Transportation (2010) 37:647–661
DOI 10.1007/s11116-010-9272-2

Scrutinizing individuals' leisure-shopping travel decisions to appraise activity-based models of travel demand

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Published online: 29 April 2010

Abstract Activity-based models for modeling individuals' travel demand have come to a new era in addressing individuals' and households' travel behavior on a disaggregate level. Quantitative data are mainly used in this domain to enable a realistic representation of individual choices and a true assessment of the impact of different Travel Demand Management measures. However, qualitative approaches in data collection are believed to be able to capture aspects of individuals' travel behavior that cannot be obtained using quantitative studies, such as detailed decision making process information. Therefore, qualitative methods may deepen the insight into human's travel behavior from an agent-based perspective. This paper reports on the application of a qualitative semi-structured interview method, namely the Causal Network Elicitation Technique (CNET), for eliciting individuals' thoughts regarding fun-shopping related travel decisions, i.e. timing, shopping location and transport mode choices. The CNET protocol encourages participants to think aloud about their considerations when making decisions. These different elicited aspects are linked with causal relationships and thus, individuals' mental representations of the task at hand are recorded. This protocol is tested in the city centre of Hasselt in Belgium, using 26 young adults as respondents. Response data are used to apply the Association Rules, a fairly common technique in machine learning. Results highlight different

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interrelated contexts, instruments and values considered when planning a trip. These findings can give feedback to current AB models to raise their behavioral realism and to improve modeling accuracy.

Keywords CNET interview · Mental representation · Activity-based models of travel demand · FEATHERS

Introduction

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

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

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

Qualitative methods on the other hand, including focus groups, in-depth interviews and participant–observer techniques, could fill in the gap left by quantitative approaches since these methods enable the integration of behavioral planning process information inside the data used to develop AB models (Doherty and Miller 2000). They are a crucial tool to extract individual's beliefs and decision processes underlying behavioral phenomena from the perspective of the agent (Goulias 2003). This way, qualitative methods can as well address the reasons *why* and *how* certain decisions are made (Bradley 2006).

This study illustrates the implementation of a qualitative approach, namely the Causal Network Elicitation Technique (CNET) interview method (Arentze et al. 2008a), to elicit individuals' reasoning behind their complex travel-related decisions. The CNET is developed based on the decision making theory of mental models (Arentze et al. 2008a), in which a decision maker considers different elements such as contextual factors, instruments of choice alternatives and subjective values before the actual choice is made. In this thought process, different considerations are linked by causal relationships, creating a temporary mental representation (MR) or mental model of a certain decision problem. To enable the elicitation of individuals' MR, the CNET is designed as a semi-structured interview method evolving around *why* and *how* questions.

Leisure trips, particularly fun-shopping related travel decisions, are chosen for the application of the CNET protocol. Previous studies (Gärling and Young 2001; Hannes et al. 2008) have indicated that people tend to use simple heuristics and automated script-based choices when engaging in typical repetitive, mandatory activities such as commuting to work or school. At the same time, individuals' MR related to discretionary activities such as leisure-shopping trips, are believed to be more complex and deliberate (Arentze et al. 2008a). Consequently, richer information about different aspects underlying travel choices can be obtained from occasional trips. Certainly, the CNET interview technique can equally be applied to elicit individuals' reasoning in other types of activity.

The CNET is carried out in the outdoor shopping area in the typical European historical city centre of Hasselt, Belgium. Participants are 26 young adults, age 22–23. Each respondent is interviewed individually concerning his thought process when deciding upon *the time of execution*, *the location* and *the transport mode* to carry out a fun-shopping activity. In these interviews, the order of related decisions is recorded, as well as all considerations involved in the decision making process and their complex intertwining. As a result of the protocol, individuals' MR of fun-shopping decision problems can be captured. This way, a rich data-set is built, comprising all considered aspects in individuals' MR. Next, a machine learning technique of the Association Rules (AR) (Agrawal et al. 1993) is applied to find strong regularities and associations in these aspects that define individuals' decision making with regard to fun-shopping.

Results of this study can be used not only as a ground for modeling assumptions concerning the order of travel-related decisions in a CPM of travel demand, but also as a means to deepen the insight into the aspects that should be taken into account in an AB model from a behavioral decision making perspective. For instance, this study reveals the importance of the *weather* in the decision to engage in fun-shopping, and in the choice of transport mode. However, *weather* conditions have never been taken into account in current AB models (Cools et al. 2010).

The remainder of this paper is structured as follows: the next section presents some theoretical background with regard to CPM. Moreover, decision making theory and MR of shopping trip decision problems are presented. The third section elaborates on the CNET interview protocol, while the fourth section presents the data analysis method of AR. Next, results are shown and discussed in "Results and discussion" section. At last, conclusions and further research issues are addressed.

Theoretical background

Activity-based modeling

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

Some AB models, e.g. Bowman and Ben-Akiva (2001), are fairly close to conventional models, since they use a similar probabilistic discrete choice framework grounded on RUM (Algers et al. 2005). Another type of AB models, such as CPM models, emphasizes the activity-travel scheduling process. The first fully operational CPM model is ALBATROSS, used to assess policy impact in the Netherlands (Arentze and Timmermans 2008). Only recently, the ALBATROSS approach is transferred to the region of Flanders in Belgium in the FEATHERS project (Arentze et al. 2008b). This CPM model frames the issues addressed in this paper, i.e. MR involved in complex leisure-shopping decision making and its proper implementation in an AB model of travel demand.

The ALBATROSS architecture applies a set of *if–then* rules, representing thought processes in which heuristics are used and updated based on individuals' experiences (Arentze and Timmermans 2008). These rules are accommodated in the rule-based engine to derive individuals' activity schedules in a household context. In detail, these rules take into account different space and time aspects, possible scheduling constraints, as well as decision trees derived from individuals' daily activity-travel diaries (Fig. 1).

In the scheduling engine, Fig. 1a, a fixed sequential decision process is assumed in which mandatory activities such as working and other fixed activities are scheduled prior to discretionary activities. Furthermore, each activity is detailed: a specific type of activity to perform, its starting time, duration, likely trip-chaining, location and transport mode choice (if needed) are determined in a priority-based sequential order. This scheduling process is summed up in Fig. 1b. The ALBATROSS only distinguishes out-home activities in detail whereas in-home activities are not differentiated. Activity categories connected to the

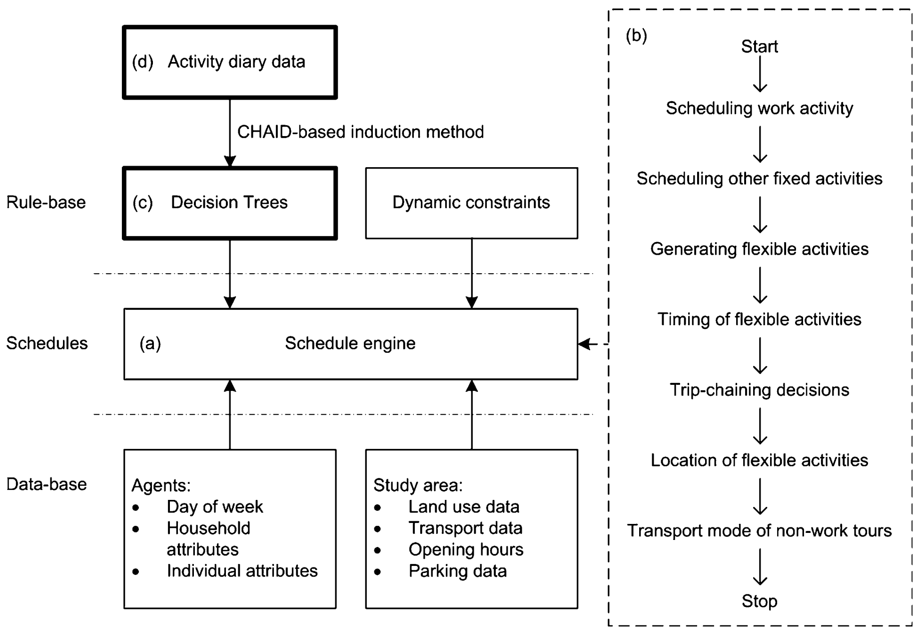

Fig. 1 Overview of the schedule engine in ALBATROSS [adapted from Arentze and Timmermans (2008)]

fun-shopping example in this study are shopping for non-daily goods and discretionary leisure trips.

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

Decision trees (Fig. 1c) are commonly derived only from quantitative observed data (Fig. 1d). From a point of view of *AB modelers*, decision trees not necessarily characterize individuals' thought process because they are generated to optimize model fit. However, from a *behavioral decision making perspective*, actual considered aspects in the thought process may be useful to be integrated in activity-travel diary data and accordingly in decision trees to improve model fit.

This paper specifically highlights differences between aspects taken into account in decision trees and in individuals' MR. Therefore, decision trees derived from data of 602 households in Flanders are compared to the outcome of the CNET interview protocol in the results section of this paper. Results can be feedback to improve the design of current activity-travel diaries, yielding improvement of modeling accuracy.

Mental representations

It is argued that making complex choices, such as in irregular travel-related decision problems, may entail deliberate thought processes preceding actual selections. During this process, different attributes and dimensions of choice options are valued (Cherubini et al. 2003) based on various observed or anticipated contexts and constraints (Gärling and Axhausen 2003). At the end, an alternative suited to individuals' goals will be chosen. In this paper, attributes of decision alternatives are referred to as instrumental aspects, features of the environment surrounding individuals are referred to as contextual aspects, and values or utilities attached to the instruments in combination with the context are referred to as evaluative aspects.

Thus, components of a decision process can be detailed as follows: Firstly, *decision alternatives* symbolize a choice-set, consisting of all possible actions or objects related to a particular decision (Arentze et al. 2008a; Gärling et al. 1998). The attractiveness of these alternatives in the choice set relies upon the nature of the task at hand and some contextual aspects surrounding it (Harte and Koele 1997). For instance, decision alternatives for travel modes to go to a conference in a neighboring country can be *car, train*, or *airplane*. Second, *contextual aspects* refer to given circumstances, including situations and constraints, which influence the outcome of a decision but cannot be controlled by a decision maker (Arentze et al. 2008a). These can be natural forces (e.g. *weather* conditions) and other constraints, categorized earlier by Hägerstrand into capability, authority and coupling constraints (Hägerstrand 1970). Thirdly, *instrumental aspects*, known as attribute variables (Arentze et al. 2008a), can be defined as any relevant characteristic of the alternatives in the choice-set that can be observed and operated by a decision maker. Instrumental aspects of travel modes to go to a conference in the example above can be *travel time, cost,* etc. At last, *evaluative aspects* are considered because a decision is supposed to be made after summing up all subjective values attached to each instrument in the context in which it occurs and relating these values to their subjective probability of occurrence (Crozier and

Ranyard 1997). While individuals' values are relatively stable across different contexts, their weight is influenced by various activating situations (Dellaert et al. 2008). For instance, when facing time restrictions, someone may prefer having *efficiency* (evaluative aspect) more than when budgets are limited.

Furthermore, different aspects involved in decision making are linked by causal relationships, creating a cognitive MR of a decision problem (Kearney and Kaplan 1997). In order to capture an individual's cognitive MR, the smallest components that constitute this representation have to be obtained. These components are referred to as *cognitive subsets* and they are derived for each basic value (evaluative aspect), by linking each value to its relevant context and instrument (Kusumastuti et al. 2009). A subset is considered to be the antecedent of decision(s) and it can be linked to other subsets, thus constituting a complex MR of a particular decision problem. Further details can be found in Kusumastuti et al. (2009).

Besides, the complexity of such decisions occurs not only because people consider a variety of aspects during the choice process, but also because there are different interrelated decisions involved in trip-making, such as when to leave, where to go and how to get there. This can be observed in consumer shopping trip decisions, when people concurrently consider the time to execute the trip, the destination and the transport mode. Considering the importance of activity planning, transport mode choices and location choices in shopping trips, these decisions are explored further in this study.

Causal Network Elicitation Technique interview

The CNET interview protocol is designed to extract individuals' considerations and interconnections between them, known as MR (Arentze et al. 2008a), starting from the smallest component of a MR, i.e. the *cognitive subset* (Kusumastuti et al. 2009). To uncover individuals' reasoning behind the actual choices, this interview method is structured along questions regarding *what* aspects appear in the thought process, *why* these elements are important and *how* they influence decisions. This section details the actual application of the CNET protocol for assessing decisions regarding fun-shopping step-by-step, starting from the specifications of the sample and the presentation of the decision context to the respondents, to the conduct of the interviews and the data recording.

The sample of this study is 26 young adults (age 22–23), all students at Hasselt University. Such a homogeneous group is deliberately chosen because research has shown the importance of individuals' characteristics, including age and gender, in influencing people's shopping behavior (Solomon et al. 2007). Additionally, individuals in the same group share typical norms and values, causing similarity and homogeneity in their behavior (Assael 1998). Young adults are targeted because they tend to shop more than the older ones (Seock and Sauls 2008).

Participants in the study are interviewed independently. Before the interview starts, the following decision problem is presented to them: *"Imagine that you have a vague plan in mind to do fun shopping in the centre of Hasselt in the near future. Fun shopping is related to collecting some shopping information (e.g. availability of stores, products that are sold, price of goods, quality of goods, etc.) Besides, you need to buy a small present for your friend. It appears that there is some time available next Saturday. You may do it next Saturday afternoon as part of your recreational activities or you may decide to choose another Saturday or a weekday."*

Within this context, respondents are asked to reflect on three decisions: the timing of the activity, the location choice in the city centre and the transport mode choice. After that, different choice alternatives for each decision are explained.

With regard to the timing, three alternative days are proposed, i.e. on the next Saturday, on another Saturday, or on a weekday. The destination choice options are described by showing a map of Hasselt city centre, divided into 3 zones based on distinctive shop characteristics: main shopping street, expensive boutique area and gallery area. At last, the transport mode choice is explained by asking respondents to imagine that they live in an area located 5–10 km away from the city centre, where a bus stop is available within walking distance. Besides, they possess a car as well as a driving license and a bicycle. In this imaginary setting, car, bus and bike can equally be considered.

After explaining the research scenario and detailing all possible decision alternatives to the respondents, the actual interview begins. The participant is initially asked to sort out the timing, the location and the transport mode decision in a sequential order, reflecting on how they will consider these choices in reality.

Next, participants' detailed deliberations related to each of these decisions are successively elicited. The first question in this elicitation process asks what considerations come to mind when making a certain decision. Here, participants are encouraged to think aloud about their thoughts when deciding upon the choice alternatives, e.g. the transport mode (car/bus/bike) to take for their fun-shopping trip to Hasselt. Answers to this question should reveal contextual, instrumental or evaluative aspects. Therefore, the interviewer has to identify the similarities of each elicited element with variables in a pre-defined code list (based on preliminary studies) and the category that it belongs to (context/instrument/evaluation). Assigned codes to responses are verified with the respondents to ensure that there is no misinterpretation between the interviewer and the interviewee. Moreover, the interviewer updates the code list during the interviews when completely new variables are mentioned.

Depending on the categorization of the mentioned variables, different questions are asked next. For instance, if respondents indicate that the *weather* (a contextual aspect) plays a fundamental role in their decision, the interviewer has to extract respondents' reasoning of *why* the *weather* is important, leading to the identification of an instrumental aspect (e.g. *shelter*) or an evaluative aspect (e.g. *comfort*). When only an evaluative aspect is mentioned, further questions of *how* this value is influenced by different choice alternatives are asked. Thus, when a contextual, an instrumental and an evaluation aspect are elicited, the interviewer records these interlocking variables as one cognitive subset. In this example, the *weather*, *shelter*, and *comfort* form one complete subset.

It is the interviewer's task to ensure that complete cognitive subsets are extracted and noted down in this structured form. When participants cannot recall any contextual aspects in particular subsets, cognitive subsets will only be composed of instrumental and evaluative aspects. In this case, it is assumed that these subsets are considered in normal situations. For instance, irrespective of contexts, a respondent normally reasons about *vehicles' speed* (an instrumental aspect) related to his need of having *freedom* (an evaluative aspect). Consequently, only *vehicles' speed* and *freedom* construct a subset. When respondents cannot bring up any more considerations, the interviewer moves to the next decisions and repeats the whole procedure.

Each participant is interviewed for about 60 min, depending on the amount of elicited variables. During the elicitation process, participant's recall of the task at hand is vital. To ensure the correct activation of fun-shopping episodic memory in respondents' minds, a slideshow of Hasselt city centre is shown during the interviews.

Association rules

This study intends to deepen the understanding of how fun-shopping related travel decisions are made, specifically about how different decisions and different considerations are linked and interconnected in individuals' MR. While the order of decisions can be assessed in a straightforward way by calculating the average ranking of each decision, finding robust associations in MR requires a more advanced method of analysis such as the application a data mining tool of AR.

The AR technique is widely used to efficiently learn the relationships between variables in a data-set using "IF (antecedent)–THEN (consequent)" forms (Agrawal et al. 1993). This technique has been previously applied to obtain decision rules from activity-diary data (Keuleers et al. 2001) and to identify temporal change in these data (Keuleers et al. 2002). In this study, the AR is applied to identify frequently occurring patterns in cognitive subsets from the fun-shopping MR data. For instance, the AR allows learning from the data that if the variable weather is observed, then the variable shelter is also inspected. Therefore, this method enables us to find robust associated variables that form complete or partial cognitive subsets in individuals' MR of decision problems. As a result, important aspects that should be taken into account in a rule-based model of travel demand can be highlighted from a behavioral decision making perspective.

Some terms commonly used in AR are: *items*, *transactions* and *itemsets*. The term of *items* is defined as a set of n binary attributes ($I = i_1, i_2, i_3, \ldots, i_n$). Therefore, each contextual, instrumental, and evaluative aspect in the fun shopping database are examples of items. A database contains a set of *transactions*, and each transaction comprises of a set of binary attributes. From *itemsets* (e.g. X and Y), a rule $X \Rightarrow Y$ can be derived, where $X, Y \subseteq I$ and $X \cap Y = \emptyset$. X and Y are *itemsets* (sets of items) and they are successively defined as *antecedent* and *consequent* of the rule. Each itemset consist of a single or combined binary attributes in a dataset.

Running AR involves two steps: determining frequent itemsets and learning strong rules from these itemsets. To decide which item(s) show up frequently, the minimum support (*minsup*) value has to be specified first. A support value is defined as a percentage of the total number of transactions in a dataset, containing an itemset. Resulting frequent itemsets are used as an input to carry on the second stage of finding strong associations. This is done by determining a minimum confidence (*minconf*) value, a ratio derived from a rule that divides the number of transactions that has all items in the antecedent (X) and the consequent (Y) by the number of transactions that includes all items in the antecedent (X).

To apply the AR, a dataset is generated, comprising the entire cognitive subsets from all respondents. Each subset from each respondent is coded as a transaction; e.g. the cognitive subset of *weather–shelter–comfort* is registered as one transaction. This way, a total amount of 98, 139 and 177 transactions is recorded for the activity scheduling, the location choice and the transport mode choice decision successively.

A low *minsup* is expected for the frequent items in this study because one respondent might elicit several subsets, yielding several transactions in the dataset, but each particular subset will only be elicited once by this respondent. Therefore the *minsup* (s) is calculated as explained in the following example: suppose that 100 transactions (T) are recorded in a dataset of 20 respondents (r), implying that 5 transactions, on average, are derived from one respondent. In these 5 transactions each subset is elicited once. Assuming that an itemset is important when at least 50% of respondents elicit it in the interview, it is expected that at least 10 transactions (t) out of 100 transactions contain the itemset. Accordingly, the *minsup* value can be calculated:

$$s = \frac{t}{T} = \frac{10}{100} = 0.1 = 10\%$$

Following this line of thought and assuming that itemsets are important when they are elicited by 1/3rd of respondents, the *minsup* used in this study is 8.9%, 6.3%, and 5% for the activity scheduling, location and transport mode choice sequentially.

Results and discussion

Results regarding the ordering of the fun-shopping related travel decisions and strong associations between variables present in cognitive subsets of the activity timing, the transport mode choice and the location choice decisions are presented below. Furthermore, these findings are related to recent AB modeling practices in the region of Flanders, i.e. the adaptation of the ALBATROSS system to characteristics of the Dutch speaking part of Belgium within the FEATHERS platform (Arentze et al. 2008b).

Order of decisions

With an average ranking of 1.12, results show that participants firstly plan the day to do the fun-shopping activity. This result supports the assumption in AB models in which the actual activity scheduling is addressed before modeling other tour- or trip-related matters (Doherty et al. 2002).

After this, respondents tend to think about how to get to the city centre (average ranking of 2.38) and then decide about the precise location (average ranking of 2.5). However, the difference in average values of the order between the transport mode choice and the location choice is fairly small, meaning that these decisions are made interchangeably. Considering the small sample size in the study, further vigorous conclusions regarding this issue are still too soon to draw. In the ALBATROSS system, the location choice is assumed to be made before the transport mode choice (Arentze and Timmermans 2008), as it has been described in the "AB modeling" section. Clearly, the relationship between these decisions is complex in nature and further study is needed to untie the sequence of decisions.

Robust associations

Learning the data using the AR, strong associations between antecedents and consequents of timing, transport mode and location decisions are retrieved. However, to get more meaningful information, results have to be brought back to the perspective of cognitive subsets (Fig. 2b). For instance, several results of the AR on the transport mode choice, indicated in a bold box in Fig. 2a, constitute a cognitive subset of *weather–shelter–comfort* in Fig. 2b.

Activity timing decision

Results of the AR show that *weather* is a frequently considered contextual aspect when deciding upon the time to do the activity (Fig. 2b). This is strongly associated with *individual's preference* of the day (instrumental aspect) and *having fun* (evaluative aspect). Furthermore *companion* appears to be an important aspect associated with the same

antecedent	consequent	SV	CV
AR results of the activity timing decision			
(c) weather	(i) preference day	0,1429	0,8750
(c) weather	(v) fun	0,1224	0,7500
(c) weather, (v) fun	(i) preference day	0,1122	0,9167
(i) pref. day, (v) fun	(c) weather	0,1122	0,7857
(i) pref. day, (c) weather	(v) fun	0,1122	0,7857
(c) weather	(i) pref. day, (v) fun	0,1122	0,6875
(i) crowdedness	(v) efficiency	0,0918	0,9000
(i) companion	(v) fun	0,0918	0,6000

context (c)	instrument (i)	value (v)
cognitive subsets of timing decision		
weather	preference day	fun
-	crowdedness	efficiency
-	companion	fun

antecedent	consequent	SV	CV
AR results of the transport mode choice			
(c) weather	(i) shelter	0,1243	0,9167
(i) shelter	(c) weather	0,1243	1,0000
(c) weather	(v) comfort	0,1130	0,8333
(i) shelter	(v) comfort	0,1073	0,8636
(c) weather, (v) comfort	(i) shelter	0,1073	0,9500
(i) shelter, (v) comfort	(c) weather	0,1073	1,0000
(i) shelter, (c) weather	(v) comfort	0,1073	0,8636
(c) weather	(i) shelter, (v) comfort	0,1073	0,7917
(i) shelter	(c) weather, (v) comfort	0,1073	0,8636
(i) travel time	(v) efficiency	0,0847	0,8333
(v) saving	(i) cost	0,0734	0,7647
(i) cost	(v) saving	0,0734	0,8125
(c) companion	(i) pref. mode choice	0,0734	0,8125
(i) pref. mode choice	(c) companion	0,0734	0,6190
(c) no bags	(i) treatment bags	0,0734	0,9286
(i) treatment bags	(c) no bags	0,0734	1,0000
(c) no bags	(v) comfort	0,0508	0,6429

context (c)	instrument (i)	value (v)
cognitive subsets of transport mode choice		
weather	shelter	comfort
-	travel time	efficiency
-	cost	saving
companion	pref. mode choice	-
no bags	treatment of bags	comfort

antecedent	consequent	SV	CV
AR results of the shopping location choice			
(c) ppp*	(i) type shop	0,1007	0,6667
(i) type shop	(c) ppp*	0,1007	0,8235
(c) ppp*	(v) efficiency	0,1007	0,6667
(i) car access	(v) efficiency	0,0863	0,9231
(i) bus access	(v) efficiency	0,0791	0,7333
(i) type shop	(v) efficiency	0,0791	0,6471
(c) ppp*, (v) efficiency	(i) type shop	0,0647	0,6429
(i) type shop, (v) efficiency	(c) ppp*	0,0647	0,8182
(i) type shop, (c) ppp*	(v) efficiency	0,0647	0,6429
(i) type shop	(c) ppp*, (v) efficiency	0,0647	0,5294

(a)

context (c)	instrument (i)	value (v)
cognitive subsets of the location choice		
ppp*	type of store	efficiency
-	access car	efficiency
-	access bus	efficiency

(b)

Fig. 2 Results of the association rules (**a**) and the summary of robust associations in cognitive subsets (**b**). *SV* support value, *CV* confidence value, *ppp** pre-planned purchase that someone has in mind, *(c)* contextual aspect (context), *(i)* instrumental aspect (instrument), *(v)* evaluative aspect (value)

evaluative aspect of *having fun*. Additionally, *having efficiency* is an important benefit that people aim at, related to *crowdedness* of the shopping location on different days.

It should be noted that different instrumental aspects of the timing alternatives can be contextual aspects of other decisions. This happens because some variables (e.g. *crowdedness*) represent characteristics of the day of choice (instrumental aspects), whereas in other decisions (e.g. transport mode choice) they are contextual factors that cannot be controlled by the decision maker when making a choice.

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

Results of the AR reveal the significance of the contextual factor *weather* in individuals' MR related to fun-shopping, an activity that can be considered as a part of non-work flexible activities in AB models. Nevertheless, *weather* conditions are not present in the decision tree (see list above). Moreover, the *weather* has never been taken into account in current AB models in general (Cools et al. 2010), and, at least to the best of our knowledge. Actual weather conditions are not even recorded in activity travel surveys, albeit the most important input to develop an AB model.

Other influential characteristics of the day of execution, such as sheer individual *preference* to fun-shop on a certain day, or likely *crowdedness* on a given time, turn out to be important aspects that have not been elaborated in the AB model to date. The same case applies for different *values (utilities)* that people attach to specific contexts and instruments, namely *fun* and *efficiency*.

On the other hand, *companionship* is an element that is clearly taken into account in most AB models. In ABLATROSS for instance, the presence of *companion* is one of the decisions that is modeled in every activity scheduling process, besides inclusion, duration, location, transport mode and trip chaining, supporting Hägerstrand's initial idea of coupling constraints (Hägerstrand 1970).

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

Transport mode decision

Results (Fig. 2b) show that *weather* is an important contextual consideration in the transport mode choice of participants. This is related to the instrument of *having shelter* and the evaluation of *having comfort*. Furthermore, *companionship* is mapped together with *individual's preference* for a specific transport mode. This result shows that when doing leisure shopping, people tend to make a trip with others. This is related to the issue of groups of people (e.g. households) as a unit of analysis in AB models instead of the individual. This issue is an actual area of research in AB modeling (Davidson et al. 2007). Result of this study supports the unit of analysis in the ALBATROSS (Arentze and Timmermans 2008).

Respondents also care about the *amount of shopping bags* that they have to carry back home. This additional contextual aspect is mapped with *the easiness to treat bags* provided by different types of transport and the benefit of *having comfort*. Besides, *travel time* is a consideration that causes the evaluation of *having efficiency*. Finally, *travel cost*, specifically for parking, fuel and bus tickets, is an additional significant aspect, linked with the benefit of *saving money*.

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

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

Shopping location decision

Results (Fig. 2b) indicate that the shopping location decision is often influenced by a *pre-planned purchase in mind* that raises a consideration of the *type of store* in a certain area and *having efficiency*. Furthermore, *accessibility for car and bus* are frequently elicited and both have a strong association with the evaluative aspect of *having efficiency*. These results clearly highlight the importance of *having efficiency* when deciding upon the actual place to go fun-shopping in Hasselt.

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

Conclusions

This paper addresses individuals' complex reasoning and associations between different decisions involved in a fun-shopping activity, namely the choice of day to do fun-shopping, the destination choice in the city centre and the transport mode choice. The CNET interview method is adapted to elicit individuals' cognitive MR, consisting of contextual, instrumental and evaluative aspects, as well as the causal relationships between these variables. Against the background of the historical city centre of Hasselt in Belgium, 26 young adults systematically reveal their considerations when scheduling a fun-shopping activity.

The study highlights the complexity in the travel-related decision making process. In particular, it illustrates how different aspects of a decision problem are mapped in individuals' MR of this decision problem. This provides a better understanding of possible behavioral interpretations of AB models of (leisure) travel demand. Therefore the approach we presented can be a foundation to empirically ground or extend assumptions used in AB models of travel demand and to add insight to aspects that should also be taken into account in activity-travel diary, specifically in a rule-based approach such as ALBATROSS. It is believed that such integrations may be important to improve model fit.

To start with, the ordering of decisions shows the sequence of different sub-choices in scheduling activity-travel. It is clear that activities are planned before making other related decisions such as where to go and how to get there. However, this study shows that the location choice is not always made before the transport mode choice, as it can be assumed in AB models such as ALBATROSS. Obviously, further study is needed to elucidate this issue.

With regard to the significant aspects that people consider when making fun-shopping related travel decisions, results clearly indicate the importance of the *weather* as a contextual aspect, especially when deciding upon the time and the transport mode. This is not taken into account in AB models to date (Cools et al. 2010). Furthermore, results indicate the importance of *companionship*, supporting the original idea of coupling constraints by Hägerstrand (1970). Besides, this research underscores individuals' search for values when making a decision, such as *having fun* and *efficiency* with regard to the timing of the activity and *having comfort*, *efficiency* and *saving money* in the transport mode choice. Ultimately, instrumental and contextual aspects influencing these goals can successfully be mapped out.

Results, specifically from the activity scheduling and the transport mode choice decision, illustrate fundamental differences between the aspects taken into account in the travel-related decision making process elicited by means of the CNET protocol, and the factors appearing in decision trees that are used in the AB model. In order to achieve a more realistic representation of individual decision making in such a model, qualitative in-depth explorations such as shown in this study constitute a vital tool to identify critical components and causal links in individuals' decision making.

This study clearly illustrates the complex nature of the individual travel related decision making process. However, future research is needed to implement these results in an AB model, to improve activity travel surveys, and to empirically ground their behavioral assumptions. Due to its small sample size and its restriction to a particular group of individuals, results cannot be generalized yet. However, some clear points of attention are marked to test in further research on a larger sample.

Additionally, each MR will be modeled as a Bayesian Decision Network (BDN) in future research. The BDN is a modeling technique to diagram and calculate the decision process by means of probabilistic reasoning and utilities (Korb and Nicholson 2003). Eventually, results of the BDNs can be compared with individuals' actual preferences for each decision, thus enabling a validation of the model.

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