheid van elk kenmerk van elke keuzemogelijkheid evalueert.

Verder is er ook nog gewoontegedrag. Gewoontes ontstaan wanneer mensen een bepaald gedrag steeds herhalen in een stabiele context. Naarmate het gedrag vaker herhaald wordt, neemt hierbij het bewuste beslissingsproces af. Hierdoor wordt het gedrag op den duur automatisch gestart door bepaalde omgevingsfactoren.

Tussen deze extremen van een doelbewuste beslissing en een automatische respons op bepaalde stimuli uit de omgeving is er echter een grote grijze zone, waartoe ook fun shopping gerelateerde beslissingen behoren. Daarom is het mogelijk dat de mentale weergave van de mensen omtrent deze beslissingen zowel elementen van bewuste overweging bevat, als automatische scripts. Scripts zijn vaste, contextspecifieke regels of heuristieken, waarbij de beslissingnemer geen alternatieven overweegt. Bijvoorbeeld, iemand kan altijd met de auto gaan fun shoppen in geval van regen, hetgeen een script is, maar bij mooi weer een weloverwogen keuze maken tussen de verschillende vervoersmogelijkheden, gebaseerd op de tijd die hij heeft, of hij alleen gaat winkelen of samen met iemand anders, enzovoort. **Het doel van dit onderzoek is dan ook het ontdekken van de inhoud van de mentale voorstelling van mensen bij het maken van een vervoerwijzekeuze en winkellocatiekeuze bij fun shopping verplaatsingen.**

Om de mentale voorstelling van fun shopping gerelateerde beslissingen bij individuen bloot te leggen, is er gebruik gemaakt van de Causal Network Elicitation Technique (CNET). In deze techniek worden vier soorten variabelen onderscheiden in de mentale weergave van een beslissingsprobleem. Beslissingsvariabelen zijn de variabelen waarover het individu een beslissing moet nemen. Contextuele variabelen zijn factoren in de omgeving die de uitkomst van een beslissing kunnen beïnvloeden, maar waarover de beslissingnemer geen controle heeft. De intrinsieke kenmerken van de verschillende keuzemogelijkheden worden weergegeven in instrumentele variabelen. Evaluatieve variabelen zijn rechtstreeks gerelateerd aan utiliteiten, en beschrijven de invloed van de instrumentele en contextuele variabelen op de fysiologische en psychologische behoeften van de beslissingnemer. De variabelen kunnen aan elkaar gekoppeld worden tot zogenaamde cognitieve subsets. Er zijn twee soorten cognitieve subsets. De contextspecifieke cognitieve subsets zijn van het type "context – evaluatie – instrument". Niet contextspecifieke subsets zijn van het type "(onder normale omstandigheden –) evaluatie – instrument".

Voor dit onderzoek is het CNET protocol vertaald naar een computergestuurde enquête. 221 respondenten zijn bevraagd in kleine, begeleide groepsessies. Het blijkt dat de verzamelde steekproef behoorlijk representatief is. De enige verstoring is het opleidingsniveau. Er blijkt een overrepresentatie te zijn van hoger opgeleiden.

Eerst is de complexiteit van het netwerk van de respondenten geanalyseerd. Hiervoor is gekeken naar het aantal verschillende variabelen dat de respondenten hebben aangeduid. Gemiddeld duiden de respondenten 44 variabelen aan. De vervoerwijzekeuze (gemiddeld 27 variabelen) blijkt significant complexer dan de winkellocatiekeuze (gemiddeld 17 variabelen). De individuele verschillen in netwerkcomplexiteit zijn groot. Het eenvoudigste netwerk van een respondent bevat slechts 10 variabelen, terwijl het meest complexe netwerk 104 variabelen telt. Ondanks deze grote individuele verschillen, blijken deze verschillen weinig gecorreleerd aan socio-demografische variabelen. Er zijn bijvoorbeeld geen significante verschillen tussen mannen en vrouwen, verschillende leeftijdscategorieën, inkomensklassen... Er is enkel een correlatie met het opleidingsniveau. Het blijkt dat respondenten met een hoger opleidingsniveau (hoger niet-universitair of universitair diploma) significant minder variabelen aanduiden dan respondenten met een lager opleidingsniveau (middelbaar onderwijs of lager). Er kan dus

geconcludeerd worden dat de netwerkcomplexiteit relatief stabiel is over de verschillende socio-demografische factoren.

Daarna is er gekeken naar verbanden die door respondenten vaak worden gelegd tussen de verschillende variabelen. Deze analyse vindt plaats door middel van associatieregels algoritmes. Dit is een "data mining" techniek die vooral in marketingonderzoek gebruikt wordt om vaak weerkerende patronen en verbanden te ontdekken in grote databases.

Voor de winkellocatiekeuze zijn de vaakst genoemde contextuele variabelen "interesse in een specifiek product" en "beschikbare tijd". Verreweg de belangrijkste evaluatieve variabele is "efficiëntie", maar ook "zekerheid", "mentaal gemak", "geld besparen" en "plezier" zijn behoorlijk belangrijk. De belangrijkste instrumentele aspecten zijn "aanwezigheid van favoriete winkel", "vertrouwdheid met de zone" en "type winkels".

De belangrijkste niet-contextspecifieke associaties die respondenten maken bij hun winkellocatiekeuze, zijn weergegeven in volgende tabel. De vaakst genoemde cognitieve subsets zijn gekoppeld aan efficiëntie: "efficiëntie – aanwezigheid van favoriete winkel", "efficiëntie – vertrouwdheid met de zone" en "efficiëntie – type winkels". Ook de associatie "geld besparen – prijs van producten in de zone" is zeer belangrijk. Verder worden de evaluatieve variabelen "zekerheid" en "mentaal gemak" beiden door een aanzienlijk aantal respondenten gekoppeld aan de instrumentele variabelen "aanwezigheid van favoriete winkel" en "vertrouwdheid met de zone". De variabele "plezier" wordt vaak gekoppeld aan de instrumenten "aanwezigheid van favoriete winkel" en "sfeer, uitstraling".

Tabel 5: Niet-contextspecifieke associaties in de winkellocatiekeuze.

<i>Evaluatie</i>	<i>Instrument</i>	<i>% van respondenten</i>
efficiëntie	favoriete winkel	28,1%
efficiëntie	vertrouwdheid	25,8%
geld besparen	prijs van producten	19,5%
efficiëntie	type winkels	19,5%
plezier	favoriete winkel	18,1%
zekerheid	favoriete winkel	17,6%
zekerheid	vertrouwdheid	17,6%
mentaal gemak	vertrouwdheid	14,5%
mentaal gemak	favoriete winkel	13,6%
plezier	sfeer, uitstraling	12,7%

Bij de contextspecifieke cognitieve subsets in de winkellocatiekeuze zijn de belangrijkste associaties gerelateerd aan de contextuele aspecten "interesse in een specifiek product" en "beschikbare tijd". Ze worden gekoppeld aan "efficiëntie", en aan de instrumentele aspecten "aanwezigheid van favoriete winkel", "type winkels" en "vertrouwdheid met de zone". Daarnaast blijken ook financiële aspecten zeer belangrijk. De contextuele variabele "soldenperiode" wordt vaak gekoppeld aan "geld besparen" en de instrumentele variabelen "prijs van producten in de zone" en "aanwezigheid van favoriete winkel". Ook "beschikbaar budget" wordt vaak gekoppeld aan "geld besparen" en "prijs van producten in de zone". Er wordt ook sterk rekening gehouden met de contextuele variabele "gezelschap", die wordt gekoppeld aan de evaluatie "plezier" en de instrumenten "aanwezigheid van favoriete winkel" en "cafés & restaurants".

Tabel 6: Contextspecifieke associaties in de winkellocatiekeuze.

<i>Context</i>	<i>Evaluatie</i>	<i>Instrument</i>	% resp.
specifiek product	efficiëntie	favoriete winkel	20,8%
specifiek product	efficiëntie	type of stores	18,1%
beschikbare tijd	efficiëntie	favoriete winkel	17,2%
specifiek product	efficiëntie	vertrouwdheid	16,7%
beschikbare tijd	efficiëntie	vertrouwdheid	16,3%
soldenperiode	geld besparen	prijs van producten	11,3%
gezelschap	plezier	favoriete winkel	11,3%
beschikbaar budget	geld besparen	prijs van producten	10,4%
soldenperiode	geld besparen	favoriete winkel	10,4%
gezelschap	plezier	café restaurant	10,0%

Bij de vervoerwijzekeuze zijn de vaakst aangeduide contextuele variabelen "beschikbare tijd", "neerslag", "bagage" en "vinden van parkeerplaats". De belangrijkste evaluatieve variabelen zijn "efficiëntie" en "vrijheid". De meest gekozen instrumentele variabelen zijn "flexibiliteit", "reistijd", "parkeergemak", "bereikbaarheid" en "bagagemogelijkheden".

De belangrijkste niet-contextspecifieke associaties bij de vervoerwijzekeuze zijn interrelaties tussen de evaluatieve aspecten "efficiëntie" en "vrijheid", en de instrumentele aspecten "flexibiliteit", "reistijd", "parkeergemak", "bereikbaarheid" en "bagagemogelijkheden". De associatie die hierbij het meeste gemaakt wordt door respondenten is "vrijheid – flexibiliteit".

Tabel 7: Niet-contextspecifieke associaties in de vervoerwijzekeuze.

<i>Evaluatie</i>	<i>Instrument</i>	<i>% van respondenten</i>
vrijheid	flexibiliteit	39,8%
efficiëntie	flexibiliteit	33,9%
efficiëntie	reistijd	33,9%
efficiëntie	parkeergemak	32,1%
vrijheid	reistijd	26,7%
efficiëntie	bereikbaarheid	26,2%
vrijheid	bereikbaarheid	24,9%
vrijheid	parkeergemak	23,1%
vrijheid	bagagemogelijkheden	20,8%
mentaal gemak	reistijd	19,0%

Wat de contextspecifieke associaties bij de vervoerwijzekeuze betreft, hechten respondenten verreweg het meeste belang aan de relatie "neerslag – fysiek comfort – aanwezigheid van beschutting". Daarnaast wordt de contextuele variabele "beschikbare tijd" vaak gelinkt aan de evaluatie "efficiëntie" en de instrumenten "reistijd", "flexibiliteit", "parkeergemak" en "directe trip". Ook de relaties "bagage – fysiek comfort – bagagemogelijkheden / fysieke moeite" zijn belangrijk. En ten slotte zijn ook de links tussen de contextuele variabele "vinden van parkeerplaats", de evaluatieve variabele "efficiëntie" en de instrumentele variabelen "parkeergemak", "bereikbaarheid" en "reistijd" behoorlijk belangrijk voor de vervoerwijzekeuze.

Table 8: Frequent itemsets TM decision (with context).

<i>Context</i>	<i>Evaluatie</i>	<i>Instrument</i>	<i>% resp.</i>
neerslag	fysiek comfort	beschutting	21,7%
beschikbare tijd	efficiëntie	reistijd	16,3%
bagage	fysiek comfort	bagagemogelijkheden	14,9%
vinden van parkeerplaats	efficiëntie	parkeergemak	12,7%
beschikbare tijd	efficiëntie	flexibiliteit	12,2%
vinden van parkeerplaats	efficiëntie	bereikbaarheid	10,0%
bagage	fysiek comfort	fysieke moeite	10,0%
beschikbare tijd	efficiëntie	parkeergemak	9,5%
beschikbare tijd	efficiëntie	directe trip	9,5%
vinden van parkeerplaats	efficiëntie	reistijd	9,0%

Er zijn ook noemenswaardige verschillen tussen verschillende socio-demografische groepen. Zo blijkt bijvoorbeeld dat het kostenaspect van de vervoerwijzekeuze meer van belang is voor ouderen en de lage inkomenscategorie, en het milieuaspect meer

meespeelt bij mannen en ouderen. Bij andere socio-demografische groepen zijn deze factoren slechts van een beperkt belang. Dit beperkte belang van kost- en milieuaspecten heeft twee belangrijke gevolgen. Ten eerste betekent dit dat campagnes voor duurzame transportmodi zich beter op de kenmerken zouden focussen die het belangrijkste zijn voor de mensen: flexibiliteit, reistijd, bereikbaarheid, beschutting, parkeergemak en bagagemogelijkheden. Momenteel focussen deze zich nog vaak op milieu- en prijsargumenten, overwegingen die dus van minder belang zijn bij de vervoerwijzekeuze voor fun shopping verplaatsingen. En ten tweede toont het aan dat kostmaatregelen, die zeer frequent worden gebruikt om aan te sturen op een meer duurzame modal split, mogelijk niet de meest doeltreffende manier zijn om dit te verwezenlijken. In een fun shopping context kunnen maatregelen beter gericht worden op de kenmerken van de verschillende vervoersmodi die het belangrijkste zijn voor de mensen. Hierbij lijken parkeermaatregelen het meeste potentieel te hebben omwille van verschillende redenen. Zo spelen ze bijvoorbeeld in op verschillende van deze kenmerken, en zijn ze specifiek van belang voor personen zonder vervoerwijze gewoonte voor fun shopping verplaatsingen, een grote doelgroep waarvan het gedrag relatief eenvoudig te veranderen is.

Contents

Preface	II
Summary	III
Samenvatting	X
Contents	XVII
List of figures	XIX
List of tables	XX
1 Introduction	- 1 -
2 Background	- 4 -
2.1 Decision making and mental representation	- 4 -
2.2 The CNET protocol	- 7 -
2.3 Elicitation techniques	- 11 -
2.3.1 CNET interview protocol	- 12 -
2.3.2 CNET card game technique	- 13 -
2.3.3 Comparison CNET interview vs. CNET card game	- 13 -
2.3.4 Computer-based survey	- 15 -
3 Survey development	- 17 -
3.1 Personal information	- 18 -
3.2 Research setting and scenario	- 19 -
3.3 Decision order and elicitation of mental representation	- 22 -
3.4 Parameter gathering	- 25 -
4 Sample	- 26 -
4.1 Sample gathering	- 26 -
4.2 Sample description	- 29 -
4.2.1 Description of socio-demographic factors	- 29 -
4.2.2 Description of respondents' overall mobility	- 36 -
5 Data analysis	- 44 -

5.1	Network complexity	- 44 -
5.1.1	Methodology	- 45 -
5.1.2	Analysis of network complexity	- 48 -
5.1.3	Conclusions network complexity	- 71 -
5.2	Variables considered most by respondents	- 72 -
5.2.1	Presence of SL variables in respondents' mental representation	- 72 -
5.2.2	Presence of TM variables in respondents' mental representation	- 75 -
5.2.3	Conclusions variables considered most by respondents	- 79 -
5.3	Frequent itemsets	- 80 -
5.3.1	Methodology	- 80 -
5.3.2	General analysis of elicited subsets	- 86 -
5.3.3	Elicited subsets in different scenarios	- 92 -
5.3.4	Elicited subsets when starting from a habit or not	- 98 -
5.3.5	Differences in elicited subsets by gender	- 103 -
5.3.6	Differences in elicited subsets for different age categories	- 108 -
5.3.7	Differences in elicited subsets for different education levels	- 115 -
5.3.8	Differences in elicited subsets for different income levels	- 120 -
5.3.9	Differences in elicited subsets for different distances to the centre	- 126 -
5.3.10	Conclusions and discussion	- 129 -
6	Conclusions	- 134 -
6.1	Findings	- 134 -
6.2	Policy impact	- 139 -
6.2.1	Policy impacts related to the SL choice	- 139 -
6.2.2	Policy impacts related to the TM choice	- 140 -
6.3	Critical reflection	- 145 -
6.4	Recommendations for further research	- 147 -
7	References	- 149 -

List of figures

Figure 1: Graphical illustration of the different variables.	- 10 -
Figure 2: Summary of the elicitation stages in the CB-CNET survey.	- 18 -
Figure 3: Different scenarios.	- 19 -
Figure 4: Shopping zones.	- 21 -
Figure 5: Elicitation of the network structure in the CB-CNET survey.	- 23 -
Figure 6: Sample divided by gender.	- 29 -
Figure 7: Sample divided by age.	- 30 -
Figure 8: Sample divided by age (categorized).	- 31 -
Figure 9: Sample divided by highest degree obtained.	- 32 -
Figure 10: Sample divided by highest degree obtained (categorized).	- 33 -
Figure 11: Sample divided by income.	- 34 -
Figure 12: Sample divided by income (categorized).	- 34 -
Figure 13: Sample divided by postal code.	- 35 -
Figure 14: Sample divided by postal code (categorized).	- 36 -
Figure 15: Sample divided by number of cars in the household.	- 37 -
Figure 16: Sample divided by the number of km. driven per year.	- 37 -
Figure 17: Sample divided by the number of km. driven per year (categorized).	- 38 -
Figure 18: Respondents' transport mode options, besides car.	- 39 -
Figure 19: Sample divided by how often respondents go to the centre of Hasselt by car/bicycle/bus.	- 40 -
Figure 20: Sample divided by parking choice.	- 41 -
Figure 21: Sample divided by parking choice (categorized).	- 42 -
Figure 22: Sample divided by frequency of fun shopping.	- 43 -
Figure 23: Overall network complexity.	- 49 -
Figure 24: Percentage of respondents indicating each SL contextual variable.	- 73 -
Figure 25: Percentage of respondents indicating each SL evaluative variable.	- 74 -
Figure 26: Percentage of respondents indicating each SL instrumental variable.	- 75 -
Figure 27: Percentage of respondents indicating each TM contextual variable.	- 76 -
Figure 28: Percentage of respondents indicating each TM evaluative variable.	- 77 -
Figure 29: Percentage of respondents indicating each TM instrumental variable.	- 78 -

List of tables

Table 1: Not context-specific associations in the shopping location choice.	VI
Table 2: Context-specific associations in the shopping location choice.	VII
Table 3: Not context-specific associations in the transport mode choice.	VII
Table 4: Frequent itemsets TM decision (with context).	VIII
Tabel 5: Niet-contextspecifieke associaties in de winkellocatiekeuze.	XIII
Tabel 6: Contextspecifieke associaties in de winkellocatiekeuze.	XIV
Tabel 7: Niet-contextspecifieke associaties in de vervoerwijzekeuze.	XV
Table 8: Frequent itemsets TM decision (with context).	XV
Table 9: Descriptive statistics of respondents' overall network complexity.	- 50 -
Table 10: Network complexity for each decision separately.	- 51 -
Table 11: Network complexity for the SL location depending on decision order.	- 51 -
Table 12: Network complexity for the TM location depending on decision order.	- 52 -
Table 13: Network complexity for each decision separately (fractions).	- 52 -
Table 14: Network complexity for both scenarios.	- 53 -
Table 15: Number of respondents that starts from habit or not for both scenarios.	- 54 -
Table 16: Network complexity of men vs. women.	- 55 -
Table 17: Network complexity of men vs. women, SL decision only.	- 55 -
Table 18: Network complexity of men vs. women, TM decision only.	- 56 -
Table 19: Network complexity for different age categories.	- 56 -
Table 20: Network complexity for different age categories, SL decision only.	- 56 -
Table 21: Network complexity for different age categories, TM decision only.	- 57 -
Table 22: Network complexity for different education levels.	- 57 -
Table 23: Network complexity SL decision for different education levels.	- 57 -
Table 24: Network complexity TM decision for different education levels.	- 58 -
Table 25: Network complexity for SL decision if it is the second decision.	- 58 -
Table 26: Network complexity for TM decision if it is the second decision	- 58 -
Table 27: χ^2 -test for correlation between SL habit and education.	- 59 -
Table 28: χ^2 -test for correlation between TM habit and education.	- 59 -
Table 29: Network complexity for different income categories.	- 60 -
Table 30: Network complexity for different income categories, SL decision only.	- 60 -
Table 31: Network complexity for different income categories, TM decision only.	- 61 -
Table 32: χ^2 -test for correlation between SL habit and income.	- 61 -

Table 33: χ^2 -test for correlation between TM habit and income.	- 61 -
Table 34: χ^2 -test for correlation between SL habit and occupation.	- 62 -
Table 35: χ^2 -test for correlation between TM habit and occupation.	- 62 -
Table 36: Network complexity for different distances from the centre, TM only.	- 63 -
Table 37: Network complexity of TM decision for different car use categories.	- 63 -
Table 38: Network complexity for different categories of fun shopping frequency.	- 64 -
Table 39: Node types SL decision.	- 65 -
Table 40: Node types TM decision.	- 65 -
Table 41: Number of SL contextual variables when starting from a habit or not.	- 66 -
Table 42: Number of SL evaluative variables when starting from a habit or not.	- 66 -
Table 43: Number of SL instrumental variables when starting from a habit or not.	- 66 -
Table 44: Number of TM contextual variables when starting from a habit or not.	- 66 -
Table 45: Number of TM evaluative variables when starting from a habit or not.	- 66 -
Table 46: Number of TM instrumental variables when starting from a habit or not.	- 67 -
Table 47: Number of SL contextual variables by decision order.	- 67 -
Table 48: Number of SL evaluative variables by decision order.	- 68 -
Table 49: Number of SL instrumental variables by decision order.	- 68 -
Table 50: Number of TM contextual variables by decision order.	- 68 -
Table 51: Number of TM evaluative variables by decision order.	- 68 -
Table 52: Number of TM instrumental variables by decision order.	- 69 -
Table 53: Contextual variables for the SL decision for different education levels.	- 70 -
Table 54: Evaluative variables for the SL decision for different education levels.	- 70 -
Table 55: Instrumental variables for the SL decision for different education levels.	- 70 -
Table 56: Contextual variables for the TM decision for different education levels.	- 70 -
Table 57: Evaluative variables for the TM decision for different education levels.	- 71 -
Table 58: Instrumental variables for the TM decision for different education levels.	- 71 -
Table 59: Frequent itemsets SL decision (normally).	- 87 -
Table 60: Frequent itemsets SL decision (with context).	- 88 -
Table 61: Frequent itemsets TM decision (normally).	- 89 -
Table 62: Frequent itemsets TM decision (with context).	- 89 -
Table 63: Frequent itemsets SL decision in different scenarios (normally).	- 92 -
Table 64: Frequent itemsets SL decision in different scenarios (context).	- 93 -
Table 65: Frequent itemsets TM decision in different scenarios (normally).	- 94 -
Table 66: Frequent itemsets TM decision in different scenarios (context).	- 95 -
Table 67: Frequent itemsets SL decision starting from a habit or not (context).	- 98 -

Table 68: Frequent itemsets SL decision starting from a habit or not (normally).	- 99 -
Table 69: Frequent itemsets TM decision starting from a habit or not (normally).	- 100 -
Table 70: Frequent itemsets TM decision starting from a habit or not (context).	- 101 -
Table 71: Frequent itemsets SL decision for different genders (normally).	- 104 -
Table 72: Frequent itemsets SL decision for different genders (contextual).	- 105 -
Table 73: Frequent itemsets TM decision for different genders (normally).	- 106 -
Table 74: Frequent itemsets TM decision for different genders (context).	- 106 -
Table 75: Frequent itemsets SL decision for different age categories (normally).	- 108 -
Table 76: Frequent itemsets SL decision for different age categories (context).	- 109 -
Table 77: Frequent itemsets TM decision for different age categories (normally).	- 111 -
Table 78: Frequent itemsets TM decision for different age categories (context).	- 112 -
Table 79: Frequent itemsets SL decision for different education levels (normally).	- 115 -
Table 80: Frequent itemsets SL decision for different education levels (context).	- 116 -
Table 81: Frequent itemsets TM decision for different education levels (normally).	- 117 -
Table 82: Frequent itemsets TM decision for different education levels (context).	- 118 -
Table 83: Frequent itemsets SL decision for different income levels (normally).	- 120 -
Table 84: Frequent itemsets SL decision for different income levels (context).	- 121 -
Table 85: Frequent itemsets TM decision for different income levels (normally).	- 122 -
Table 86: Frequent itemsets TM decision for different income levels (context).	- 124 -
Table 87: Frequent itemsets TM for different distances to the centre (normally).	- 126 -
Table 88: Frequent itemsets TM for different distances to the centre (context).	- 127 -

1 Introduction

Since the 1970's, there has been a quasi linear growth in the yearly number of vehicle kilometers travelled (European Commission, 2001). Even though most people agree that the improved mobility of the last decades has had many benefits to economy and society (Tu, 2008), both policy makers and citizens are becoming more and more aware of the negative side effects of abundant car use. Even though traffic safety is steadily improving, road accidents remain one of the most important causes of death for young people in developed countries (Evans, 2004). Although vehicles are getting more fuel efficient and less polluting, emission impacts on human health and on the environment are still immense (Beckx, 2009). Traffic jams result in millions of hours of time loss, corresponding to an economic cost of approximately 114 million euro in 2002 (Logghe & Vanhove, 2004; Tampère, 2004). Because of these problems, there is a need to accomplish a substantial shift towards more sustainable mobility behavior.

It appears that most of the increase in the number of vehicle kilometers driven in Flanders in the last decade is caused by passenger travel, not by freight traffic. Passenger travel by car has increased by 30 percent since 2001, while freight traffic by road has only risen by 5 percent in this time period. This increase in passenger travel is mainly caused by an increase in leisure trips, like fun shopping, of which the impact is often underestimated (Crevits, 2010; Het Nieuwsblad, 2010). The increasing importance and number of leisure trips is not only noticeable in Flanders, but also in many other developed countries and regions, and the trend has been pointed out in international scientific literature before (e.g. Kiiskilä & Kalenoja, 2001; Schlich, Schönfelder, Hanson, & Axhausen, 2004).

Especially in city centers, abundant (car) mobility is very undesirable because a lot of people are exposed to its numerous negative side effects. Emissions that are emitted in a city centre are inhaled by more people, causing negative health effects (Beckx, 2009). Also the noise and smell caused by the vehicles will hinder more people. Cars also take up a lot of public space, which is valuable in a city centre and could be put to better use. The presence of cars also causes a devaluation of the city view (Miermans, 2005).

Because of these problems related to car mobility, and because most shopping trips are directed towards the city centers, a shift towards more sustainable fun shopping behavior is desirable. In order to encourage more sustainable leisure shopping behavior, some Travel Demand Management (TDM) measures have already been implemented in the past (Kusumastuti, Hannes, Janssens, Wets, Dellaert, & Arentze 2009a). A TDM measure is basically any measure that aims to reduce travel demand, or to redistribute the demand in space, in time or by transport mode in order to reduce its negative impacts (Chen & Miles, 1999). A well-known example is the London congestion charge system, where cars entering the city centre are charged with a tribute, or the access control system in Barcelona, where environmentally sensitive areas are only accessible to authorized vehicles. Examples in Hasselt, the city in which this research is conducted, are for instance the construction of bus lanes, the implementation of parking restricting measures and the introduction of car free zones.

TDM measures influence the features that characterize the different travel modes (Loukopoulos, Jakobssen, Gärling, Schneider, & Fujii, 2004). That is why TDM measures can be implemented more effectively if these policies are aimed at contextual, evaluative and instrumental aspects that have a strong influence on people's decision making. This means that travel choices should be studied at a disaggregate level, as the outcome of each individual's decision process (Kusumastuti et al., 2009a).

Rational decision making theory states that a decision maker activates a complex and deliberative cognitive process to try to come up with the best possible solution when he is faced with a new or infrequently occurring decision problem (Kusumastuti et al., n.d.). In this decision process, different considerations are linked by the decision maker by means of causal relations (Kusumastuti, Hannes, Janssens, Wets, & Dellaert, 2010). This way, a temporary mental representation of the decision problem is created in which the decision maker details relevant attributes of the different alternatives and judges their subjective values, attractiveness or suitability (Dellaert, Arentze, & Timmermans, 2008; Kusumastuti et al., 2009a).

This master thesis research uses the Causal Network Elicitation Technique (CNET) protocol to study individuals' decision making behavior. The CNET protocol is a technique to research deliberate decision making from a descriptive point of view. It focuses on the mental representation of the decision problem, and allows to model the obtained data as

a decision network (e.g. a Bayesian Belief Network) (Kusumastuti et al., 2009a). Originally, the CNET protocol was a qualitative semi-structured face-to-face interview technique that has been developed recently at Eindhoven University of Technology. The CNET interview protocol elicits respondents considerations and the links between them by asking pre-defined questions, and codes the answers using a pre-coded list of variables. Later, the CNET card game technique was developed by Kusumastuti et al. (2009a), which differs from the interview protocol because it does not require respondents to spontaneously recall their considerations, but makes use of visual cues by presenting the possible variables to the respondents and asking them which aspects are important for their decision. In this master thesis research, the card game technique is translated to a dynamic computer-based survey.

The main research question in this master thesis is as follows: *"What are individuals' motivations and reasons behind their decisions related to the transport mode choice and shopping location choice in leisure shopping?"*. Related subquestions are: *"What considerations and associations are most prevalent?"*, *"Do patterns differ among different socio-demographic groups (e.g. differences among age categories, between men and women, between lower educated and higher educated,...)?"*, *"What are possible explanations for differences that appear?"* and *"What is the impact of these findings for policy makers?"*. To answer these questions, mental representation data were gathered from 221 respondents who live in the outskirts of the city centre of Hasselt.

The remainder of this report is structured as follows: in section 2, the theoretical background is presented, explaining human decision making and the CNET protocol; in the third section, the development of the survey is explained in more detail; in the fourth section, the sample gathering is described, as well as the socio-demographic and mobility characteristics of the sample; and in the fifth section, the data are analyzed. The network complexity of different socio-demographic groups is compared making use of significance testing, it is investigated which variables are elicited by most respondents, and association rules are analyzed. In the final section, the most important conclusions of this research are presented, policy impacts are discussed, a critical reflection is made and recommendations for further research are presented.

2 Background

In this section, the theoretical background is provided to understand the rest of this master thesis. In section 2.1, decision making in general and mental representation in particular are explained. Section 2.2 explains more about the general structure of the CNET protocol. Finally, section 2.3 goes into detail about the different elicitation techniques of the CNET protocol.

2.1 Decision making and mental representation

One of the first theories that tried to explain people's decision making process is rational choice theory. It assumes that people calculate the likely costs and benefits of any action before deciding what to do (Scott, 2000). This means that a decision maker activates a complex and deliberative cognitive process to try to come up with the best possible solution when he is faced with a new or infrequently occurring decision problem (Kusumastuti et al., n.d.). Rational choice theory assumes an individual is a "homo economicus". That is, an individual who is fully informed, is able to process all information in a conscious and accurate way, and is entirely self-interested. The latter means that the individual for instance does not care about aspects like fairness or reciprocity (Henrich et al., 2001; Kroneberg, 2006). The decision maker is faced with a set of alternative choice options, of which he is assumed to choose the alternative that yields the highest expected utility (Doyle, 1998; Hannes, Janssens, & Wets, 2009a; Hannes, Kusumastuti, Janssens, Vanhoof, Wets, & Espinosa, 2009b).

Although the theory offers valuable insights, it is also often criticized because of its unrealistic assumptions. People do not always make a rational choice, but make decisions based on emotions as well. For instance, someone might buy a sports car, while a roomy family car would be much better suited for his family situation, and less costly. Furthermore, most people are not entirely self-interested either. For instance, suppose an individual is offered a choice between receiving 500 euro for himself, and nothing for his friend, or his friend and himself each receiving 499 euro. The fully self-interested individual will choose the 500 euro, because it yields him 1 additional euro compared to the alternative choice. However, in reality, many people will kindly choose the scenario in which both themselves and their friend receive 499 euro. And finally, it is highly

unrealistic to assume individuals are fully informed about all decisions, because in all decisions at least some information is unavailable or only obtainable at a high cost. For instance, one of the main risks of buying a second-hand car is finding out later that you have bought a car with hidden flaws you were unaware of at the time of the decision (Myers, 2007).

So, it can be seen that people rarely make fully rational and objective decisions because of cognitive limitations and uncertainty. Rather, people's decision making process can be seen as a heuristic process. The core of this heuristic decision making theory is that decision making under uncertainty often rests on a limited number of simplifying heuristics, rather than extensive algorithmic processing (Gilovich, Griffin, & Kahneman, 2002). Heuristics are efficient rules of thumb of the type if-then(-else) to get to a decision relatively easily, and they are based on experiences and knowledge. They allow people to have an idea about how to weigh the different choice alternatives and their characteristics, but they do not guarantee that the optimal decision is made because the underlying reasoning or knowledge can be incomplete or biased (Everson & Hammer, 2005). Especially when the same decisions are repeated multiple times, like in daily-travel for instance, people do not bother to go through the whole complex decision procedure all the time. Thus, heuristic decisions are in this case commonly used to reduce the mental effort that is required for weighting and judging the possible decision alternatives (Kusumastuti et al., 2010).

However, for new or occasional decisions, it is possible that people do not have ready-made heuristics for all possible occurring contexts in the decision environment. In this case, rational decision making can be activated. Research shows that, in case of a new or infrequently occurring decision problem, the decision maker activates a complex and deliberative cognitive process to try to make the best decision (Kusumastuti et al., n.d.). In this decision process, different considerations are linked by the decision maker by means of causal relations (Kusumastuti et al., 2010). This way, a temporary mental representation of the decision problem is created in which the decision maker details relevant attributes of the different alternatives and judges their subjective values, attractiveness or suitability (Dellaert et al., 2008; Kusumastuti et al., 2009a).

In addition to rational and heuristic decision-making, there is also habitual behavior. Habits are a form of automatic response that develop as people repeat actions in stable

circumstances (Verplanken & Wood, 2006). When initially performing an action, people consciously decide what to do and how to do it in order to achieve certain outcomes, and avoid others. As people repeat these actions, the conscious decision making process recedes, and the actions come to be cued by the environment. More specifically, habit formation involves the creation of an association in memory between the action and stable features of the context in which they are performed. This means that recurring contextual characteristics come to trigger habitual responses directly, without any input from people's intentions or decisions to act (Verplanken & Wood, 2006).

Of course, there is a large twilight zone between these extremes of a fully conscious and deliberate decision, and a fully automated habitual response. Fun shopping also belongs to this twilight zone. For most people, fun shopping is not an activity that is executed daily, or even weekly. Furthermore, it is subject to a changing context: an interest in a specific product, the weather, having a companion with you or not, the available time to execute the activity... Some of these features will differ from time to time. Therefore, fun shopping related decisions will not be fully automated for most people. On the other hand, since fun shopping is executed every so often, it can be expected that at least some aspects of fun shopping related decisions will become automated to some degree. That is why some respondents' mental representation about fun shopping decisions may contain both elements of conscious deliberation and automated scripts. Scripts are in fact fixed, context-specific rules or heuristics, in which no alternatives are perceived (Hannes et al., 2009a). For instance, an individual could always choose to go fun shopping by car in case it rains, which is a script, but make a careful deliberation between car and bike in case it is sunny, based on the time he has available, whether he has a companion or not and the number of shopping bags he expects to take home. This is in line with Kroneberg's (2006) finding that two processes manipulate rational decision making. The first process is that the situation or context can activate certain mental models that have a significant impact on subsequent behavior. The second is that people can make a decision based on different degrees of rationality, sometimes engaging in a systematic consideration of the consequences of a decision, but sometimes automatically following a set of predefined rules.

The intention of this research is to discover the content of the mental representation for the transport mode and shopping location decision in fun shopping activities. It tries to

find out what variables are important in respondents' mental representation, and what associations are often made.

2.2 The CNET protocol

The CNET protocol is a method to gather an individual's context-specific mental representation that captures the value requirements, instruments of the shopping trip's decision alternatives, relevant contextual factors and the causal relationships between these variables (Dellaert et al., 2008). It is a relatively new technique to structure and represent an individual's mental representation of a decision-making process, that has recently been developed at Eindhoven University of Technology. However, although it is a new technique, it is partly based on existing techniques. At some points, there are similarities with the cognitive mapping technique, which is based on the Personal Construct Model of Kelly (1995), and the Laddering Technique of Clarke et al. (2001) that are often used in management research (op. cit.: den Hartog, 2004, pp. 37-38).

Kelly (1995) supposes that individuals develop hypotheses or images about reality, based on the structure of their existing personal beliefs, and the evidence they get from their perception of the environment. Based on these experiences, people estimate the chance that a particular consequence of their behavior will actually occur. Based on these estimations they develop expectancies about the way the world works, and they constantly check these expectations with the outcomes of their behavior. This way, decision making processes are led by the way people anticipate events. However, this Personal Construct Model is an oversimplified representation of reality (den Hartog, 2004).

In Cognitive Mapping, respondents' knowledge is made accessible by means of a visual model. A cognitive map consists of a number of concepts and their cause-and-effect relations. They are graphically represented by concepts that are linked by arrows. To construct the cognitive maps, the researcher will help respondents express their knowledge in such a way that a useable model arises (den Hartog, 2004).

Another approach is the Laddering Technique, that looks for profound meanings of characteristics and relations between the characteristics under investigation. The

technique aims to discover means-goal chains, where you start from a certain characteristic, and climb up to the consequences of these characteristics and the values behind these consequences. Climbing to higher values occurs by means of why-questions (den Hartog, 2004).

In the CNET protocol, four types of variables are distinguished: decision variables, contextual variables, instrumental variables and evaluative variables (Kusumastuti, Hannes, Janssens, Wets, & Dellaert, 2009b).

The choice alternatives represent the action alternatives or options that can be chosen by the individual (Arentze, Dellaert, & Timmermans, 2008). This choice set is defined before the individual takes the decision. Choice alternatives are represented in decision variables. These are the variables the decision maker has to decide about. The attractiveness of the choice alternatives in the choice set depends on the nature of the task, the attributes or characteristics of the alternatives (instrumental variables) and environmental factors that can influence the individual's choice (contextual variables). The problem gets more complex when certain activities require multiple interrelated decisions (Kusumastuti et al., 2009b).

The different choice alternatives all have different characteristics or attributes, leading to different consequences. The characteristics of the alternatives are considerations that could play a part for the respondents in certain decisions. These considerations are called instrumental variables (den Hartog, 2004). Instrumental aspects can be observed and operated by the decision maker himself (Kusumastuti et al., 2009a).

Contextual variables refer to given circumstances, situations and constraints in the decision environment that influence the outcome of a decision, but that cannot be controlled by the decision maker himself (Arentze et al., 2008; Kusumastuti et al., n.d.). Contextual variables can be for instance natural forces, capability constraints, coupling constraints and authority constraints. The weather is an example of a natural force. Capability constraints relate to human's biological restrictions, like the need to eat and sleep; coupling constraints are imposed by the activity schedule of others, for instance because certain activities require meeting people at the same time and place; and authority constraints are related to regulations of external institutions, like opening hours of shops (Hägerstrand, 1970; Kusumastuti et al., 2009a).

Evaluative variables differ from contextual and instrumental variables because their judgment is always subjective, while the judgment of contextual and instrumental variables can be both subjective or objective. Evaluative variables are directly related to utilities (den Hartog, 2004). They describe the impact of the state of the contextual and instrumental variables on the more fundamental physiological and psychological needs for the decision maker's well-being (Dellaert et al., 2008). There is typically a many-to-one relation between instrumental variables and evaluative variables (den Hartog, 2004).

The last elements are the causal links between the contextual, instrumental and evaluative variables to get to a network. The causal network represents individual's beliefs about how different variables activate the consideration of other decision-related variables (Kusumastuti et al., 2009b).

The smallest building block of a decision network, that represents the respondent's mental representation of the decision process, is called a "cognitive subset". A cognitive subset is a set consisting of a contextual variable, an evaluative variable and an instrumental variable (Kusumastuti et al., 2009a). However, in frequently repeated travel decisions, habit formation can occur (Verplanken & Wood, 2006). Therefore, Kusumastuti et al. (n.d.) argue there is a need to register another type of cognitive subset, that is considered in all circumstances; i.e. normally (habit) – value – instrument.

The links between the different variables are shown in an example in Figure 1. It can be seen that both decisions are interconnected, since they both contribute to the total utility gained by the individual. In the example, the transport mode mainly depends on the weather conditions (contextual aspect). Mind that there is no causal connection between a decision variable and a contextual variable, since the decision has no influence on the context (den Hartog, 2004). The weather is an important consideration because different vehicles offer a different protection (shelter) against bad weather (instrumental aspect), and because the individual pursues the benefit of having comfort (evaluative aspect). As a result, the cognitive subset "weather – shelter – comfort" is registered in the mental representation of the transport mode choice. The same line of thought applies to the cognitive subsets of the shopping location choice. Note that, in this example, the two cognitive subsets relate to the same evaluative aspect, efficiency. This is an illustration of

the many-to-one relation between the instrumental variables and the evaluative variables (Kusumastuti et al., n.d.).

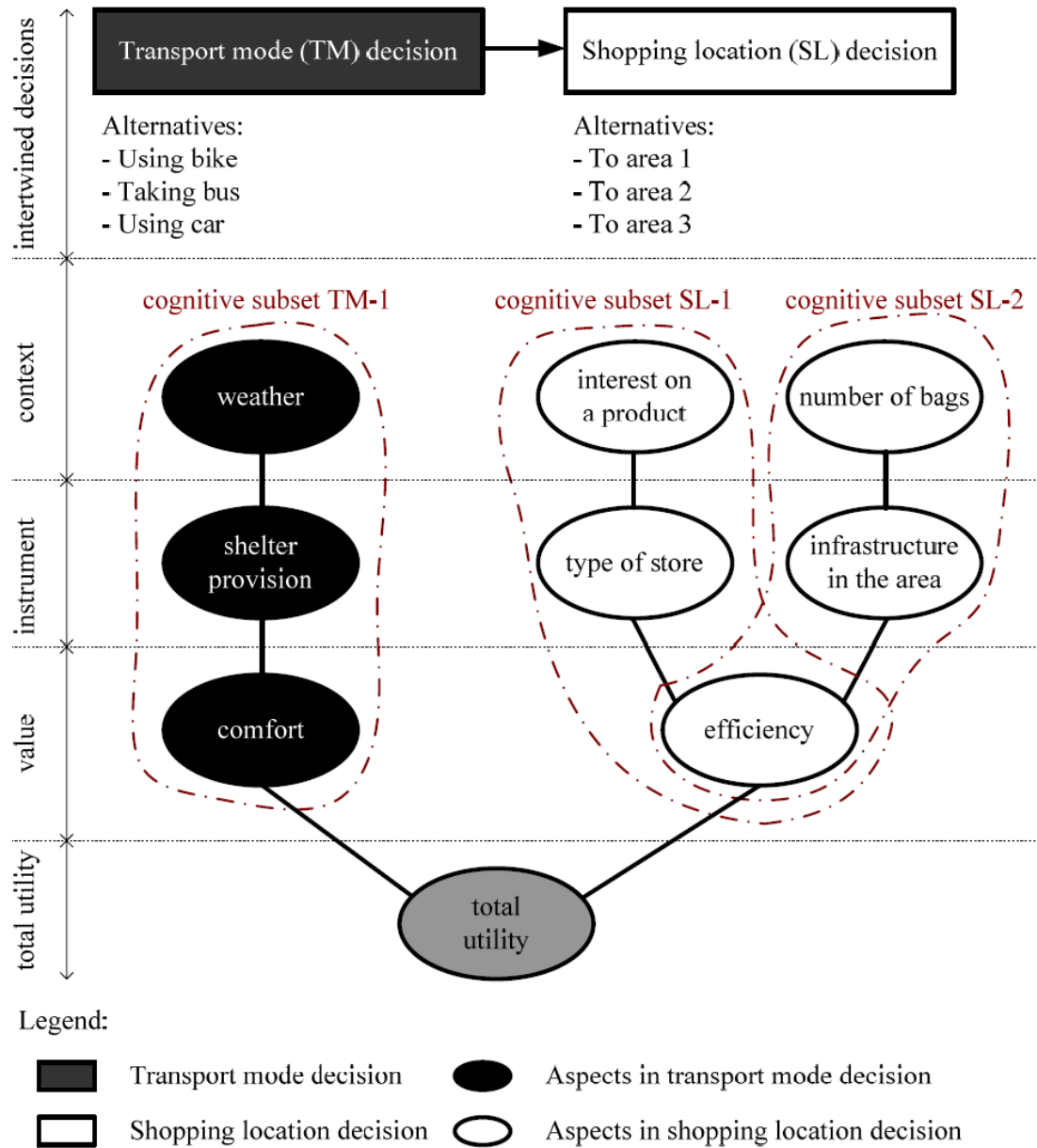


Figure 1: Graphical illustration of the different variables.
Source: Kusumastuti et al. (n.d.).

The different types of variables can be combined to form a decision network (den Hartog, 2004). Decision networks are structures, containing nodes and arcs to connect the nodes, that are used to model decision-making processes in the presence of uncertainty

(Korb & Nicholson, 2003). In computational decision network representation, the individual then attaches probabilities to the different states of these variables, and weights to the different evaluative variables that are relevant for the decision. Based on these weights, the partial utilities of the evaluative variables are joined together to an overall utility. This overall utility is decisive for the individual's eventual decision. The individual will pick the alternative that yields the highest overall utility (Kusumastuti et al., 2009a).

Hence, to construct the mental model of an individual in the form of a decision network, the following information has to be gathered in four steps (den Hartog, 2004):

1. The order in which the different decisions are taken
2. The cognitive subsets that are present in the respondent's decision network (Kusumastuti et al., 2009b)
3. The Conditional Probability Table that is related to the variable nodes
4. The relative weight of the evaluative variables that are mentioned during the elicitation process

The main focus of this master thesis research will be on step 2, the content of respondents' decision network. Analyzing the quantitative modeling aspects is beyond the scope of this study. That is why the final two steps will not be explained into detail. Also modeling the gathered data in a decision network is not dealt with in this thesis. Readers that are interested in the analysis of the conditional probabilities, the utilities and their weights, or in modeling respondents' mental representation in a decision network are advised to read the forthcoming paper of Kusumastuti et al. (n.d.).

2.3 Elicitation techniques

In this section, the different techniques to elicit respondents' mental representation are explained. These are varying forms of the CNET protocol. First, the CNET interview protocol is explained. Second, the CNET card game technique is clarified. Next, a comparison between both techniques is made. And finally, the computer-based CNET survey is explained.

2.3.1 CNET interview protocol

Originally, the CNET was developed as a semi-structured interview protocol. In the CNET interview protocol, the interviewer asks the respondent what his considerations are when making the decision of interest (den Hartog, 2004). The respondent's answers are checked with a pre-defined list of variables. The interviewer looks for the variable in the list that is closest to the respondent's answer. Ideally, all possible contextual, evaluative and instrumental variables that could be present in respondents' mental representation of the decision of interest are in this list. The list is formulated based on an extensive literature review, and should be fine-tuned and completed based on pilot research. The interview protocol offers the flexibility to add additional variables to the list in case none of the variables in the list is appropriate (Arentze et al., 2008). One of the main advantages of the pre-defined list of variables is that it limits the subjective interpretation, restricting the variations in interpretation between different interviewers to a minimum (De Ceunynck, Kusumastuti, Hannes, Janssens, & Wets, n.d.; den Hartog, 2004).

In the interview protocol, the interviewer starts by asking the respondent: "*What are your considerations when making this choice?*". The protocol provides a subsequent question for each variable type that is mentioned by the respondent, which will result in a linked variable of a different type. If the respondent mentions an instrumental variable, the interviewer asks: "*Why does this consideration influence your choice?*". In case the level of the evaluative variables is still not reached after this first why-question, the question has to be repeated until the respondent elicits an evaluative variable. When the respondent mentions an evaluative variable first, it has to be checked how this evaluative variable is contributory to a certain decision. That is why the following continuation question is asked: "*How is this consideration influenced by your choice?*". This question will lead to the identification of instrumental variables and/or contextual variables that will influence the evaluative variable. In case the respondent mentions a contextual variable, it is necessary to find out which instrumental and evaluative variables it influences. A why-question has to be asked to find these elements that are influenced by the contextual variable: "*Why does this context influence your choice?*". In case this results in the elicitation of an instrumental variable, the why-question is repeated until an evaluative variable is reached (den Hartog, 2004).

As soon as the entire cognitive subset is formed, the respondent is asked whether there are still other considerations that affect his choice. The respondent is supposed to mention all aspects that influence his choice. If the respondent cannot come up with additional aspects that influence his decision, the elicitation process for that decision is completed (Kusumastuti et al., 2009a).

2.3.2 CNET card game technique

Based on pilot studies using the CNET interview protocol, a new technique that makes use of the same structures as the interview protocol was developed by Kusumastuti et al. (2009a). The CNET card game technique differs from the interview protocol because it does not require respondents to spontaneously recall their relevant considerations for the decision. In stead, all possible variables are written down on cards (Kusumastuti et al., 2009a).

The cards are shown to the respondent one by one, and for each variable, the respondent is asked whether it is an important consideration to him in that decision or not. First, all contextual variables are shown to the respondent, who classifies them as either an important consideration or not. Then, for each contextual variable that the respondent considers to be important, the respondent is presented with cards that contain evaluative and instrumental variables. Respondents are asked to link these variables to form cognitive subsets. So, the CNET card game technique makes use of written cues in stead of spontaneous recalling (Kusumastuti et al., 2009a).

2.3.3 Comparison CNET interview vs. CNET card game

It is important to keep in mind that the choice of the method will have an impact on the results. Since respondents are asked questions related to their past behavior, an important remark is related to the retrieval of individuals' episodic memory during the interview. Cognitive research shows that an individual is likely to assess his perceived effort against the accuracy of the stored information: the more important an event is to an individual, the more he is able to remember it correctly. The opposite is also true: when an event is less significant, it is harder to recall (Kusumastuti et al., 2009a). This implies that, the more important the decision is to the respondent, the more likely it is

that he will be able to recall important elements in the decision making process. However, choices about a transport mode or a shopping location are only of moderate importance in everyday life. This indicates that it is likely that respondents will not be able to recall all important considerations related to these decisions.

In order to activate the correct episodic memory and to increase the accuracy of the responses, researchers can apply manipulation strategies, e.g. by providing some cues in the questions (Kusumastuti et al., 2009a). With regard to this, it has been indicated that aided recalls (i.e. closed questions like in the card game method) generate better levels of accuracy than unaided recalls (i.e. open-ended questions like in the interview method) (Cannell, Oksenberg, & Converse, 1979), which is an important advantage of the CNET card game technique. One of the most important reasons for this is that fun shopping related decisions are likely to be, at least to some extent, a habit, as was indicated in section 2.1. So even in case the respondent makes a conscious deliberation, there will still be some degree of automaticity in the decision making process. According to Palmeri (2001), breaking up an automated complex action into component parts requires deliberate thought. That is why it is very likely that, when being asked to break down this action in small components, crucial elements will be forgotten. So, when respondents are asked to recall their considerations for fun shopping related decisions spontaneously, like in the interview protocol, it is very likely that they will forget to mention aspects that are in fact very important to their decision. Providing written cues avoids this problem, and provides better results (Palmeri, 2001).

To capture all possible considerations, the pre-coded list of variables should be made as extensive as possible. This can be cumbersome for a researcher, since he has to conduct an extensive literature study to formulate the list, and pilot studies should be carried out to refine it. Furthermore, the closed question format might not be flexible enough to capture new possible aspects from the respondent that are not represented in the pre-defined list. On the contrary, in the interview protocol, respondents are not shown the list of variables, which makes it more likely that they will spontaneously come up with new variables that are not considered before by the researcher. Another disadvantage of the closed method is the possibility to introduce some bias due to the presentation of pre-coded variables to the respondents and the presence of the interviewer: there is a risk of giving socially desirable responses. This means that the respondent will adjust his answers to make a better impression on the interviewer. This risk is also present in the

interview protocol, but to a lesser degree. For instance, when the respondent is asked in the card game technique whether he considers the variable "environmental concern", he is quite likely to say he does, because he will think that saying he is not concerned about the environment will give a negative impression to the interviewer. However, it is less likely that he would spontaneously mention it as a consideration during the interview protocol (Kusumastuti et al., 2009a).

Since the retrieval process can be very demanding and difficult for respondents, there is a possibility that a respondent feels pressured to give an answer, because he might find it humiliating if he cannot come up with enough considerations. Another risk is that he could also just reply anything that comes to his mind, just to satisfy the interviewer and try to keep the interview as short as possible.

One final point of attention is the preference of the respondents. Kusumastuti et al. (2009a) asked their respondents which of both techniques they prefer. Respondents stated a distinct preference for the card game technique.

Considering the advantages and disadvantages of each elicitation method, a researcher should be well aware of the impact of the methods used on research outcomes. Which method to use depends on the aim of the study.

2.3.4 Computer-based survey

Based on experiences with the CNET interview protocol and the card game technique, a computer-based CNET survey (CB-CNET) was developed. As indicated in the previous section, the CNET card game technique has some important advantages over the CNET interview protocol: written cues provide better results (Cannell et al., 1979; Palmeri, 2001), the card game technique lays a lower burden to the respondents and respondents like it better than the interview technique (Kusumastuti et al., 2009a). That is why the CB-CNET survey is based on the card game technique.

A computer-based survey has many advantages over a face-to-face survey (Boardman, Greenberg, Vining, & Weimer, 2005):

- The marginal costs of a computer-based survey are low. Once the survey is developed, which corresponds with a high initial fixed cost, the costs of administering an additional survey are low. This makes it well-suited for large data-gatherings, like this research.
- Computer-based surveys can store the survey data immediately in a database, saving processing time and costs.
- Computer-based surveys avoid interviewer biases.

However, a computer-based survey also has a downside: not everyone is able to work with a computer. This means that some socio-demographic groups, like people who are less able to work with a computer, are likely to be underrepresented (e.g. elderly).

The structure of the CB-CNET survey is explained into more detail in the next chapter.

3 Survey development

In this chapter, the CB-CNET survey is explained in detail. The four phases of the survey protocol are highlighted.

This survey is the result of a joined project with multiple contributors. In this project, the conceptual framework was developed first, based on an extensive literature review and pilot studies. This resulted in a first draft of the survey software. Then, an iterative process took place, in which the software was systematically improved, both with respect to the content and the background code. The software development occurred in English since two contributors to the project are English-speaking. As soon as the software was finalized, it was translated to Dutch, the mother tongue of the respondents. Then, the survey was administered in small group sessions (see section 4.1 for more detail about the group sessions). Finally, after the data gathering, a database was built to store the survey data.

The conceptual framework of the survey was developed by Diana Kusumastuti and Els Hannes. The software was written in the programming language Java by Maikel León Espinosa. Dr. Benoît Depaire helped debugging the software, and built the database. Prof. dr. ir. Benedict G.C. Dellaert, prof. dr. Geert Wets and prof. dr. Davy Janssens are responsible for creating the framework in which this research could take place.

My own contributions to this project are the following:

- I assisted in the testing and improving of the survey in subsequent versions
- I translated the English survey software to Dutch
- I gathered most of the sample, and I also dealt with all communication with respondents (more information about the sample gathering can be found in section 4.1)
- I managed the group sessions, together with Els Hannes

The four stages in the survey are shown in the following figure. The first part is the gathering of the personal information, that will be explained in detail in section 3.1. In section 3.2, the research setting and scenario is discussed. Section 3.3 explains how the

decision order and the mental representation are elicited. And finally, section 3.4 will briefly discussed the parameter estimation.

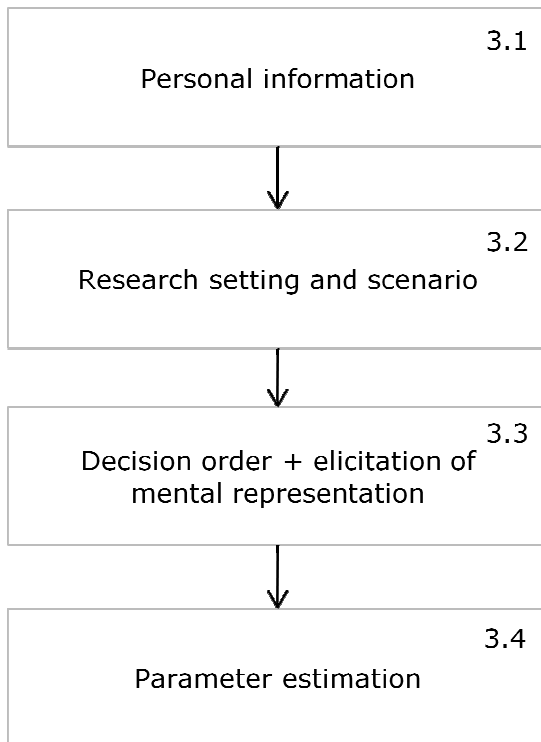


Figure 2: Summary of the elicitation stages in the CB-CNET survey.
Source: Kusumastuti et al. (n.d.)

3.1 Personal information

In the first part of the survey, respondents are asked for their personal information. It concerns basic socio-demographic characteristics like age, place of residence, gender, income, education... and some behavioral characteristics like for instance their annual mileage, how often they use particular transport modes to go to the city centre, etc.

This information will be used for two purposes. First, it is used to check the representativeness of the sample. More details about this are provided in section 4.1. Later, it is also used in the analyses of the mental representation to see whether different socio-demographic groups have a different mental representation for the decision problem. These analyses can be found in chapter 5.

3.2 Research setting and scenario

Next, the research setting is explained to the respondent. First, one of two scenarios is randomly shown to the respondent, either a time pressure scenario or a no time pressure scenario. These scenarios are chosen because it is expected that people who experience time pressure, make decisions in a faster, less-considered way than people who do not experience time pressure.

Throughout the survey, a short description of this scenario is shown at the left side of the screen as a reminder. The scenarios are presented in the following figure.

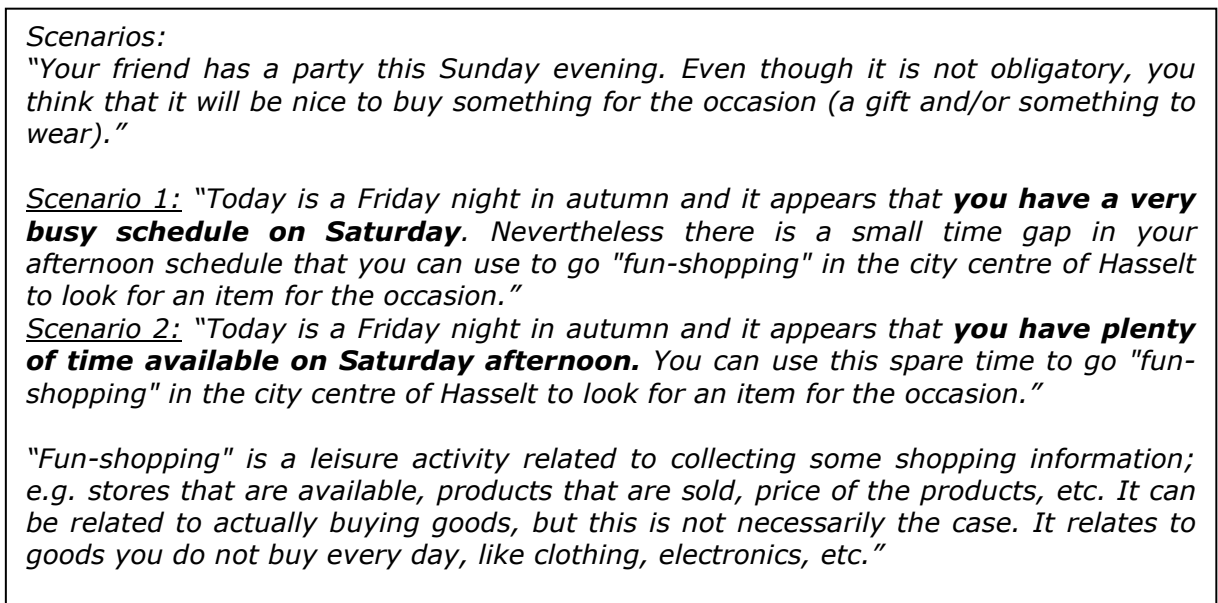


Figure 3: Different scenarios.

Next, respondents are told that they are supposed to give their considerations for two decisions:

- How they go to the city centre: the transport mode (TM) choice
- Where exactly they go to first: the shopping location (SL) choice

Concerning the TM choice, respondents are told that they have to suppose that they have access to a car and a bike in their household. They are also told that they have a bus stop within walking distance, which is the case for all people that live in the environment

of Hasselt as a result of the Decree of Basic Mobility (Van Brempt, 2006). All respondents are recruited from an area of 3-10 km away from the city centre.

Concerning the SL choice, the city centre of Hasselt is subdivided into three zones, as shown in Figure 4 on the next page. The first zone is the main shopping street Koning Albertstraat – Demerstraat. Here, mainly gift shops (e.g. FotoKado, Bozzy,...) and chain stores (e.g. H&M, C&A, Esprit, Zara, Bershka...) are located. Zone 2 is the boutique area, which is mainly characterized by boutiques selling exclusive designer clothing (e.g. Armani, Versace, Delvaux, Burberry, Stijn Helsen,...). Finally, zone 3 is characterized by shopping malls (e.g. MediaMarkt, Albert Gallery).

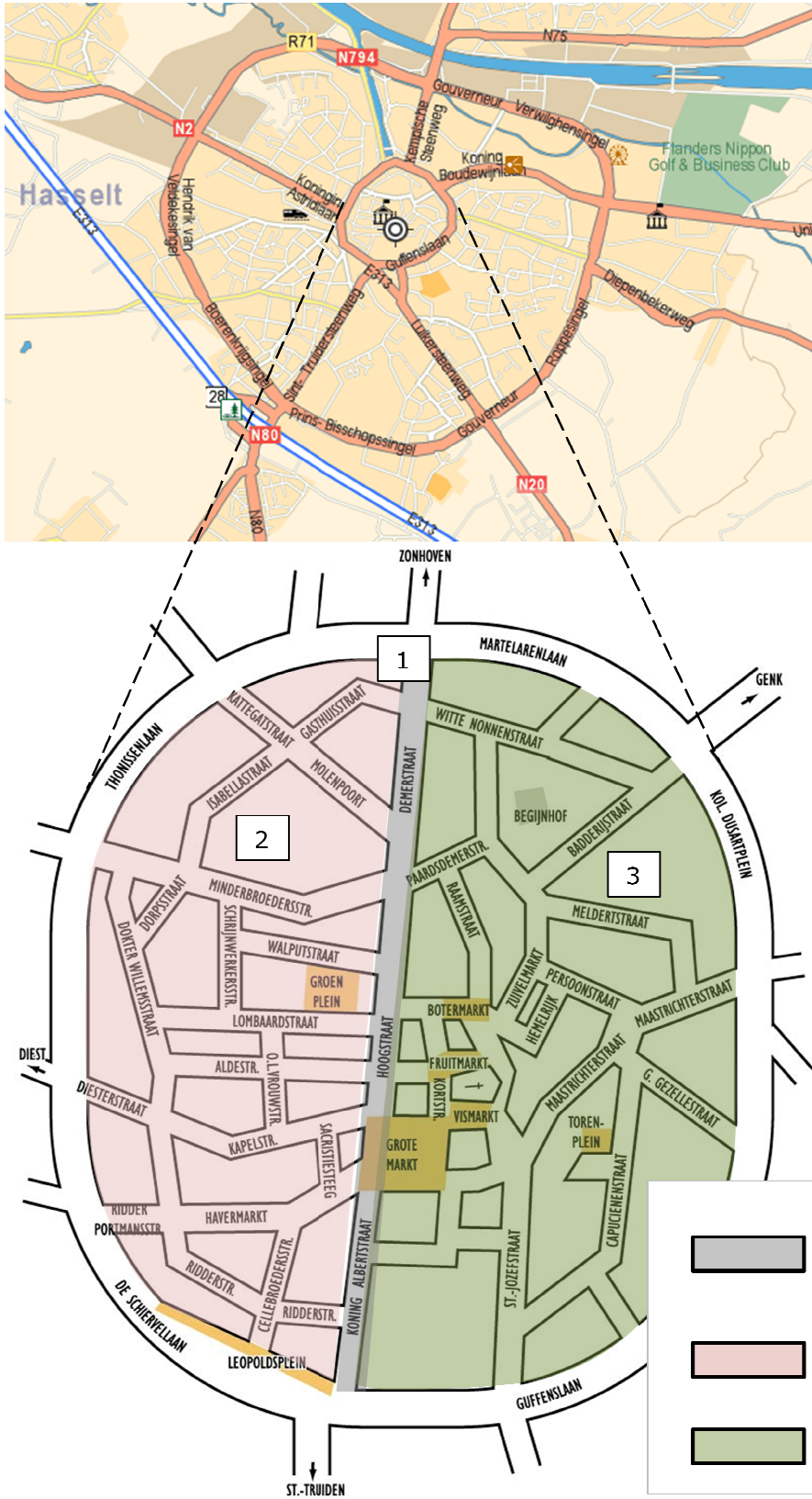


Figure 4: Shopping zones.

3.3 Decision order and elicitation of mental representation

In the next step, respondents are asked which of both decisions they will take first, and which decision second. Then, respondents are asked to indicate whether their decision-making for this decision depends on certain circumstances, indicating heuristic or rational decision-making, or whether this choice can be made spontaneously, which indicates habitual decision-making. This is called the split-elicitation procedure: based on the respondent's answer, different elicitation paths are followed (Kusumastuti et al., n.d.). Both paths are shown in Figure 5 on the next page.

Suppose that a respondent indicates that his TM choice depends on circumstances. Then, revealing these influencing contextual aspects is the first step. For instance, suppose a respondent reasons that he bikes if it is not raining, and takes the car in case he has limited time available. In this case, the respondent will indicate that "precipitation" and "time availability" are contextual aspects that influence his TM choice. Respondents are asked to pick all contexts that have an influence on their TM choice from a predefined list of contextual variables. The list contains a wide variety of contextual aspects, like coupling constraints (i.e. companionship), natural forces (e.g. weather conditions), TDM measures (e.g. bus frequency, bus fares, parking costs...) and other contexts and constraints like time availability, parking space availability etc. (Kusumastuti et al., n.d.). In total, there are 27 contextual variables for the TM decision, and 16 for the SL decision. These lists of contextual variables and their definitions can be found in Annex 2. The predefined variables are chosen and defined based on literature and preliminary studies that made use of the CNET interview protocol and the CNET card game technique (Kusumastuti et al., 2009a, 2009b). To ensure that all respondents have the same interpretation of these variables, the definition of a variable is shown in the interface when respondents pass their mouse on it. Respondents are asked at the start of the survey to limit their choice of contextual variables to the most important ones to reduce the burden that is placed upon them.

Split elicitation procedure [a]

(The example below is an example when the transport mode decision is selected first when ordering the decisions)

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...

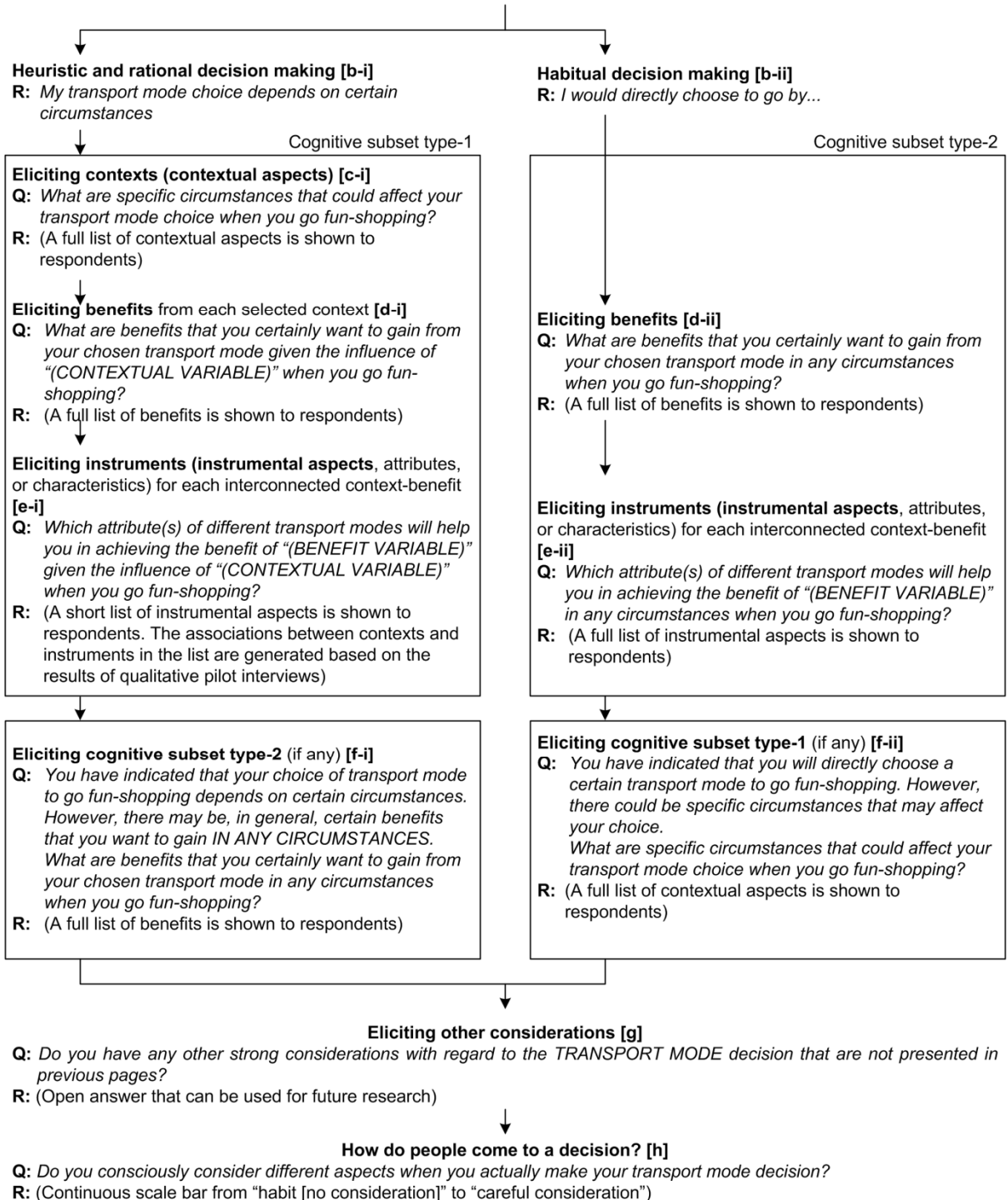


Figure 5: Elicitation of the network structure in the CB-CNET survey. Source: Kusumastuti et al. (n.d.).

Next, respondents are asked to indicate the values that are influenced by each contextual variable. For this, a list of 15 predefined evaluative aspects is shown. This list is the same for both the TM decision and the SL decision, and is also shown in Annex 2. Finally, the cognitive subsets are completed by asking the respondent for the instruments that are related to each selected context-value combination. Here, the interface automatically generates questions depending on the respondent's previous variable selection, because not all instruments can be related to all contexts (for instance, it is obvious that the instrument "shelter provision" has nothing to do with the contextual aspect "time available") (Kusumastuti et al., n.d.). To lower the burden placed on the respondent, irrelevant instrumental aspects are omitted from the list. Which links between contextual variables and instrumental variables are irrelevant was determined based on literature, pilot tests using the interview protocol and the card game technique (Kusumastuti et al., 2009a, 2009b) and common sense.

When the respondent is finished eliciting these cognitive subsets of the type "context - value - instrument", he is asked whether there are still considerations that come to his mind that are considered in any circumstances. These are cognitive subsets of the type "normally - value - instrument".

However, in case the respondent initially points out that he would directly choose a certain TM, regardless of contextual aspects, a different elicitation path is carried out to obtain the respondent's generalized representations from values. In this case, the procedure starts with the elicitation of all pursued values, followed by linking the related instruments. Here, the full list of instruments is shown, containing 25 and 23 variables for the TM and SL choice respectively. These lists can be found in Annex 2 as well. This results in cognitive subsets of the type "normally - value - instrument" (Kusumastuti et al., n.d.).

After the elicitation of these cognitive subsets, the respondent is presented with a list of contextual variables, and has the opportunity to indicate whether there are contextual variables that could influence his decision nevertheless. This stage is not compulsory. Respondents can skip it if there are no contextual variables that influence their decision. In case there are, the respondent is asked to link the relevant evaluative and instrumental aspects to the contextual variable(s).

The elicitation procedure ends with an open-ended question, where respondents are asked whether there are still additional considerations that are relevant for their decision, and that are not presented in the lists. The results of this question can be used as input to complete or improve the list of variables in future research.

3.4 Parameter gathering

The last part of the survey, the parameter estimation, consists of validating the elicited mental representation by asking the respondents' actual choice in different scenarios containing the elicited variables, asking for the probabilities of the different states of the variables and weighting the evaluative variables. These data are required for computational decision networks. However, this is beyond the scope of this research. That is why this chapter will not go into detail about these parts of the survey. Readers who are interested in these steps are referred to Kusumastuti et al. (n.d.). Readers who are interested in the results of these analyses are referred to future papers by Kusumastuti et al.

4 Sample

In this chapter, first, it is explained how the sample was gathered. The snowball sampling technique, which has been used to gather respondents, is explained in general, and its implementation in this research is clarified. In section 4.2, the socio-demographic and mobility-related characteristics of the sample are analyzed into more detail to check the sample's representativeness.

4.1 Sample gathering

Gathering enough respondents was one of the major challenges in this research because of many reasons.

To start with, an important problem was that it would be impracticable to let respondents fill in the survey from their own computer at home. It is unlikely that respondents would fill in a survey of one to two hours attentively and truthfully from their home. This would yield incomplete and/or unreliable data. Therefore, respondents were asked to come to Hasselt University to fill out the survey in small guided group sessions. This ensures that respondents who participate are very motivated to cooperate. An additional advantage of this approach was that it would allow the researchers to provide respondents with personal guidance in case they had questions, or in case any problems would occur. The downside of this approach is of course that the length of the survey in combination with the necessity of making a trip, lays a heavy burden upon the respondents, making many people reluctant to participate. That is why it was decided to offer a gift certificate of 20 euro of a store of the Delhaize Group as an incentive.

Also, respondents had to meet some requirements. They had to be of age (18 or older), be in the possession of a driving license and live outside of the outer ring of Hasselt (R71), but maximum 10 km. from the city centre. These requirements were imposed in order to make it a real life sample, and to recruit a group with a similar choice set available.

To gather the sample of respondents, the snowball sampling method was used. Snowball sampling is a special nonprobability sampling method that is most often used when the

desired sample characteristic is rare (StatPac Inc., 2009). It is a chain referral method where a sample is constructed from a base of initial contacts, who are asked to provide introductions to their associates, who, in turn, are asked to refer to others. This process continues until a sufficiently large sample has been built (Baarda & de Goede, 2001; Wright & Stein, 2005). The rare characteristic we were looking for was a high willingness to cooperate in the research, combined with living in the outskirts of Hasselt.

Snowball sampling is sometimes criticized because it comes at the expense of introducing bias to the sample, because the technique reduces the likelihood that a good cross section is selected from the population (StatPac Inc., 2009; Wright & Stein, 2005). That is why it is important to gather socio-demographic characteristics and to search the database for biases caused by underrepresentation or overrepresentation of certain groups.

Respondents were recruited in a number of ways. The snowball was started by addressing the committee members of associations, sports clubs... that are situated in the area of interest. These people were aimed at because, in general, these people are quite socially committed. Therefore, the chance that they were willing to cooperate in the survey was larger. They were asked whether they were willing to participate themselves, and whether they were willing to forward the message to friends, colleagues, relatives and members of their association. In total, about 550 people committee members were contacted this way.

In addition to the e-mails sent to the committee members of associations, people were also informed about the survey in a number of ways. To start with, some advertisements were placed to announce that Hasselt University was looking for volunteers to participate in the survey. First, researchers placed an announcement in "De Nieuwe Hasselaar", a local magazine that is monthly delivered to all residents of Hasselt. Later, a few very helpful respondents placed an announcement in "Het Belang van Limburg", a newspaper that focuses on inhabitants of the province of Limburg (of which Hasselt is the capital), and in a local school magazine in Alken, a neighboring municipality of Hasselt. Additionally, flyers were placed at a physiotherapist's office in Kermt, one of the formerly independent municipalities of Hasselt.

People who were interested in participating in the survey were asked to send an e-mail with their personal information (name, age, address) to subscribe. Then, the researchers sent them an e-mail with a list of group sessions from which respondents could choose. They were asked to indicate all sessions that would suite them, and also indicate their preference. Based on respondents' availabilities, they were divided among the group sessions. Respondents then received an e-mail, indicating the group session to which they were assigned and a route description. Finally, a reminder of the appointment was sent by e-mail to the respondents 48 hours before the group session.

To gather additional respondents while the group sessions had already started, respondents who seemed to be enthusiastic about the survey during the group sessions were asked whether they knew other people that could be interested in the survey. Also, when sending a reminder to people for a session that had some spaces available, it was indicated that respondents were allowed to bring additional guests (e.g. partner, children, parents,...).

These efforts resulted in a total of 282 people who subscribed to participate in the survey. Of these 282 people, 234 were assigned to a group session. This means that 48 respondents dropped out because they did not provide their availabilities. Out of these 234 respondents who were assigned to a group session, 207 showed up. This is a drop out of 27 respondents that were absent without notification or with a late notification during the day of the group session itself. This drop out was however somewhat balanced because there were also 16 respondents that showed up unexpectedly. Most of them accompanied another respondent that was notified that some places were still available in the group session. This resulted in a total of 223 filled out surveys. So in total, we faced a drop out of 21% of the respondents that subscribed initially, which is very low, taking into account the fact that it snowed on the two days that most respondents were scheduled, making the roads difficult to drive on. This indicates that asking the respondents to clearly commit themselves to participate (they have to send an e-mail to subscribe and a second one to provide their availabilities), in combination with a personalized approach, results in low drop out, even in case of strongly impeding circumstances like snowfall (Myers, 2007).

In the end, two respondents were omitted from the dataset because they faced major difficulties in filling out the survey. This made it very clear that the results of these two

surveys were highly unreliable. So, in the end, the research resulted in 221 fully filled out surveys, that are analyzed in chapter 5 in this thesis.

In total, 19 group sessions were held, the first one on December 12th 2009, the last one on December 23rd 2009. 7 sessions took place in the morning, 6 in the afternoon and 6 in the evening. 4 of them were held on Saturdays, while the other 15 were held on weekdays. Each session had a capacity of 16 respondents

4.2 Sample description

The intention of this section is to check the representativeness of the sample by looking at its composition. In the first section, the socio-demographic variables (e.g. gender, income, education,...) are analyzed, and in the second section, mobility-related variables (e.g. vehicle ownership, annual mileage,...) are examined.

4.2.1 Description of socio-demographic factors

4.2.1.1 Gender

The following figure shows that the sample consists of somewhat more women than men. However, both groups are sufficiently represented to draw valid conclusions.

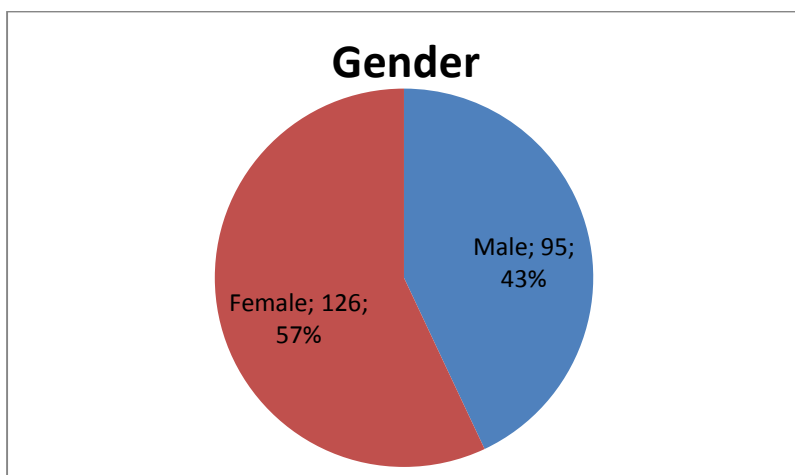


Figure 6: Sample divided by gender.

4.2.1.2 Age

At a first glance, it can be seen in the graph below that virtually all ages between 18 and 70 are represented in the survey. Only respondents of over 70 years old are underrepresented. Probably this is because relatively little people in this age category are able to use a computer. These people had less chance of being informed about the possibility to participate in the survey, since most respondents were contacted by e-mail. Moreover, they probably did not consider themselves suitable to participate in the survey, since the e-mails and advertisements explicitly mentioned that the survey was computer-based. Also, since the elderly are in general less mobile than other age categories, the fact that they had to come to the campus to fill out the survey could have been a barrier for them to participate. Minors are not present in the sample because respondents were obliged to have a driving license.

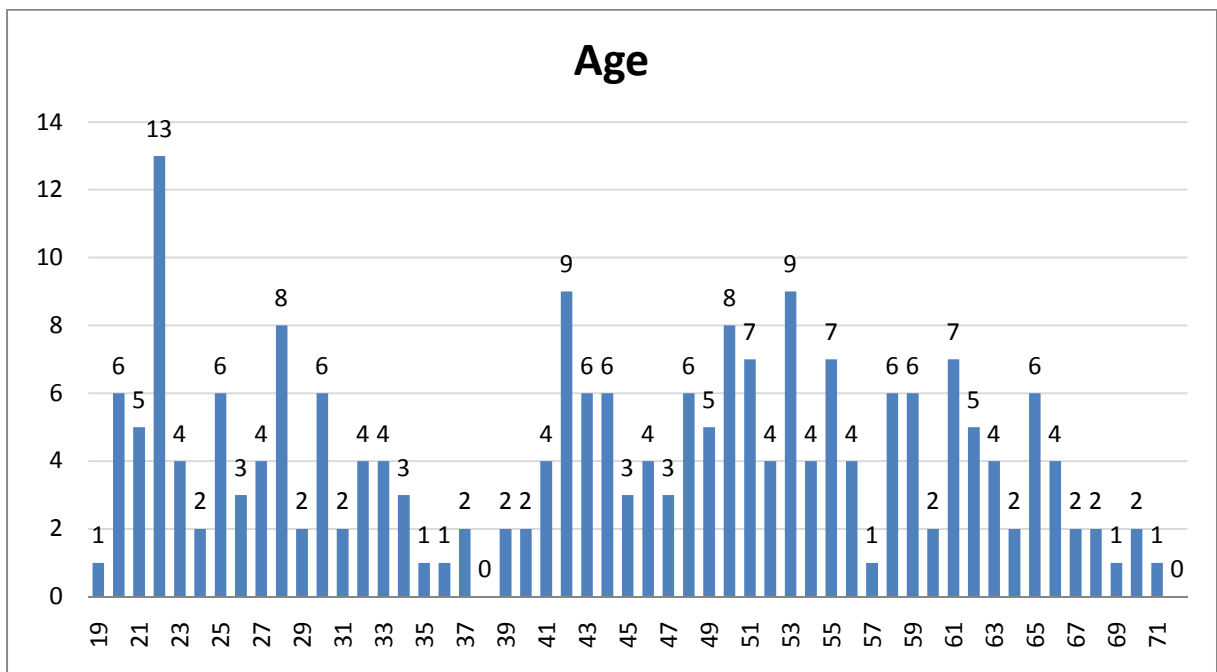


Figure 7: Sample divided by age.

For the purpose of further analysis, respondents need to be classified in different age groups. A distinction is made between respondents who are younger than thirty, people in their thirties, forties, fifties and respondents who are sixty or older. Since there is only one 19-year-old respondent, and only three respondents who are 70 or older, it does not

make sense to assign them to separate categories. That is why the youngest category is -30 and the oldest 60 or older. This is shown in the following figure. People in their thirties are slightly underrepresented in the sample. Underrepresentation of respondents in their thirties is something that is observed quite often in scientific research making use of a survey (e.g. Janssens, Moons, Nuyts, & Wets, 2009; Verhagen, 2007). A possible explanation is that these people in general have little time because many of them have small children and a job.

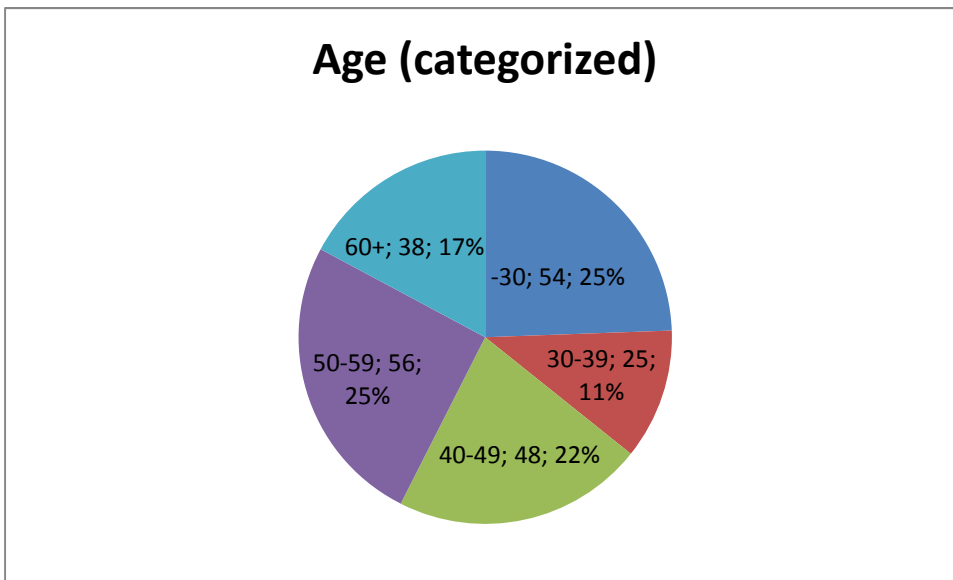


Figure 8: Sample divided by age (categorized).

4.2.1.3 Education

Figure 9 shows that the survey sample contains few semiskilled respondents. There are three possible explanations for this. The most plausible explanation is that lower educated people are less responsive to cooperate in surveys. It has been shown in previous researches that this group is traditionally more difficult to reach in surveys (e.g. Janssens et al., 2009). Since mainly associations were contacted, another possibility is that lower educated people are underrepresented in these associations. Consequently, less lower educated people would have received an invitation to participate in the survey. A third possibility is that lower educated respondents are less inclined to work with computers.

On the other hand, there is a clear overrepresentation of highly skilled respondents. Possibly, they are more aware of the importance of research, or they might be overrepresented in associations. Another contributing factor is that university staff was invited to participate in the survey.

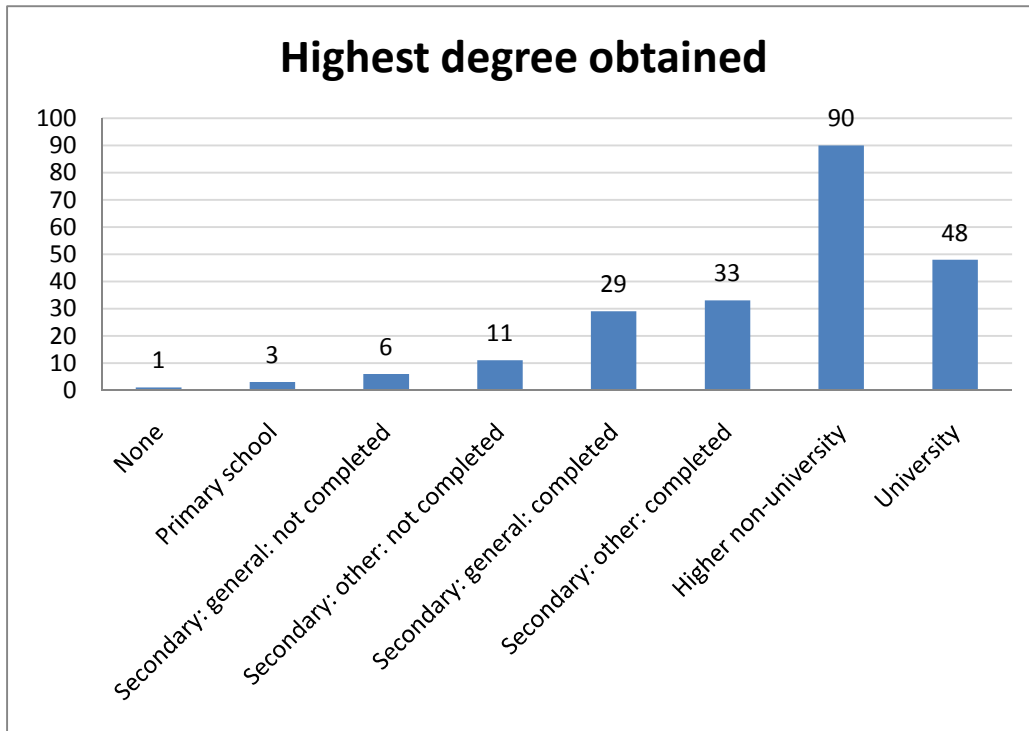


Figure 9: Sample divided by highest degree obtained.

For further analysis, respondents will be classified in three categories based on their education level: secondary school or lower, higher non-university and university.

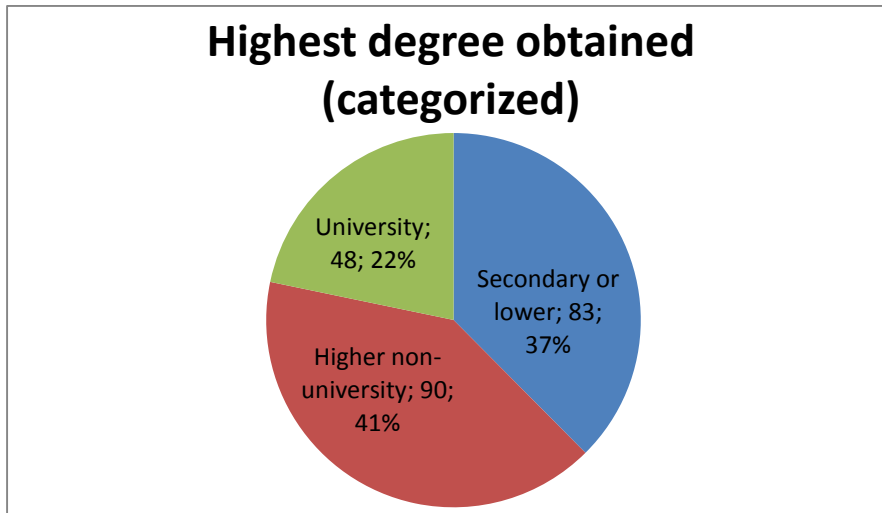


Figure 10: Sample divided by highest degree obtained (categorized).

4.2.1.4 Income

The next distinction is made among different income categories. Respondents were asked for the monthly net income of the household they are part of. Net monthly income is defined as the total amount of money earned by all family members, excluding maintenance allowance to be paid and child allowance, but including incoming maintenance allowance. As can be seen in the following graph, the majority of the respondents state a monthly net household income in the range 1001-5000€. Households with very low incomes (max. 1000 €/month) and households with very high incomes (more than 5000 €/month) are relatively underrepresented. 24 respondents (11%) indicated they would rather not state their income.

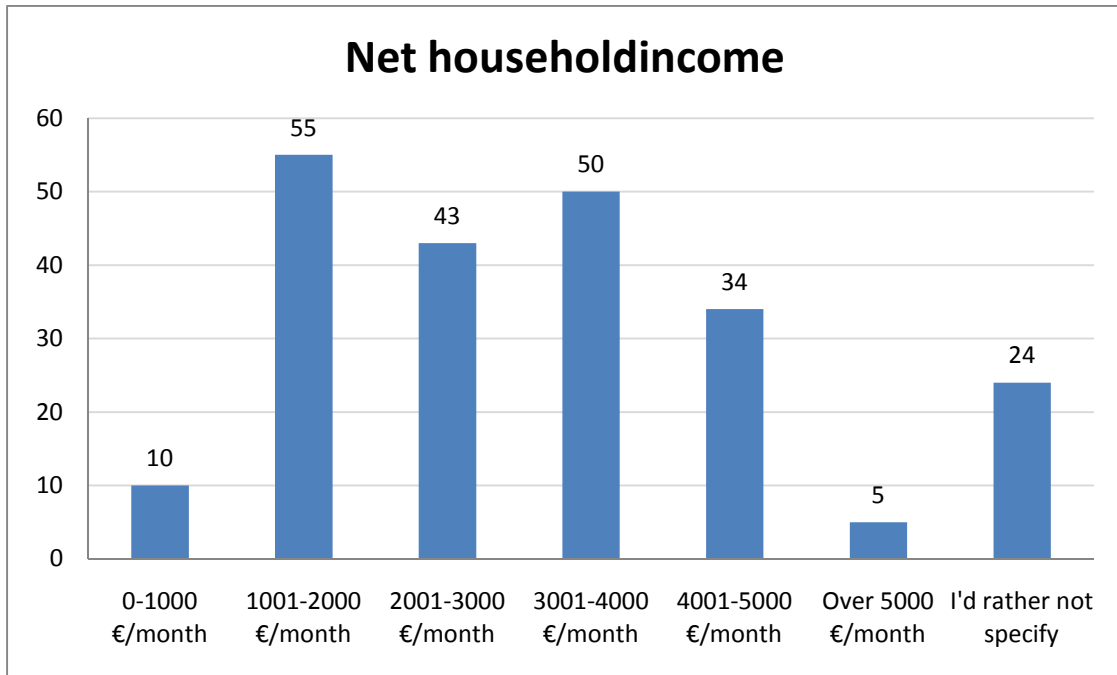


Figure 11: Sample divided by income.

For further analysis, 3 income groups will be distinguished (low, medium and high). The category "I'd rather not specify" will be omitted from this analysis.

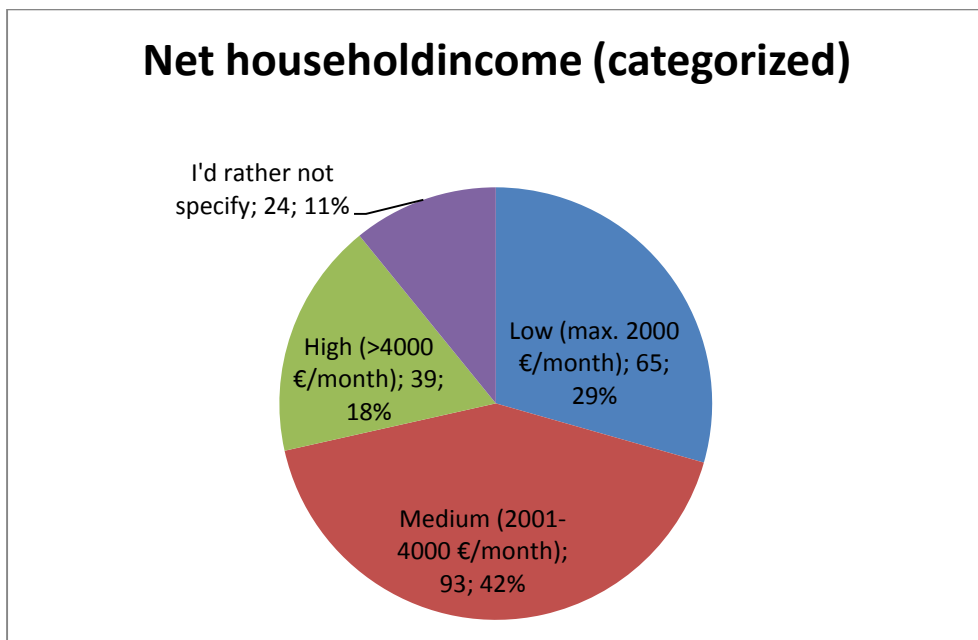


Figure 12: Sample divided by income (categorized).

4.2.1.5 Residence

For privacy reasons, respondents were not asked for their full address. However, they were asked to give their postal code. The results are indicated below.

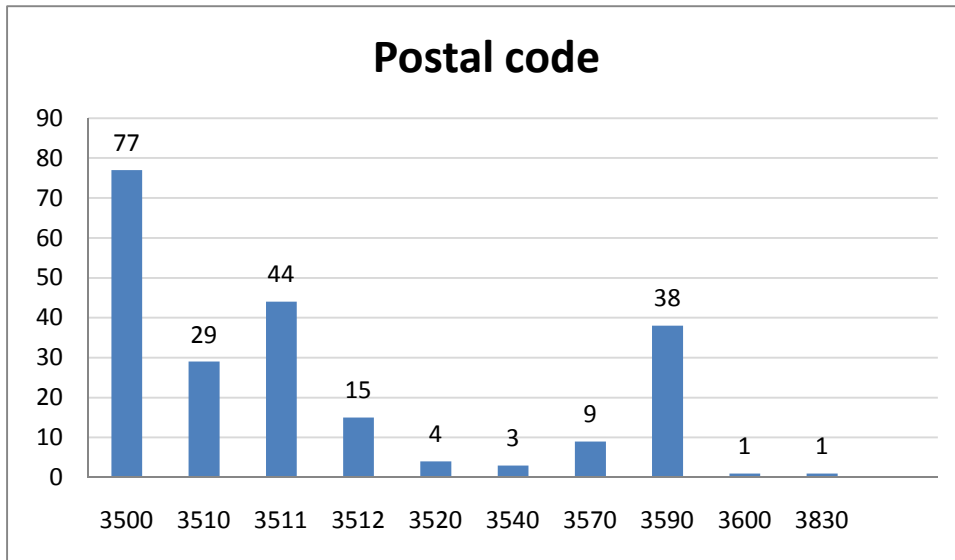


Figure 13: Sample divided by postal code.

This postal code can be used as a proxy for the distance respondents have to travel to get to the city centre of Hasselt. Respondents who have postal code 3500 live near the city centre. The zone 3500 covers approximately up to 4 km from the city centre. Respondents who indicated postal codes 3510, 3511 and 3512 live in the formerly independent municipalities in the suburban area of Hasselt. These postal codes correspond approximately with a distance of 4 to 7 km from the city centre of Hasselt. Other postal codes correspond with a distance of 7 to 10 km from the city centre, since only respondents who live less than 10 km from the city centre of Hasselt were allowed to participate in the survey.

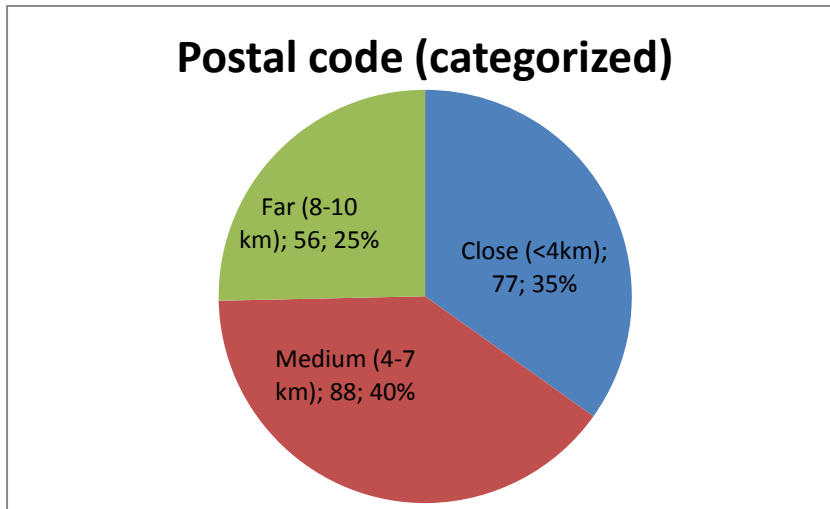


Figure 14: Sample divided by postal code (categorized).

4.2.1.6 Conclusion about socio-demographic representativeness

Taking into account the large risk of a significant bias in the sample, it can be concluded that a relatively representative sample was obtained. There is a good representativeness of both genders, most age categories, income categories and area of residence. There is only one strong disruption in the survey, namely the education level. Higher educated respondents are quite strongly overrepresented, while lower educated respondents on the other hand are underrepresented. In this survey, 62% of the respondents obtained a higher degree (higher non-university degree or university degree), while only 25% of the Belgian population has a higher degree (Belgian Federal Government, 2009a). It will be important to keep this in mind.

4.2.2 Description of respondents' overall mobility

4.2.2.1 Car ownership

As can be seen from Figure 15, most respondents state that their household has 1 or 2 cars. Few households possess 3 or more cars. Only 1 respondent states that his/her household did not possess a car.

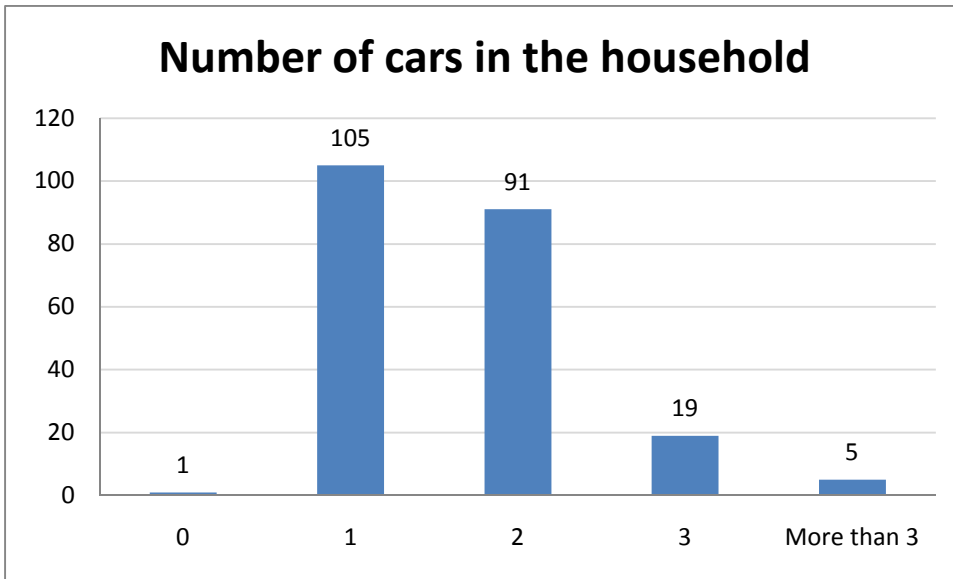


Figure 15: Sample divided by number of cars in the household.

4.2.2.2 Km driven per year

Respondents were also asked to estimate the number of kilometers they drive per year. Results are shown in the next figure. Respondents who drive extremely much (>30000 km/year) or very little (1000 km/year or less) are somewhat underrepresented. 2 respondents indicate they do not drive at all. 2 respondents state they do not have any idea about how much they drive in a year.

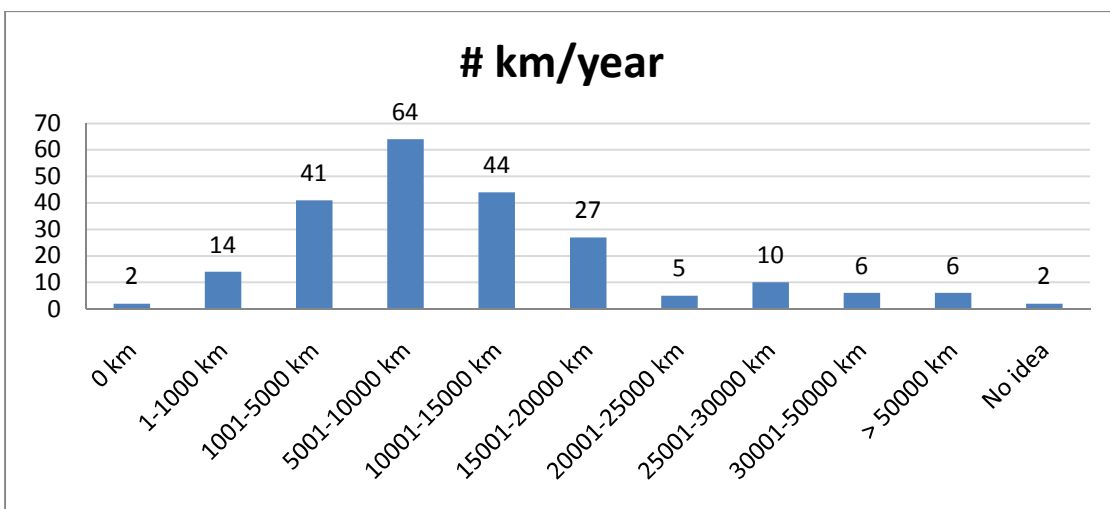


Figure 16: Sample divided by the number of km. driven per year.

Based on the number of kilometers they drive per year, respondents are categorized in three classes: respondents who drive little (max. 5000 km/year), respondents who drive a moderate amount (5001-15000 km/year), and respondents who drive a lot (>15000 km/year).

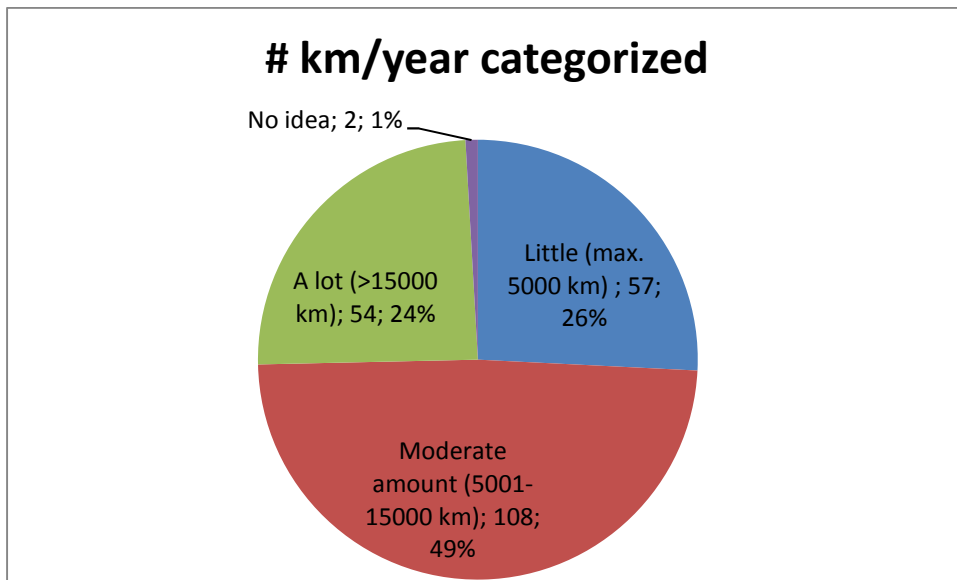


Figure 17: Sample divided by the number of km. driven per year (categorized).

4.2.2.3 TM options

Respondents were asked to indicate what other transport options they have, besides car. More than 90% of them indicate they have access to a bicycle. It also appears that few respondents have access to other means of motorized transport like a moped or motorcycle.

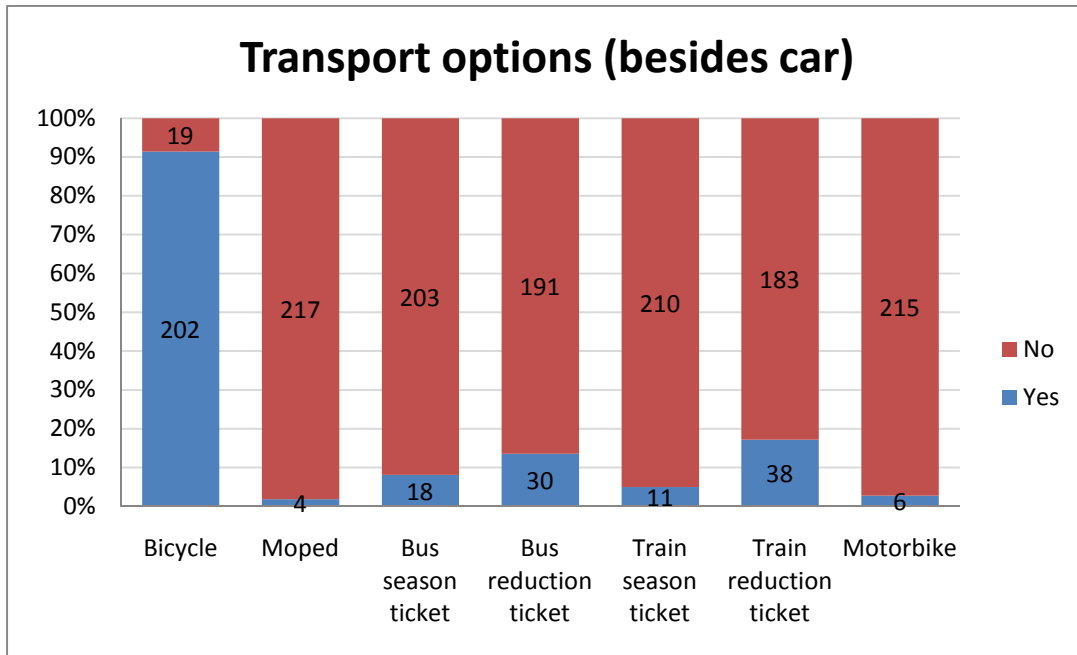


Figure 18: Respondents' transport mode options, besides car.

4.2.2.4 TM choices

Respondents were also asked to indicate how often they go to the city centre of Hasselt by car/bus/bike in autumn. This was decided because we wanted to make sure respondents made a similar imagination of the circumstances they could, in general, encounter in the survey scenario. However, the survey technique does not allow to influence the respondent's answers by detailing the circumstances too much. This is because respondents will not mention these circumstances anymore as contextual aspects that influence their consideration, because they will see them as a given fact instead of a consideration. That is why it was chosen to give them a general guideline by indicating a season. Of the four seasons, autumn and spring are the most "average" seasons. Winter and summer have more extreme weather conditions, with an important impact on transport mode choice (Cools, 2009). For instance, in summer there will be a lot more bicyclists, while in winter there are very few. Autumn was chosen because the survey took place in December, so respondents would probably have more difficulty recalling their behavior in spring than in autumn.

In total, 30 different respondents indicated that they go to the city centre of Hasselt (almost) daily (2 respondents indicated to go to the city centre almost daily for two modes). A total of 87 different respondents indicated to go to the city centre of Hasselt multiple times a week or daily (this is not presented in Figure 19), which is about 39% of our total sample.

As can be seen in Figure 19, a substantial amount of respondents (24%) never goes to the city centre by car. These respondents already make use of sustainable transport modes, so TDM measures should not specifically be targeted to them, although some TDM measures could benefit them (e.g. better bike infrastructure, higher bus frequencies). On the other hand, more than half of the respondents indicated they never go to the city centre by bike or by bus. They are the main target group of TDM measures that are aimed at making fun shopping travel behavior more sustainable. For people who go to the city centre of Hasselt often (daily or a few times a week), bike and car appear to be equally popular. Bus is considerably less popular to use daily or multiple times a week. A large fraction of respondents (57%) state that they occasionally (weekly or monthly) go to the city centre by car.

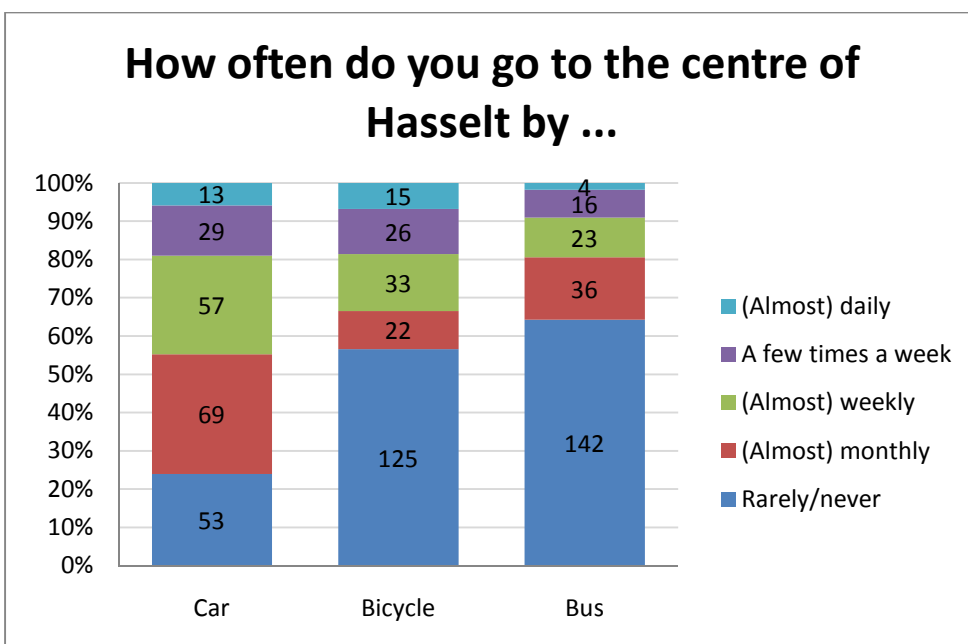


Figure 19: Sample divided by how often respondents go to the centre of Hasselt by car/bicycle/bus.

4.2.2.5 Parking choice

Respondents were also asked where they park when they go to the city centre by car. By far the largest part of respondents usually parks on a free parking space when they go to the city centre of Hasselt by car. This is not surprising, since Hasselt has a number of free parking lots at the edge of the city centre. 32 respondents state that they never go to the city centre by car.

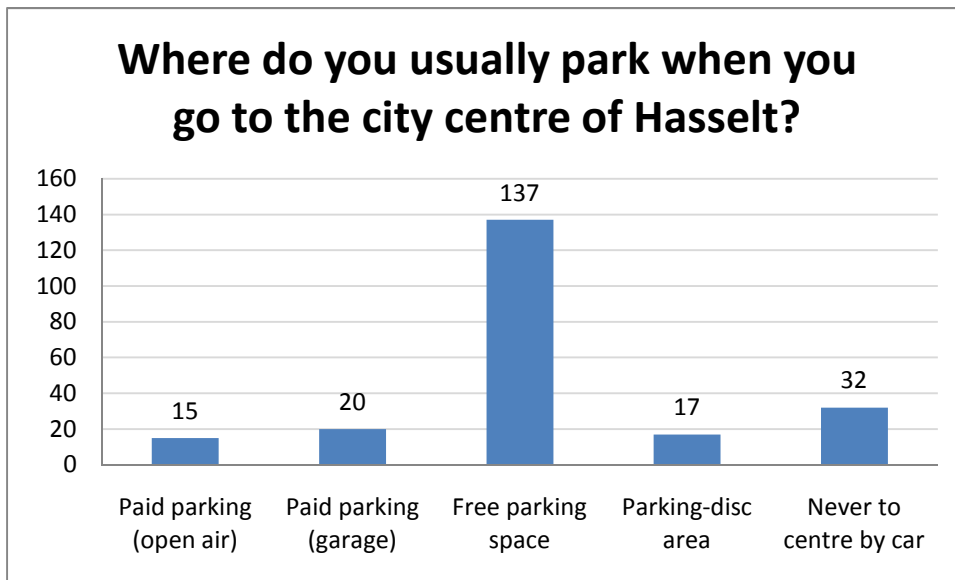


Figure 20: Sample divided by parking choice.

For further analysis, distinction will be made between respondents who use a paid parking, respondents who use a free parking (including parking-disc area) and respondents who never go to the city centre by car.

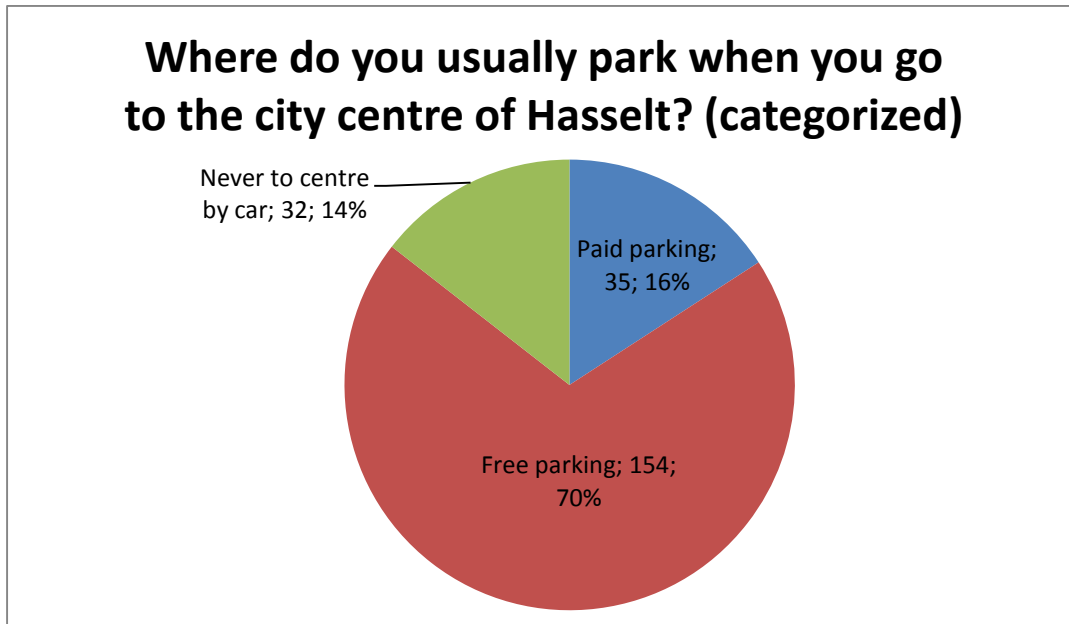


Figure 21: Sample divided by parking choice (categorized).

4.2.2.6 Fun shopping frequency

Respondents were also asked how often they go fun shopping on average. Figure 22 shows that respondents that go fun shopping rarely, are underrepresented. This is not a surprise, since the advertisements and contact e-mails clearly mentioned the survey would be on fun shopping. It can be assumed that most people who go fun shopping that little, just do not like fun shopping. So either they did not consider themselves fit for the survey, or they simply do not only dislike executing fun shopping itself, but also filling in two-hour-surveys about it.



Figure 22: Sample divided by frequency of fun shopping.

4.2.2.7 Conclusions about mobility-related representativeness

It is not possible to determine whether the mobility behavior of the sample is “representative”, since figures for some of these measures will strongly differ from city to city, or are not available (e.g. where people usually park, how often they execute fun shopping,...). It can however be concluded that respondents in this research have a higher than average car and bike ownership, compared to the rest of the urban district Hasselt – Genk, investigated in the Research of Mobility Behavior (OVG) Hasselt – Genk. Less than 1% of the respondents in this sample states there are no cars in his or her household, while 12% of the households in Hasselt – Genk does not own a car, and only 9% of respondents has no access to a bicycle, while 19% of the households in Hasselt - Genk owns no bicycles (Nuyts & Zwerts, 2001). Although this could be seen as a sample bias, it is in fact desirable for this survey, because one of the basic assumptions of the survey is that all respondents have access to car, bike and bus. Combined with the finding that few respondents have access to other means of transport like moped or motorcycle, and the fact that the Decree of Basic Mobility guarantees a bus stop within walking distance to all respondents in a residential area (Van Brempt, 2006), the assumption of a uniform choice set (bike, bus and car) for all respondents is valid.

5 Data analysis

In this chapter, the gathered data is analyzed. The chapter is structured as follows. In the first section, the complexity of the respondents' elicited network is investigated. In section 5.2, it is analyzed which variables are elicited by most respondents. Section 5.3 investigates the associations that are made most often by respondents. The chapter ends with section 5.3.10, in which the results are discussed, and policy implications are presented.

5.1 Network complexity

In this section, the complexity of the respondents' elicited network is investigated. As a measure for the complexity of the network, the number of nodes of the decision network is calculated. Basically, this corresponds to simply calculating the number of different variables in each network. It will be interesting to see whether the network complexity differs among different subcategories of respondents in the sample, because it will be of influence for further analyses and for further research. For socio-demographic groups who elicit a more complex network, each element or association will have a relatively lower importance on average, because there are many aspects that are taken into account. Hence, changing one element will have a smaller effect on people who have a more complex mental representation. Furthermore, it is also important to take into account that the chance that each element or association is present in the mental representation is higher for groups that elicit a more complex network. In case the analysis shows that certain socio-demographic groups have a more complex mental representation than others, this will be especially important to keep in mind in case some socio-demographic groups are underrepresented or overrepresented in the sample.

In the first part, the methodology that is used is presented. Next, the network complexity is analyzed, in general and for different subcategories of the sample (e.g. different age groups, different income levels,...). The section ends with conclusions.

5.1.1 Methodology

To determine whether the network complexity is different for different subcategories of the sample, significance testing is used. First, the testing for significance between means is presented, and next, the χ^2 -test is explained. The theory in this section is based on Anderson, Sweeney & Williams (2005).

5.1.1.1 Testing significance of differences between means

To determine whether there are differences in the network complexity between different subcategories in our sample of respondents, first, descriptive statistics will be calculated using the "Data Analysis Toolpak" that can be downloaded for Microsoft Excel 2007. This generates a general description of the different subgroups. For significance testing, only the mean, the standard deviation and the size of the group ("count") are required in strict sense.

Testing for significance will be done by means of a comparison between the 95%-confidence interval of the different subgroups. If it can be assumed that the number of variables that the respondents elicit is approximately normally distributed, the 95%-confidence interval can be easily calculated. The central limit theory states that the sample distribution of the sample average \bar{x} can be approximated by the normal distribution if the sample size is sufficiently large. In statistics, it is common to consider a sample size of 30 or more to be sufficiently large to assume that the distribution approximates the normal distribution. However, if the population distribution is hill-shaped and symmetric, even sample sizes as small as 5 to 10 can be sufficient to apply the central limit theorem.

The 95% confidence interval (95% CI) can be calculated using the following formula:

$$\bar{x} \pm z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \quad (\text{formula 1})$$

Where \bar{x} = mean number of variables indicated by respondents in the subgroup
 $z_{\alpha/2}$ = standard value indicating the confidence level. For calculating the 95% confidence interval, this value is 1,96

σ = population standard deviation
 n = sample size (number of respondents)

A major difficulty in using this formula is that in most cases, the population standard deviation σ is unknown. This is also the case in this research. However, Anderson et al. (2005) state that, in case of a large sample ($n \geq 30$), the population standard deviation σ can be replaced by the sample standard deviation s . Hence, the formula that will be used to calculate the confidence intervals is the following:

$$\bar{x} \pm z_{\alpha/2} \frac{s}{\sqrt{n}} \quad (\text{formula 2})$$

The interpretation of the analysis is rather straightforward. The zero hypothesis is that the means of the different socio-demographic groups are equal. If there is no overlap between two 95% confidence intervals, one can be at least 95% sure that both means are different from each other, so the zero hypothesis can be rejected, and it can be concluded that the confidence intervals are significantly different at a significance level of 95%. However, if there is an overlap between the intervals, the zero hypothesis can not be rejected, so it can not be concluded that both means are different from each other.

As an example, this calculation is written out for the analysis in section 5.1.2.1. Note that confidence intervals that are placed between round brackets do not fulfill the condition of $n \geq 30$. So, it is unsure whether they do indeed approximate a normal distribution. Hence they can not be used to draw conclusions about significance.

5.1.1.2 Chi-square test of independence

The chi-square test of independence tests whether 2 variables are independent from each other. In other words, does the state for one variable (e.g. gender) influence the outcome for a second variable (e.g. whether you have a habit for one particular travel mode or not). The zero hypothesis is that variable 1 is independent from variable 2. If this hypothesis can be rejected, the alternative hypothesis (variable 1 is not independent from variable 2) is true.

All possible combinations of both variables are put in a table, the so-called χ^2 -table, and the number of observations for each cell is calculated. Each row represents a category of variable 1, and each column a category of variable 2. If the expected frequencies can be determined under the assumption that variable 1 and 2 are independent, it is possible to determine whether there is a significant difference between the observed frequencies and the expected frequencies.

The expected frequencies can be calculated by means of the following formula:

$$e_{ij} = \frac{(\text{Row } i \text{ total})(\text{Row } j \text{ total})}{\text{Sample size}} \quad (\text{formula 3})$$

Statistical significance can then be tested by calculating χ^2 and comparing it to the appropriate critical value in the χ^2 -table. χ^2 is calculated by means of the following formula:

$$\chi^2 = \sum_i \sum_j \frac{(f_{ij} - e_{ij})^2}{e_{ij}} \quad (\text{formula 4})$$

Where f_{ij} = Observed frequency for the χ^2 -category in row i and column j

e_{ij} = Expected frequency for the χ^2 -category in row i and column j based on the assumption of independence

For n rows and m columns in the χ^2 -table, the test has a χ^2 -distribution with $(n-1)(m-1)$ degrees of freedom if the expected frequencies for all categories are 5 or more.

Based on the significance level and the degrees of freedom, the critical value can be determined from a standardized table of the χ^2 -distribution. When the calculated χ^2 -value is higher than this critical value, the zero hypothesis that both variables are independent can be rejected.

5.1.1.3 Conclusion

In significance testing, the network complexity of certain subcategories of respondents is compared by formulating a confidence interval of the mean number of variables indicated by the group. The zero hypothesis is that the means of the different subcategories are equal. In case there is no overlap between two confidence intervals, it can be concluded

that the means are significantly different from each other. In other words, it indicates that the network elicited by members of one subcategory is in general more complex than the network elicited by members of another subcategory.

The chi-square test is used to test whether 2 variables are independent from each other. The zero hypothesis is that both variables are independent from each other. In case the calculated χ^2 is higher than the critical value, the zero hypothesis that both variables are independent can be rejected.

So, the difference is that significance testing is used to compare means with each other. It indicates whether the mental representation of a certain subcategory is more complex than the mental representation of another subcategory. The chi-square test on the other hand will only allow to check whether 2 (socio-demographic) variables are correlated. This information can be helpful to explain differences that appear from the significance tests.

5.1.2 Analysis of network complexity

5.1.2.1 Overall network complexity

The distribution of the overall network complexity (for both decisions) is shown below. It appears that the range of the complexity of the elicited network is very wide. This indicates that some respondents have a lot of scripts that are available for making these decisions, while others have few.

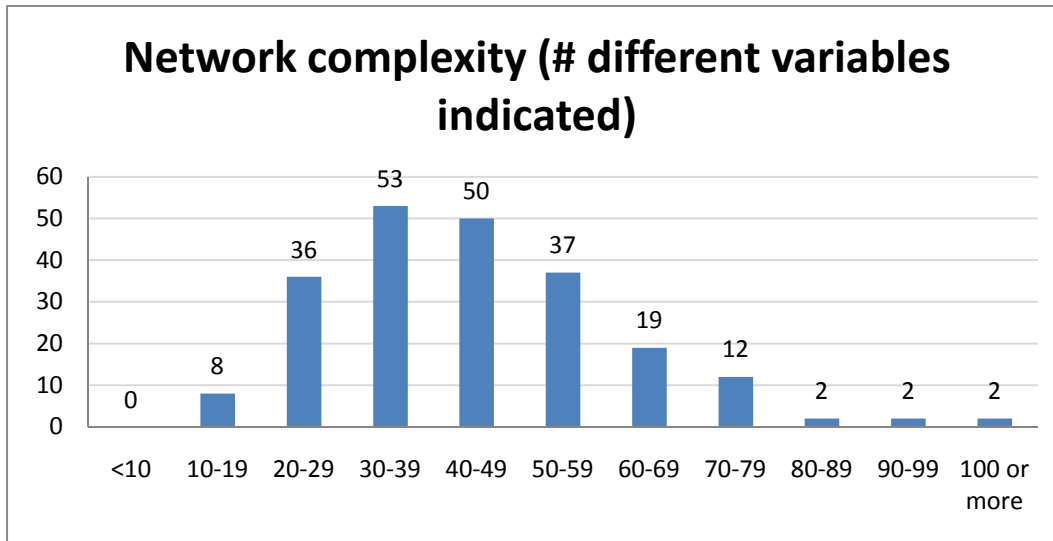


Figure 23: Overall network complexity.

Table 9 shows descriptive statistics of the respondents' network complexity. The mean, median and mode are three centre measures of a dataset. The mean is calculated by summing up all values (the value "sum" in the table) and dividing this number by the number of observations ("count"), the median is the middle value of the list when all observations are sorted in increasing order, and the mode is the value that appears most often in the dataset (Wong & Lee, 2005). The standard error, standard deviation, sample variance and range are measures of dispersion. The standard error refers to the standard deviation of the point estimator. This is in fact a measure that balances the dispersion with the size of the sample. The variance is based on the difference between each observation and the mean. The standard deviation is the positive root of the variance. The range is the difference between the highest value in the dataset ("maximum") and the lowest value in the dataset ("minimum") (Anderson et al., 2005). Skewness is a measure of the asymmetry of the distribution. A skewness of zero indicates a symmetrical distribution. The kurtosis is a measure indicating the "peakness" of the distribution: in case of a negative kurtosis, the top of the distribution is rather flat, and in case of a positive kurtosis, the top is spiky. In case the skewness and kurtosis are zero, the distribution is normal distributed. In case the skewness and kurtosis are in the range [-1, 1], the distribution can be considered as approximately normal distributed (Doorn & Rhebergen, 2006). Note that, for the rest of the analyses, not the full tables of descriptive statistics will be presented, since a profound analysis of most of the values is beyond the scope of this research. Only the 95% CI, that is not calculated in this table,

but will be calculated for the comparing analyses, and the values that are needed to calculate it (mean, standard deviation and count) will be shown. For the full tables, the reader is referred to Annex 3.

Table 9: Descriptive statistics of respondents' overall network complexity.

	<i>Overall network complexity</i>
Mean	44,1991
Standard Error	1,142025
Median	42
Mode	37
Standard Deviation	16,97742
Sample Variance	288,2329
Kurtosis	0,9673
Skewness	0,795924
Range	94
Minimum	10
Maximum	104
Sum	9768
Count	221

In Table 10, the network is split in two networks, one for each fun shopping related decision that was enquired. As stated before, to determine whether the mean number of variables indicated in both decisions are statistically significantly different, the 95% CI is calculated by means of Formula 2.

As an example, the calculation of the 95% CI of the SL decision is written out entirely.

$$\begin{aligned}
 \text{95\% CI SL: } & \left[\bar{x} - z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \quad ; \quad \bar{x} + z_{\alpha/2} \frac{\sigma}{\sqrt{n}} \right] \\
 & \left[16,742 - 1,96 \cdot \frac{7,994}{\sqrt{221}} ; 16,742 + 1,96 \cdot \frac{7,994}{\sqrt{221}} \right] \\
 & [15,688; 17,796]
 \end{aligned}$$

From the following table, it appears there is no overlap between both intervals. This indicates that both means are significantly different from each other. So, respondents indicate significantly more variables for their TM choice than for their SL choice.

Table 10: Network complexity for each decision separately.

	<i>SL decision</i>	<i>TM decision</i>
Mean	16,74208	27,45701
Standard Deviation	7,994401	11,27484
Count	221	221
95% CI	[15,688; 17,796]	[25,970; 28,944]

This could mean that respondents' mental representation for the TM decision is more complex than for the SL decision, unless there is a different explanation. A first possible explanation could be that an imbalance in the order in which respondents take the decisions causes the difference. It is possible that, while eliciting their representation for their first decision, respondents learn that, the more variables they pick, the more subsequent questions they get. In other words, it is possible that most respondents start with the TM decision, and then pick less variables from the SL choice lists because they learned that this will shorten the survey.

This possibility is investigated in the following two tables. The findings are peculiar. The first table does indeed confirm the hypothesis of picking less variables for the second decision: when the SL decision is the first decision to be made, the respondent picks significantly more variables than when it is the second decision. However, this effect is not present for the transport mode decision. So concerning this hypothesis, the results are inconclusive. This finding is further investigated in section 5.1.2.5.

Table 11: Network complexity for the SL location depending on decision order.

	<i># SL variables picked when SL is FIRST decision</i>	<i># SL variables picked when SL is SECOND decision</i>
Mean	20,65714	14,24306
Standard Deviation	7,387584	6,876784
Count	70	144
95% CI	[18,926; 22,388]	[13,120; 15,366]

Table 12: Network complexity for the TM location depending on decision order.

	<i># TM variables picked when TM is FIRST decision</i>	<i># TM variables picked when TM is SECOND decision</i>
Mean	26,66667	26,11429
Standard Deviation	10,14993	8,409006
Count	144	70
95% CI	[25,009; 28,325]	[24,144; 28,084]

Because the CB-CNET is a technique that makes use of written cues, another possible explanation for this difference is the fact that the lists of variables for the transport mode decision are longer than the lists of variables for the shopping location decision (83 and 53 variables in total, respectively). To compensate for this difference in the number of variables, the previous analysis is repeated by making use of the fraction of the variables that each respondent indicates. The fraction of variables indicated is simply the percentage of the total number of different variables that is indicated by the respondent in that decision. It is calculated by dividing the number of variables that are indicated for the decision by the total number of possible variables for that decision.

Descriptive statistics for the fractions of variables are presented in the following table. Here, both intervals are overlapping, so the null hypothesis that both means are equal cannot be rejected at the 95% confidence level. This indicates that the percentage of indicated variables for both decisions is not significantly different. So this supports the suspicion that the higher number of variables that is indicated for the TM decision is the result of the longer lists of variables.

Table 13: Network complexity for each decision separately (fractions).

	<i>SL decision (fraction)</i>	<i>TM decision (fraction)</i>
Mean	0,315888	0,330807
Standard Deviation	0,150838	0,135841
Count	221	221
95% CI	[0,29600; 0,33578]	[0,31290; 0,34872]

5.1.2.2 Network complexity in different scenarios

As was indicated in section 3.2, respondents were presented one of two different scenarios, either a scenario that states that they have little time to perform a fun shopping activity ("Time pressure scenario"), or one that states that they have plenty of time available ("No time pressure scenario"). The following table presents statistics for the network complexity for both scenarios.

It was expected that respondents indicate less considerations when they are presented with a time pressure scenario because people then could have a tendency to fall back on predefined simple mental scripts instead of making conscience deliberations. These scripts would in general consist of less variables than a conscience deliberation. However, this assumption is not confirmed here. There is no significant difference in the complexity of the elicited network between both scenarios.

Table 14: Network complexity for both scenarios.

	<i>Time pressure scenario</i>	<i>No time pressure scenario</i>
Mean	45,25455	43,15315
Standard Deviation	17,93947	15,97965
Count	110	111
95% CI	[41,903; 48,607]	[40,180; 46,126]

Possibly, this lack of difference between both scenarios is caused by the nature of the survey. Another approach to see the impact of the scenario, is how respondents start their elicitation. Recall from section 3.2 that respondents have the choice to indicate whether their choice is a habit (they always go fun shopping using the same TM or always go fun shopping at the same SL first), or whether it depends on circumstances. Respondents who start from a habit are first presented with a list of evaluative aspects, but are asked afterwards whether there are contextual aspects that could influence their choice nevertheless. For respondents who indicate that their choice depends on circumstances, it is the other way round. However, it is possible that respondents who are in the time pressure scenario start more often from a habit, but still end up indicating as much variables as respondents in the no time pressure scenario because of the cueing caused by the presentation of the list. So, another way of looking for an influence of the scenario is checking whether respondents who are presented with the time pressure

scenario start more often from a habit than respondents who are presented with the no time pressure scenario. However, even without using the χ^2 -test it is very clear from the following table that there are no differences between both scenarios considering the number of respondents that start from a habit.

Table 15: Number of respondents that starts from habit or not for both scenarios.

<i>Shopping location choice</i>			
	<i>Habit</i>	<i>No habit</i>	
<i>Time pressure</i>	63	47	110
<i>No time pressure</i>	64	47	111
<i>Transport mode choice</i>			
	<i>Habit</i>	<i>No habit</i>	
<i>Time pressure</i>	54	56	110
<i>No time pressure</i>	52	59	111

The only remaining explanation is that respondents are asked to consciously recall their considerations in the scenario during a long survey, while in real-life situations, time pressure forces them to make a quick (and possibly suboptimal) decision. Probably, this causes respondents not to really "feel" the time pressure, resulting in indicating more variables than are actually considered in a real time pressure scenario. However, it is not correct to conclude that these considerations are not of importance to the respondent! Probably they have indicated additional variables that they do consider in a no time pressure scenario. So basically, respondents in a time pressure scenario simply provide all their scripts, instead of only giving the ones that are activated when they experience time pressure. This result could be interpreted as an indication that respondents did not really consider the scenario, but that they provide all possible scripts for all circumstances.

Possibly, respondents who are confronted with a time pressure scenario will go through a simplified decision making process in reality, in which they tend to fall back on the script(s) they use most often. This way, they simplify the decision making process by ignoring aspects that are not considered as essential given the circumstances, for efficiency purposes (Palmeri, 2001). So it can be expected that people act more from a habit when they are confronted with time pressure. Eliciting a mental representation while actually simulating time pressure in an experiment could be an interesting topic for further research.

5.1.2.3 Differences between different socio-demographic groups

In this section, the network complexity of different socio-demographic groups is analyzed. In the first section, the database will be split by gender. Next, a distinction is made between different age categories. Then, the network complexity of different education levels is analyzed. Subsequently, a distinction between different income levels is made. The section concludes with a split based on the distance of the place of residence to the city centre.

5.1.2.3.1 Gender

In the following table, descriptive statistics are presented for the network complexity for men and women. It appears that men indicate approximately as many variables as women. So the popular (sexist) thought that women are more complex than men is not confirmed by this survey.

Table 16: Network complexity of men vs. women.

	<i>Men</i>	<i>Women</i>
Mean	44,51579	43,96032
Standard Deviation	17,0524	16,98489
Count	95	126
95% CI	[41,087; 47,945]	[40,994; 46,926]

However, it is still possible that for both decisions separately, differences between men and women do occur. The following tables provide results for the SL and TM choice respectively. It appears that for both decisions, results for men and women are strongly similar.

Table 17: Network complexity of men vs. women, SL decision only.

	<i>Men SL</i>	<i>Women SL</i>
Mean	17,04211	16,51587
Standard Deviation	8,744501	7,406737
Count	95	126
95% CI	[15,283; 18,801]	[15,223; 17,809]

Table 18: Network complexity of men vs. women, TM decision only.

	<i>Men TM</i>	<i>Women TM</i>
Mean	27,47368	27,44444
Standard Deviation	10,25924	12,02435
Count	95	126
95% CI	[25,411; 29,537]	[25,344; 29,544]

5.1.2.3.2 Age

For the following table, the database was split into different age categories as explained in the sample description. It seems that elderly people indicate slightly more variables than younger people. However, there are no statistically significant differences among the different age groups.

Table 19: Network complexity for different age categories.

	<i>19-29</i>	<i>30-39</i>	<i>40-49</i>	<i>50-59</i>	<i>60-71</i>
Mean	43,42593	42,16	43,75	44,58929	46,63158
Standard Deviation	14,17891	16,65753	19,04809	17,48535	17,89522
Count	54	25	48	56	38
95% CI	[39,644; 47,208]	([35,630; 48,690])	[38,361; 49,139]	[40,009; 49,169]	[40,942; 52,322]

From the following two tables, it is clear that there are no significant differences among different age groups for both decisions separately either.

Table 20: Network complexity for different age categories, SL decision only.

	<i>19-29 SL</i>	<i>30-39 SL</i>	<i>40-49 SL</i>	<i>50-59 SL</i>	<i>60-71 SL</i>
Mean	17,18519	16,32	15,5	16,91071	17,71053
Standard Deviation	6,998852	8,355238	7,737722	7,781743	9,750698
Count	54	25	48	56	38
95% CI	[15,318; 19,052]	([13,045; 19,595])	[13,311; 17,689]	[14,873; 18,949]	[14,611; 20,811]

Table 21: Network complexity for different age categories, TM decision only.

	<i>19-29 TM</i>	<i>30-39 TM</i>	<i>40-49 TM</i>	<i>50-59 TM</i>	<i>60-71 TM</i>
Mean	26,24074	27,48148	27,3913	27,67857	28,92105
Standard Deviation	8,971517	13,87408	12,48017	11,1308	11,28113
Count	54	27	46	56	38
95% CI	[23,848; 28,634]	([22,248; 32,714])	[23,784; 30,998]	[24,764; 30,594]	[25,334; 32,508]

5.1.2.3.3 Education

In Table 22, a distinction is made between different education levels. From preliminary analysis, it appears that results of respondents with a higher non-university degree and respondents with a university degree are strongly similar. That is why it is decided to combine them to one single category "higher educated". It appears that lower educated respondents indicate significantly more variables than higher educated respondents.

Table 22: Network complexity for different education levels.

	<i>Lower educated</i>	<i>Higher educated</i>
Mean	49,45783	41,03623
Standard Deviation	19,13259	14,7284
Count	83	138
95% CI	[45,342; 53,574]	[38,579; 43,493]

It is interesting to see whether this difference between higher educated and lower educated respondents could be attributable to one of both decisions alone. The following two tables indicate that, for both decisions, higher educated respondents indicate significantly less variables than lower educated respondents. So the differences in the complexity of the network are not attributable to one of both decisions alone.

Table 23: Network complexity SL decision for different education levels.

	<i>Lower educated SL</i>	<i>Higher education SL</i>
Mean	18,80723	15,5
Standard Deviation	7,9441	7,792238
Count	83	138
95% CI	[17,098; 20,516]	[14,200; 16,800]

Table 24: Network complexity TM decision for different education levels.

	<i>Lower educated TM</i>	<i>Higher educated TM</i>
Mean	30,6506	25,53623
Standard Deviation	13,49565	9,231934
Count	83	138
95% CI	[27,747; 33,555]	[23,996; 27,076]

A possible explanation is that higher educated respondents learn faster about the structure of the survey. By this is meant that they could be more shrewd than lower educated respondents. They are probably more likely to find out, while eliciting their considerations for the first decision, that indicating less variables will lead to a shorter survey. This could lead (some of) them to indicate less variables for the second decision, hence resulting in a lower number of indicated variables overall. In the following two tables, results are shown when the SL decision and the TM decision is the second decision, respectively. There are no statistically significant differences between both education categories. So we can conclude that higher educated respondents do not indicate less variables because they learn from the elicitation of the first decision that indicating more variables increases survey length, resulting in a lower number of variables indicated for the second decision.

Table 25: Network complexity for SL decision if it is the second decision.

	<i>SL 2nd decision lower educated</i>	<i>SL 2nd decision higher educated</i>
Mean	16,04255319	13,37113402
Standard Deviation	7,27998282	6,534076681
Count	47	97
95% CI	[13,962; 18,124]	[12,071; 14,671]

Table 26: Network complexity for TM decision if it is the second decision

	<i>TM 2nd decision lower educated</i>	<i>TM 2nd decision higher educated</i>
Mean	26,77419355	25,58974359
Standard Deviation	9,182264345	7,822766871
Count	31	39
95% CI	[23,542; 30,006]	[23,135; 28,045]

It is also possible that higher educated respondents start more often from a habit than lower educated respondents, what could lead to a lower number of variables indicated because respondents who start from a habit are less likely to indicate contextual

variables. In the following two tables, relevant values for the chi-square test of independence are presented for both decisions separately. Note that, for both decisions, respondents who indicate that they have a habit are merged to one category. Distinguishing the different habit categories (zone 1, zone 2 or zone 3; and car, bike, bus respectively) would make some expected value classes lower than 5, which is not allowed. It can be seen that there is no relation between the education level and indicating to have a habit for either a shopping zone or a transport mode.

Table 27: χ^2 -test for correlation between SL habit and education.

	<i>Observed values</i>			<i>Expected values</i>		
	<i>No</i>	<i>Yes, SL habit</i>	<i>Row total</i>	<i>No</i>	<i>Yes, SL habit</i>	<i>Row total</i>
Secondary or lower	46	37	83	47,7	35,3	83
Higher education	81	57	138	79,3	58,7	138
Col. total	127	94	221	127	94	221
	χ^2		<i>df</i>	<i>Critical value</i>		<i>Significance?</i>
χ^2 -test	0,225		1	3,841		Not significant

Table 28: χ^2 -test for correlation between TM habit and education.

	<i>Observed values</i>			<i>Expected values</i>		
	<i>No</i>	<i>Yes, TM habit</i>	<i>Row total</i>	<i>No</i>	<i>Yes, TM habit</i>	<i>Row total</i>
Secondary or lower	39	44	83	39,8	43,2	83
Higher education	67	71	138	66,2	71,8	138
Col. total	106	115	221	106	115	221
	χ^2		<i>df</i>	<i>Critical value</i>		<i>Significance?</i>
χ^2 -test	0,051		1	3,841		Not significant

One final explanation is that higher education, combined with a higher intelligence, allows respondents to make a clearer distinction between the most essential elements in their decision making process and less important items. As mentioned in section 3.3, it is clearly asked to limit the elicitation to the most crucial variables. So possibly, higher educated respondents simply manage to comply to this request better than lower educated respondents. This could also be an indication that the technique is too difficult for lower educated respondents. This suspicion is supported by an unpublished analysis performed by Kusumastuti et al., that is beyond the scope of this master thesis. From this analysis, it appears that the elicited network of lower educated respondents is less

accurate in predicting their stated preference in hypothetical scenarios. This means lower educated respondents are less consistent in their survey responses, which is a clear suggestion that lower educated respondents have more difficulties with the survey than higher educated respondents.

5.1.2.3.4 Income

In the following table, the network complexity is presented distinguishing between different income categories. There seems to be a slight tendency that respondents in the low income category indicate more variables, but the difference is not significant. Possibly, this finding is related to the fact that lower educated respondents indicate less variables than higher educated respondents, because it can be assumed that lower educated respondents have a lower income in general.

Table 29: Network complexity for different income categories.

	<i>Low income</i>	<i>Medium income</i>	<i>High income</i>	<i>I'd rather not say</i>
Mean	48,07692	42	44,33333	42
Standard Deviation	19,18846	15,127	16,05473	18,00483
Count	65	93	39	24
95% CI	[43,412; 52,742]	[38,926; 45,074]	[37,294; 47,372]	([34,796; 49,204])

Also, if we look in the next two tables at the influence of income on both decisions separately, no significant differences appear.

Table 30: Network complexity for different income categories, SL decision only.

	<i>Low income SL</i>	<i>Medium income SL</i>	<i>High income SL</i>	<i>I'd rather not say SL</i>
Mean	18,36923	15,86022	16,89744	15,5
Standard Deviation	9,336704	7,650791	7,411921	5,618293
Count	65	93	39	24
95% CI	[16,099; 20,639]	[14,305; 17,415]	[14,571; 19,223]	([13,252; 17,748])

Table 31: Network complexity for different income categories, TM decision only.

	<i>Low income TM</i>	<i>Medium income TM</i>	<i>High income TM</i>	<i>I'd rather not say TM</i>
Mean	29,70769	26,13978	27,4359	26,5
Standard Deviation	12,01395	9,827414	10,91063	14,45834
Count	65	93	39	24
95% CI	[26,787; 32,629]	[24,143; 28,137]	[24,012; 30,860]	([20,716; 32,284])

It is also verified whether there is a correlation between the income and starting from a habit or not. The results in the tables below show that there is no significant correlation for either of both decisions.

Table 32: χ^2 -test for correlation between SL habit and income.

	<i>Observed values</i>			<i>Expected values</i>		
	<i>No</i>	<i>Yes, SL habit</i>	<i>Row total</i>	<i>No</i>	<i>Yes, SL habit</i>	<i>Row total</i>
Low income	39	26	65	37,4	27,6	65
Medium income	57	36	93	53,4	39,6	93
High income	21	18	39	22,4	16,6	39
I'd rather not say	10	14	24	13,8	10,2	24
Col. Total	127	94	221	127	94	221
	χ^2		<i>df</i>	<i>Critical value</i>		<i>Significance?</i>
χ^2 -test	3,391		3	7,815		Not significant

Table 33: χ^2 -test for correlation between TM habit and income.

	<i>Observed values</i>			<i>Expected values</i>		
	<i>No</i>	<i>Yes, TM habit</i>	<i>Row total</i>	<i>No</i>	<i>Yes, TM habit</i>	<i>Row total</i>
Low income	34	31	65	31,2	33,8	65
Medium income	48	45	93	44,6	48,4	93
High income	17	22	39	18,7	20,3	39
I'd rather not say	7	17	24	11,5	12,5	24
Col. total	106	115	221	106	115	221
	χ^2		<i>df</i>	<i>Critical value</i>		<i>Significance?</i>
χ^2 -test	4,684		3	7,815		Not significant

Closely related to this is the possibility that there is a correlation between employment and whether the respondent starts from a habit or not. The χ^2 -tests for both decisions are shown below. A distinction is made between three categories: not working (e.g. students, pensioners, housewives/househusbands,...), white collars (e.g. public servants, employees) and other (e.g. self employed, liberal profession,...). However, the results show that there is no significant correlation between both variables.

Table 34: χ^2 -test for correlation between SL habit and occupation.

	<i>Observed values</i>			<i>Expected values</i>		
	<i>No</i>	<i>Yes, SL habit</i>	<i>Row total</i>	<i>No</i>	<i>Yes, SL habit</i>	<i>Row total</i>
Not working	47	37	84	48,3	35,7	84
White collar	71	47	118	67,8	50,2	118
Other	9	10	19	10,9	8,1	19
Col. Total	127	94	221	127	94	221
	χ^2		<i>df</i>	<i>Critical value</i>		<i>Significance?</i>
χ^2 -test	1,224		2	5,991		Not significant

Table 35: χ^2 -test for correlation between TM habit and occupation.

	<i>Observed values</i>			<i>Expected values</i>		
	<i>No</i>	<i>Yes, TM habit</i>	<i>Row total</i>	<i>No</i>	<i>Yes, TM habit</i>	<i>Row total</i>
Not working	34	50	84	40,3	43,7	84
White collar	61	57	118	56,6	61,4	118
Other	11	8	19	9,1	9,9	19
Col. Total	106	115	221	106	115	221
	χ^2		<i>df</i>	<i>Critical value</i>		<i>Significance?</i>
χ^2 -test	2,589		2	5,991		Not significant

5.1.2.3.5 Distance

Another possibility is that the distance to the city centre will have an influence on considerations related to the TM decision. That is why in the following table, a distinction is made between respondents who live close to the city centre of Hasselt (<4 km), at a medium distance (5-7 km) or far away from the city centre (8-10). However, there

appear to be no significant differences in the network complexity between the different distance classes.

Table 36: Network complexity for different distances from the centre, TM only.

	<i>Close (<4 km) TM</i>	<i>Medium (5-7 km) TM</i>	<i>Far (8-10 km) TM</i>
Mean	26,45455	27,875	28,17857
Standard Deviation	10,23737	12,58426	10,53325
Count	77	88	56
95% CI	[24,168; 28,742]	[25,246; 30,504]	[25,420; 30,938]

5.1.2.4 Differences related to overall mobility

Also, the number of kilometers that respondents drive in a year could have an influence on their TM considerations, because it is plausible that people who drive more have a stronger car-habit. This could lead to indicating less variables. However, this suspicion is not confirmed by Table 37. Respondents who drive a moderate amount of kilometers seem to indicate slightly more variables, but the difference is not statistically significant.

Table 37: Network complexity of TM decision for different car use categories.

	<i>Max. 5000 km/year TM</i>	<i>5001-15000 km/year TM</i>	<i>> 15000 km/year TM</i>
Mean	26,19298	28,94444	25,05556
Standard Deviation	9,521477	11,67699	9,353471
Count	57	108	54
95% CI	[23,721; 28,665]	[26,742; 31,146]	[22,561; 27,551]

It is also possible that people who go fun shopping often have a different mental representation than people who do not go fun shopping that often. It is assumable that people who go fun shopping more often have stronger habits, since the frequency a behavior is performed has a strong influence on habit formation (Verplanken & Wood, 2006). Because of this, it is possible that respondents who go fun shopping often indicate less considerations. However, this assumption is not confirmed by the following table. On the contrary, respondents who go fun shopping more often seem to indicate slightly more variables than respondents who go fun shopping less often, but the difference is not statistically significant. Possibly, this is because respondents who go fun shopping more

often have more pre-defined mental scripts, resulting in a higher number of variables present in their mental representation.

Table 38: Network complexity for different categories of fun shopping frequency.

	Rarely if ever	A few times a year	(nearly) monthly	A few times a month
Mean	41,21429	42,04762	43,375	48,20896
Standard Deviation	17,26347	17,61154	16,92933	15,76392
Count	14	84	56	67
95% CI	([32,171; 50,257])	[38,282; 45,814]	[38,941; 47,809]	[44,434; 51,984]

5.1.2.5 Differences in node types

Up to now, no distinction was made regarding the content of the elicited networks. In other words, we only looked at the total number of variables that was elicited, not at what types of variables were elicited.

From the following two tables, it is clear that for both decisions, respondents indicate contextual variables significantly least. They indicate significantly more evaluative variables, but by far the most instrumental variables. These conclusions were expected and they are rather straightforward because of the survey setup. A large part of this difference in number of items that is indicated, is caused by the one-to-many structure of the cognitive subsets: for each contextual variable that is indicated, one or more evaluative variables have to be indicated, and for each evaluative variable one or more instrumental variables have to be indicated. Also, respondents are strongly encouraged (but not forced) to indicate only the most important contextual and evaluative aspects for their decisions to limit the length of the survey, as was explained in section 3.3. However, they are not told to limit the number of instrumental variables because this does not influence the survey length. Therefore, it is logical that instrumental variables are indicated far most.

In accordance with the finding that respondents indicate more variables for the TM decision than for the SL decision (see section 5.1.2.1), respondents systematically indicate significantly more variables for each variable type in the TM decision.

Table 39: Node types SL decision.

	Contextual var. SL	Evaluative var. SL	Instrumental var. SL
Mean	3,19457	4,466063	8,113122
Standard Deviation	1,859415	2,33841	4,534801
Count	221	221	221
95% CI	[2,950; 3,440]	[4,158; 4,774]	[7,515; 8,711]

Table 40: Node types TM decision.

	Contextual var. TM	Evaluative var. TM	Instrumental var. TM
Mean	4,361991	5,624434	9,506787
Standard Deviation	3,385155	2,426958	4,400021
Count	221	221	221
95% CI	[3,916; 4,808]	[5,304; 5,944]	[8,927; 10,087]

5.1.2.5.1 Habit & node type

An interesting finding from the previous section is the fact that respondents who start their elicitation by indicating that the choice is a habit, do not elicit less variables than respondents who indicate that the choice is not a habit. However, there could still be a difference in the content of their networks. For instance, one of both groups could indicate more evaluative variables but fewer instrumental variables, which results in an overall similar network complexity. However, the following 6 tables indicate there are no significant differences between respondents with a habit and respondents without a habit for any of the variables of both decisions. However, respondents with a habit seem to indicate slightly less contextual variables for both decisions than respondents without a habit. This is rather straightforward, since respondents who indicate that they have a habit are not obliged to indicate contextual variables, while respondents who do not start from a habit are required to indicate at least one contextual variable.

Table 41: Number of SL contextual variables when starting from a habit or not.

	<i>No habit SL contextual</i>	<i>Habit SL contextual</i>
Mean	3,456693	2,840426
Standard Deviation	1,693854	2,017681
Count	127	94
95% CI	[3,162; 3,752]	[2,432; 3,248]

Table 42: Number of SL evaluative variables when starting from a habit or not.

	<i>No habit SL evaluative</i>	<i>Habit SL evaluative</i>
Mean	4,464567	4,468085
Standard Deviation	2,107414	2,630271
Count	127	94
95% CI	[4,099; 4,831]	[3,936; 5,000]

Table 43: Number of SL instrumental variables when starting from a habit or not.

	<i>No habit SL instrumental</i>	<i>Habit SL instrumental</i>
Mean	8,102362	8,12766
Standard Deviation	4,200972	4,973552
Count	127	94
95% CI	[7,371; 8,833]	[7,122; 9,134]

Table 44: Number of TM contextual variables when starting from a habit or not.

	<i>No habit TM contextual</i>	<i>Habit TM contextual</i>
Mean	4,943396	3,826087
Standard Deviation	3,236195	3,444449
Count	106	115
95% CI	[4,327; 5,559]	[3,197; 4,455]

Table 45: Number of TM evaluative variables when starting from a habit or not.

	<i>No habit TM evaluative</i>	<i>Habit TM evaluative</i>
Mean	5,54717	5,695652
Standard Deviation	2,342697	2,510238
Count	106	115
95% CI	[5,101; 5,993]	[5,237; 6,155]

Table 46: Number of TM instrumental variables when starting from a habit or not.

	<i>No habit TM instrumental</i>	<i>Habit TM instrumental</i>
Mean	9,132075	9,852174
Standard Deviation	4,066297	4,677763
Count	106	115
95% CI	[8,358; 9,906]	[8,997; 10,707]

5.1.2.5.2 Decision order & node type

Another interesting finding that needs further investigation is the fact that chapter 5.1.2.3 showed that respondents indicate significantly less SL variables when SL is the second decision, but that this is not the case when the TM decision is the second decision. When the TM decision is the second decision to be taken, respondents indicate as much variables as when it is the first decision.

From the following three tables, it is clear that the lower amount of variables is not the result of one variable type alone. For all three types of variables, respondents who elicit their SL considerations second indicate significantly less variables than respondents who elicit their SL considerations first. This is somewhat logical. If respondents start by eliciting fewer contextual variables, they have to elicit fewer evaluative and instrumental variables too. So basically, changes in the number of contextual variables elicited propagate through the network.

Table 47: Number of SL contextual variables by decision order.

	<i># SL contextual variables when SL first</i>	<i># SL contextual variables when SL second</i>
Mean	4	2,652778
Standard Deviation	1,857222	1,561421
Count	70	144
95% CI	[3,565; 4,435]	[2,398; 2,908]

Table 48: Number of SL evaluative variables by decision order.

	<i># SL evaluative variables when SL first</i>	<i># SL evaluative variables when SL second</i>
Mean	5,428571	3,840278
Standard Deviation	2,197307	2,064225
Count	70	144
95% CI	[4,914; 5,944]	[3,503; 4,177]

Table 49: Number of SL instrumental variables by decision order.

	<i># SL instrumental variables when SL first</i>	<i># SL instrumental variables when SL second</i>
Mean	10,27143	6,777778
Standard Deviation	4,259419	3,992028
Count	70	144
95% CI	[9,273; 11,269]	[6,126; 7,430]

The next three tables show the same analysis for the TM choice. Here, however, there are no statistically significant differences.

Table 50: Number of TM contextual variables by decision order.

	<i># TM contextual variables when TM first</i>	<i># TM contextual variables when TM second</i>
Mean	3,928571	4,034722
Standard Deviation	2,305139	2,679665
Count	70	144
95% CI	[3,389; 4,469]	[3,597; 4,473]

Table 51: Number of TM evaluative variables by decision order.

	<i># TM evaluative variables when TM first</i>	<i># TM evaluative variables when TM second</i>
Mean	5,157143	5,597222
Standard Deviation	1,923431	2,291118
Count	70	144
95% CI	[4,707; 5,607]	[5,223; 5,971]

Table 52: Number of TM instrumental variables by decision order.

	<i># TM instrumental variables when TM first</i>	<i># TM instrumental variables when TM second</i>
Mean	8,771429	9,458333
Standard Deviation	3,506398	4,338597
Count	70	144
95% CI	[7,950; 9,592]	[8,749; 10,167]

It is curious that respondents indicate less variables for the second decision when this is the SL decision, but not when the TM is the second decision. Now that we know that these differences are not caused by one single node type, there are two possible explanations remaining.

A first one is that it is caused by the fact that the TM decision appears to require a longer elicitation on average. It means that, after having done the long TM elicitation, respondents get a bit negligent for the second decision, the SL decision. So basically, some form of "survey fatigue" arises. However, if they start by doing the shorter SL elicitation, this fatigue to start with the TM decision, which is second, does not appear.

A second possibility is that respondents are more willing to do an effort for their TM decision than for the SL decision, perhaps because they find it a more important decision than their SL choice. This would mean that, after having already done a full elicitation, their motivation to elicit their SL considerations is lower than their motivation when they have to elicit their TM considerations.

5.1.2.5.3 Education & node type

Chapter 5.1.2.3 also showed that higher educated respondents indicate significantly less variables than lower educated respondents for both decisions, so it will be interesting to see what variable types exactly cause these differences. Results are shown in the following 6 tables. For the SL decision, respondents with a higher education indicate significantly less instrumental variables than lower educated respondents. For the TM decision, respondents with a higher education degree indicate significantly less contextual variables. However, also for the non-significant differences, there is a trend that higher educated respondents indicate less variables than lower educated respondents. So, most of the difference in the network complexity is caused by the

instrumental variables in the SL decision, and by the contextual variables in the TM decision, although higher educated respondents also indicate less variables of the other types, but these differences are not significant.

Table 53: Contextual variables for the SL decision for different education levels.

	<i>Secondary or lower contextual SL</i>	<i>Higher education contextual SL</i>
Mean	3,566265	2,971014
Standard Deviation	1,802388	1,863761
Count	83	138
95% CI	[3,178; 3,954]	[2,660; 3,282]

Table 54: Evaluative variables for the SL decision for different education levels.

	<i>Secondary or lower evaluative SL</i>	<i>Higher education evaluative SL</i>
Mean	4,987952	4,152174
Standard Deviation	2,255043	2,33945
Count	83	138
95% CI	[4,503; 5,473]	[3,762; 4,542]

Table 55: Instrumental variables for the SL decision for different education levels.

	<i>Secondary or lower instrumental SL</i>	<i>Higher education instrumental SL</i>
Mean	9,277108	7,413043
Standard Deviation	4,502881	4,424102
Count	83	138
95% CI	[8,308; 10,246]	[6,675; 8,151]

Table 56: Contextual variables for the TM decision for different education levels.

	<i>Secondary or lower contextual TM</i>	<i>Higher education contextual TM</i>
Mean	5,325301	3,782609
Standard Deviation	4,361999	2,472444
Count	83	138
95% CI	[4,387; 6,263]	[3,371; 4,195]

Table 57: Evaluative variables for the TM decision for different education levels.

	<i>Secondary or lower evaluative TM</i>	<i>Higher education evaluative TM</i>
Mean	6,216867	5,268116
Standard Deviation	2,828635	2,080637
Count	83	138
95% CI	[5,608; 6,826]	[4,921; 5,615]

Table 58: Instrumental variables for the TM decision for different education levels.

	<i>Secondary or lower instrumental TM</i>	<i>Higher education instrumental TM</i>
Mean	10,45783	8,934783
Standard Deviation	4,799139	4,052946
Count	83	138
95% CI	[9,426; 11,490]	[8,259; 9,611]

5.1.3 Conclusions network complexity

This section examined the complexity of the respondents' elicited network. There appear to be large individual differences among respondents. The simplest network that is elicited contains only 10 different variables, the most complex one 104. On average, respondents indicate 44 variables that have an influence in their fun shopping related decisions.

The TM decision appears to be significantly more complex than the SL decision (27 variables vs. 17 variables on average, respectively). However, it is possible that this difference is, at least partially, attributable to the longer variable lists of the TM decision. A remarkable finding is also that respondents indicate more variables for the SL decision when it is the decision they elicit first, while the number of variables in the TM decision is not different depending on whether it is elicited first or second. Another finding is that the network is not significantly different between the time pressure and the no time pressure scenario, as far as the number of nodes is concerned.

Even though individual differences are large, remarkably enough, there are little differences between the average number of elicited variables for different socio-demographic groups. The network complexity is not significantly different between men

and women, between different age groups and between different income categories. Furthermore, it is also not related with the people's annual mileage and with how often people execute fun shopping. There is only one socio-demographic variable that has an influence on the network complexity, and that is education level. It appears that higher educated respondents indicate significantly less variables than lower educated respondents for both decisions. For the SL decision, the difference is mainly because higher educated respondents indicate less instrumental variables, while in the TM decision, they mainly indicate less contextual variables. Probably, the reason why higher educated respondents indicate significantly less variables than lower educated respondents, is because it is explicitly asked to limit the elicitation to the most important variables for the decision. Most likely, higher educated respondents are more able to make a distinction between the most important variables and less important variables, resulting in a lower number of elicited variables. Unfortunately, this is also a sign that the research method might be too difficult for lower educated people. Further research is needed to elucidate this.

So, it can be concluded that the network complexity is quite constant among different socio-demographic groups. For future research, this implies that there will be little or no biases on network complexity caused by the underrepresentation or overrepresentation by certain socio-demographic groups in the sample. This is a very positive finding.

5.2 Variables considered most by respondents

In this section, it is investigated how often the variables of each list appear in respondents' mental representation. In other words, how many respondents indicate a variable at least once during their elicitation? First, this analysis is performed for the SL decision, and next it is performed for the TM decision.

5.2.1 Presence of SL variables in respondents' mental representation

In the following figure, all contextual variables that can be related to the SL decision are shown. The variable "normally" is indicated by most respondents (96,8). This is in fact a variable that is automatically added to the subset in case the respondent indicates a cognitive subset without a contextual aspect. So this shows that 96,8% of all

respondents elicit at least one cognitive subset of the type “normally – value – instrument” for the SL decision.

By far the most common “real” contextual variables are “interest in a specific product”, which is indicated by 68,3% of respondents, and “time available”, which is indicated by 49,3% of respondents. So, the fact whether the respondent has an interest in a specific product type (a clothing product, or a non-clothing product like electronics) has a major impact on respondents’ SL choice, and also the amount of time they have available to perform the fun shopping activity is an important contextual aspect. Other variables that are considered by at least 20% of respondents in the SL decision are “companion”, “budget availability”, “weather”, “crowdedness in centre”, “sale season” and “parking space near zone”.

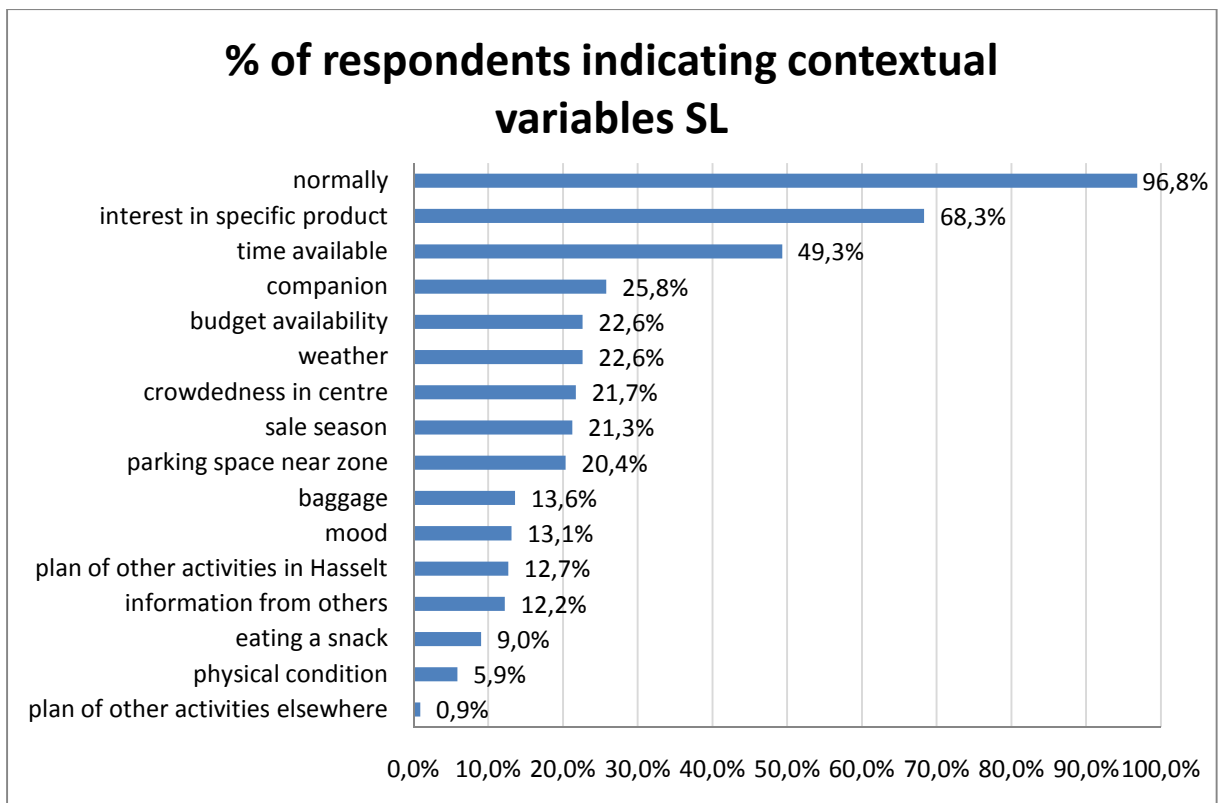


Figure 24: Percentage of respondents indicating each SL contextual variable.

In Figure 25, the number of respondents who indicate a certain evaluative aspect of the SL decision is shown. The evaluative aspect “efficiency” is mentioned by 76,5% of respondents, which makes it by far the most important value in the SL choice. Other

important evaluative aspects in the SL decision that are mentioned by more than 40% of respondents are "assurance and certainty", "convenience", "saving money" and "fun".

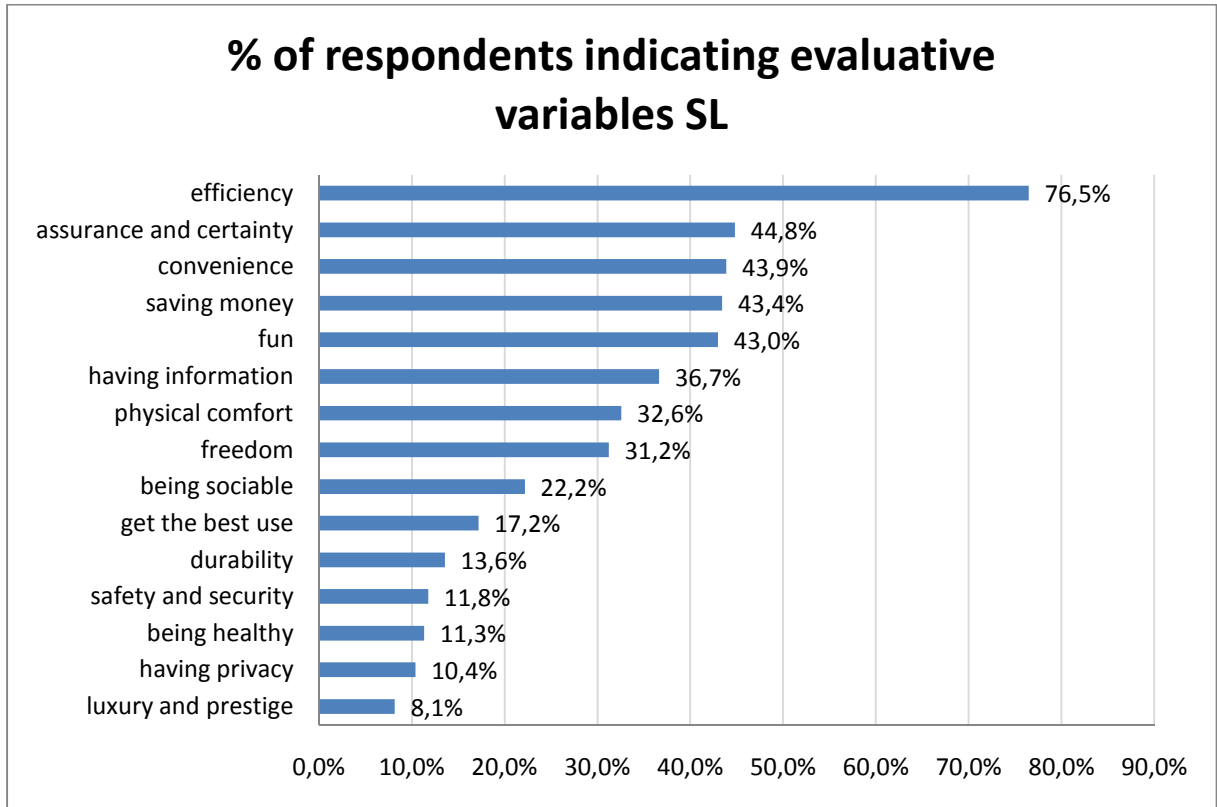


Figure 25: Percentage of respondents indicating each SL evaluative variable.

In Figure 26, the number of respondents who indicate a certain instrumental aspect of the SL decision is shown. Respondents state that the most important instrumental aspect of an SL is whether their favorite shop is present there or not. Other important aspects that are mentioned by more than 50% of respondents are the familiarity with the zone, type of stores in the zone (mainly clothing or non-clothing), the product prices in the zone, the accessibility of the zone and the quality of the products sold in the zone.

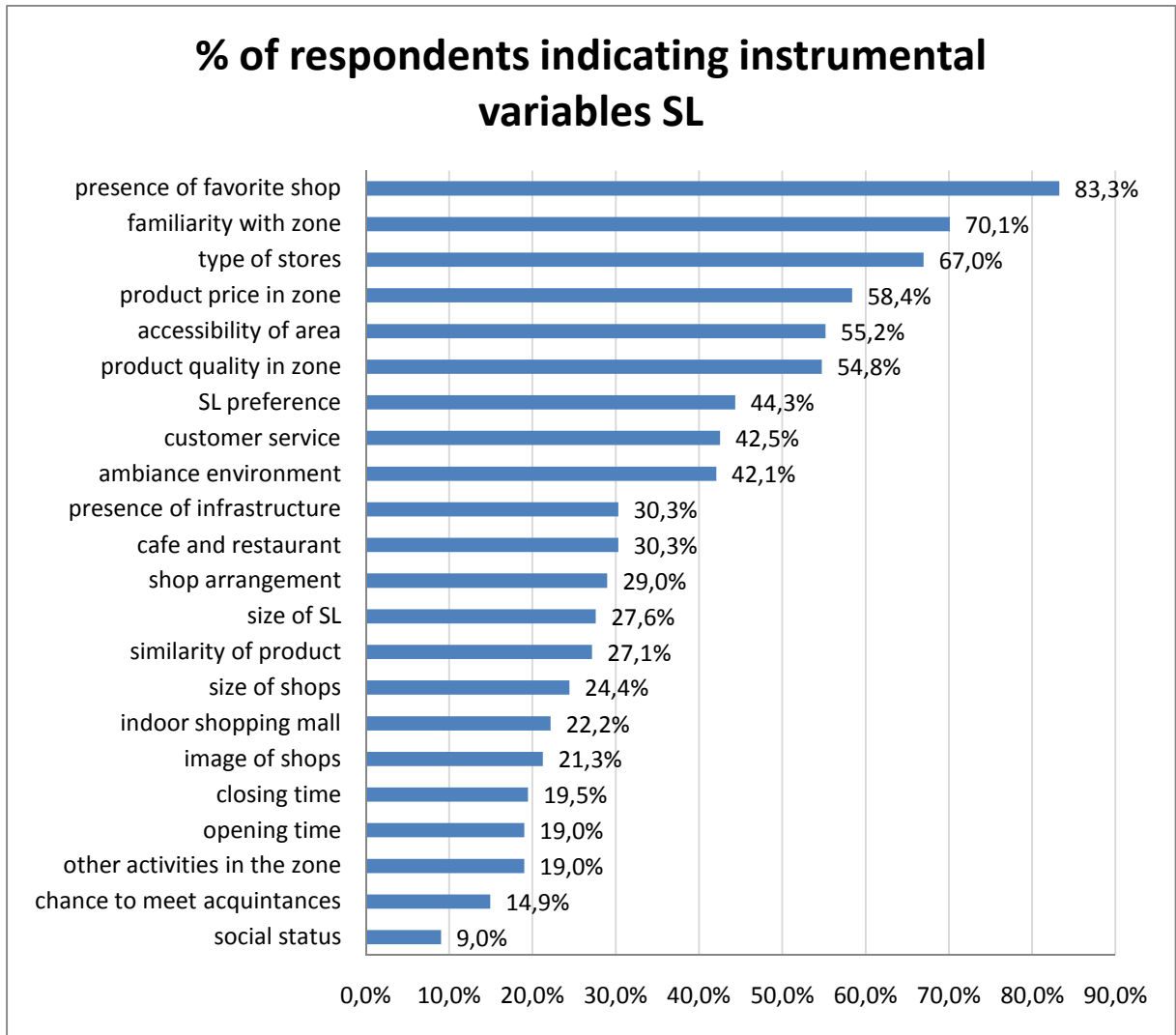


Figure 26: Percentage of respondents indicating each SL instrumental variable.

5.2.2 Presence of TM variables in respondents' mental representation

Again, the fact that "normally" is presented in the mental representation of the TM decision of 97,3% of all respondents shows that most people indicate at least one value – instrument relationship that they always consider, irrespective of contextual aspects.

Contexts that are mentioned most often are time available and precipitation. So, exactly like in the SL choice, the time people have available to execute their fun shopping activity has a major impact on their decisions. The finding that precipitation has an

important influence on the TM choice is in line with international literature (e.g. Cools, 2009; Khattak & De Palma, 1997).

Other items that are mentioned by more than one third of respondents are the amount of baggage respondents expect they will have to take home, and how easily respondents expect to find a parking space ("parking space availability").

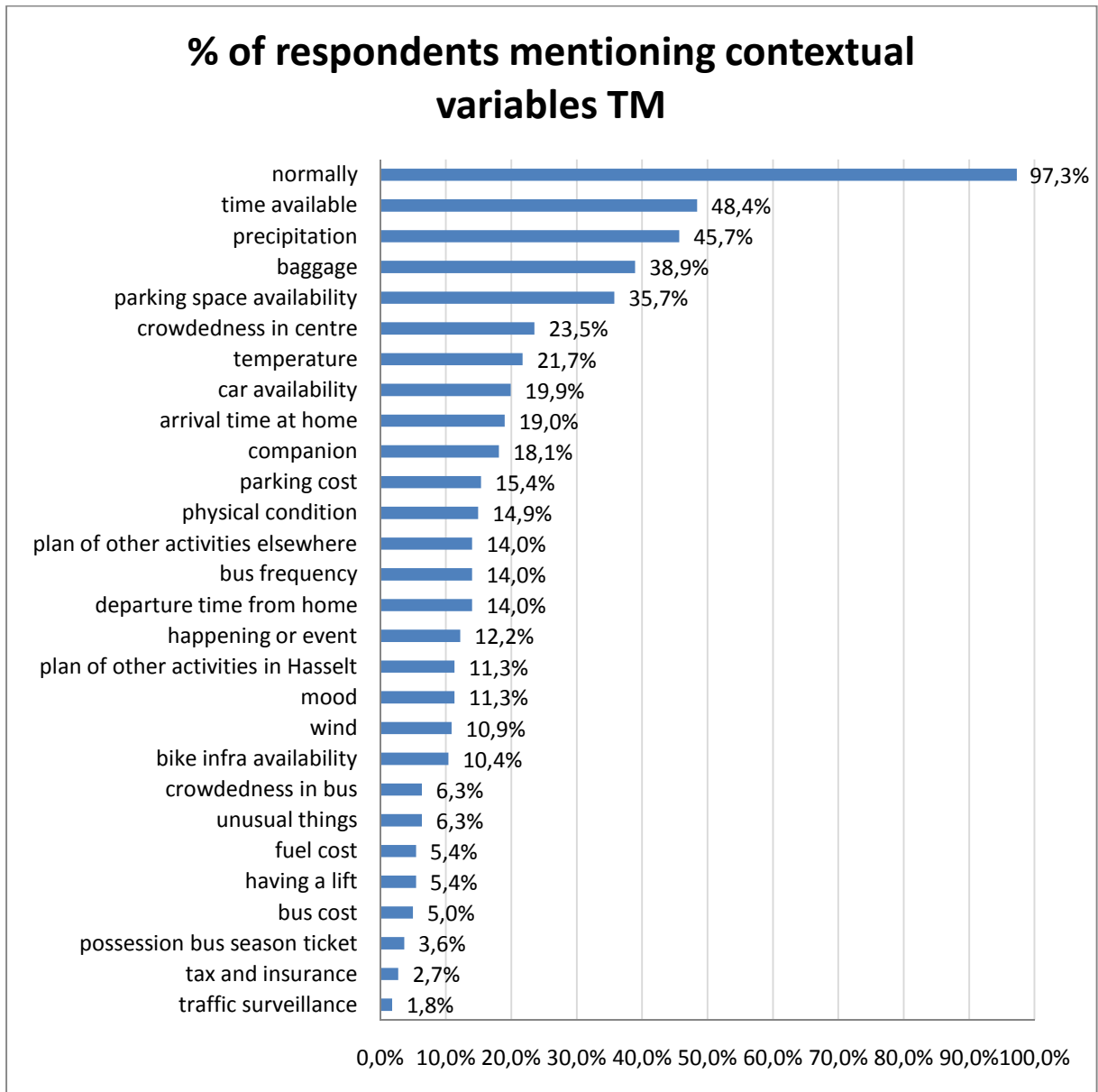


Figure 27: Percentage of respondents indicating each TM contextual variable.

Figure 28 shows by how many respondents a certain evaluative variable is chosen for the TM decision. Efficiency is the most important evaluative aspect (82,8%). Freedom, indicated by 75,6% of respondents, is also a very important value respondents want to gain from their TM choice. Physical comfort and convenience are other evaluative aspects that more than half of the respondents consider when making a TM decision for their fun shopping activity.

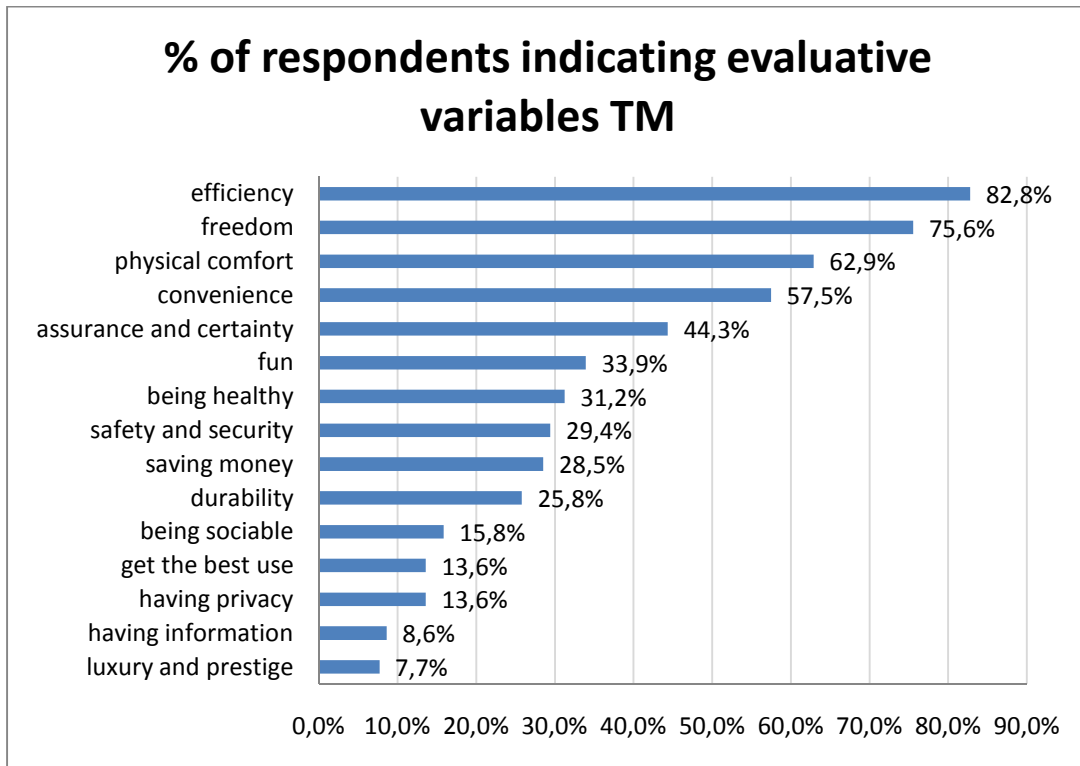


Figure 28: Percentage of respondents indicating each TM evaluative variable.

Figure 29 indicates that the instrumental measures that are chosen by respondents most often are flexibility, travel time, accessibility and easiness for parking. Also the treatment of bags is considered important by many respondents.

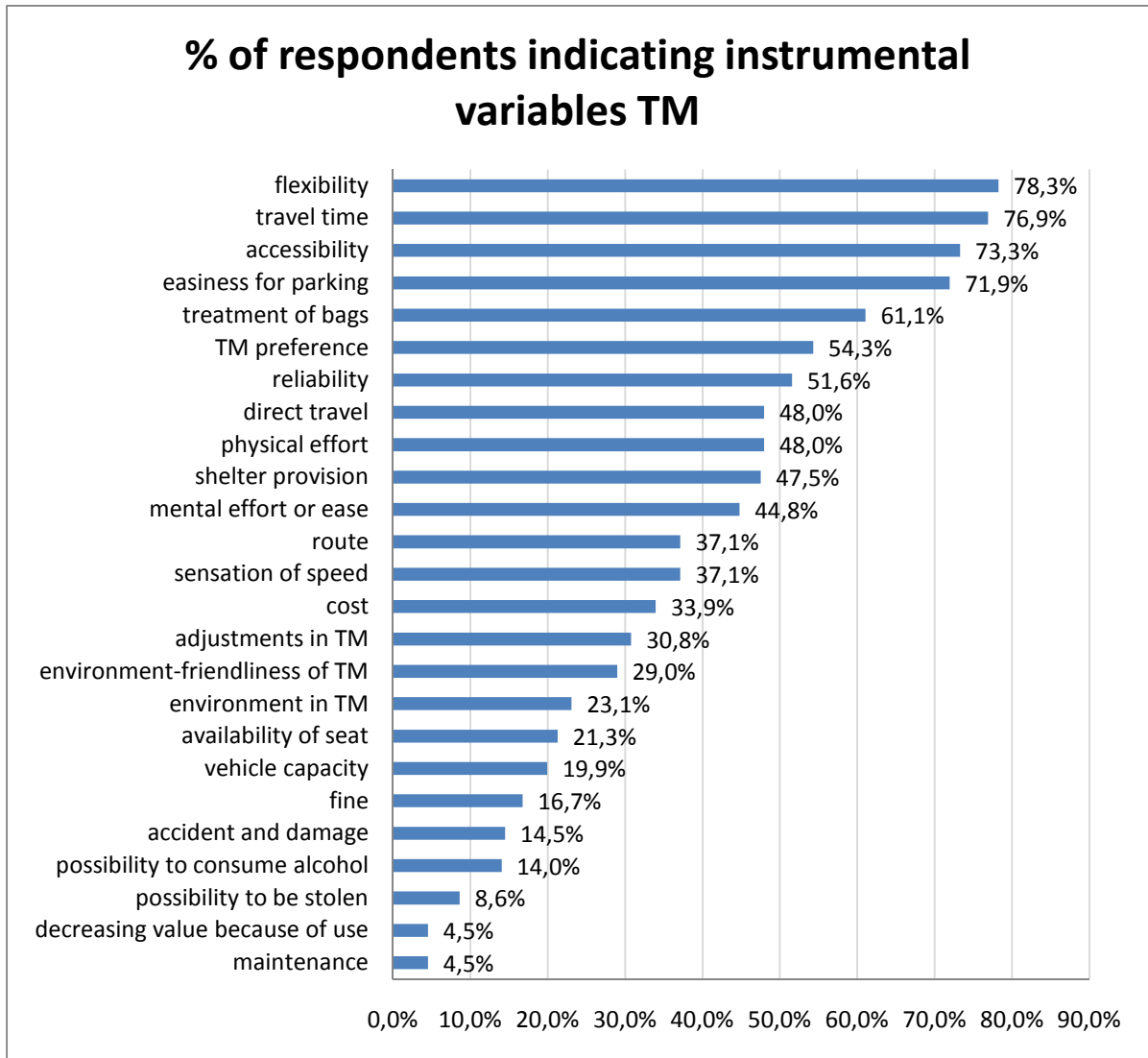


Figure 29: Percentage of respondents indicating each TM instrumental variable.

5.2.3 Conclusions variables considered most by respondents

In the SL choice, "interest in a specific product" and "time available" are the most important contextual aspects. "Efficiency" is by far the value that is mentioned by most respondents. The most important instrumental aspects of a SL are "presence of favorite shop", "familiarity with zone", "type of stores", "product price in zone", "accessibility of area" and "product quality in zone".

In the TM choice, "time availability" is one of the most important contextual variables, like in the SL choice. "Precipitation", "baggage" and "parking space availability" are other important contextual variables. Like in the SL choice, "efficiency" is considered to be the most important evaluative aspect, but other important values are "freedom", "physical comfort" and "convenience". The most important instrumental aspects in the TM decision are "flexibility", "travel time", "accessibility" and "easiness for parking".

It is not surprising that efficiency is the most important evaluative aspect in both decisions, since people have little time available nowadays, or at least have the feeling that they do. That is why they want to "waste" as little time as possible, even while executing leisure activities like fun shopping.

From a societal point of view, it is regrettable that the aspect "durability" only has a moderate importance. Especially in the TM decision (indicated by 25,8% of respondents), since sustainable transport is a hot issue at the moment. Policy makers are becoming more and more aware of the importance of preserving the world's natural resources to ensure a healthy and pleasant environment for ourselves and future generations. That is why in the last few years a lot of measures are introduced to encourage sustainable transportation (e.g. premiums for private persons who buy a car with a low emission of CO₂, tax deductibility for leasing cars dependent on CO₂ emission, premiums for soot filters, improvements to the public transport system, bike rewards...) and planned for the future (e.g. emission permits for aviation, introduction of road pricing,...). But, as is shown here, durability is not a major consideration of the broad public in the transport mode choice yet.

It is also important to keep in mind that most measures that are implemented to encourage sustainable transport modes are price measures. However, it can be seen that

“saving money” is not one of the most important evaluative aspects in respondents’ TM choice either, since only 28,5% of respondents considers it in their TM decision. That is why it is not surprising that the peak in fuel prices in Belgium in 2008 had little impact: although the fuel prices were on average 14% higher than in 2007, it only resulted in a 1% decrease in the total amount of person car kilometers (Belgian Federal Government, 2009b). So, it is not sure that price measures are the best way to encourage a sustainable TM choice. It seems that measures that increase the efficiency, freedom, comfort or convenience of sustainable transport modes can be far more effective. In section 6.2, measures to encourage sustainable transport modes are dealt with in more detail.

5.3 Frequent itemsets

This section investigates which associations are made most often between the variables of the different types. First, in section 5.3.1, the used methodology is explained. In section 5.3.2, the most common subsets are presented. In the following sections, the database is split into different subgroups, based on the presented scenario (0), on whether respondents start their elicitation from a habit or not (5.3.4) and on socio-demographic variables (5.3.5 until 5.3.9). This segmentation will allow to tailor measures or communication better to the most important considerations of each subgroup. It has been shown often in marketing research that a segmented approach can achieve better results at a lower cost than developing one program for the full population (Brijs, 2009; Weggemans & Schreuders, 2005).

5.3.1 Methodology

5.3.1.1 Association rules

The CB-CNET survey results in an extensive database, that should be analyzed in an efficient way. It was decided to apply association rule mining to the data to analyze the cognitive subsets that are elicited by respondents.

Association rule mining is an important topic in data mining. Data mining is a process of discovering valuable information from large amounts of data stored in databases, data warehouses or other information repositories. This valuable information can be for instance patterns, associations, changes, anomalies and significant structures. Hence, data mining attempts to extract potentially useful knowledge from data (C. Zhang & S. Zhang, 2002).

Data mining is different from traditional statistics. Formal statistical inference is assumption-driven in the sense that a hypothesis is formed and validated against the data while data mining is discovery-driven in the sense that patterns and hypotheses are extracted automatically from data. So, in other words, data mining is data driven, while statistics are human driven. Data mining is needed because potential patterns are often not apparent, and the amount of data in most applications is too large for manual analysis (C. Zhang & S. Zhang, 2002).

Association rule mining is the discovery of association relationships or correlations among a set of items. These associations are often represented in a rule form, showing attribute-value conditions that occur frequently together in a given set of data. An association rule in the form of $X \rightarrow Y$ is interpreted as "database tuples that satisfy X are likely to also satisfy Y". Association analysis is widely used in transaction data analysis for direct marketing, catalog design and other business process decision making (C. Zhang & S. Zhang, 2002).

Association rule mining is a notable technique for summarization. Association rule mining techniques find all associations from a database of the form: IF {set of values} THEN {set of values} (C. Zhang & S. Zhang, 2002). It is widely used to discover underlying relationships between variables in a data set in an efficient manner. The technique was first introduced in the nineties to find regularities in transaction data in supermarkets. Since then, it has been applied in a variety of fields, such as marketing, e-commerce, health, bioinformatics, transportation and traffic safety (Kusumastuti et al., 2009a).

In this study, association rules are used as a tool to describe frequent patterns of cognitive subsets generated from elicited data about respondents' mental representation for fun shopping related decisions. In order to have a better understanding of association

algorithms, their terminology is discussed here below. The examples that are presented are based on Kusumastuti et al. (2009a).

Association rule mining can be formally defined as follows (Kusumastuti et al., 2009a; C. Zhang & S. Zhang, 2002): $I = \{i_1, i_2, i_3, \dots, i_k\}$ is a set of items. For example, "weather", "comfort" and "shelter" are examples of items in the fun shopping database.

$D = \{t_i, t_{i+1}, \dots, t_n\}$ is a dataset consisting of different transactions t . Each t comprises of a set of items ($t \subseteq I$) (Kusumastuti et al., 2009a).

Example:

This example and the following examples of this section are obtained from Kusumastuti et al. (2009a). A set of data derived from the CNET card game contains 5 cognitive subsets t , and each consists of different items I :

1. Weather, shelter, comfort
2. Time available, travel time, efficiency
3. Time available, flexibility, freedom
4. Existing time, flexibility, efficiency
5. Companion, chance to sit, comfort

In general, there are two important steps when running association rules analyses: determine frequent itemsets and determine robust associations from the data set. Frequent item sets are single items or combinations of items that frequently appear in the data set. What is meant with "frequently", is determined from the minimum support value (minsupp) (Geurts, 2006). The support value indicates how often a single item or combination of items appears in the data (Kusumastuti et al., 2009a). An itemset in the database is considered as a frequent itemset if its support is equal to, or greater than, the threshold minimal support that is defined by the user (C. Zhang & S. Zhang, 2002). So, a high support value indicates that the combination of items can be commonly found in the database. The support value is usually expressed as a percentage of the total number of transactions in the database that contains the combination of items (Kusumastuti et al., 2009a).

Example:

This example shows how to calculate the support for items from the fun shopping data set above.

Support for size 1:

$$\text{supp}(\text{time available}) = 2/5 = 40\%$$

$$\text{supp}(\text{weather}) = 1/5 = 20\%$$

Support for size 2:

$$\text{supp}(\text{time available, travel time}) = 1/5 = 20\%$$

If the user specified the minsupp in this example at 30%, this would mean that the size 1 item (weather) (supp=20%) and size 2 items (time available, travel time) (supp=20%) are not considered as frequent item sets. Therefore, they are not used in further steps to generate strong associations.

After determining the frequent itemsets from the database, the association rules can be ran. Like the support value in the frequent item sets, an important measure in association rules is the confidence of the rule. The confidence is the ratio derived from the number of transactions that have all items in the antecedent (if) and the consequent (then), divided by the number of transactions that include all items in the antecedent (if). Or in other words (Kusumastuti et al., 2009a):

Data set D contains a rule of $x \rightarrow y$ (x = consequent, y = antecedent), where $x \subset I$, $y \subset I$ and $x \cap y = \emptyset$. The confidence of this rule is $c\%$. So this means that:

$$c = \frac{\text{supp}(x \cap y)}{\text{supp}(x)}$$

Like the minsupp defines which itemsets are "frequent", the minimum confidence (minconf) value specifies which associations are "strong".

Example:

The confidence of the rule *time available* \rightarrow *travel time* can be calculated as follows:

$$C_{(\text{time available} \rightarrow \text{travel time})} = 1/2 = 50\%$$

Because, when "time available" was indicated, in 1 out of 2 cases "travel time" was also indicated. So, of all transactions containing "time available", 50% also contains "travel time". If a minconf of 70% was specified, the rule *time available* \rightarrow *travel time* would not be considered as a strong association.

5.3.1.2 Data preparation and analysis

From the survey, we get the compilation of the cognitive subsets for each respondent. Recall that each subset consists of one set of contextual-instrumental-evaluative aspects, or instrumental-evaluative aspects. Each subset of each respondent is coded as a transaction.

However, we expect a low support value for the cognitive subsets because several transactions come from the same respondent. Respondents can only elicit a specific combination of context-instrument-evaluation once, leading to a low support value. Based on this reasoning, we can calculate the minsupp for each analysis as is shown in the following example (Kusumastuti et al., 2009a, p. 30):

Suppose that in a data set, 20 respondents each generate 5 cognitive subsets, resulting in a data set consisting of 100 cognitive subsets or transactions (T). Suppose that one particular subset is elicited by 50% of respondents in the survey. This means that 10 respondents have elicited the subset, so 10 transactions (t) in the dataset contain that particular itemset. So, then, the support can be calculated as follows:

$$supp = \frac{t}{T} = \frac{10}{100} = 0,1 = 10\%$$

So even though the subset is elicited by half of the respondents, it is still only present in 10% of the transactions in the database.

There is a major downside to this low expected support value. Ideally, one would run association rules to the entire database, containing all cognitive subsets and all socio-demographic variables and search for interesting associations. This way, no important associations in the database can be overlooked. However, since the minsupp should be set low enough to capture important associations between contextual, evaluative and instrumental variables, the software would generate a lot of associations that are irrelevant for the research. For instance, associations between different socio-demographic factors, like for instance a high correlation between a high education and a high income, or between a high income and the number of cars in a household. This way, thousands of association rules would be generated, that need to be manually checked for relevant associations. Another disadvantage is that it is very difficult to compare different socio-demographic groups this way, because the results of a socio-demographic group

are not grouped together, but scattered throughout the extensive list of frequent itemsets that is generated.

That is why it is decided to manually split the full database based on socio-demographic variables, for instance men vs. women, higher educated vs. lower educated, etc. This, however, has the drawback that databases of different sizes will be compared to each other. In that case, it is not possible to make reliable conclusions based on the confidence value. An example will clarify this. For instance, if 2 respondents in a dataset consisting of a total of 10 respondents indicate a particular cognitive subset, and 200 respondents in a different dataset of 1000 respondents indicate that subset as well, both analyses will result in a confidence level of 20% for that particular subset. However, it is clear that someone can have more confidence in the result of the larger dataset. Therefore, it is decided not to analyze the confidence level, which makes the analysis in fact an analysis of frequent itemsets in stead of an association rules analysis.

A weakness of this approach is that any possible strong associations between multiple socio-demographic factors and cognitive subsets can not be discovered this way. Investigating the link between multiple socio-demographic variables and cognitive subsets is a topic for further research.

Based on preliminary analyses, it is decided not to use one fixed minsupp for each analysis, but to always present the 10 most prevalent cognitive subsets in the analyses in the following section. The reason for this is that it is difficult to find one suitable minsupp for all analyses, because a support that is fit for one analysis will be too high or too low for an other analysis. This will result in an overload of frequent itemsets, or in no or very little frequent itemsets. The former problem would make analyzing the results cumbersome, while the latter will not make it possible to draw many conclusions. So, showing the 10 most important frequent itemsets will allow to make sufficient differentiations between analyses, while avoiding not being able to see the wood from the trees anymore. However, this could give difficulties in analyzing and comparing the results, since the most important frequent itemset in one analysis can have a lower support value than, for instance, the fifth most important frequent itemset in another analysis. To be able to compare the different analyses, the support value is provided in the tables in the column "csupp".

"Csupp" stands for "compensated support". This value is based on the support value of the itemset in the database. The support value is adjusted because it is hard to interpret. The support value shows in fact how much percent of the database consists of this itemset. However, in this research, each respondent elicits multiple cognitive subsets (so multiple transactions of the database are related to one person), and each cognitive subset can only be elicited once by a respondent. Therefore, the support value is difficult to interpret. The csupp accounts for this problem by multiplying the support value by the number of transactions in the database, and dividing it by the number of respondents in the database. This results in a value indicating the percentage of respondents that elicited the subset. So, the csupp simply shows how much percent of respondents elicited that particular cognitive subset.

Furthermore, the analyses are split into analyzing cognitive subsets of the type "context - value - instrument" and "normally - value - instrument". This is done because they are difficult to compare, since, purely from a probabilistic point of view, the chance that one particular set consisting of three elements is selected is smaller than the chance that one particular set of two elements is selected. Preliminary analyses showed that analyzing them together results in a list of frequent itemsets mainly consisting of the subsets of the "normally - value - instrument" type. So, if this split is not made, it will not be possible to draw many conclusions about the influence of contextual variables.

5.3.2 General analysis of elicited subsets

The structure of this section is as follows. First, a general analysis of the elicited subsets of both decisions is presented. Then, for both decisions, some more detailed further analyses are performed. It will be checked whether there are differences between respondents in a time pressure scenario and respondents in a no time pressure scenario, respondents who start their elicitation from a habit and respondents who do not start from a habit, between men and woman, among different age categories, between different income categories and between different education levels. Finally, one additional analysis is performed for the TM decision. It is checked whether there are differences between respondents in different distance classes from the city centre. The section ends with conclusions.

5.3.2.1 General analysis of elicited subsets of SL decision

In the following table, the 10 most frequent itemsets of the “normally – value – instrument” type are shown for the SL decision.

Table 59: Frequent itemsets SL decision (normally).

<i>Value</i>	<i>Instrument</i>	Csupp
efficiency	favorite shop	28,1%
efficiency	familiarity	25,8%
saving money	product price	19,5%
efficiency	type of stores	19,5%
fun	favorite shop	18,1%
certainty	favorite shop	17,6%
certainty	familiarity	17,6%
convenience	familiarity	14,5%
convenience	favorite shop	13,6%
fun	ambiance	12,7%

The most important associations respondents make in their SL decision are “efficiency – presence of favorite shop” and “efficiency – familiarity with the zone”, which are elicited by more than 25% of respondents. Furthermore, it can be noted that “presence of favorite shop” and “familiarity” are also often mentioned in combination with the values “assurance and certainty” and “convenience”. Since these variables are the ones that are mentioned by most respondents (see section 5.2.1), this is not very surprising. Another association made by many respondents is “saving money – product price in zone”. And the link between the value “fun” and the instruments “presence of favorite shop” and “ambiance environment” are also among the 10 most frequent itemsets in the SL decision.

The following table shows the most frequent context-specific itemsets for the SL decision.

Table 60: Frequent itemsets SL decision (with context).

<i>Context</i>	<i>Value</i>	<i>Instrument</i>	Csupp
specific product	efficiency	favorite shop	20,8%
specific product	efficiency	type of stores	18,1%
time available	efficiency	favorite shop	17,2%
specific product	efficiency	familiarity	16,7%
time available	efficiency	familiarity	16,3%
sale season	saving money	product price	11,3%
companion	fun	favorite shop	11,3%
budget available	saving money	product price	10,4%
sale season	saving money	favorite shop	10,4%
companion	fun	cafe restaurant	10,0%

Recall from section 5.2.1 that "interest in specific product" was the contextual aspect that was mentioned by most respondents. Most respondents state they consider this most often in combination with the value "efficiency". Instruments that help them gain efficiency, given the influence of interest in a specific product, are "presence of favorite shop", "type of stores" and "familiarity with the zone". "Time available" was also mentioned by many respondents and is also mainly associated with "efficiency". The instruments that are linked to this are "presence of favorite shop" and "familiarity with the zone". Furthermore, there are three money-related subsets that respondents consider import: "sale season – saving money – product price in zone", "budget availability – saving money – product price in zone" and "sale season – saving money – presence of favorite shop". Also, the context "companion" and the value "fun" are often together linked to the instruments "presence of favorite shop" and "café and restaurant".

5.3.2.2 General analysis of elicited subsets of TM decision

In the following table, frequent itemsets for the TM decision are displayed that respondents consider in any circumstances.

Table 61: Frequent itemsets TM decision (normally).

<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
freedom	flexibility	39,8%
efficiency	flexibility	33,9%
efficiency	travel time	33,9%
efficiency	easiness parking	32,1%
freedom	travel time	26,7%
efficiency	accessibility	26,2%
freedom	accessibility	24,9%
freedom	easiness parking	23,1%
freedom	treatment bags	20,8%
convenience	travel time	19,0%

The table shows that the most important associations of the type "value – instrument" are in fact mainly important interrelations between the values "efficiency" and "freedom" and the instruments "flexibility", "travel time", "easiness for parking" and "accessibility". The top ten is rounded out with the subsets "freedom – treatment of bags" and "convenience – travel time".

Table 62 shows frequent itemsets for the TM decision that are related to a contextual aspect.

Table 62: Frequent itemsets TM decision (with context).

<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
precipitation	physical comfort	shelter	21,7%
time available	efficiency	travel time	16,3%
baggage	physical comfort	treatment bags	14,9%
parking availability	efficiency	easiness parking	12,7%
time available	efficiency	flexibility	12,2%
parking availability	efficiency	accessibility	10,0%
baggage	physical comfort	physical effort	10,0%
time available	efficiency	easiness parking	9,5%
time available	efficiency	direct travel	9,5%
parking availability	efficiency	travel time	9,0%

The subset that is indicated most is "precipitation – physical comfort – shelter provision". "Time available" is mainly linked to the value "efficiency". So, the amount of time people

have available for their fun shopping activity strongly influences their consideration to choose an efficient transport mode. To gain this efficiency, given the influence of "time available", the most important instrumental aspects are "travel time", "flexibility", "easiness for parking" and "direct travel".

"Baggage" is often associated with "physical comfort", and the instruments that help to gain this physical comfort are "treatment of bags" and "physical effort". So the fact that different modes have different possibilities to handle bags and the physical effort that is related to this are important characteristics of the different TMs that are considered, given the amount of baggage they expect to bring home.

"Parking space availability" is mainly linked to the evaluative aspect "efficiency", and the instrumental aspects "easiness for parking", "accessibility" and "travel time".

5.3.2.3 Conclusions general analysis of elicited subsets of both decisions

The most important associations respondents make in their SL decision in any circumstances are "efficiency – presence of favorite shop" and "efficiency – familiarity with the zone". "Presence of favorite shop" and "familiarity with the zone" are also often mentioned in combination with the values "assurance and certainty" and "convenience". For the context-dependent subsets, "Interest in a specific product" is a contextual variable that is often mentioned combined with the value "efficiency" and the instruments "presence of favorite shop", "type of stores" and "familiarity with the zone". The fact that the instruments "ambiance environment" and "café and restaurant" are also present in the list of 10 most important subsets indicates that a mix in functions in the shopping area is important as well.

The most important associations of the type "normally – value – instrument" in the TM choice are interrelations between the values "efficiency" and "freedom" and the instruments "flexibility", "travel time", "easiness for parking" and "accessibility".

The most important context-specific subset in the TM decision is "precipitation – physical comfort – shelter provision". Remarkably enough, the other weather-related contextual variables temperature and wind are not among the most important associations made in

the TM decision. This indicates that respondents not really bother that much about the temperature or the wind for their TM choice, but only about precipitation.

Other context-specific frequent itemsets are "baggage – physical comfort – treatment of bags/physical comfort", and "parking space availability – efficiency – easiness for parking/accessibility/travel time".

One final remark is that the value "freedom" is very important in the frequent itemsets of the type "value – instrument", but not present in any of the most common context-specific subsets. So, apparently, freedom is something that is an important consideration for respondents, but that is not influenced strongly by contextual aspects.

One final finding is that for the SL decision, the context-dependent frequent itemsets have slightly higher csupp values than for the TM decision, while the frequent itemsets without a contextual variable have much higher csupp values in the TM decision than in the SL decision. So, context-dependent frequent itemsets are more important for the SL decision, while not context-dependent frequent itemsets are most important in the TM decision. This means that respondents' SL choice depends more strongly on circumstances, while for the choice of a TM, most reasoning is irrespective of circumstances. This indicates that the TM choice is more a habit than the SL choice, which is in line with the finding that more respondents start their elicitation for the TM decision from a habit than for the SL decision (see section 0).

5.3.3 Elicited subsets in different scenarios

5.3.3.1 Elicited subsets for SL decision in different scenarios

Below, the frequent itemsets of the time pressure scenario and the no time pressure scenario are shown for cognitive subsets that are considered in any circumstances. Note that associations that appear in the top ten of both scenarios are marked in the same color. Associations that are not marked are not present in the top ten of the other scenario.

Table 63: Frequent itemsets SL decision in different scenarios (normally).

<i>Time pressure scenario</i>			<i>No time pressure scenario</i>		
<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
efficiency	favorite shop	29,1%	efficiency	favorite shop	27,0%
efficiency	familiarity	27,3%	efficiency	familiarity	24,3%
efficiency	type of stores	22,7%	fun	favorite shop	19,8%
saving money	product price	20,9%	fun	ambiance	18,0%
certainty	familiarity	20,9%	saving money	product price	18,0%
certainty	favorite shop	18,2%	certainty	favorite shop	17,1%
fun	favorite shop	16,4%	efficiency	type of stores	16,2%
convenience	familiarity	16,4%	convenience	favorite shop	14,4%
efficiency	accessibility	13,6%	certainty	familiarity	14,4%
fun	type of stores	13,6%	efficiency	product price	13,5%

“Efficiency – presence of favorite shop” and “efficiency – familiarity with zone” are the most common associations in both scenarios. The most important difference is that respondents attach somewhat more value to associations related to “assurance and certainty” and “efficiency” in the no time pressure scenario, while in the no time pressure scenario, associations related to “fun” are more important.

The next table shows the context-specific frequent itemsets of the SL decision in different scenarios.

Table 64: Frequent itemsets SL decision in different scenarios (context).

<i>Time pressure scenario</i>				<i>No time pressure scenario</i>			
<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>	<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
specific product	efficiency	familiarity	23,6%	time available	efficiency	favorite shop	20,7%
specific product	efficiency	favorite shop	23,6%	specific product	efficiency	favorite shop	18,0%
time available	efficiency	familiarity	20,9%	specific product	efficiency	type of stores	16,2%
specific product	efficiency	type of stores	20,0%	companion	fun	cafe restaurant	12,6%
sale season	saving money	product price	13,6%	time available	efficiency	familiarity	11,7%
sale season	saving money	favorite shop	13,6%	companion	fun	favorite shop	10,8%
time available	efficiency	favorite shop	13,6%	companion	fun	ambiance	9,9%
budget availability	saving money	product price	12,7%	specific product	efficiency	familiarity	9,9%
sale season	saving money	product quality	11,8%	sale season	saving money	product price	9,0%
companion	fun	favorite shop	11,8%	companion	being sociable	cafe restaurant	9,0%

Concerning the context-specific associations, the most important association in the time pressure scenario is "interest in specific product – efficiency – familiarity with zone", while in the no time pressure scenario, this is the link between "time available – efficiency – presence of favorite shop". "Interest in specific product – efficiency – presence of favorite shop", is in both scenarios very important.

The most important difference between both scenarios here is the importance of associations containing the value "saving money" in the time pressure scenario, while the link between "companion", "fun" and several instruments ("café and restaurant", "presence of favorite shop" and "ambiance environment") is important in the no time pressure scenario.

5.3.3.2 Elicited subsets for TM decision in different scenarios

In the following table, the frequent itemsets of the time pressure scenario and the no time pressure scenario are shown for cognitive subsets that are considered in any circumstances.

Table 65: Frequent itemsets TM decision in different scenarios (normally).

<i>Time pressure scenario</i>			<i>No time pressure scenario</i>		
<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
efficiency	flexibility	39,1%	freedom	flexibility	41,4%
freedom	flexibility	38,2%	efficiency	travel time	34,2%
efficiency	easiness parking	33,6%	efficiency	easiness parking	30,6%
efficiency	travel time	33,6%	efficiency	flexibility	28,8%
freedom	accessibility	30,9%	freedom	travel time	25,2%
efficiency	accessibility	29,1%	efficiency	accessibility	23,4%
freedom	travel time	28,2%	freedom	easiness parking	23,4%
freedom	easiness parking	22,7%	freedom	treatment bags	22,5%
convenience	travel time	20,9%	efficiency	treatment bags	22,5%
convenience	flexibility	20,0%	efficiency	direct travel	18,9%

The top ten looks rather similar for both decisions. The most important difference is that the subset "freedom – accessibility" is very important in the time pressure scenario (csupp = 30,9%), while it is not among the ten most important ones in the no time pressure scenario.

Another difference is that in the time pressure scenario, respondents consider convenience more often than respondents in the no time pressure scenario (combined with the instruments "travel time" and "flexibility"). So mental ease is considered more important in case the respondent experiences time pressure than in case there is no time pressure.

In the following table, the context-specific frequent itemsets are shown for the TM decision in different scenarios.

Table 66: Frequent itemsets TM decision in different scenarios (context).

<i>Time pressure scenario</i>				<i>No time pressure scenario</i>			
Context	Value	Instrument	Csupp	Context	Value	Instrument	Csupp
precipitation	physical comfort	shelter	26,4%	precipitation	physical comfort	shelter	17,1%
time available	efficiency	travel time	19,1%	time available	efficiency	travel time	13,5%
baggage	physical comfort	treatment bags	18,2%	parking availability	efficiency	easiness parking	13,5%
time available	efficiency	flexibility	15,5%	baggage	physical comfort	treatment bags	11,7%
parking availability	efficiency	travel time	11,8%	parking availability	efficiency	accessibility	10,8%
parking availability	efficiency	easiness parking	11,8%	baggage	physical comfort	physical effort	9,9%
time available	efficiency	easiness parking	10,9%	departure time	freedom	flexibility	9,0%
crowdedness in centre	efficiency	easiness for parking	10,9%	time available	efficiency	flexibility	9,0%
time available	freedom	flexibility	10,0%	time available	efficiency	direct travel	9,0%
time available	efficiency	direct travel	10,0%	time available	efficiency	easiness parking	8,1%

The two most frequent itemsets are the same in both scenarios, “precipitation – physical comfort – shelter provision” and “time available – efficiency – travel time”. In the rest of the frequent itemsets, there are some differences, but there is no real trend in the differences. Most frequent itemsets that appear in one scenario but not in the other have two out of three variables in common with a frequent itemset in the other scenario, so these differences are not really distinct.

Note that the csupp value for the frequent itemsets in the time pressure scenario is once more substantially higher than for the frequent itemsets in the no time pressure scenario.

5.3.3.3 Conclusions elicited subsets in different scenarios

Concerning the SL decision, in both the time pressure scenario and the no time pressure scenario, efficiency-related subsets are most important. The fact that even respondents in the no time pressure scenario value efficiency that strongly endorses the previously mentioned suspicion that even for leisure activities, efficiency is becoming more and more important because most people have little time available nowadays.

From the analysis of the "normally" subsets, it appears that "assurance and certainty" is the second most important value in the SL decision in a time pressure scenario. It is linked with the instruments "familiarity with zone" and "presence of favorite shop". This indicates that, in case of time pressure, respondents go to places they are familiar with, or to their favorite stores to be sure that they will find what they are looking for. In the no time pressure scenario on the other hand, "fun" is valued higher, which means that people just want to have a good time when they are not experiencing time pressure.

The analysis of the context-specific subsets of the SL decision indicates that respondents in a time pressure scenario attach a lot more value to "saving money" than respondents in the no time pressure scenario. This indicates that respondents get more price-conscious in case of time pressure. This could mean that respondents basically simplify their SL choice by omitting other product-related characteristics, and just want to focus on buying a suitable product that is not too expensive, rather than spending time searching for the product that would satisfy them most. So in case of time pressure, they are looking for an acceptable solution instead of the optimal solution.

Respondents in the no time pressure scenario on the other hand mainly indicated that the contextual aspect "companion" is very important, mostly related to the value "fun". So basically they do not want to just have a good time themselves, but also want to make sure their partner or friends have a good time too when they accompany them. So, in case of a no time pressure scenario, the opinion of their companion will be taken into account, having a strong influence on decisions. However, in case of time pressure, the opinion of company seems to matter less. So, whether the person goes fun shopping by himself or with a companion will not be an important contextual consideration in case of time pressure, since his or her opinion is less taken into account.

Another finding was that the csupp value is consistently higher for the frequent itemsets of the time pressure scenario than for the no time pressure scenario in the SL decision. This is especially the case for the most frequent context-specific subsets. This indicates that, in a time pressure scenario, most respondents reason from a few main lines of thoughts, while in case of a no time pressure scenario, respondents' reasoning is rather dispersed. So, in case of no time pressure, respondents all seem to have "their own reasons", while their thoughts are more similar in case of time pressure. This indicates that respondents' SL choice is more easy to predict in case of time pressure than in case of no time pressure.

In the TM decision, "efficiency" and "freedom" related subsets are very important in any circumstances. They are mainly linked to instruments like flexibility and travel time. "Precipitation – physical comfort – shelter provision" is the most important context-specific cognitive subset in both scenarios. However, this association is mentioned by far more respondents in the time pressure scenario (26,4%) than in the no time pressure scenario (17,1%). A possible explanation is that some respondents think that, if they have no time pressure, they can more easily reschedule their activity a few hours to wait until there is no precipitation anymore, which lowers the importance of having shelter. So, in case of the no time pressure scenario, precipitation is considered by less respondents for the TM decision, because they are likely to choose to reschedule their activity. Respondents in the time pressure scenario, on the other hand have the feeling that they are forced to do the fun shopping activity now, whether there is precipitation or not. So they feel they do not have this option of rescheduling, but only the option to change their transport mode (e.g. not going by bike, but going by car or bus instead).

Recall from section 3.2 that the decision when to go fun shopping (and the possibility of rescheduling) is not investigated in this research. However, if this reasoning about the set "precipitation – physical comfort – shelter provision" is correct, this indicates that omitting one of these three interrelated decisions can decrease the accurateness of the elicitation process, because respondents have difficulties reasoning about 2 of these decisions while not taking into account the third one, that is fixed in the scenario description. So, in other words, even if the research setting does not allow rescheduling, it is possible that respondents do consider it unconsciously: if they have no time pressure, they might think about rescheduling the activity in case of bad weather conditions, which reduces the importance of the association "precipitation – physical

comfort – shelter provision”. Whether omitting one of the decisions from the research has an impact on the results or not is a topic for further research.

Like in the SL decision, in the TM decision there is also a clear trend of consistently higher csupp values for the frequent itemsets of the time pressure scenario than for the no time pressure scenario. This supports the previously mentioned idea that, in a time pressure scenario, many respondents reason from some main lines of thoughts, while in case of a no time pressure scenario, respondents reasoning is rather dispersed.

5.3.4 Elicited subsets when starting from a habit or not

5.3.4.1 Elicited subsets for SL decision when starting from a habit or not

In the following table, the not context dependent frequent itemsets are presented for respondents who start from an SL habit and respondents who do not start from an SL habit.

Table 67: Frequent itemsets SL decision starting from a habit or not (context).

<i>Starting from an SL habit</i>			<i>Not starting from a SL habit</i>		
<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
efficiency	favorite shop	35,1%	efficiency	favorite shop	22,8%
efficiency	familiarity	34,0%	efficiency	familiarity	19,7%
efficiency	type of stores	29,8%	saving money	product price	16,5%
certainty	favorite shop	28,7%	fun	favorite shop	15,0%
certainty	familiarity	26,6%	fun	ambiance	11,8%
saving money	product price	23,4%	efficiency	type of stores	11,8%
fun	favorite shop	22,3%	saving money	product quality	11,0%
convenience	favorite shop	21,3%	efficiency	customer service	11,0%
convenience	familiarity	21,3%	certainty	familiarity	11,0%
efficiency	product price	20,2%	efficiency	accessibility	10,2%

It appears that both groups of respondents attach most importance to frequent itemsets related to “efficiency”. The subsets “efficiency – presence of favorite shop” and “efficiency – familiarity with zone” are the most important ones for both groups. Respondents that start from an SL habit also attach a lot of importance to “assurance

and certainty”, which they relate to the instruments “presence of favorite shop” and “familiarity with zone”. Respondents who do not start from an SL habit on the other hand attach a relatively higher importance to fun-related frequent itemsets. Also saving money-related frequent itemsets are relatively more important to respondents without SL habit.

In Table 68, the not context dependent frequent itemsets are presented for respondents who start from an SL habit and respondents who do not start from an SL habit.

Table 68: Frequent itemsets SL decision starting from a habit or not (normally).

<i>Starting from an SL habit</i>				<i>Not starting from a SL habit</i>			
<i>Context</i>	<i>Value</i>	<i>Instr</i>	<i>Csupp</i>	<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
time available	efficiency	favorite shop	21,3%	specific product	efficiency	type of stores	24,4%
sale season	saving money	product price	17,0%	specific product	efficiency	favorite shop	24,4%
time available	efficiency	familiarity	16,0%	specific product	efficiency	familiarity	18,9%
specific product	efficiency	favorite shop	16,0%	time available	efficiency	familiarity	16,5%
specific product	certainty	favorite shop	14,9%	companion	fun	favorite shop	15,0%
specific product	efficiency	familiarity	13,8%	time available	efficiency	favorite shop	14,2%
budget availability	saving money	product price	12,8%	companion	fun	cafe restaurant	12,6%
sale season	saving money	favorite shop	12,8%	companion	fun	ambiance	11,0%
sale season	saving money	product quality	10,6%	specific product	having info	product price	11,0%
specific product	certainty	familiarity	10,6%	parking space	efficiency	accessibility	10,2%

For respondents who do not start from an SL habit, subsets that are related to “interest in a specific product” are by far most important. Subsets related to “time available” and “companion” are also quite important to them. Respondents that start from a habit on the other hand mention that “time available” and “sale season” are most important to them, and “interest in a specific product” as well, but to a somewhat lesser degree.

5.3.4.2 Elicited subsets for TM decision when starting from a habit or not

In the following table, the not context dependent frequent itemsets are presented for respondents who start from a TM habit and respondents who do not start from a TM habit.

Table 69: Frequent itemsets TM decision starting from a habit or not (normally).

<i>Starting from a TM habit</i>			<i>Not starting from a TM habit</i>		
<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
freedom	flexibility	53,0%	efficiency	easiness parking	32,1%
efficiency	flexibility	48,7%	freedom	flexibility	25,5%
efficiency	travel time	43,5%	freedom	easiness parking	24,5%
freedom	travel time	39,1%	efficiency	travel time	23,6%
freedom	accessibility	33,9%	efficiency	accessibility	20,8%
efficiency	easiness parking	32,2%	efficiency	flexibility	17,9%
efficiency	accessibility	31,3%	freedom	accessibility	15,1%
convenience	travel time	30,4%	freedom	treatment bags	15,1%
efficiency	treatment bags	27,0%	convenience	easiness parking	13,2%
convenience	flexibility	26,1%	freedom	travel time	13,2%

It appears that both groups of respondents attach most importance to freedom- and efficiency-related subsets. There are some differences between both groups, but no real patterns occur, except that respondents that do not start from a TM habit attach relatively more importance to the instrumental aspect "easiness for parking". They relate it most often to the values "efficiency", "freedom" and "convenience".

In the following table, the not context-specific frequent itemsets are presented for respondents who start from a TM habit and respondents who do not start from a TM habit.

Table 70: Frequent itemsets TM decision starting from a habit or not (context).

<i>Starting from a TM habit</i>				<i>Not starting from a TM habit</i>			
<i>Context</i>	<i>Value</i>	<i>Instr</i>	<i>Csupp</i>	<i>Context</i>	<i>Value</i>	<i>Instr</i>	<i>Csupp</i>
time available	efficiency	flexibility	13,0%	precipitation	physical comfort	shelter	34,0%
time available	efficiency	travel time	12,2%	baggage	physical comfort	treatment bags	21,7%
precipitation	physical comfort	shelter	10,4%	time available	efficiency	travel time	20,8%
baggage	physical comfort	treatment bags	8,7%	parking availability	efficiency	easiness for parking	17,9%
time available	efficiency	easiness parking	7,8%	parking availability	efficiency	accessibility	14,2%
time available	efficiency	accessibility	7,8%	baggage	physical comfort	physical effort	14,2%
time available	efficiency	direct travel	7,8%	baggage	efficiency	treatment bags	12,3%
parking availability	efficiency	easiness for parking	7,8%	parking availability	efficiency	travel time	11,3%
activities elsewhere	efficiency	travel time	7,8%	time available	efficiency	direct travel	11,3%
time available	freedom	flexibility	7,0%	time available	efficiency	flexibility	11,3%

It appears that “time available” is the contextual aspect that respondents with a TM habit consider most. It is nearly always linked to the value of efficiency. “Flexibility”, “travel time”, “easiness for parking”, “accessibility” and “direct travel” are the instrumental aspects that help these respondents gain the value of “efficiency”, given the influence of “time availability”.

For respondents that have no TM habit, “precipitation” is by far the most often indicated contextual aspect. Also the contextual aspects “baggage” and “parking space availability” are strongly considered by respondents without a TM habit. “Baggage” is often linked to the value of “physical effort” and the instrument “treatment of bags”. The contextual aspects “parking space availability” and “time available” are also present in the list of ten most important subsets.

5.3.4.3 Conclusions elicited subsets for starting from a habit or not

In any circumstances, both groups of respondents attach most importance to efficiency-related frequent itemsets in the SL decision. Respondents that start from an SL habit also consider subsets related to "assurance and certainty" important, while respondents that do not start from an SL habit attach more importance to fun-related subsets. Considering the context-specific subsets, "interest in a specific product" is most important to respondents without an SL habit. Also subsets related to "time available" and "companion" are important to them. Respondents that start from a habit mention that "time available" and "sale season" are most important to them, but also "interest in a specific product" is mentioned quite often.

It is remarkable that respondents that do not start from an SL habit attach a relatively higher importance to "saving money" related subsets in all circumstances, while respondents that start from an SL habit attach a higher importance to the contexts "sale season" and "budget availability". However, it should be mentioned that, in absolute terms, respondents who start from an SL habit also indicate "saving money" related subsets that are not context-dependent more often.

The large differences in the csupp values between both groups are the result of the survey structure. Respondents who indicate that they start from a habit, start the elicitation with the not context-specific subsets, and can later indicate context-specific subsets (optional). Respondents who do not start from a habit, on the other hand, first elicit context-specific subsets, and can later indicate not context-specific subsets (optional). This results in higher csupp values for not context-specific frequent itemsets for respondents who start from a habit, while the context-specific frequent itemsets have higher csupp values for respondents who do not start from a habit. Taking this into account, we get to the conclusion that respondents who start from an SL habit attach a substantially higher importance to "saving money" than respondents who do not start from an SL habit.

Concerning the TM choice, both groups of respondents attach most importance to freedom- and efficiency-related subsets in any circumstances. The most important difference between both groups of respondents is the fact that the instrumental variable "easiness for parking" is relatively more important to respondents who do not start from

a TM habit. For the context-specific subsets, respondents with a TM habit indicate that the contextual aspect "time available" is most important to them. Respondents without a TM habit indicate that the context of "precipitation" is far most important to them, but many of them also consider "baggage" and "parking space availability".

This analysis makes in fact a distinction between respondents who have a TM habit, and choice travelers. It has been noted before in scientific research that it is often difficult to break an undesirable TM habit, because habits are triggered by the social and/or physical environment the person is embedded in (Bargh & Chartrand, 1999; Verplanken & Wood, 2006). However, changing the environment is a process that requires a lot of time, effort and money. That is why it is probably more efficient to focus on the category of choice travelers. In this survey, nearly 50% of respondents indicate that they do not have a TM habit for fun shopping trips. So, if it would be possible to shift these people's TM choice in a way that they choose car less often, this would have a substantial impact on the modal split of fun shopping trips at a lower cost than breaking the habit of people who always choose car. From both the not context-specific and the context-specific frequent itemsets, it appears that variables related to parking space are important to people who have no TM habit. So, this result indicates that parking restricting measures can have a major impact on the TM choice of choice travelers.

5.3.5 Differences in elicited subsets by gender

5.3.5.1 Elicited subsets for SL decision by gender

In the following table, frequent itemsets that are considered in any circumstances are presented for men and women.

Table 71: Frequent itemsets SL decision for different genders (normally).

<i>Men</i>			<i>Women</i>		
<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
efficiency	favorite shop	28,4%	efficiency	favorite shop	27,8%
efficiency	familiarity	24,2%	efficiency	familiarity	27,0%
certainty	familiarity	20,0%	efficiency	type of stores	23,0%
saving money	product price	18,9%	fun	favorite shop	22,2%
certainty	favorite shop	18,9%	saving money	product price	19,8%
efficiency	accessibility of area	15,8%	certainty	favorite shop	16,7%
efficiency	type of stores	14,7%	certainty	familiarity	15,9%
convenience	favorite shop	14,7%	convenience	familiarity	15,9%
certainty	type of stores	13,7%	fun	type of stores	13,5%
fun	ambiance	12,6%	fun	ambiance	12,7%

Both men and women attach most importance to efficiency-related subsets. Also the link between "saving money" and "product price in zone" is approximately equally important for both genders. The most important difference is that men attach a higher importance to associations related to "assurance and certainty", while for women, subsets related to "fun" are more important.

The next table presents the context-specific frequent itemsets of men and women.

Table 72: Frequent itemsets SL decision for different genders (contextual).

<i>Men</i>				<i>Women</i>			
<i>Context</i>	<i>Value</i>	<i>Instr</i>	<i>Csupp</i>	<i>Context</i>	<i>Value</i>	<i>Instr</i>	<i>Csupp</i>
specific product	efficiency	favorite shop	24,2%	time available	efficiency	familiarity	19,8%
specific product	efficiency	type of stores	21,1%	time available	efficiency	favorite shop	19,0%
specific product	efficiency	familiarity	14,7%	specific product	efficiency	favorite shop	18,3%
time available	efficiency	favorite shop	14,7%	specific product	efficiency	familiarity	18,3%
specific product	efficiency	product price	12,6%	companion	fun	favorite shop	15,9%
specific product	having info	product price	11,6%	specific product	efficiency	type of stores	15,9%
specific product	certainty	product quality	11,6%	budget availability	saving money	product price	13,5%
specific product	certainty	favorite shop	11,6%	sale season	saving money	favorite shop	12,7%
time available	efficiency	familiarity	11,6%	sale season	saving money	product price	11,9%
sale season	saving money	product price	10,5%	companion	fun	cafe restaurant	10,3%

For the context-specific frequent itemsets on the other hand, differences are more pronounced. "Interest in specific product" has a huge importance to men (7 out of the 8 most important context-specific frequent itemsets are related to it), while there are multiple contextual aspects that are important to women. To them, "time availability" has the most impact on their SL choice. "Interest in a specific product" is their second most important contextual aspect. Also, there are two subsets related to the context "companion" and the value "fun" that they consider important, and they indicate that "sale season" and "budget availability" are important to them because it has an impact on the value of "saving money".

5.3.5.2 Elicited subsets for TM decision by gender

Table 73: Frequent itemsets TM decision for different genders (normally).

Men			Women		
Value	Instrument	Csupp	Value	Instrument	Csupp
freedom	flexibility	36,8%	freedom	flexibility	42,1%
efficiency	travel time	31,6%	efficiency	flexibility	37,3%
efficiency	flexibility	29,5%	efficiency	travel time	35,7%
efficiency	easiness parking	28,4%	efficiency	easiness parking	34,9%
efficiency	accessibility	22,1%	freedom	accessibility	31,0%
freedom	treatment of bags	22,1%	freedom	travel time	30,2%
freedom	travel time	22,1%	efficiency	accessibility	29,4%
freedom	easiness for parking	18,9%	freedom	easiness parking	26,2%
efficiency	treatment of bags	17,9%	convenience	flexibility	21,4%
durability	environment-friendliness	17,9%	convenience	travel time	20,6%

Concerning the not context-specific subsets of the TM decision, the differences between men and women are very small. The main difference is that women attach some importance to the value of “convenience”, while this is less important to men.

Table 74: Frequent itemsets TM decision for different genders (context).

Men				Women			
Context	Value	Instr	Csupp	Context	Value	Instr	Csupp
precipitation	physical comfort	shelter	23,2%	precipitation	physical comfort	shelter	20,6%
time available	efficiency	travel time	14,7%	baggage	physical comfort	treatment bags	17,5%
parking availability	efficiency	easiness parking	12,6%	time available	efficiency	travel time	17,5%
baggage	physical comfort	treatment bags	11,6%	time available	efficiency	flexibility	16,7%
car availability	freedom	flexibility	10,5%	parking availability	efficiency	travel time	12,7%
parking availability	efficiency	accessibility	9,5%	parking availability	efficiency	easiness parking	12,7%
time available	efficiency	easiness parking	9,5%	baggage	physical comfort	physical effort	11,1%
baggage	physical comfort	physical effort	8,4%	time available	efficiency	direct travel	11,1%
time available	certainty	travel time	8,4%	time available	freedom	flexibility	11,1%
crowdedness in centre	efficiency	easiness parking	8,4%	parking availability	efficiency	accessibility	10,3%

Concerning the context-specific frequent itemsets, it can be noted that subsets related to "time available" have a higher importance for women than for men. Another remarkable finding is that car availability is an important consideration for men, but not for women.

5.3.5.3 Conclusions differences in elicited subsets by gender

In all circumstances, both men and women attach most importance in their SL choice to efficiency-related subsets, and "saving money – product price in zone" is also equally important for both. Men attach a higher importance to "assurance and certainty", while women consider "fun" more important. Concerning the context-specific subsets, men attach major importance to "interest in specific product", while women have multiple important contextual aspects: time availability, interest in a specific product, companion (linked to the value of fun) and sale season and budget availability (linked to the value of saving money).

These findings indicate two things. Firstly, they show that Cyndi Lauper does have a point when she sings that "girls just wanna have fun" (although they appreciate efficiency even more). And secondly, it also shows that the (sexist) statement of some men, i.e. that women spend too much money on shopping, is in fact incorrect, since it is shown here that women attach more importance to saving money in their SL choice than men. A possible explanation could be that women go fun shopping more often than men. This requires them to be more economic in their expenditures when they go fun shopping. Men on the other hand go fun shopping less often, so on average they can spend more money each time.

Concerning the TM decision, the differences are small for the not context-specific frequent itemsets. For the context-specific frequent itemsets, it appears that women attach somewhat more value to subsets that are related to the context of "time available", while men consider "car availability" rather strongly. The latter finding is quite remarkable. A common idea is that, in case a household does not have a car for each person with a license, the man will take the car more often than the women. She will then have to take other TMs more often. However, this idea is not supported by the research results.

5.3.6 Differences in elicited subsets for different age categories

In section 4.2.1.2, a distinction was made between five age categories: 19-29, 30-39, 40-49, 50-59 and 60+. To analyze the network complexity, this was a logical choice. However, analyzing the frequent itemsets of five different age categories is very cumbersome. That is why it is decided to distinguish between three different age categories: young (19-39), middle-aged (40-59) and elderly (60 or older).

5.3.6.1 Elicited subsets for SL decision for different age categories

Table 75: Frequent itemsets SL decision for different age categories (normally).

<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
<i>Young (19-39)</i>		
efficiency	type of stores	30,4%
efficiency	familiarity	27,8%
fun	favorite shop	25,3%
efficiency	favorite shop	25,3%
fun	type of stores	22,8%
certainty	familiarity	21,5%
saving money	product price in zone	19,0%
certainty	favorite shop	19,0%
fun	ambiance	17,7%
fun	familiarity	17,7%
<i>Middle-aged (40-59)</i>		
efficiency	favorite shop	27,9%
efficiency	familiarity	26,0%
saving money	product price	17,3%
fun	favorite shop	16,3%
certainty	favorite shop	15,4%
convenience	favorite shop	14,4%
efficiency	type of stores	13,5%
saving money	product quality	13,5%
saving money	favorite shop	12,5%
certainty	familiarity	12,5%

<i>Elderly (60 and older)</i>		
efficiency	favorite shop	34,2%
saving money	product price	26,3%
certainty	familiarity	23,7%
efficiency	product price	21,1%
certainty	favorite shop	21,1%
convenience	familiarity	21,1%
efficiency	familiarity	21,1%
efficiency	customer service	18,4%
having info	product price	15,8%
saving money	product quality	15,8%

For the cognitive subsets that are considered in any circumstances, it appears that young people attach more importance to efficiency-related cognitive subsets. It also appears that fun-related frequent itemsets are also very important to young people, while they are less important to the other age groups. Respondents from the middle-age and the elder group on the other hand seem to attach more importance to saving money-related associations. And for elderly, subsets related to “assurance and certainty” are also very important.

Table 76: Frequent itemsets SL decision for different age categories (context).

<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
<i>Young (19-39)</i>			
specific product	efficiency	familiarity	27,8%
specific product	efficiency	type of stores	26,6%
specific product	efficiency	favorite shop	25,3%
time available	efficiency	familiarity	21,5%
budget availability	saving money	product price in zone	20,3%
time available	efficiency	favorite shop	20,3%
specific product	having info	product price	16,5%
companion	fun	favorite shop	12,7%
time available	efficiency	closing time	12,7%
time available	efficiency	accessibility	12,7%

<i>Middle-aged (40-59)</i>			
specific product	efficiency	favorite shop	20,2%
time available	efficiency	favorite shop	16,3%
sale season	saving money	product price	15,4%
time available	efficiency	familiarity	15,4%
sale season	saving money	favorite shop	14,4%
specific product	efficiency	type of stores	14,4%
sale season	saving money	product quality	12,5%
crowdedness in centre	efficiency	favorite shop	12,5%
companion	fun	favorite shop	11,5%
specific product	efficiency	familiarity	11,5%
<i>Elderly (60 and older)</i>			
specific product	efficiency	favorite shop	13,2%
time available	efficiency	favorite shop	13,2%
sale season	saving money	customer service	13,2%
sale season	saving money	favorite shop	13,2%
companion	fun	cafe restaurant	13,2%
companion	fun	ambiance	13,2%
specific product	certainty	customer service	10,5%
specific product	having information	customer service	10,5%
specific product	efficiency	product price	10,5%
specific product	efficiency	type of stores	10,5%

There are some interesting differences between the context-specific frequent itemsets in the SL decision of the different age categories. Although frequent itemsets related to "interest in specific product" are important to all age categories, they are clearly more important to the category of young people than to the other age categories. For elderly, frequent itemsets related to companion are important, as well as sale season-related frequent itemsets, remarkably enough.

5.3.6.2 Elicited subsets for TM decision for different age categories

Table 77: Frequent itemsets TM decision for different age categories (normally).

<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
<i>Young (19-39)</i>		
efficiency	travel time	46,8%
efficiency	flexibility	44,3%
freedom	flexibility	40,5%
efficiency	easiness for parking	35,4%
efficiency	accessibility	34,2%
freedom	travel time	29,1%
efficiency	direct travel	24,1%
convenience	travel time	24,1%
convenience	flexibility	22,8%
physical comfort	treatment of bags	21,5%
<i>Middle-aged (40-59)</i>		
freedom	flexibility	43,3%
efficiency	flexibility	31,7%
efficiency	easiness for parking	31,7%
freedom	accessibility	29,8%
efficiency	travel time	28,8%
freedom	easiness for parking	26,9%
freedom	treatment of bags	26,9%
freedom	travel time	26,9%
efficiency	accessibility	23,1%
efficiency	treatment of bags	22,1%
<i>Elderly (60 or older)</i>		
freedom	accessibility	31,6%
freedom	flexibility	28,9%
efficiency	easiness for parking	26,3%
durability	environment-friendliness	26,3%
saving money	cost	23,7%
durability	easiness for parking	23,7%
convenience	flexibility	21,1%
freedom	easiness for parking	21,1%
freedom	travel time	21,1%
efficiency	travel time	21,1%

For the TM decision, young people consider efficiency-related associations most important. They also attach some importance to freedom- and convenience-related subsets, and also the set “physical comfort – treatment of bags” is considered.

People of the middle-age category attach more or less the same weight to freedom-related subsets as to efficiency-related ones. Other values are not present in their most frequent itemsets.

Elderly attach less importance to efficiency. Freedom-related cognitive subsets are most important to them. They also consider the environment-friendliness and the cost-aspect of the TM.

Table 78: Frequent itemsets TM decision for different age categories (context).

<i>Context</i>	<i>Value</i>	<i>Instr.</i>	<i>Csupp</i>
<i>Young (19-39)</i>			
time available	efficiency	travel time	27,8%
precipitation	physical comfort	shelter	25,3%
baggage	physical comfort	treatment bags	20,3%
parking availability	efficiency	easiness parking	19,0%
parking availability	efficiency	travel time	16,5%
car availability	freedom	flexibility	16,5%
parking availability	efficiency	accessibility	15,2%
time available	efficiency	direct travel	15,2%
car availability	efficiency	travel time	12,7%
time available	efficiency	flexibility	12,7%
<i>Middle-aged (40-59)</i>			
precipitation	physical comfort	shelter	20,2%
baggage	physical comfort	treatment bags	12,5%
time available	efficiency	flexibility	12,5%
time available	efficiency	travel time	12,5%
parking availability	efficiency	easiness parking	10,6%
baggage	efficiency	treatment of bags	9,6%
time available	freedom	flexibility	8,7%
crowdedness in centre	efficiency	easiness parking	8,7%
precipitation	physical comfort	treatment bags	8,7%
parking availability	efficiency	accessibility	7,7%

<i>Elderly (60 or older)</i>			
precipitation	physical comfort	shelter	18,4%
time available	efficiency	TM preference	15,8%
baggage	physical comfort	treatment bags	10,5%
baggage	physical comfort	accessibility	10,5%
baggage	physical comfort	physical effort	10,5%
precipitation	being healthy	easiness parking	10,5%
crowdedness in centre	durability	accessibility	10,5%
bike infra availability	freedom	accessibility	10,5%
time available	efficiency	flexibility	10,5%
time available	efficiency	easiness parking	10,5%

Concerning the context-specific frequent itemsets of the TM decision, the subsets “precipitation – physical comfort – treatment of bags” and “baggage – physical comfort – treatment of bags” are among the most important frequent itemsets in all age categories.

Young people also attach a lot of importance to time-, parking space- and car availability-related frequent itemsets. Not surprisingly, baggage-related frequent itemsets are important considerations for elderly.

5.3.6.3 Conclusions elicited subsets for different age categories

For the SL decision, it appears that young people attach most importance to “efficiency” and “fun” in all circumstances. However, elderly attach much importance to having fun, given the influence of companion. It is also remarkable that the elderly strongly consider itemsets related to the combination “sale season – saving cost”.

In the TM decision, young people attach most importance to efficiency-related aspects. This is probably because many young people have little time because they have a job and small children. For middle-aged respondents, efficiency- and freedom-related frequent itemsets are most important. Elder people attach most importance to freedom-related subsets. They often mention the environment-friendliness and the cost of the TM as well. Concerning the context-related subsets, time-, parking space- and car availability related subsets are most important to young people, middle-aged people attach most importance to time availability-related subsets and elderly consider

baggage-related frequent itemsets. The finding that “car availability” is important to young people has two reasons. First, some of these people still live with their parents and do not have a car of their own, but they are allowed to use the parents’ car when they do not need it. And second, it appears that young families have in general less cars than older families (except for families with a head of household older than 65) (Janssens et al., 2009). So, many of them will only have one car that they share with their partner, which imposes that they will have to take into account whether they can use it or their partner needs it.

It is remarkable that findings for both decisions indicate that elderly are the age category that most strongly considers saving money. One possible reason is that their current retirement pay is lower than the income they earned when they were still employed. This could give them the feeling that they have to make their decisions in a more economic way. Another possible explanation is that they are more economic because they are raised close to or during the second World War, and that they learned to be more careful with money in that period.

One final finding is that young people have substantially higher csupp values for both context-related subsets as for subsets that are considered in all circumstances. This indicates that reasoning is more similar among young people than among older people.

5.3.7 Differences in elicited subsets for different education levels

5.3.7.1 Elicited subsets for SL decision for different education levels

Table 79: Frequent itemsets SL decision for different education levels (normally).

<i>Lower educated</i>			<i>Higher educated</i>		
<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
saving money	product price	25,3%	efficiency	favorite shop	32,6%
saving money	product quality	20,5%	efficiency	familiarity	29,7%
efficiency	favorite shop	20,5%	efficiency	type of stores	21,7%
certainty	familiarity	20,5%	certainty	favorite shop	20,3%
efficiency	familiarity	19,3%	fun	favorite shop	19,6%
saving money	favorite shop	15,7%	convenience	familiarity	16,7%
efficiency	type of stores	15,7%	saving money	product price	15,9%
fun	favorite shop	15,7%	certainty	familiarity	15,9%
having info	product price in zone	15,7%	efficiency	accessibility	15,2%
fun	cafe restaurant	13,3%	convenience	favorite shop	15,2%

In all circumstances, lower educated respondents very strongly consider subsets related to saving money in their SL decisions. They mostly relate it to the product price in the zone, the product quality in the zone, and the presence of their favorite shop.

Higher educated respondents on the other hand mainly consider efficiency-related frequent itemsets. They relate it most often to presence of favorite shop, familiarity with the zone, type of stores and accessibility of the area.

Table 80: Frequent itemsets SL decision for different education levels (context).

<i>Lower educated</i>				<i>Higher educated</i>			
<i>Context</i>	<i>Value</i>	<i>Instr.</i>	<i>Csupp</i>	<i>Context</i>	<i>Value</i>	<i>Instr.</i>	<i>Csupp</i>
sale season	saving money	product price	16,9%	specific product	efficiency	favorite shop	24,6%
budget availability	saving money	product price	14,5%	specific product	efficiency	type of stores	22,5%
specific product	efficiency	favorite shop	14,5%	specific product	efficiency	familiarity	18,8%
time available	efficiency	favorite shop	14,5%	time available	efficiency	favorite shop	18,8%
time available	efficiency	familiarity	14,5%	time available	efficiency	familiarity	17,4%
sale season	saving money	favorite shop	13,3%	crowdedness in centre	efficiency	favorite shop	12,3%
companion	fun	cafe restaurant	13,3%	companion	fun	favorite shop	10,9%
specific product	efficiency	familiarity	13,3%	time available	efficiency	accessibility	10,9%
companion	fun	ambiance	12,0%	specific product	certainty	favorite shop	9,4%
companion	fun	favorite shop	12,0%	companion	being sociable	favorite shop	8,7%

For the context-specific frequent itemsets for lower educated respondents, the same pattern appears as in the not context-specific frequent itemsets. Again, money-related frequent itemsets are most important.

Higher educated respondents' SL choice on the other hand is most influenced by frequent itemsets that are related to "interest in a specific product-efficiency". Also the combination "time available - efficiency" is rather important for them.

5.3.7.2 Elicited subsets for TM decision for different education levels

Table 81: Frequent itemsets TM decision for different education levels (normally).

<i>Lower educated</i>			<i>Higher educated</i>		
<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
efficiency	easiness parking	37,3%	efficiency	flexibility	42,0%
freedom	flexibility	36,1%	freedom	flexibility	42,0%
freedom	easiness parking	27,7%	efficiency	travel time	39,1%
freedom	travel time	25,3%	efficiency	easiness parking	29,0%
efficiency	travel time	25,3%	efficiency	accessibility	27,5%
efficiency	accessibility	24,1%	freedom	travel time	27,5%
freedom	accessibility	21,7%	freedom	accessibility	26,8%
efficiency	flexibility	20,5%	freedom	treatment bags	24,6%
convenience	accessibility	19,3%	efficiency	treatment bags	21,0%
convenience	easiness parking	19,3%	convenience	flexibility	20,3%

For the not context-specific frequent itemsets in the TM, differences between lower educated and higher educated respondents are in fact rather small. Both groups consider efficiency- and freedom-related subsets most important. It seems that the freedom-related subsets are somewhat more important to lower educated respondents, while the efficiency-related subsets have a slightly higher importance to the higher educated respondents, although the differences are small.

Table 82: Frequent itemsets TM decision for different education levels (context).

<i>Lower educated</i>				<i>Higher educated</i>			
<i>Context</i>	<i>Value</i>	<i>Instr.</i>	<i>Csupp</i>	<i>Context</i>	<i>Value</i>	<i>Instr.</i>	<i>Csupp</i>
precipitation	physical comfort	shelter	18,1%	precipitation	physical comfort	shelter	23,9%
time available	efficiency	travel time	16,9%	baggage	physical comfort	treatment bags	16,7%
parking availability	efficiency	easiness parking	12,0%	time available	efficiency	travel time	15,9%
baggage	physical comfort	treatment bags	12,0%	parking availability	efficiency	easiness parking	13,0%
parking availability	certainty	easiness parking	12,0%	time available	efficiency	flexibility	13,0%
time available	freedom	flexibility	12,0%	time available	efficiency	direct travel	10,9%
time available	efficiency	easiness parking	10,8%	parking availability	efficiency	accessibility	10,1%
time available	efficiency	flexibility	10,8%	parking availability	efficiency	travel time	10,1%
time available	efficiency	accessibility	10,8%	baggage	physical comfort	physical effort	10,1%
crowdedness in centre	efficiency	easiness parking	9,6%	activities elsewhere	efficiency	travel time	9,4%

For the context-specific frequent itemsets, there are some differences between higher educated and lower educated respondents, but there is no real trend noticeable.

5.3.7.3 Conclusions elicited subsets for different education levels

In all circumstances, lower educated respondents strongly consider saving money-related frequent itemsets in their SL decision. This is also shown in the context-specific frequent itemsets, where sale season- and budget availability-related subsets have a high importance. This could indicate that lower educated respondents have lower incomes, hence they are forced to be more economic. Higher educated respondents on the other hand attach most importance to efficiency-related frequent itemsets. Probably, they have higher incomes, so for them the need to save money is lower. But on the other hand, to earn this higher income, a lot of them have busy jobs, which is probably the reason why efficiency is very important to them (the "time is money" principle).

While there are remarkable differences in the SL decision, TM considerations are relatively similar for both education levels. This is remarkable, since section 5.1.2.3 indicated that the network complexities differ significantly among both education levels for both decisions.

It is remarkable that lower educated respondents indicate in the SL decision that cost-considerations are very important to them, while these considerations do not appear in their elicitation of the TM decision. So, lower educated respondents want to save money on their actual fun shopping activity, but not on their transport to perform this activity. Possibly, this is because it is relatively easier to save a significant amount of money on fun shopping than on transport. For instance, buying a pair of jeans from a chain store instead of a boutique can save you something like 50 or 100 euro, while choosing to go fun shopping by bike or bus instead of car will not save you more than a couple of euro. However, since Kusumastuti et al. (2009b) state that fun shopping decisions are interrelated, this could indicate that, despite the fact that it is not shown in the frequent itemset analysis, lower educated respondents will be more affected by measures that increase the costs of car use.

Even more remarkable is the finding that, in general, the csupp value of the frequent itemsets is in both decisions noticeably higher for higher educated respondents than for lower educated respondents. This is counterintuitive. The opposite would be expected, since section 5.1.2.3 indicated that higher educated persons have a significantly lower network complexity. The higher values for the frequent itemsets can indicate two things. Either it means that higher educated respondents' reasoning is more similar than lower educated respondents', or it could mean that lower educated respondents experience more difficulties in eliciting their considerations, resulting in a more scattered pattern. The latter means that they have more difficulties in expressing their decision making process, which results in some errors and random noise in the dataset. Because of these errors and random noise, the patterns that appear will be less distinct (this corresponds to a lower csupp value).

5.3.8 Differences in elicited subsets for different income levels

5.3.8.1 Elicited subsets for SL decision for different income levels

Table 83: Frequent itemsets SL decision for different income levels (normally).

<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
<i>Low income</i>		
efficiency	familiarity	23,1%
efficiency	favorite shop	21,5%
saving money	product price	20,0%
fun	favorite shop	18,5%
fun	ambiance	16,9%
saving money	product quality	16,9%
fun	customer service	16,9%
certainty	familiarity	16,9%
efficiency	customer service	15,4%
saving money	favorite shop	15,4%
<i>Medium income</i>		
efficiency	favorite shop	31,2%
efficiency	familiarity	31,2%
efficiency	type of stores	22,6%
convenience	favorite shop	20,4%
certainty	familiarity	20,4%
certainty	favorite shop	19,4%
saving money	product price	18,3%
fun	favorite shop	17,2%
convenience	familiarity	16,1%
efficiency	accessibility	14,0%
<i>High income</i>		
efficiency	favorite shop	41,0%
efficiency	familiarity	28,2%
efficiency	type of stores	28,2%
saving money	product price	23,1%
certainty	favorite shop	20,5%
efficiency	product price	17,9%
having information	favorite shop	17,9%
efficiency	accessibility	15,4%
fun	favorite shop	15,4%
convenience	familiarity	15,4%

“Efficiency – presence of favorite shop” and “efficiency – familiarity with zone” are the most important frequent itemsets for all income categories. The most remarkable finding, however, is that “saving money – product price in zone” is very important in all three income categories. Furthermore, “convenience” has a somewhat higher importance to the middle-income category.

Table 84: Frequent itemsets SL decision for different income levels (context).

<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
<i>Low income</i>			
specific product	efficiency	favorite shop	21,5%
specific product	efficiency	familiarity	20,0%
time available	efficiency	familiarity	16,9%
sale season	saving money	product price	15,4%
companion	fun	favorite shop	15,4%
sale season	saving money	favorite shop	13,8%
time available	efficiency	favorite shop	12,3%
companion	fun	cafe restaurant	10,8%
specific product	efficiency	type of stores	10,8%
time available	efficiency	customer service	10,8%
<i>Medium income</i>			
specific product	efficiency	type of stores	21,5%
specific product	efficiency	favorite shop	18,3%
specific product	efficiency	familiarity	16,1%
time available	efficiency	favorite shop	16,1%
time available	efficiency	familiarity	16,1%
budget availability	saving money	product price	11,8%
specific product	having info	product price	10,8%
crowdedness in centre	efficiency	favorite shop	10,8%
sale season	saving money	favorite shop	9,7%
sale season	saving money	product quality	9,7%

<i>High income</i>			
specific product	efficiency	favorite shop	35,9%
time available	efficiency	favorite shop	30,8%
specific product	efficiency	type of stores	28,2%
specific product	efficiency	familiarity	17,9%
time available	efficiency	familiarity	17,9%
companion	fun	cafe restaurant	15,4%
specific product	certainty	product quality	15,4%
companion	being sociable	ambiance	12,8%
parking space	efficiency	infrastructure	12,8%
specific product	efficiency	product price	12,8%

For the context-specific frequent itemsets, the most important sets are again the same for all three income categories. Here, however, there is a difference concerning the importance of money-related subsets. While sale season-related (and to a lesser extent budget availability-related) subsets are quite important for respondents in the low and medium income category, they are not strongly considered by respondents in the high-income category. Also note that subsets related to the context of companion are important for both the low-income and the high-income category, but not for the medium-income category.

5.3.8.2 Elicited subsets for TM decision for different income levels

Table 85: Frequent itemsets TM decision for different income levels (normally).

<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
<i>Low income</i>		
efficiency	easiness parking	33,8%
freedom	flexibility	32,3%
efficiency	travel time	30,8%
freedom	easiness parking	29,2%
efficiency	flexibility	26,2%
freedom	accessibility	24,6%
efficiency	accessibility	21,5%
freedom	travel time	21,5%
saving money	cost	18,5%
saving money	easiness parking	18,5%

<i>Medium income</i>		
freedom	flexibility	41,9%
efficiency	flexibility	37,6%
efficiency	travel time	35,5%
efficiency	easiness parking	34,4%
efficiency	accessibility	31,2%
freedom	travel time	28,0%
freedom	accessibility	26,9%
efficiency	treatment bags	22,6%
physical comfort	treatment bags	22,6%
convenience	travel time	22,6%
<i>High income</i>		
efficiency	travel time	43,6%
freedom	flexibility	41,0%
efficiency	flexibility	38,5%
freedom	treatment bags	28,2%
freedom	travel time	28,2%
freedom	accessibility	25,6%
efficiency	easiness parking	25,6%
efficiency	accessibility	20,5%
efficiency	treatment bags	20,5%
freedom	direct travel	20,5%

For the not context-specific subsets for the TM decision, there are little differences between the different income categories. The only (small) difference is that, in the lowest income category, two saving money-related subsets appear, while the other two categories attach more importance to associations related to the instrument "treatment of bags".

Table 86: Frequent itemsets TM decision for different income levels (context).

<i>Context</i>	<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
<i>Low income</i>			
precipitation	physical comfort	shelter	18,5%
time available	efficiency	travel time	16,9%
baggage	physical comfort	treatment bags	15,4%
arrival time home	efficiency	travel time	13,8%
baggage	physical comfort	physical effort	12,3%
time available	efficiency	flexibility	10,8%
time available	freedom	flexibility	10,8%
parking cost	saving money	easiness parking	10,8%
precipitation	physical comfort	treatment bags	10,8%
crowdedness in centre	efficiency	easiness parking	9,2%
<i>Medium income</i>			
precipitation	physical comfort	shelter	25,8%
time available	efficiency	travel time	15,1%
baggage	physical comfort	treatment bags	15,1%
time available	efficiency	flexibility	11,8%
parking availability	efficiency	easiness parking	11,8%
crowdedness in centre	efficiency	accessibility	9,7%
parking availability	efficiency	accessibility	9,7%
baggage	physical comfort	physical effort	9,7%
time available	efficiency	direct travel	8,6%
crowdedness in centre	efficiency	easiness parking	7,5%
<i>High income</i>			
precipitation	physical comfort	shelter	23,1%
parking availability	efficiency	easiness parking	23,1%
car availability	efficiency	travel time	20,5%
temperature	physical comfort	shelter	20,5%
baggage	physical comfort	treatment bags	17,9%
time available	efficiency	travel time	15,4%
time available	efficiency	easiness parking	15,4%
time available	efficiency	flexibility	15,4%
parking availability	efficiency	accessibility	15,4%
parking availability	efficiency	travel time	15,4%

Concerning the context-specific frequent itemsets of the TM decision, there are more differences. The higher the income, the more importance is attached to associations related to the context of parking space availability. Some associations that are more often made by respondents with a lower income are "arrival time at home – efficiency – travel time" and "parking cost – saving money – easiness for parking". Respondents with

a higher income on the other hand also consider the subsets "temperature – physical comfort – shelter provision" and "car availability – efficiency – travel time".

5.3.8.3 Conclusions elicited subsets for different income levels

For the SL decision, the not context-specific frequent itemsets are relatively comparable among the different income levels. Most remarkable is that "saving money – product price in zones" is an important association for all income categories. For the context-specific frequent itemsets, it appears that frequent itemsets related to the context "sale season" are important for the low- and medium income category, but not for the high-income category. These results indicate that respondents of all income categories are in general cost-conscious when making an SL decision. However, respondents with a high income appear not to consider sale season. This could implicitly mean that they do not like to go fun shopping in the sale season, because they do not have to take their expenditures that strongly into account, and there are other factors related to the sale season that make them want to avoid it (e.g. in the sale season the city centre is crowded, the service quality is lower, difficulties to find a parking space, crowded busses,...).

For the TM decision, not context-specific considerations are more or less the same for all income categories. The only difference is that the low-income category attaches some importance to the value of saving money in the TM decision, while the high-income category considers the treatment of bags more. The most apparent difference concerning context-specific associations is the fact that the high-income category attaches more importance to the availability of parking space than lower income categories.

The finding that "car availability" is only an important consideration for respondents with a high income is very remarkable, since the high-income category on average possesses more vehicles than the other income categories. According to OVG Flanders, low income households own on average 0,76 cars, medium income households 1,46 cars and high income households 1,98 (Janssens et al., 2009). There is no clear explanation for this finding.

It also appears that frequent itemsets for the high-income category have a clearly higher csupp value than the lower income category, especially for the SL decision. So this

indicates that respondents in the high-income category have a more similar reasoning than respondents in the low income category.

5.3.9 Differences in elicited subsets for different distances to the centre

5.3.9.1 Elicited subsets for TM decision for different distances to the centre

In this section, respondents' postal code is used as a proxy for their distance to the city centre. This will allow to check whether respondents who live close to the city centre have other considerations than respondents who live further away from the city centre. This analysis will only be performed for the TM decision. Table 87 shows the not context-specific frequent itemsets for different distances to the city centre, and Table 88 shows the context-specific frequent itemsets for different distance classes.

Table 87: Frequent itemsets TM for different distances to the centre (normally).

<i>Value</i>	<i>Instrument</i>	<i>Csupp</i>
<i>Close to the city centre (<4 km)</i>		
efficiency	travel time	36,4%
efficiency	flexibility	33,8%
efficiency	easiness parking	33,8%
freedom	flexibility	29,9%
efficiency	accessibility	27,3%
freedom	easiness parking	24,7%
freedom	accessibility	19,5%
freedom	travel time	19,5%
convenience	easiness parking	18,2%
convenience	travel time	18,2%

<i>Medium distance to the city centre (4-7 km)</i>		
freedom	flexibility	47,7%
efficiency	flexibility	31,8%
efficiency	travel time	31,8%
efficiency	easiness parking	30,7%
freedom	travel time	30,7%
freedom	treatment bags	27,3%
freedom	accessibility	26,1%
efficiency	accessibility	26,1%
efficiency	treatment bags	23,9%
convenience	travel time	22,7%
<i>Far from the city centre (8-10 km)</i>		
freedom	flexibility	41,1%
efficiency	flexibility	37,5%
efficiency	travel time	33,9%
efficiency	easiness parking	32,1%
freedom	accessibility	30,4%
freedom	travel time	30,4%
freedom	treatment bags	26,8%
efficiency	accessibility	25,0%
freedom	easiness parking	25,0%
convenience	flexibility	23,2%

For subsets that are considered in any circumstances, differences are very small.

Table 88: Frequent itemsets TM for different distances to the centre (context).

Context	Value	Instrument	Csupp
<i>Close to the city centre (<4 km)</i>			
precipitation	physical comfort	shelter	27,3%
baggage	physical comfort	treatment bags	18,2%
time available	efficiency	travel time	16,9%
parking availability	efficiency	easiness parking	14,3%
time available	efficiency	flexibility	13,0%
parking availability	efficiency	travel time	13,0%
baggage	physical comfort	physical effort	11,7%
time available	efficiency	direct travel	11,7%
crowdedness in centre	efficiency	accessibility	10,4%
time available	certainty	travel time	9,1%

<i>Medium distance to the city centre (4-7 km)</i>			
time available	efficiency	travel time	15,9%
precipitation	physical comfort	shelter	14,8%
car availability	freedom	flexibility	13,6%
parking availability	efficiency	accessibility	12,5%
parking availability	efficiency	easiness parking	12,5%
time available	efficiency	flexibility	10,2%
time available	freedom	flexibility	10,2%
baggage	physical comfort	treatment bags	10,2%
departure time from home	freedom	travel time	9,1%
time available	efficiency	easiness parking	9,1%
<i>Far from the city centre (8-10 km)</i>			
precipitation	physical comfort	shelter	25,0%
baggage	physical comfort	treatment bags	17,9%
time available	efficiency	travel time	16,1%
time available	efficiency	flexibility	14,3%
baggage	physical comfort	physical effort	14,3%
time available	efficiency	easiness parking	12,5%
car availability	efficiency	travel time	10,7%
time available	efficiency	direct travel	10,7%
parking availability	efficiency	easiness parking	10,7%
time available	efficiency	sensation of speed	10,7%

Regarding the context-specific frequent itemsets, the most apparent difference is the fact that car availability is important for respondents who live at a medium and a far distance from the city centre. It is not considered by many respondents who live close to the city centre. It also appears that respondents that live at a short or a long distance from the city centre attach more importance to the amount of baggage they expect to bring home. And finally, respondents who live at a short or medium distance to the city centre consider the context "parking space availability" more strongly than respondents who live at a long distance from the city centre.

5.3.9.2 Conclusions elicited subsets for different distances to the city centre

The most important difference is the fact that car availability is very important to respondents who live at a medium or a long distance from the city centre, while it is not very important to respondents that live close to the city centre. The reason for this is

probably that bicycle has a much larger share of the modal split at shorter distances, while car has a larger share at longer distances (Janssens et al., 2009). This means that car availability is less important to respondents who live close to the city centre because they are in general more willing to make this short trip by bicycle, while respondents who live at a medium or a far distance have a stronger preference to use the car, which makes car availability an important aspect in case the household does not own a car for each person with a driving license.

Another finding is that the csupp values of the context-specific frequent itemsets are lower for respondents who live at a medium distance from the city centre. This indicates that the TM choice for these respondents is less dependent on circumstances than for respondents who live close to the city centre or far from the city centre. There is no clear explanation for this.

5.3.10 Conclusions and discussion

In this section, the findings from the frequent itemsets analyses are summarized. In all analyses, the frequent itemsets are split in not context-specific frequent itemsets and context-specific frequent itemsets. Findings regarding the SL decision are presented first. Second, findings for the TM decision are reported. In both sections, first the general conclusions for the full database are presented. Second, the results of the analyses of different subcategories are shown. Only differences between the different subcategories will be discussed, similarities between the subcategories will not be mentioned.

5.3.10.1 SL decision

The most important not context-specific frequent itemsets are related to efficiency: "efficiency – presence of favorite shop", "efficiency – familiarity with the zone" and "efficiency – type of stores". The association "saving money – product price" is also important to many respondents. Furthermore, the values "assurance and certainty" and "convenience" are both quite often related to the instrumental aspects "familiarity with zone" and "presence of favorite shop", and the value "fun" is related to "presence of favorite shop" and "ambiance environment".

The most important context-specific frequent itemsets are also related to the value of efficiency, e.g. "interest in specific product – efficiency – presence of favorite shop", "interest in specific product – efficiency – type of stores", "time available – efficiency – presence of favorite shop". Also frequent itemsets related to the value "saving money" are rather important. This variable is mainly related to the contexts "sale season" and "budget availability". And also the context "companion" and the value "fun" are often linked, together with the instruments "presence of favorite shop" and "café and restaurant".

In the time pressure scenario, it appears that respondents attach more importance to associations with the values "efficiency" and "assurance and certainty" in any circumstances in the SL choice, while respondents in the no time pressure scenario attach a higher importance to associations related to the value of "fun". For the context-specific frequent itemsets, it is remarkable that respondents in a time pressure scenario attach more value to the contexts "sale season" and "budget availability" because of their influence on the value of "saving money". Respondents in a no time pressure scenario on the other hand attach more importance to the context of "companion", linked to the values "fun" and "being sociable" and the instruments "café and restaurant" and "ambiance environment".

It appears that respondents who start their elicitation from an SL habit attach a higher importance to the value of "assurance and certainty", which they can gain from the instrumental aspects "presence of favorite shop" and "familiarity with zone". The most important contextual variables for respondents who start from a habit are related to the contextual aspects "time available" and "sale season". For respondents who do not start from a habit, "interest in a specific product" is by far the most important contextual aspect. They also attach high importance to the presence of a companion. So it appears that most people who have a habit of always going to the same SL do so because they are sure that they will manage to execute their fun shopping activity successfully in that zone. However, when they have very little or plenty of time, or in case of the sale season, they might occasionally choose a different SL. The SL choice of people who do not have an SL habit will mainly depend on their interest in a specific product, which indicates that they attach high value to efficiency. On the other hand, they also value the opinion of their companion. The fact that "companion" is such an important contextual aspect for respondents with no SL habit, but is of little importance to respondents

without an SL habit, could indicate that people with an SL habit tend to go fun shopping alone more often, while people without an SL habit usually go fun shopping with somebody else.

There are also some differences between men and women. It appears that women attach a higher importance to associations related to the value "fun" in their SL choice in all circumstances. For the context-specific associations, it appears that men almost solely consider the contextual aspect "interest in specific product". This indicates that men execute fun shopping in a more purposeful way than women. Women on the other hand consider multiple contextual aspects. They mainly consider "time available", but also "interest in specific product", "companion", "sale season" and "budget availability".

Looking at the differences between different age categories, it appears that young people in all circumstances attach more importance to efficiency- and fun-related subsets in the SL decision. Elderly attach more importance to "saving money" and "assurance and certainty". Concerning context-specific frequent itemsets, it appears that young people attach most importance to the context "interest in a specific product", while many elderly consider "sale season" and "companion". This indicates that young people want to execute their fun shopping activities in a quick and purposeful way. It also indicates that elderly shop more economically. Furthermore, the fact that they strongly consider "companion" indicates that they either attach more importance to the opinion of companion when they go fun shopping, or it can also indicate that they go fun shopping more often with someone.

In all circumstances, lower educated respondents attach most importance to the value "saving money" in their SL decision. Higher educated respondents on the other hand attach far most importance to subsets related to "efficiency". Also for the context-specific frequent itemsets, lower educated respondents attach most importance to money-related contexts such as "sale season" and "budget availability". The SL decision of higher educated respondents, however, is most influenced by the context "interest in specific product".

The differences between different income categories are small in the SL decision. The main difference is that, the lower the income is, the more important the context "sale season" is. So, this indicates that mainly people with a lower income will go fun shopping

in the sale season to save money, which makes sense. Another finding is that the context "companion" is important to both the low income and the high income category, but not to the medium income category.

5.3.10.2 TM decision

In the TM choice, the most important not context-specific associations that are made by respondents are interrelations between the values "efficiency" and "freedom" and the instruments "flexibility", "travel time", "easiness for parking", "accessibility" and "treatment of bags".

Concerning the context-specific frequent itemsets in the TM decision, "precipitation – physical comfort – shelter provision" is by far the most important association made by respondents. Furthermore, the context "time available" is often linked with the value "efficiency" and the instrumental aspects "travel time", "flexibility", "easiness for parking" and "direct travel". Furthermore, the subsets "baggage – physical comfort – treatment of bags / physical effort" are also important to many respondents. And the links between "parking space availability", "efficiency" and the instrumental aspects "easiness for parking", "accessibility" and "travel time" are also quite important to respondents.

There appear to be few differences between both scenarios for the TM decision. This indicates that time pressure has a less important influence on the TM choice than on the SL choice, were there were some important differences.

The contextual aspect "time available" is the most important one for respondents who have a TM habit, even more important than "precipitation". For respondents who do not start from a TM habit, "precipitation" is by far the most important contextual aspect, followed by "baggage" and "parking space availability".

Differences between men and women are small in the TM decision. The only difference is the fact that women attach a higher importance to the context "time available", while men indicate that "car availability" is quite important to them. This could indicate that women are more willing than men to change to slower modes like for instance bicycle when they have enough time, while the presence of the contextual aspect "car

availability" in many men's mental representation could indicate that they will nearly always take the car in case this is possible.

Younger people attach most importance to efficiency-related subsets in the TM decision, while older people attach more importance to freedom-related subsets. It is also remarkable that elderly attach a lot of importance to choosing a sustainable TM, and they also take the value "saving money" into account in their TM decision. Concerning the context-specific frequent itemsets, the main differences are that young people attach a lot of importance to the contexts "parking space availability" and "car availability", while elderly consider "baggage" very important.

It appears that lower educated and higher educated respondents' reasoning is quite similar for the TM decision. There are some differences, but there is no real pattern noticeable.

In all circumstances, saving money is considered by the low income category, but not by the other categories. For the context-specific frequent itemsets, the low income category attaches importance to the contexts "arrival time at home" and "parking cost". Respondents of the high income category attach a higher than average importance to the context "parking space availability", and they are the only income category that considers "car availability" and "temperature".

From the analysis of respondents who live at different distance classes from the city centre, it appears that the context "car availability" is important to respondents who live at a medium or far distance from the city centre, but not to respondents who live close to the city centre. Furthermore, respondents who live either short to the city centre or a long distance from the centre attach more importance to the context "baggage" than respondents who live at a medium distance. And "parking space availability" is more important to respondents who live a short or medium distance from the centre than it is to respondents who live at a long distance from the centre.

6 Conclusions

This chapter contains the conclusions of this research. First, the most important findings will be presented. Next, a critical reflection is made on the research method in general, and this research in particular. The chapter will end with recommendations for future research.

6.1 Findings

In this thesis, people's decision making process for SL and TM decisions for fun shopping trips are examined. Research shows that decision makers activate a complex and deliberative cognitive process to come up with the best possible solution when they are faced with a new or infrequently occurring decision problem (Kusumastuti et al., n.d.). Different considerations are linked by the decision maker by means of causal relations (Kusumastuti et al., 2010). This way, a temporary mental representation of the decision problem is created (Dellaert et al., 2008). The mental representation can contain both elements of conscious consideration and automated scripts.

To investigate the mental representation, the Causal Network Elicitation Technique (CNET) is used. CNET was developed originally as a face-to-face interview technique, but in this thesis, the technique is translated to a computerized survey: the CB-CNET. It distinguishes four types of variables. Decision variables are the aspects the decision maker has to make a decision about (Kusumastuti et al., 2009a). Contextual variables represent environmental influences that are beyond the control of the decision maker (Arentze et al., 2008). Instrumental variables describe the characteristics of the different decision alternatives (den Hartog, 2004). And finally, evaluative variables describe the impact of the contextual and instrumental variables on the physiological and psychological needs of the decision maker (Dellaert et al., 2008).

221 respondents have filled out the CB-CNET survey in small group sessions. Despite the fact that the sample method that is used, namely the snowball sampling technique, has a clear risk of sample biases, it can be concluded that the sample of this research is fairly representative. Concerning the socio-demographic factors, there is one distortion in the sample, namely the education level. Higher educated respondents are overrepresented in

the sample. The representativeness of the mobility characteristics of the sample are more difficult to judge because official figures are unavailable. However, it can be concluded that the sample of this research owns more cars and bicycles than average. This is in fact a highly desirable bias, because it means that the assumption that respondents have a choice between the options car, bike and bus is valid.

The first element of the mental representation that is investigated is the complexity of the network. The number of nodes is used as a proxy to determine the network complexity. It appears that the number of nodes is 44 on average, and there are very little differences among different subgroups of the sample. The only significant difference is noted for dividing the sample based on education level. Higher educated respondents indicate significantly less variables than lower educated respondents. Probably this is because higher educated respondents are more able to distinguish between the most important and less important considerations in their decision making process. So this indicates that, in the CB-CNET survey, little bias is introduced by differences in the number of variables indicated by different socio-demographic groups because of distortions in the sample.

For the analysis of the content of the network, we return to the research questions concerning respondents' mental representation that are formulated in the introduction. They are answered here to summarize the conclusions. The question about the policy impacts of the findings, is answered in the next section (6.2).

What are individuals' motivations and reasoning behind their decisions related to the transport mode choice and shopping location choice in leisure shopping? What considerations and associations are most prevalent?

The contextual variables that are indicated in the SL decision by most respondents are "interest in a specific product" and "time availability". The value that is by far most important is "efficiency", but also "assurance and certainty", "convenience", "saving money" and "fun" are fairly important. The instruments "presence of favorite shop", "familiarity with zone" and "type of stores" are indicated by most respondents.

Associations that are often made by respondents in the SL decision in any circumstances, are mainly related to efficiency: "efficiency – presence of favorite shop", "efficiency –

familiarity with the zone" and "efficiency – type of stores". Also "saving money – product price" is important to many respondents. Furthermore, the evaluative aspects "assurance and certainty" and "convenience" are often related to the instruments "presence of favorite shop" and "familiarity with zone".

The most important context-specific frequent itemsets for the SL choice contain the contexts "specific product" and "time available", which are linked to value "efficiency" and the instruments "presence of favorite shop", "type of stores" and "familiarity with the zone". Next, "sale season" and "budget availability" are considered most important, which are related to the value "saving money", and the instruments "product price" and "presence of favorite shop". And finally, the influence of companion is also quite important because of its impact on the value "fun". Instrumental aspects that can help to gain fun, giving the influence of companion, are "presence of favorite shop" and "café and restaurant".

In the TM decision, contextual variables that are most indicated are "time available", "precipitation", "baggage" and "parking space availability". The most important evaluative aspects are "efficiency" and "freedom". The instruments that are indicated by most respondents are "flexibility", "travel time", "accessibility", "easiness for parking" and "treatment of bags".

The most important not context-specific associations respondents make in the TM decision, are interrelations between the values "efficiency" and "freedom", and the instruments "flexibility", "travel time", "easiness for parking", "accessibility" and "treatment of bags".

For the context-specific frequent itemsets in the TM decision, the association "precipitation – physical comfort – shelter provision" is by far indicated by most respondents. Furthermore, the context "time available" is linked by many respondents to the value "efficiency" and the instrumental aspects "travel time", "flexibility", "easiness for parking" and "direct travel". Also, the context "baggage" is quite often linked to the value "physical comfort" and the instruments "treatment of bags" and "physical effort". Also the contextual aspect "parking space availability" is often linked to the evaluative aspect "efficiency" and the instrumental aspects "easiness for parking", "accessibility" and "travel time".

Are there any differences in the mental representation between different subgroups?

Even though these most important considerations are, in general, important to most socio-demographic groups, there are some differences among different subgroups of the sample. These differences can be used to target intervention strategies and campaigns in a segmented way, which is generally considered to be a more effective approach (Brijs, 2009; Weggemans & Schreuders, 2005). For the purpose of succinctness, explanations for these differences are not provided here.

In the SL choice, in all circumstances, efficiency-related subsets have a relatively lower importance to elderly and lower educated. For all other subgroups, it is of crucial importance in the SL decision. Saving money has a relatively lower importance for young, higher educated and middle-income respondents. However, it has a higher importance to elderly, and it is by far the most important consideration for lower educated respondents. Subsets related to the value "fun" have a fairly low importance to people in time pressure, people who start from an SL habit, men, elderly and people from a high-income household. They have a fairly high importance to people in the no time pressure scenario, people who do not start from a habit, women, young people and people from a low-income household. "Assurance and certainty" is less important to people without time pressure and people without an SL habit. It has a higher than average importance to people in time pressure, people who have an SL habit, elderly and respondents from the middle-income category. The value "convenience" has a lower importance to people who do not start from a habit, young people, lower educated people and both the low-income and the high-income categories. It has a high importance to people from the middle-income group. Furthermore, the value "having information" is only a relatively important consideration for elderly and people from the high-income category.

Concerning the context-specific frequent itemsets of the SL decision, subsets related to the context "interest in specific product" have a relatively lower importance to people without time pressure, people who start from an SL habit, women, middle-aged people and elderly, and lower educated. However, they are of crucial importance to people who do not start from an SL habit, young people and higher educated. The contextual aspect "time available" has a lower importance to people who do not start from an SL habit,

men and elderly. It is, however, very important to people who start from an SL habit, women and middle-aged people. The aspects "sale season" and/or "budget availability" have a rather low importance to respondents in the no time pressure scenario, respondents with an SL habit, men, higher educated and high-income respondents. They are however very important to respondents in the time pressure scenario, respondents without an SL habit, middle-aged people and elderly, and low-income respondents. They are even the most important contextual aspects to lower educated people. Young people attach a high importance to "budget availability", but not to "sale season". "Companion" has a lower than average importance to people in the time pressure scenario, people with an SL habit, men, higher educated and the middle-income category. However, it is quite important to people in the no time pressure scenario, people without an SL habit, women, elderly, lower educated and both the low- and high-income category. The context "crowdedness in the centre" has a fairly high importance to middle-aged, higher educated and medium-income people. "Parking space availability" is a contextual aspect that is sometimes considered by people in the no time pressure scenario.

In the TM decision, in all circumstances, freedom-related subsets have a relatively lower importance to young people and to people who live close to the city centre. They have a relatively higher importance to elderly. Subsets related to the value "efficiency" are somewhat less important to elderly. They are, however, of crucial importance to young people and people who live close to the city centre. Furthermore, subsets related to "convenience" have a slightly higher than average importance to people in time pressure, people that start from a TM habit, women, young people, lower educated, the low-income and high-income category and people who live close to the city. However, it is not among the most frequent itemsets of men, middle-aged people and higher educated. The value "durability" also has some importance to men, and it even has a very high importance to elderly. The value "saving money" is considered by elderly and respondents from the low-income category. "Physical comfort" is considered by the medium-income category.

Concerning the context-specific frequent itemsets in the TM decision, "precipitation" has a somewhat lower importance to respondents with a TM habit and respondents who live at a medium distance from the city centre. "Time available" has a lower than average importance to people without time pressure, people without a TM habit, men and respondents from the high income category. It is however more important to people with

time pressure, people who have a TM habit and women. The contextual aspect "baggage" is relatively little considered by people with a TM habit, young people, lower educated and people who live at a medium distance from the city centre. On the other hand, it is relatively strongly considered by people without TM habit, elderly and people who live far from the city centre. "Parking space available" is of a lower importance to respondents with a TM habit, middle aged and elder respondents, low-income respondents and respondents who live far from the city centre. They are of a higher than average importance to young people and high-income respondents. The contextual aspect "crowdedness in centre" is considered by respondents in the time pressure scenario, men, middle-aged and elder people, lower educated, low- and middle-income people and by people who live close to the city centre. "Car availability" is an aspect that is fairly important to men, young people, high-income people, and people who live at a medium or a far distance from the city centre. "Activities elsewhere but Hasselt" is considered by some respondents with a TM habit and higher educated. "Temperature" is only considered by people from high-income households. "Departure time from home" is important to some people who live at a medium distance from the city centre. And finally, the contextual aspects "arrival time at home" and "parking cost" are only important considerations to respondents from the low-income category.

6.2 Policy impact

In this section, the policy impacts of the findings in this thesis are discussed. In section 6.2.1, the policy impacts concerning the SL decision are discussed, and 6.2.2 presents the policy impacts of the TM choice.

6.2.1 Policy impacts related to the SL choice

Concerning the SL decision, the findings in this thesis indicate two important things. On the one hand, cities should make sure that their city centre is organized in an efficient way in order to make it attractive for fun shopping. In general, efficiency can for instance be obtained by creating sufficient short-term parking spaces nearby, walking lines without detours, a high density and by grouping comparable stores together. Important instruments mentioned by respondents to obtain efficiency are the presence of the respondents' favorite store, familiarity with the zone and type of stores. To quicken the

process of getting familiar with an area, policy makers should make sure to create a good legibility of their city centre (Lynch, 1960). Since respondents attach great importance to the presence of their favorite shop, cities should try to attract as much popular stores as possible. For instance, data shows that store chains like H&M, Esprit, Zara,... are popular with many shoppers, hence the presence of these stores is important to attract shoppers.

On the other, it is also important to create a sufficient mix of functions and a pleasant ambience, which is particularly important for people who are not in a hurry while executing fun shopping. A well-known example of such an area is Covent Garden in London. Here, different types of stores and other functions like cafés and restaurants are mixed very well, and a nice atmosphere is created by street shows and street musicians.

6.2.2 Policy impacts related to the TM choice

For policies that try to influence the TM choice, the impact of the findings in this thesis are quite far-reaching. A first important consequence of the findings in this thesis is that the advertisements to promote sustainable TMs should be seriously reconsidered. At this moment, many campaigns are aimed at the fact that public transport and bicycle are cheap and environment-friendly. These are in fact two of the most important advantages of these sustainable TMs, but it appears that respondents do not really consider them in their TM choice. Advertising campaigns should focus more on the considerations that are really important in people's decision making process.

Furthermore, the results indicate that cost measures can only accomplish limited results, because few respondents take cost aspects into account in their TM decision. Furthermore, the socio-demographic groups that take it most into account, are elderly and people from low income households. Traditionally, these are not groups on which policy makers would want to focus cost measures, because they are already weaker and more vulnerable societal groups.

Instead, it appears that policy makers should try to improve the competitive position of sustainable transport modes by focusing their efforts on the fields of flexibility, travel time, accessibility, shelter provision, easiness for parking and treatment of bags. These are the characteristics that respondents consider most crucial for gaining the benefits of

efficiency and freedom, which are the most important evaluative aspects for their TM choice.

Improving the competitive position of sustainable modes can be achieved means of pull and push measures. Pull measures are measures that stimulate the use of alternative transport modes by making them more attractive. So in other words, they are soft measures that try to encourage people to deliberately chose a more sustainable transport mode. Push measures on the other hand are measures that aim at discouraging car use by reducing its attractiveness. Hence, these are hard measures that try to force people to use a more sustainable transport mode (Schuitema, Steg, & Vlek, 2003).

In the following sections, some possible policy measures to encourage sustainable transport modes are presented that aim at the TM characteristics that are elicited most by respondents. The measures to encourage alternative modes at these fields (pull measures) are presented first. Measures that aim at restricting car at these fields (push measures) are presented next.

6.2.2.1 Pull measures bus

The flexibility of bus could be improved by extending the time window of the bus service. This could, for instance, allow fun shoppers to combine their fun shopping activity more easily with evening leisure activities. It could also be improved by increasing the number of bus stops, but this comes at the expense of a longer travel time, which is also an important consideration. Increasing bus frequency can also improve flexibility, since respondents then do not need to keep track of time that much (i.e. it is not a problem if they miss a bus, since the next one will arrive shortly later) and can use it more easily to combine trips. However, public transport modes are by definition less flexible than individual transport modes like car and bike. It will not be trivial to make public transport competitive to the other modes in this respect.

The travel time of the bus can be improved in many ways. Infrastructural adaptations like bus lanes or coordinated traffic lights are one option. Reducing the number of stops improves the travel time, but, as mentioned before, this comes at the expense of a lower flexibility. In some situations the implementation of a hierarchical bus network can be useful. Splitting the network in feeder lines and trunk lines with fewer stops has the

potential to reduce travel time (Nielsen et al., 2005). However, this requires well-gearred schedules, smooth transfers and a very punctual service. Otherwise the gain in time on the trunk line is nullified by the time loss of the transfer.

Bus accessibility can be improved by making sure that places of interest in Hasselt city centre have a bus stop nearby. In Hasselt, this is the case for most places of interest. Because of the Decree of Basic Mobility, inhabitants of all residential areas around Hasselt have a bus stop within walking distance, most of them offering a direct connection to Hasselt's station (Van Brempt, 2006). From Hasselt's station, the Centre Shuttle and the Boulevard Shuttle offer good access to many places of interest.

The negative influence of precipitation can be reduced by making sure that shelter is provided at bus stops.

Easiness for parking is, of course, one of the main advantages of public transport, since public transport passengers do not need to park at all, so at this field, no improvements are possible.

Treatment of bags in public transport could, for instance, be improved by installing some hooks for shopping bags at the bus stops in the city centre, so that passengers do not need to hold the bags while waiting. It could also be possible to install hooks at some seats in the bus to improve the treatment of the bags during the trip.

6.2.2.2 Pull measures bike

The bicycle is a very flexible transport mode by nature. A policy measure that can help to improve this flexibility even more is the further implementation of restricted one-way traffic (i.e., bicyclists are allowed to ride in the opposite direction in a one-way street). Despite the fact that critics sometimes argue that this is a measure that will have a negative impact on traffic safety, international research proves them wrong (Vaneerdewegh, 2004).

Bicycle travel time can be improved by means of bicycle underpasses or fly-overs for important bicycle routes at major roads. This avoids long waiting times at crossings or a time loss caused by detours. A rather progressive idea is the introduction of a green

wave for bicyclists on important bicycle routes, like for instance in the Danish city Odense (WHO, n.d.). Another possibility is to avoid that bicyclists have to make detours by limiting the mesh of bicycle infrastructure. Bicycle accessibility can be improved by this measure as well.

In theory, a bicycle is a lot easier to park than a car. However, in practice, this is not always the case in a city centre. Often a lot of attention is spent to car parking facilities, but not to bicycle parking facilities. In Hasselt, bicycle parking facilities are present at some locations in the city centre. However, only one monitored bicycle parking is present. Regrettably, it is situated in the boutique area, which is probably not the best suited area for a bicycle parking, and it is not central in the city centre. Furthermore, it is rather small. Providing additional monitored bicycle parking locations would improve the easiness for parking as well as the parking quality and safety.

Influencing shelter provision or the treatment of bags for bicycles is very difficult at a local policy level. Probably, these will always be two limiting factors for bicycle use. However, especially the importance of the treatment of bags indicates that many people have little willingness to do physical effort to travel. This is regrettable, since choosing a TM that requires physical effort has important health benefits. It can help avoiding some of the health problems that are currently seen as a major problem in Belgium, like cardiovascular diseases and obesity.

6.2.2.3 Push measures car

The flexibility of the car can be decreased by means of parking restricting measures. For instance, aboveground parking spaces could be removed in the entire city centre of Hasselt. Restrictions on parking time are another, less drastic measure. However, this softer measure has the disadvantage of generating traffic searching for an available parking space, which has a negative impact on vulnerable road users' safety, city centre livability etc. Car flexibility can also be lowered by introducing one-way traffic in the city centre. In Hasselt, one-way traffic is already implemented at most streets inside the inner ring.

Parking restricting measures will, of course, also have a major impact on the easiness of parking. Although Hasselt has already implemented some parking restricting measures,

parking in Hasselt is still rather easy. There are a lot of parking spaces, and many of them are free. To encourage sustainable transport modes, parking spaces inside the inner ring could be removed or reduced, and the free parking lots could be transformed to paid parking. Even applying a very low charge at the free parking lots can already have a noticeable effect, since there is a huge difference in peoples mind between "free" and a very low charge (Ariely, 2009).

A major downside of parking restricting measures is that the support for these measures is low in general, because entrepreneurs are convinced that parking restricting measures are an important cause of the vacancy that is currently a problem in many city centers (De Standaard, 2010). They fear the competition of stores and shopping centers that are located at suburban areas that are easily accessible by car. An example of such a location in the environment of Hasselt is the Genkersteenweg/Hasseltweg. However, Miermans and Van Moerkerke (2005) state that parking restricting measures can increase parking comfort, make the city centre more attractive and liveable, and save a lot of space that can be put to better use. This means that parking restricting measures, when they are implemented well-considered and enforced strictly, will increase the attractiveness of the city centre, in stead of decreasing it. This is however only the case for city centers that have enough regional attraction. For instance, it would not be a good idea to remove all parking places in the centre of a small municipality.

The results of this thesis show that variables related to parking are particularly important to respondents without a TM habit. Furthermore, it appears that nearly 50% of respondents state that they do not have a TM habit for fun shopping trips. Since it is much more difficult to influence the travel behavior of someone with a TM habit than someone without a habit (Bargh & Chartrand, 1999; Verplanken & Wood, 2006), this implies that parking restricting measures can have a significant impact on the modal shift of fun shopping trips relatively efficiently.

It is important to keep in mind that "parking restricting measure" is not necessarily the same as "raising parking fares". On the contrary, raising parking fares is a cost measure, hence it will mainly influence the socially weaker groups. Limiting the number of parking spaces and making a clear distinction between short-term parking spaces and long-term parking spaces could be more effective. A less strict measure could be the provision of park-and-ride at the outskirts of the city. The downside of this measure is that it will not

reduce the number of people who go to the city centre by car, but it has the advantage that less cars will go into the city centre.

Furthermore, the travel time of car can be increased by for instance adjusting traffic lights in such a way cars have to stop more often. For instance, in the environment of the city centre, this could be done by including a green phase exclusively for vulnerable road users. The downside is that this will have a negative impact on the environment by increasing emissions. Other possible measures to increase travel time by car are lowering the speed limits and adjusting the road layout (e.g. narrowings of the road, speed bumps, etc.).

Car accessibility can be diminished by limiting the number of approaching roads towards the centre, or introducing one-way traffic. Also limiting the number of parking spaces will have a negative impact on car accessibility, since parking is a crucial part of accessibility (Miermans & Van Moerkerke, 2005).

6.3 Critical reflection

In this research, the CNET protocol was translated for the first time to a computer-based survey, instead of a face-to-face interview technique. Even though the experiences with this technique and the obtained results are, in general, very positive, some minor downsides came to the surface throughout the survey. These are summarized here.

A first weakness of the method is the omission of the when-decision from the protocol. The choice to omit this decision from the survey is justified by the fact that the workload of the survey would otherwise get too high, and because of the fact that previous research (Kusumastuti et al., 2009a) showed that respondents face most difficulty with this decision because of its abstract nature. However, research shows that the TM-, the SL- and the when-decision are interrelated (Dellaert et al., 2008; Kusumastuti et al., 2009a). This means that omitting one of these decisions from the protocol could also have an influence on the other two decisions.

Another weakness is the fact that different people can use the same expression to indicate completely different things (Hannes et al., 2009b). This problem is partly taken

care of by including the definitions of the variables in the survey. However, even then, it is highly unlikely that there will be no differences in interpretation. Possibly, respondents do not read the definition because they think they understand the content of a variable by simply looking at its name. Another possibility is that they misinterpret the definition. De Ceunynck et al. (n.d.) investigated the intercoder reliability of the CNET interview protocol. Intercoder reliability is the general term for the degree to which different coders that judge an aspect of a message or object get to the same conclusion (Lombard, Snyder-Duch, & Campanella Bracken, 2008). In this research by De Ceunynck et al. (n.d.), the intercoder reliability is measured by having two interviewers code the same interview, and check the consistency among their findings. Even though the intercoder reliability is high, there are still some differences between both interviewers caused by disagreements about the content of particular variables (De Ceunynck et al., n.d.). The point is that, if there are even differences in interpretation between two well-trained respondents with an excellent knowledge of the list of variables, it can be stated with near certainty that there will be even more differences between the interpretations of 221 untrained individuals, even when the definitions of the variables are provided.

Another weakness is that different dimensions of daily activity travel planning, i.e. the destination and mode choice, are not sequential stages within the decision process, even though they are often modeled that way. Rather, they are seen as being part of an integrated problem (Hannes et al., 2009a). So, it is possible that people see the TM and SL decision in fun shopping as an integrated problem. However, the survey setup requires respondents to look at this problem as a sequential problem. So possibly, developing a way to question the different decision aspects as an integrated process can be an improvement to the research method. This is a topic for further research.

Another issue is that the use of a computer can be barrier to certain socio-demographic groups, especially elderly and lower educated. It is important to keep in mind that these socio-demographic groups are likely to be underrepresented in computer-based research, and that their results could possibly be somewhat less reliable because of their lower skills in working with a computer.

One final point of attention is that the CB-CNET presupposes that a number of specifications are made in advance. First, the decision dimensions (the decision variables for a specific problem) have to be defined in advance. Defining the decision variables is

not always straightforward, since a decision dimension is often conditionally dependent on other decision dimensions. Second, the protocol assumes that the choice alternatives of each decision are known in advance. Thirdly, besides the pre-defined list of decision variables, a pre-classified and pre-coded list of variables is formulated in advance, containing all relevant contextual, instrumental and evaluative variables for a specific decision problem. This is a very cumbersome part, since determining all possible variables in advance requires an extensive literature review and pilot testing, and it is impossible to be sure in advance that the list is exhaustive. In the CNET interview protocol, this is not a major problem because the technique is flexible enough to add new variables to the list in the course of the research (den Hartog, 2004). However, the CB-CNET does not really offer this flexibility. There is an open-ended question at the end of the elicitation of each decision, where people can add additional considerations that come to their mind that are not present in the lists of variables. However, in case the answers to this question indicate that there are variables missing, it is quite difficult to still include them during the research for two reasons. First, since it is desirable to gather the data in a short time period, the time to make adaptations to the survey software is very limited. And second, including additional variables in the course of the data gathering can bias the results, since not all respondents are presented the same lists of variables in that case. It is important to keep this in mind. However, for this research, the answers to the open ended question do not indicate any missing variables, which is positive.

6.4 Recommendations for further research

An interesting topic for future research is to repeat the survey in other cities. This would allow to draw conclusions about the generalizability of the results. It will be interesting to see whether respondents from other cities have the same considerations. It will also be interesting to see whether the average number of variables in the mental representation is that stable over different socio-demographic groups in other cities as well.

Another interesting topic for further research is the transferability of the method. It would be interesting to see whether the CNET protocol could also be used to investigate the decision making process of other decisions problems.

Furthermore, it is not sure whether the scenario (time pressure or no time pressure) is taken sufficiently into account. Even though there are differences regarding the most important associations in respondents' mental representation, respondents' network complexity is the same in both scenarios, which is somewhat unanticipated. It would be interesting to perform an experiment in which time pressure is actually physically simulated, to check whether this influences the results.

Another interesting topic for further research is the link between multiple socio-demographic factors and elicited cognitive subsets. The data analysis method used in this research does not allow to capture these links.

And finally, this research shows that it could be possible that omitting one of the interrelated fun shopping trip decisions from the survey (SL-, TM- or when-decision) has an impact on the results of the other decisions. Investigating whether this has indeed an impact, and if yes, what kind of impact, is an interesting topic for future research. Another aspect that needs further investigation is whether respondents consider these decisions as part of an integrated process, or as sequential problems.

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Richting: **master in de verkeerskunde-mobiliteitsmanagement**

Jaar: **2010**

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Voor akkoord,

De Ceunynck, Tim

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