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An interactive computer-based interface to support the discovery of individuals' mental representations and preferences in decisions problems: An application to travel behavior

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ABSTRACT

Growing emphasis is currently given in decision modeling on process data to capture behavioral mechanisms that ground decision-making processes. Nevertheless, advanced applications to elicit such data are still lacking. The Causal Network Elicitation Technique interview and card-game, both face-to-face interviews, are examples of a behavioral process method to obtain individuals' decision-making by eliciting temporary mental representations of particular problems. However, to portray and model these representations into formal modeling approaches, such as Bayesian decision networks, an extensive set of parameters has to be gathered for each individual. Thus, data collection procedures for large sample groups can be costly and time consuming. This paper reports on the methodological conversion and enhancement of the existing elicitation methods into a computer-based interface that allows to not only uncover individuals' mental representations but also to automate the generation of preference parameter elicitation questions. Results of such studies can be used to understand individuals' constructs and beliefs with respect to decision alternatives, predict individuals' decision behavior at a disaggregate level, and to assess behavioral changes due to differences in contexts and constraints.

1. Introduction

In the past decades, many attempts have been made to understand human activity and decision patterns using revealed and stated preference travel surveys. However, these types of data are criticized for being inadequate to understand decisions processes that precede the measured travel outcomes (Pendyala & Bricka, 2006). Revealed and stated preference data may very well answer questions such as *what, when, where, whose* (or *with whom*) activity-travel plans are executed, but they cannot sufficiently explain *why* and *how* a person comes to certain decisions (Bradley, 2006). Behavioral planning process data (e.g. Doherty & Miller, 2000) are believed to shed light on individuals' beliefs and constructs that ground behavioral phenomena from the viewpoint of agents (Goulias, 2003).

To deepen the insight into the underlying decision mechanisms, an elaborate computerized elicitation to capture individuals' mental representations (MRs) of decision problems is proposed based on the *Causal Network Elicitation Technique* (CNET) (Arentze, Dellaert, & Timmermans, 2008). This approach is similar to *the laddering technique*, in which an in-depth interview protocol is conducted using probing questions, such as *what*, *how* and *why* certain aspects are important in a decision. Furthermore, decision *contexts* play an important role in the evaluation of *benefits*, yielding different weights in different contexts (Shafir, 2007). For example, in the transportation field, contextual aspects such as weather conditions affect individuals' actual transport mode choices (e.g. Kusumastuti et al., 2009). Thus, various contexts in decision mechanisms should be captured to fully understand decisions, along with individuals' pursued benefits and characteristics (or instruments) of decision alternatives. The CNET interview protocol can reveal these interconnected sets of *context–instrument–benefit*. This approach has been modified to suit a fun-shopping application to assess contextual differences in the benefit activation (Kusumastuti et al., 2009).

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This research paper reports on the methodological conversion of the face-to-face CNET interview protocol to an advanced computer-based survey (CB-CNET), in which predefined variables are shown as cues to respondents. The dynamic nature of the interface enables us to ask different questions to respondents depending on their previous selections. This procedure advances our knowledge about the associations between *contexts, instruments* and *benefits*. The protocol also captures different decision-making styles and discerns MRs driven by habit or conscious consideration. Moreover, the interface has an automatic question generation feature for parameters (i.e. probabilities and weights) based on the elicited MRs, enabling these representations to be modeled as Bayesian decision networks (DNs), an artificial intelligence technique that supports decision-making. Unlike other artificial intelligence methods (e.g. decision-tree) that commonly learn an aggregate representation from survey data, Bayesian DN is able to model every individual's decision process separately. Thus, it is suited to represent behavioral planning process data.

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

The remainder of this paper is structured as follows: the next section presents some theoretical background regarding rational decision-making theory, MRs and Bayesian DNs. Next, the CNET interview protocol is explained and discussed, followed by the description of the CB-CNET interface. Moreover, some results of an individual's MR obtained using the interface are presented. At last, some conclusions are drawn and further research issues are addressed.

2. Theoretical background

This study aims at developing an advanced computer interface to investigate individuals' decision-making processes, especially when engaging in complex activities. These thought processes are reflected in their MRs, activated temporarily when solving problem tasks (Arentze et al., 2008). Furthermore, elicited aspects and concepts in these representations can be modeled as Bayesian DNs. Thus, the interface is grounded in the theory of *decision-making, MRs*, and *Bayesian DN*. These concepts are elucidated in the following subsections.

2.1. Rational decision-making theory and an example of individuals' mental representations

Rational decision-making theory argues that when facing novel or infrequent decision problems, an individual decision maker activates a complex and deliberate cognitive process to come up with the best possible solution (Payne, Bettman, & Johnson, 1993). In this process, a set of *alternative actions* is built and assessed based on their *instruments* in relation to individual's *goals and pursued benefits* and occurring *contexts* (Fig. 1).

Decision alternatives ([a] in Fig. 1), also referred to as *decision strategies* (e.g. Payne et al., 1993), represent a choice set of possible *actions* or *objects* that can be used to resolve particular problems (Arentze et al., 2008; Gärling, Laitila, & Westin, 1998). Examples of transport mode alternatives to go fun-shopping to the city centre are using *car, bus*, or *bike*. *Contextual aspects* ([b] in Fig. 1) are described as any given circumstances, situations and constraints in the decision environment that cannot be controlled by decision makers albeit strongly affecting choice outcomes (Arentze et al., 2008). Many studies (e.g. Gärling & Axhausen, 2003; Gärling et al., 2002; Schlich & Axhausen, 2003; Stern & Richardson, 2005) have indicated the importance of contexts in people's travel decisions. These aspects can be natural forces such as weather conditions and other constraints that have been categorized earlier by Hägerstrand (1970) into *capability, authority* and *coupling constraints. Instrumental aspects* ([c] in Fig. 1) are defined as observable characteristics of the decision alternatives. Existing studies (Dellaert, Arentze, & Timmermans, 2008; Harte & Koele, 1997) refer to this concept as *attribute variables*. *Travel time, cost*, etc. are examples of the instruments of different transport options. Lastly, *benefits* (or utilities) are explained as subjective estimated benefits of alternatives concerning their instruments in the arisen contexts ([d] in Fig. 1), such as *efficiency, comfort*, etc. In the end, it is assumed that decision makers sum-up these (partial) utilities and select an alternative that has the highest overall utility value.

During the decision processes, a decision maker activates a temporary MR in his working memory based on his existing knowledge (Kearney & Kaplan, 1997). Constructing a MR requires a decision maker to recall, reorder and summarize relevant information in his long-term memory (Cox, 1999). It may involve translating and representing this information into other forms, supporting coherent reasoning in a connected structure (Kolloffel, Eysink, & de Jong, 2010; Tabachneck-Schijf, Leonardo, & Simon, 1997).

In the cognitive MR of travel decisions, different *contexts, instruments* and *benefits* are linked and mapped in a causal network (Arentze et al., 2008). The smallest component that composes an individual's MR is referred to as a *cognitive subset,* which is defined as one unit of interconnected *context–instrument–benefit* aspects (Kusumastuti, Hannes, Janssens, Wets, & Dellaert, 2010). One subset can be linked to other subsets, creating a MR of a certain problem task.

However, not every travel decision is made consciously and cautiously. In frequently repeated daily-travel such as commuting to work or school, travel decisions are often made out of habit (Hannes, Janssens, & Wets, 2008). This grounds the needs to register another cognitive subset type in "normal" conditions (or usual situations); i.e. *normally* (*habit*)–*instrument*–*benefit.*

The complexity of travel decisions occurs not only because of the variety of aspects that people consider simultaneously during the thought process but also because in many cases, different decisions are interconnected. For instance, when planning a leisure-shopping trip, an individual initially decides upon the transport mode option before thinking about the exact location to go to, or vice versa. In the example (Fig. 2), the transport mode choice mainly depends on *weather conditions* (context). This happens because various vehicles offer different protection or *shelter* (instrument) in case of bad weather and due to an individual's pursued benefit of having *comfort* (benefit). As a result, the first transport mode subset {*weather, shelter, comfort*} in this MR is registered. Using the same line of thought, the cognitive subsets for the location choice is elicited and mapped. Detailed discussions can be found in previous reports (e.g. Kusumastuti et al., 2010).

2.2. Modeling individuals' mental representations using Bayesian decision networks

A Bayesian DN is an extension of a Bayesian network (BN) that combines *probabilistic reasoning* and *utilities*, allowing decision makers to estimate expected utility values of choice alternatives. This modeling approach enables us not only to model interconnected variables in individuals' MRs but also to represent

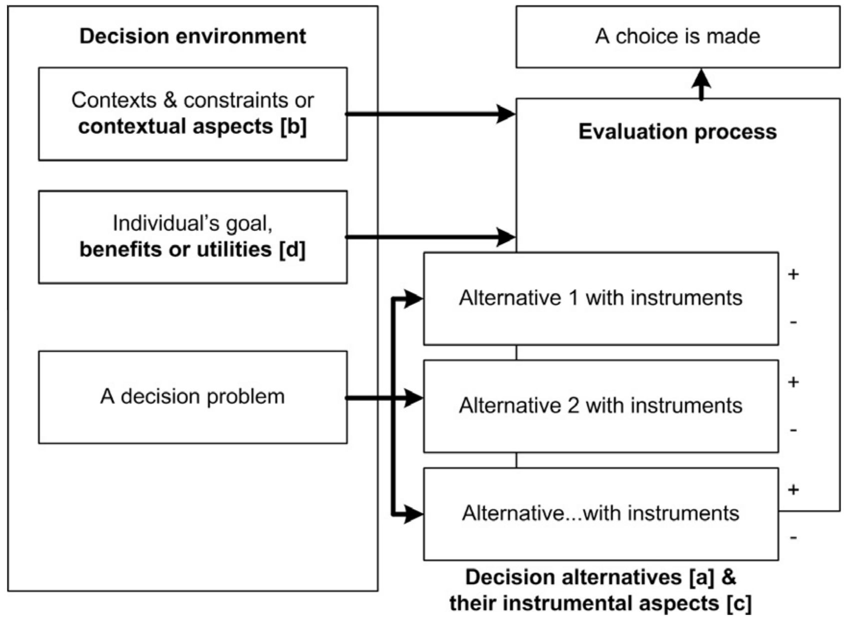


Fig. 1. A rational decision-making scheme.

sequential decision-making. Both facets cannot be retained by more common knowledge representations, such as a decision-tree classifier model.

A BN is a directed-acyclic-graph (Korb & Nicholson, 2003). It contains *nodes* that represent a random set of variables in a specific field, and directed *arcs* that indicate inter-dependencies between the linked nodes. The strength of these relationships relies on conditional probability distributions of the joined nodes.

Building a Bayesian DN requires some steps: (1) determining nodes and their states, (2) revealing the network structure, (3) specifying conditional probabilities and utilities, and (4) evaluating the decision network. These steps are detailed below successively.

2.2.1. Nodes and states

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

All possible aspects (i.e. context, instrument, benefit) and states used in this study have been identified and listed by the researchers from the results of preliminary in-depth studies. Furthermore, all applied nodes are limited to discrete nodes, which means that variables must hold one of their states at a time. For instance, the contextual aspect of *weather conditions* has two states {*bad, good*}, the instrumental aspect of *vehicle's speed* contains three states {*low, medium, high*}, and all benefits, such as *having comfort*, entail two states {*none, all*}. *Decision nodes* represent the decisions being made, and their states indicate the choice alternatives or strategies used to solve the problem. At last, *utility nodes* symbolize subjective utility functions and they do not have any states. When there is more than one utility node in the network, the total utility is the sum of all partial-utilities.

2.2.2. Network structure

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

In general, depending on the purpose of the study, the structure of a network can directly be specified by researchers, experts, or learned from a database. Since this study focuses on modeling individuals' MRs at a disaggregate level, relevant aspects and network structures should be determined by individuals as experts of their daily-travel decisions. Modeling cognitive MRs as Bayesian DNs has been previously discussed in literature (Hannes et al., 2010). However, to have a better notion of the elicitation interface, this model is detailed below.

The Bayesian DN allows us to model *sequential decision-making*, thus it is suited to model individuals' MRs of complex travel tasks that typically consist of interconnected decisions. An arc between two decisions is referred to as a *precedence* or *no-forgetting link*, implying that a decision maker takes into account previous decision(s) when making the next one(s). The example of a simple network with two sequential decisions can be seen in the example (Fig. 3).

Suppose that a cognitive subset {*weather, shelter, comfort*} is elicited by a respondent when considering the transport modes {*car, bus, bike*} to go shopping. *Weather* {*bad, good*}, represents weather conditions. *Shelter* {*not needed, needed*} symbolizes the need to have a shelter, as different transport modes vary in that respect. Logically, this need is driven by weather conditions, i.e. when the weather is bad, the necessity to have shelter increases. *Comfort* corresponds to the benefit that someone wants to gain from using different transport modalities. Thus, its states of {*none, all*} are also influenced by weather conditions. This subset is modeled in Fig. 3a.

The shopping location decision is influenced by an *individual's interest in a specific product* as well as the *number and size of goods being purchased* (Fig. 3b). Both contexts lead to the benefit of having *efficiency*. In the model, we differentiate the efficiency gained in different situations, e.g. [*efficiency*_1] and [*efficiency*_2], allowing us to assess the impact of every context on the benefit level separately. In the end, both benefits lead to the same partial utility of having efficiency.

The applied modeling approach (Fig. 3) differs from the existing approaches in some respects. For instance, our model regards

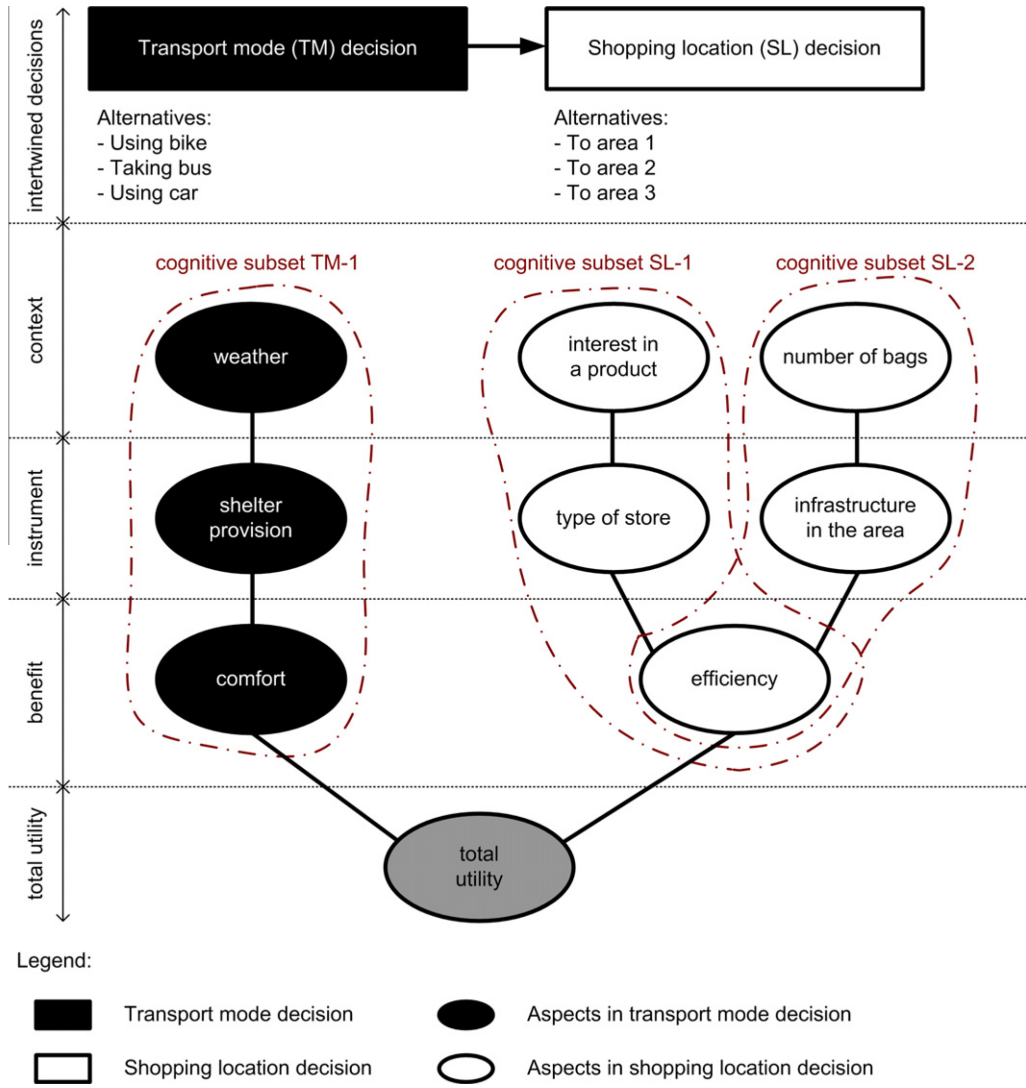


Fig. 2. An example of an individual's MR.

the characteristics of the choice alternatives (instruments) as aspects known prior to making choices. Thus, they are parents of the decision nodes. In contrast, other studies (e.g. Arentze et al., 2008) consider these characteristics as the outcome of decisions. Moreover, our proposed approach uses a fixed structure to model a cognitive subset, simplifying the automatic generation of Bayesian DNs.

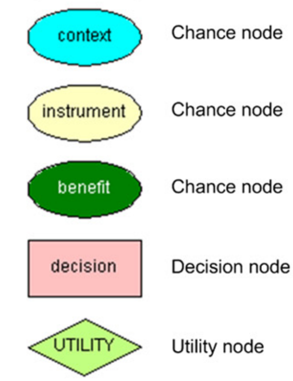
2.2.3. Conditional probability and utility table

After all nodes and the network structure have been specified and determined, the relationships between the linked nodes have to be quantified in conditional probability tables (CPTs). Each chance node contains a CPT, representing individuals' belief of occurrence of particular states given the combination of the parents' states. For example, consider *comfort* [*C*] {*none* [*N*], *all* [*A*]} in the cognitive subset example of {*weather, shelter, comfort*} in Fig. 3a. Since this node has *weather* [*W*] {*bad* [*B*], *good* [*G*]}) and *transport mode decision* [*TM*] {*car, bus, bike*} as parents, the CPT of having *all comfort* takes the joint values $\{P(C = A|W, TM)\}$. Suppose that an individual estimates these values as $\{\langle 0.5\rangle, \langle 0\rangle, \langle 1\rangle, \langle 1\rangle, \langle 0.6\rangle, \langle 0\rangle\}$ (Fig. 3c), meaning that if a *car* is used when the weather is *good* then the chance to gain the benefit of having *comfort* is 50%, if a bus is used in that context, then the probability to acquire this benefit drops to 0% (for instance because it is too hot inside the bus), and so forth. It should be noted that the joint values of all states in one node have to sum-up to 1. Therefore, the joint values for having *no comfort* are $\{P(C = N|W, TM)\} = 1 - \{P(C = A|W, TM)\}$.

The example above shows that the probability assessments of a node that has many parents (or when the parent nodes have many states) are very large. Imagine a child node that has five parents. If each node has two states, the CPT of this child node requires $2^{5+1} = 64$ probabilities. Given the nature of this study to individually model people's travel behavior, respondents' subjective probability judgments are needed for the CPTs of each individual's Bayesian DN. This imposes a challenge to reduce respondents' burden. For this reason, each partial benefit variable is linked to only one context (Fig. 3a and b), assuming that there are no interactions between different contexts that lead to the same desired benefits.

Each utility node has a utility table (UT). Since this type of nodes does not contain any states, it directly describes the utilities of the parents' states. In the example above, the utility node COMFORT has a benefit *comfort* as a parent, hence the utilities for having *all* and *no* comfort are assessed by assuming that having no benefit always equals 0 while having all benefit is valued 100 (Fig. 3c). When there are two identical benefits that lead to the same utility (e.g. *efficiency* in Fig. 3b), these values are propagated equally (see the UT EFFICIENCY in Fig. 3c).

Legend for Bayesian DN:



Legend for CPTs and UTs:

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

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

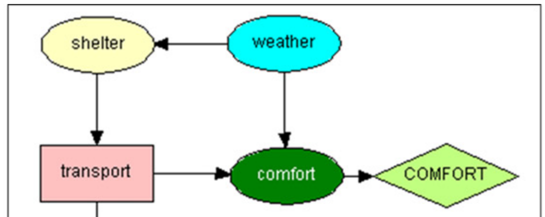
CPT Weather (W)
P(W=G)
0.5

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

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

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

Fig3c. CPTs and UTs



Fi3a. Modeling the first cognitive subset

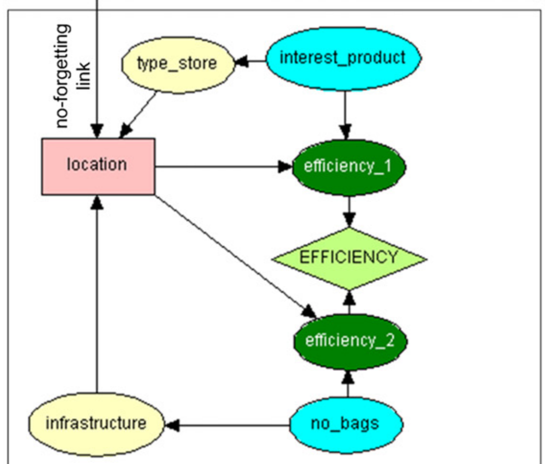


Fig3b. Modeling the second and third cognitive subset

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

Fig3d. Utility of comfort

Calculations:

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

Fig3e. No evidence

Calculations:

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

Fig3f. An evidence that the weather is bad

Fig. 3. Modeling cognitive subsets.

An individual may consider the importance of various utilities in reality differently (Arentze et al., 2008; Dellaert et al., 2008). For instance, a busy person may prioritize having *efficiency* over *comfort*. Therefore, it is important to take the weight of partial-utilities into account in the UT. For the sake of simplicity of the example in Fig. 3, *comfort* and *efficiency* are weighted equally. However, the developed interface should allow for its assessments.

2.2.4. Evaluating decision networks

The Bayesian DN can be solved after all probabilities, utilities and their weights are inputted in the CPTs and UTs. Compiling a Bayesian DN combines utility and probability theories, allowing the *expected utility values* (EU) of each decision alternative given any available evidence (e) to be calculated (Korb & Nicholson, 2003).

$$EU(D|e) = \sum_i P(O_i|e, D) \times U(O_i|D)$$

e = evidence, D = non-deterministic decision alternative with possible outcome states O_i. $U(O_i|D)$ = utility of each state of the outcomes, given alternative D is taken. $P(O_i|e, D)$ = conditional probability distribution over possible outcome states, given evidence e is observed and action D is taken.

Examples of detailed calculations (Fig. 3e and f) are exemplified only for modeling one subset of {*weather, shelter, comfort*}. The utilities of comfort $\{U(C|W, TM)\}$ are shown in Fig. 3d. Using the CPT and UT data (Fig. 3c) and the utility calculations (Fig. 3d), the EU for the transport mode options are calculated.

The calculations (Fig. 3e) show that given an unknown state of weather (50–50% chance that the weather is good or bad), taking car maximizes the utility (75), followed by bike (50) and bus (30). Additionally, some evidence can be entered in the network based on some observations and accordingly the network can be inferred. For instance, when the weather is (or expected to be) bad (Fig. 3f), the EU of choosing bike drops to 0. Using the same technique, the evidence that the weather is nice can also be entered, resulting in the new EU of each decision option.

This example shows that a Bayesian DN can be used to predict every individual's travel behavior, assuming that people always take the alternative that maximizes their utility. However, the example is fairly simple since it allows for only one decision and one subset. In reality, individuals' MRs can be more complex with multiple decisions and a number of subsets, as it will be addressed later and shown in Fig. 9. To compute complex networks, Bayesian software is commonly used, such as Hugin software (HUGIN EXPERT, n.d.).

2.3. Conclusions

This section shows that the data collection procedure to capture individuals' MRs and model them as Bayesian DNs should be divided into several parts. Firstly, the sequence of decision-making should be identified. Furthermore, important aspects considered when solving the decision problem have to be elicited and the interconnection between them (i.e. the cognitive subsets) should be specified. Next, the probabilities and utilities have to be collected, as well as the utility weights. Since the whole elicitation procedure is quite intense and demanding, it is important to keep the balance between the sought-after information and respondents' burden. The developed computer interface takes these issues into account.

3. Conventional elicitation techniques

This section discusses conventional elicitation techniques to extract individuals' MRs, emphasizing on the *hard* and *soft-elicitation* procedures. Following that, the CNET interview protocol is summarized and the experience of using this protocol is explained subsequently.

3.1. Soft vs. hard-elicitation techniques

The differences in elicitation techniques have been assessed before. For instance, Russell et al. (2004) have conducted a study to compare *soft* and *hard-laddering* methods. Results show that different approaches result in different network complexity levels. Similarly, two CNET methods have been tested (Kusumastuti et al., 2009). The fist method is *the CNET interview*, resembling the *soft-elicitation* technique (Arentze et al., 2008). The second one is the *CNET card-game*, akin to the *hard-elicitation technique*. Results support the existing research outcomes by Russell et al. (2004). Participants' MRs extracted from the CNET card-game are more complex and elaborate than the ones derived from the CNET interview.

Results of these studies suggest that researchers should be aware of the impact of elicitation methods on research outcomes. The advantages and disadvantages of both elicitation techniques have been previously discussed in the literature (e.g. Grunert & Grunert, 1995; Russell et al., 2004). Additionally, respondents from the preliminary study indicate that the CNET card-game is preferable to the CNET interview because of the easiness, comprehensiveness, and the way it represents their actual thought processes (Kusumastuti et al., 2009). Based on results of both CNET techniques, the CB-CNET interface is developed to facilitate the automation of the data collection procedure.

3.2. The CNET interview protocol

In brief, the CNET interview protocol is developed to reveal people's MRs in a face-to-face semi-structured interview setting (Arentze et al., 2008), starting from the elicitation of cognitive subsets (Kusumastuti et al., 2009). Firstly, participants are asked to order the sequence of their decision-making. Afterwards, the elicitation procedure begins by asking participants about considerations that come to their mind when making the first decision. Any open answers to this question are coded using a predefined code list and categorized as contextual aspect, instrumental aspect or benefit. Depending on the categorization of the elicited variables, other probing questions of *how* and *why* such a variable influences their decision choice are asked next. These questions continue until a complete subset is elicited and recorded. Afterwards, an interviewer goes back to the first question to ask about respondent's other thought factors.

3.3. Experiences with the CNET interview protocol

Previous study (i.e. Kusumastuti et al., 2009) reports that the average time to complete the CNET interview is about 1 h per respondent. However, eliciting the affecting factors in decisions and their interconnections is not sufficient to model participants' MRs as Bayesian DNs. The data has to be inputted and each respondent's Bayesian DN graph has to be drawn manually. Moreover, parameters have to be gathered based on their unique networks, preventing to capture such data immediately in face-to-face interviews. It means that post-questionnaires, designed for each individual, are sent after the interviews. This whole procedure can take at least 8 h of the researcher's time to complete, added with additional 2 h of participant's time to answer the post-questionnaire. The inability to ask parameter questions directly in the interview may add-up respondents' burden to recall the decision problem and reactivate the MR. Overall, the whole procedure is time consuming (Kusumastuti et al., 2009), enhancing the need to automate the entire process in a computer-based elicitation interface.

4. Computer-based elicitation technique

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

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

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

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

It is concluded in the theoretical background that the computerized interface to capture and model individuals' MRs should be divided into several stages, as it is detailed in Fig. 4. An additional step is added in the interface to capture the individuals' actual preferences in different scenarios to enable model validations. Some screenshots of the English version of the interface can be seen in Fig. 5.

4.1. Research setting and scenario

The survey starts by asking the participants to give their personal information, such as their residence, education, and occupation. This data can be used to cluster the elicited MRs based on socio-demographic characteristics. Afterwards, the research scenarios are explained to the respondents.

The CB-CNET is implemented to assess individuals' travel behavior when engaging in leisure-shopping activities in a city centre. Hasselt, a typical European historic city in Belgium, is chosen as a case study to implement the interface. Since Hasselt is located in the Dutch speaking part of the country, the whole survey is conducted in Dutch. The example of the scenario can be seen in Fig. 6. A short description of the task is always shown in the interface as a reminder throughout the whole survey (Fig. 5).

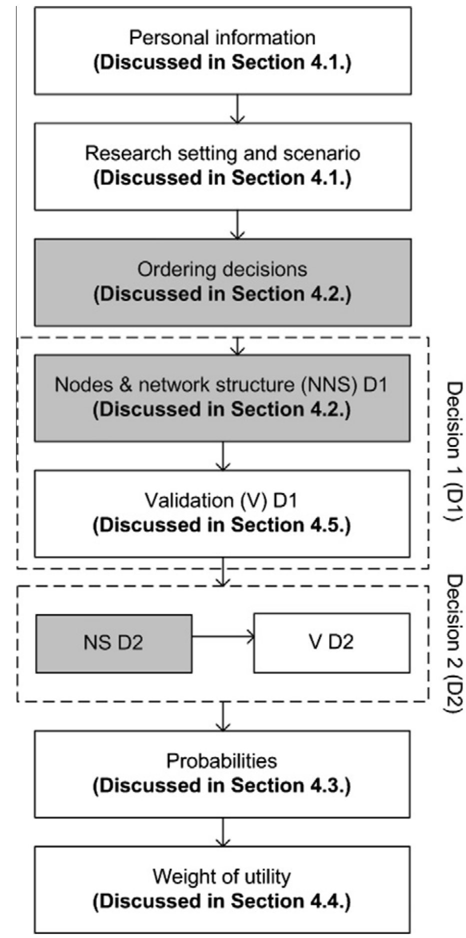


Fig. 4. Summary of the elicitation stages in CB-CNET.

After this, the respondents are asked to reflect on two decisions: *how* to get to the city centre (transport mode decision) and *where* exactly to go to (shopping location decision). Following that, all decision alternatives are explicated. The *transport modes* are explained by reminding the respondents that they are living in Hasselt outskirts. All respondents are recruited from this area (3–10 km away from the city centre). They own at least a bike and a driving license. A bus stop is located within walking distance of their home, which is the case for everyone who lives near Hasselt. Accordingly, different predefined transport mode options (i.e. *car, bus,* and *bike*) can equally be considered. The *location choices* are elucidated by showing a map of Hasselt city centre divided into three zones, derived from results of a preliminary study on participants' mental map: *the main shopping street, the expensive boutique area* and *the gallery area*.

4.2. Eliciting nodes and specifying network structure

The elicitation procedure begins after describing the research setting and scenario. Initially, the participants are asked to rank their decisions from the one that they think of first to last. Based on this, the respondents are asked to contemplate their decision-making, i.e. whether their decisions vary depending on certain circumstances, indicating *heuristic* or *rational decision-making*, or whether a choice is made spontaneously, representing *habitual*

Fig. 5. Screenshots of the CB-CNET interface.

Scenarios:

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

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

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

Fig. 6. The example of the scenario.

decision-making. This part is defined as the *split-elicitation procedure* because based on respondents' indications, different elicitation paths are followed ([a] in Fig. 7).

Suppose that a respondent indicates that his transport choice depends on some contexts then revealing these factors is targeted next, forming *situation models* (Wyer, 2007). For instance, a participant reasons that he bikes whenever the *weather* is nice and takes his car if the *time* is limited. In this case, *weather conditions* and *time availability* are registered as his influencing contexts. To elicit these variables, participants are asked to sort out all contexts that could affect their transport choices in a predefined list of contexts ([c–i] in Fig. 7). This list contains a wide variety of contextual aspects, ranging from coupling constraints (i.e. *companionship*), natural forces (e.g. *weather conditions*, *wind*, etc.), Travel Demand Management measures (e.g. *bus frequency*, *parking cost*, *bus fare,* etc.), to other contexts and constraints (*time availability*, *parking availability*, etc.). In total, there are 27 and 16 contextual variables for the transport and location decisions respectively. These predefined variables are developed based on literature and preliminary studies using the CNET interviews (Kusumastuti et al., 2009). To ensure that all respondents have uniform interpretations of these variables, the definition is shown in the interface whenever respondents pass their mouse on one of them.

Each aspect is normally represented in a discrete node with 2–3 states. Cost-related variables usually have three states, such as *parking cost* {*free*, $\langle$2 *euro/hour*, $\rangle$2 *euro/hour*}. Consequently, the impact of different pricing policies on individuals' travel behavior can be assessed in relation to other affecting contexts. The maximum number of seven states is observed for a contextual aspect of *having information from others* {*no advice, positive advice for area* 1, *negative advice for area* 1, + *area* 2, − *area* 2, + *area* 3, − *area* 3} in the shopping location decision.

Afterwards, the respondents have to reveal the interconnected *benefits* for each context ([d–i] in Fig. 7). For this purpose, 15 benefits are shown in a predefined benefit list (e.g. *having fun, physical comfort*, etc.). Next, the full cognitive subsets are elicited by interrogating the intertwining *instrument*(*s*) for each selected *context–benefit* ([e–i] in Fig. 7). The interface automatically generates questions depending on respondents' previous variable selections. Here, short lists of instrumental aspects appear. These lists contain various numbers of instruments depending on the chosen context. They were identified using the CNET card-game method. For instance, *weather conditions* connects with 15 instruments (the longest list) whilst *tax and insurance* links to three instrumental aspects (the shortest list). After this procedure is completed, *the first cognitive subset type of* {*context, instrument, benefit*} can be registered.

When a respondent initially points out that he would directly choose a certain transport mode regardless specific contexts, another elicitation path is carried out to obtain the *generalized representations* from values (Wyer, 2007) ([b–ii] in Fig. 7). The procedure begins with extracting all pursued *benefits* from the chosen transport mode, followed by revealing the linked instruments. The full list of instruments is shown, containing 25 and 23 variables for the transport and location choices respectively. As a result, *the second cognitive subset type of* {*normally, instrument, benefit*} can be noted down.

Additionally, participants are asked if they have other considerations that are not presented in the lists. An additional question of how participants are actually making a choice is also asked ([h] in Fig. 7) to re-confirm their previous answers in the split-elicitation page ([a] in Fig. 7). Detailed stages and explanations of the CB-CNET elicitation part can be seen in Fig. 7.

4.3. Probabilities

Probabilities are assessed based on the relationships between parent and child nodes. Theoretically, these probabilities are gathered for each node. Practically, this is infeasible, considering the amount of questions that respondents have to answer. Therefore, some assumptions are made.

First, probabilities of certain contexts to occur should be assessed based on individuals' beliefs. However, these contexts are observed or expected at the decision time. For instance, when deciding upon the transport mode, an individual already has preliminary knowledge of the (expected) *weather conditions* during the trip (bad or good), allowing some evidence to be set in the network. The initial probabilities before evidence are distributed equally across variable states, e.g. *weather*{*bad, good*} = $\langle 0.5, 0.5\rangle$. Hence, the participants are not asked to indicate these values, solving the problem when participants' initial probability knowledge is lacking. Next, the probabilities of instruments rely on the context states. However, from the previous calculation (Fig. 3), these values are not used to calculate the EU of the choice alternatives. This implies that any inputted values on these nodes will not change the calculated results. Therefore, they are not collected. This node type is elicited only to find out which attributes of the decision alternatives are important to gain certain benefits in particular contexts.

The mentioned considerations let us focus solely on the probabilities of benefits, based on contexts and decisions. Since the benefits always have two states, the probabilities can be assessed only for one state (see Section 2.2.3). The CB-CNET allows questions to be generated automatically based on participants' variable selections. For instance, when a benefit of having *comfort* {*none, all*} is elicited due to *weather conditions* {*bad, good*} and the *transport mode* options {*car, bus, bike*}, this question is asked:

> "Imagine that the weather is bad when you go fun-shopping in Hasselt. In this case, how big is the chance that you will gain the benefit of having comfort when you use car/bus/bike?"

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

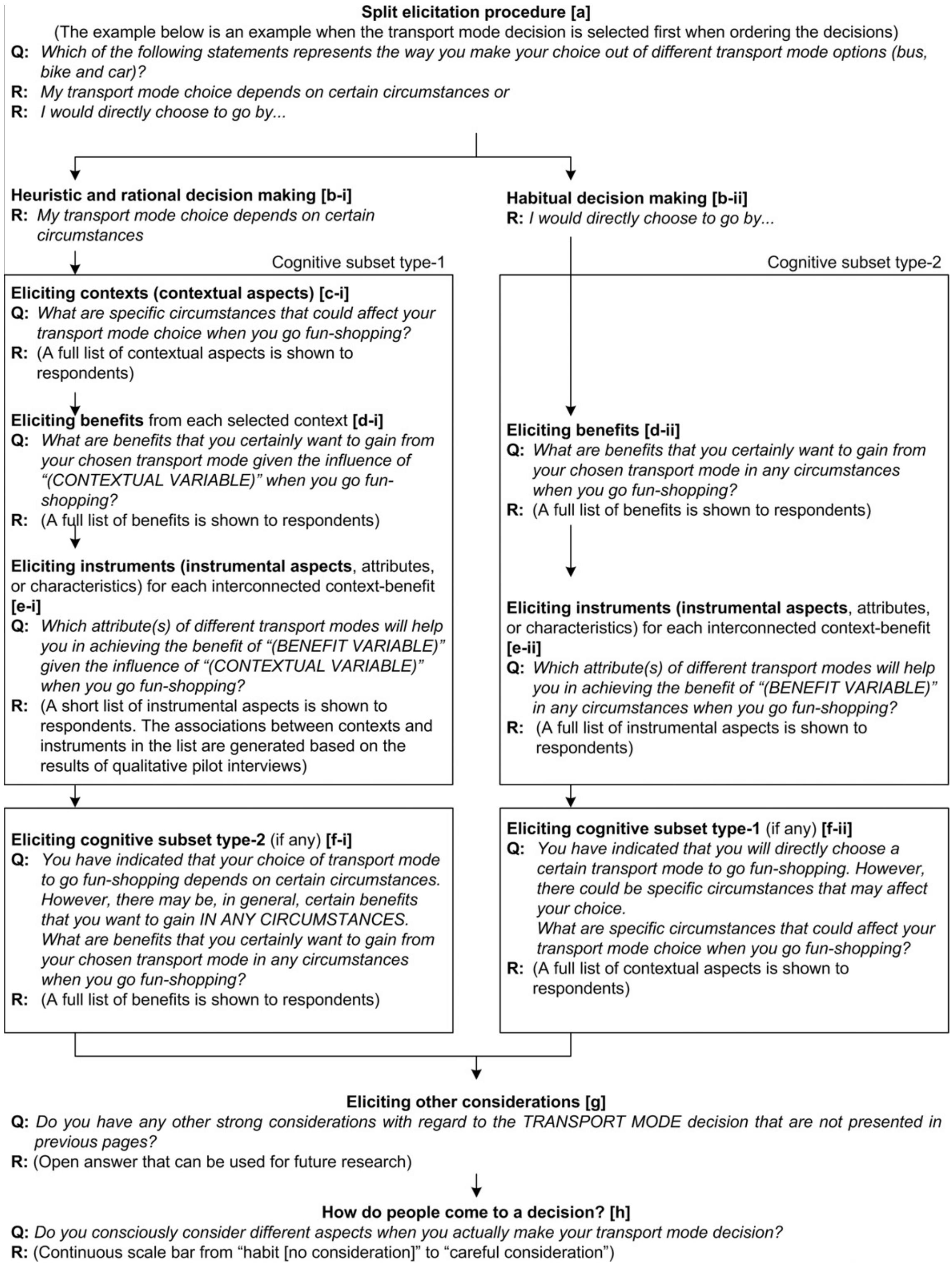


Fig. 7. Elicitation of the network structure in CB-CNET.

4.4. Weight of utility

The utility weights are calculated in two ways: (1) rating of single-benefits and (2) rating of combined-benefits in a conjoint experiment using fractional factorial design profiles. In the first experiment, participants are asked to indicate the importance of gaining benefits when they go shopping. Respondents can freely indicate their answers in continuous response bars, ranging from *not important* (0) to *extremely important* (100). Each value is divided by the sum of the elicited benefit values, yielding each utility weight. Results of Bayesian DNs using single-benefits can be compared with the ones calculated using the experimental design.

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

FFD allows us to economically assess "causal-effect" relationships between factors in an experiment, because instead of running 32 full factorial designs a 1/2 fractional run of 18 or a 1/4 fractional run of eight can also be sufficient. These designs should fulfill adequate properties of being *balanced* and *orthogonal*, meaning that all combinations of levels (or states), e.g. *high* [+] and *low* [−], appear as frequently in the design and the correlations between all attributes are "0". Nevertheless, it can only assess *main-effects* while *interaction-effects* are assumed to be "0". The *main-effect* shows the effect of single factors on the dependent variable and the *interaction-effect* indicates the effect of combined independent variables. In this study, FFD is used to calculate the partial-utility weights. A detailed discussion is out of the scope of this paper.

FFD is written in a notation 2_R^{k-p}, where two represents the *number of attribute levels*; k symbolizes *the number of attributes*, $k - p$ stands for the *extent of fractionation*, and R signifies the *resolution*. The resolution indicates the shortest length of "word" in the generator set (see e.g. NIST/SEMATECH, n.d. for detailed explanations). This study implements 2_{IV}^{7-3} design (Table 1), meaning that seven benefits are assessed in the total number of 16 runs (profiles), each benefit has two levels, and a resolution IV design is used. Such designs can be obtained from other literature (e.g. Box, Hunter, & Hunter, 1978; Montgomery, 2000; NIST/SEMATECH, n.d.).

The respondents are asked to value the profiles separately concerning their chance to execute the leisure-shopping activity (0–100%). Each profile contains combinations of seven benefit states. These benefits are taken from the survey. Thus, the same FFD is used for all participants, but the assessed benefits differ from one respondent to another. The response column in Table 1 shows an example of a respondent's answers.

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

$$\text{Total Utility} = part\_worth\_X1 + part\_worth\_X2 + \cdots + part\_worth\_Xn$$

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

Table 1
2_{IV}^{7-3} FFD design with response.

Profile	X1	X2	X3	X4	X5	X6	X7	Response
1	+	+	+	+	+	+	+	1
2	+	+	+	–	+	–	–	0.1
3	+	+	–	+	–	+	–	0.49
4	+	+	–	–	–	–	+	0.07
5	+	–	+	+	–	–	–	0.34
6	+	–	+	–	–	+	+	0
7	+	–	–	+	+	–	+	0
8	+	–	–	–	+	+	–	0
9	–	+	+	+	–	–	+	0.13
10	–	+	+	–	–	+	–	0.12
11	–	+	–	+	+	–	–	0.79
12	–	+	–	–	+	+	+	0.08
13	–	–	+	+	+	+	–	0
14	–	–	+	–	+	–	+	0
15	–	–	–	+	–	+	+	0
16	–	–	–	–	–	–	–	0

$$\text{Assessment} = C + b1X1 + b2X2 + \ldots + b7X7$$

C = constant represents basic use or average assessment of profiles, Xn = benefits assessed, bi = estimated part-worth.

The example of the regression equation from the example in Table 1 is shown below. Values (C, $b1, \ldots, b7$) are taken from Table 2. Partial-utilities are defined as *factor importance* or the effect of attributes on the utility. To calculate these values, the range of part-worth for each benefit is estimated, divided by the sum of part-worth ranges, multiplied by 100% (Table 3).

$$\text{Utility} = 0.195 + 0.055X1 + 0.153X2 + 0.16X3 + 0.149X4 + 0.051X5 + 0.016X6 - 0.35X7$$

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

Traditional conjoint experiments using full-profiles are commonly used for less than 10 attributes (Hair et al., 2005). It is believed that the accuracy of full-profile designs reduces as the number of attributes grows beyond 10 due to respondents' fatigue, memory limitation, and information overload (Pullman, Dodson, & Moore, 1999). However, the maximum number of attributes that one respondent can assess has never been determined (Pullman et al., 1999). A benchmark of maximum 30 attributes is often used (e.g. Green & Srinivasan, 1990). This study applies a seven-attribute design because results of our pilot study show that respondents tend to indicate 6–7 benefits. Moreover, our survey to 221 respondents supports this finding as the average number of selected benefits equals seven.

4.5. Model validation

The last part of the survey is designed to gather sufficient data for model validations. Respondents' actual transport mode preferences are asked according to individuals' initial selected contexts. For instance, a respondent elicits *weather conditions*, *time availability*, and *companionship* as contexts that affect his transport mode. Thus, questions are asked, based on different schemes (see Fig. 8). Ultimately, these preferences are compared with the Bayesian DN results to check the model accuracy.

4.6. Compiling Bayesian DNs

An additional program is written to automate the generation of Bayesian DNs from individuals' elicited MRs. Specialized Bayesian network software, i.e. Hugin Researcher 7.2 (HUGIN EXPERT, n.d.), is used to compute all networks. An example of an individual's Bayesian DN derived from CB-CNET can be seen in Fig. 9. This example illustrates the use of a Bayesian DN to predict individuals' travel behavior. Furthermore, behavioral changes due to some influential contexts can be assessed. For instance, with no evidence, the network predicts that taking the car yields the highest utility value (53.30) ([a] in Fig. 9). However, when some evidence is entered (i.e. there is plenty of time available, car is not available, it is not a windy day, and the weather is good) the utility of taking the bike increases (41.64) and the utility of taking the car decreases (35.80) ([b] in Fig. 9).

4.7. Conclusions

This section details the development of the computer-based elicitation technique, named the CB-CNET, and its application in leisure-trip related decisions. This interface is used to gather data

Table 2
An example of regression coefficients.

Coefficients[a]						
Model		Unstandardized coefficients		Standardized coefficients	*t*	Sig.
		B	Std. error	Beta		
1	(Constant)	.195	.067		2.898	.020
	B1	.055	.067	.184	.817	.437
	B2	.153	.067	.511	2.267	.053
	B3	.016	.067	.054	.242	.815
	B4	.149	.067	.499	2.211	.058
	B5	.051	.067	.172	.762	.468
	B6	.016	.067	.054	.242	.815
	B7	−.035	.067	−.117	−.520	.617

[a] Dependent variable: response.

Table 3
An example to calculate factor importance of each benefit.

Estimating part-worths			Calculating factor importance	
Attributes	Levels	Estimated part-worth	Range part-worth	Factor importance (%)
X1	+	0.055	0.11	11.58
X1	−	−0.055		
X2	+	0.153	0.306	32.21
X2	−	−0.153		
X3	+	0.016	0.032	3.37
X3	−	−0.016		
X4	+	0.149	0.298	31.37
X4	−	−0.149		
X5	+	0.051	0.102	10.74
X5	−	−0.051		
X6	+	0.016	0.032	3.37
X6	−	−0.016		
X7	+	−0.035	0.07	7.37
X7	−	0.035		
Total range part-worth			0.95	

"Which transport mode (car, bus or bike) will you choose given the following scenario?"
Scenario 1:
- *It is raining*
- *You have plenty of time available*
- *You go fun-shopping alone*

Scenario 2:
- *It is sunny*
- *You have plenty of time available*
- *You go fun-shopping with someone*

Etc.

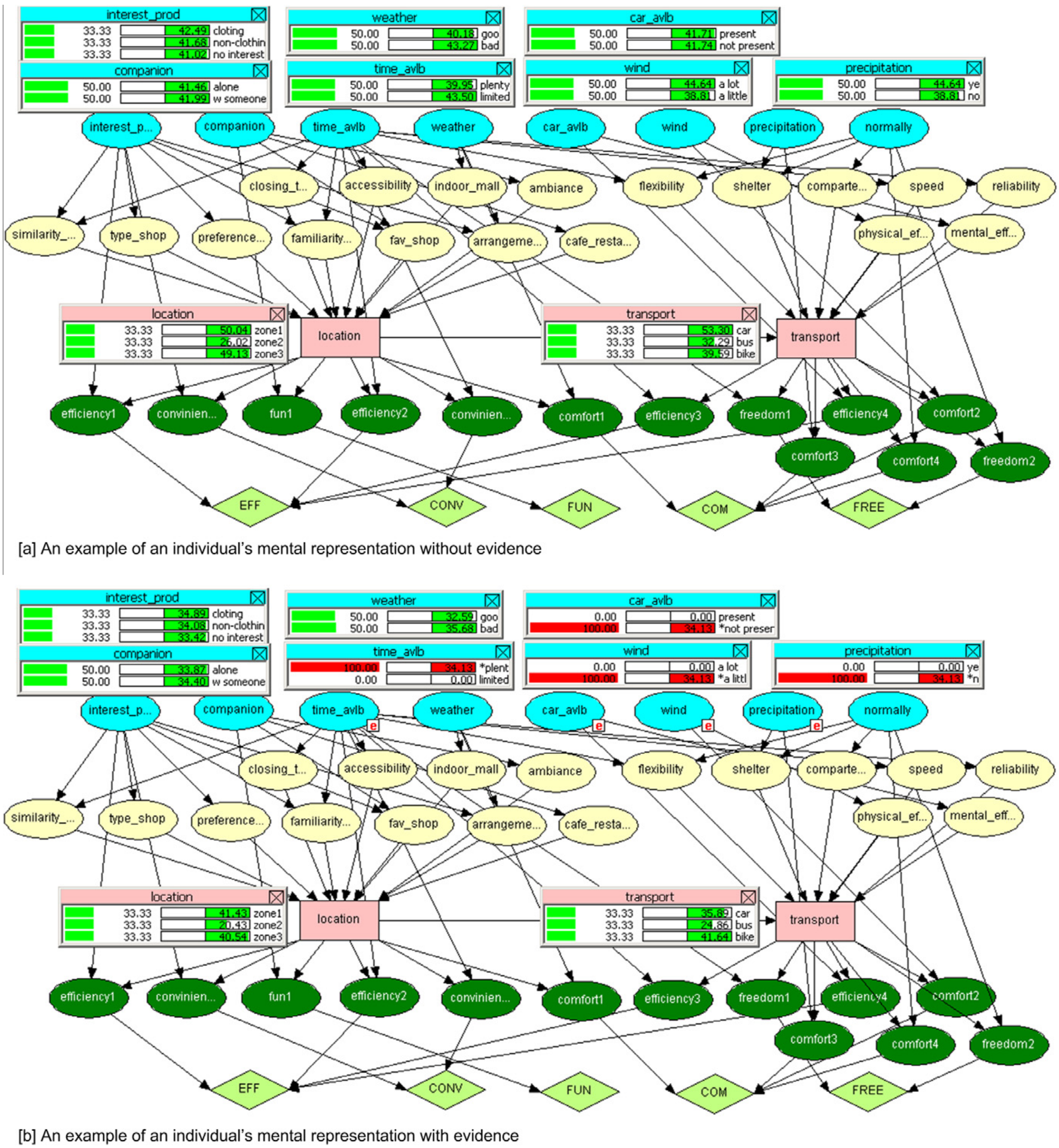
Fig. 8. Validation scheme.

from 221 respondents. The use of the interface significantly reduces the time to collect the data in comparison to the face-to-face CNET interview protocol because the parameters can automatically and directly be gathered during the survey. In average, the whole survey lasts for about 2–3 h, per group session of about 20 respondents, in comparison to the CNET interview that took about 10 h to finish, per respondent.

5. General conclusions and discussions

The computerized approach (such as the CB-CNET) allowed us to construct mental representations (MRs) interactively with respondents, measure their preferences, and to generate an individual level decision model. For this purpose, the CB-CNET protocol is broken down into several stages and implemented in the interface accordingly.

The first stage aims at eliciting aspects, constructs and beliefs considered in the decision processes using probing questions and elucidating the interconnections between them. They are represented in *cognitive subsets*, consisting of interconnected *contexts*, *benefits, and instruments*. Accordingly, individuals' MRs can be represented as decision models (i.e. Bayesian decision networks). In the second stage, questionnaires are generated automatically to gather probabilities and utilities based on the individuals' network structures. These values are obtained in the conditional probability and utility tables and they are used to determine the strength of relationships between the linked aspects. Subsequently, the utility weights have to be set. The application allows two ways to generate utility weights based on rating experiments: using separate assessments of single-utilities and evaluations of combined seven-utilities in Fractional Factorial Design profiles. At last, the interface generates some questions to investigate individuals' actual preferences, enabling the constructed models to be validated.



[a] An example of an individual's mental representation without evidence

[b] An example of an individual's mental representation with evidence

Fig. 9. Example of an individual's mental representation derived from the CB-CNET.

Using a computer survey in this type of study has many advantages not only because the questions can be automatically generated but also because interviewers' bias can be lessened. Moreover, data can be collected easier, quicker and cheaper for large sample groups. The CB-CNET survey is applied to assess leisure-shopping travel behavior in the city centre of Hasselt, in Belgium, focusing on individuals' *transport mode* and *location* choices. This interface has successfully been applied to gather data from 221 people who are living in the outskirts of Hasselt.

There are some limitations in this study. For instance, the activity scheduling decision is given in the scenario, implying that participants cannot opt not to go for leisure-shopping activities. The model also assumes that there are no interaction-effects of various contexts that yield the same pursued benefit. For instance a respondent indicates that contextual aspects of *weather conditions* {*bad, good*} and *wind conditions* {*not windy, windy*} are linked to the same benefit of *having comfort*. Suppose the respondent indicates that if the *weather condition* is *good* and it is *windy* then his chance of having the *benefit of comfort* when biking is really *low*. However when the *weather* is still *good* but it is *not windy*, the *probability to gain comfort increases* when bike is used. Thus, there is interaction between variable *weather* and *wind conditions*. The interactions between contextual aspects could be addressed in the future research to improve Bayesian DN modeling accuracy. Additionally, one way to calculate utility weights in the survey is using the fixed seven-utility design. Needless to say, the later problem can be fixed in future research if needed, based on results of calculations of current data.

Some follow-up analyses on the Bayesian DN models derived from the data of 214 respondents are conducted to calculate the predictive accuracy of the models. Participants' actual transport mode choices in different scenarios as reported in the CB-CNET survey data are used as a benchmark to calculate how well the DN models predict the choices indicated by participants. Results show that the accuracy of DN models is around 67%, implying that in 67% of the cases these models can correctly predict participants' transport mode and location choices under various contexts and constraints. Additional analyses are done to compare the prediction of Bayesian DN models to the decision-tree model. Both modeling techniques use the MR data gathered using CB-CNET survey. Results of this study are reported in an upcoming publication. Moreover, the impact of time availability to perform leisure-shopping activities on cognitive representations will be investigated. In addition, future studies should investigate individuals' travel behavior when performing other activities. Undoubtedly, the CB-CNET can be adapted to assess different activities as well.

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