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Abstract

We introduce a utility theory-based model of consumers' mental representation of attributes and benefits in decisions between complex alternatives. The model relies on the fact that there are cognitive costs and gains to activating additional decision components in mental representations. The gains are that with every component the individual is better able to discriminate between choice alternatives and the probability of making the best choice increases. The costs are the additional mental effort that is required to evaluate the decision components. We propose that a component is activated in a mental representation only if the expected gains of doing so exceed the mental costs of the evaluation. This proposition is formalized in a utility model where a decision component is cognitively activated if the utility variation caused by the component's levels exceeds a mental cost threshold. This model allows us to decompose the utility of alternatives from mental representations of decisions without the need to observe choices. We illustrate the proposed approach using data on 594 individuals' mental representations of a hypothetical shopping decision problem.

Keywords

Consumer Decision Making, Mental Representations of Decisions, Utility Models, Attribute-Benefit Relationships

To improve their product offering and guide possible innovations marketing managers need to develop a good understanding of the choices that their customers make. Traditionally, choice modeling is used to guide marketing actions by deriving the value of different product features in consumer choice (McFadden 1986). In addition, techniques such as means-end chain elicitation and (hard) laddering allow marketers to gain insight in the underlying benefits that consumers look for in the choices that they make (Gutman 1982; Reynolds and Gutman 1988; Ter Hofstede, Steenkamp, and Wedel 1998; 1999). Only recently researchers have combined these lines of investigation and have included measures of attribute-benefit relationships in models of consumer choice to also model how underlying benefits affect consumers' choices (Arentze, Dellaert and Chorus 2014; Ashok, Dillon and Yuan 2002; Chandukala, Edwards and Allenby 2011; Dellaert and Stremersch 2005; and Luo, Kannan, Ratchford 2008).

In this paper we build on this recent stream of research. However, rather than adding attribute-benefit relationships to a model of consumer choice, we develop a formal model to decompose consumers' attribute and benefit utilities directly from mental representations of decisions without a need to observe choices. Theoretically, we start from the observation that consumers' mental representations of complex decision problems enable them to mentally simulate the likely consequences of decisions before they are implemented (Johnson-Laird 2001; Weber and Johnson 2006). By identifying (in their mental representation) how the potential choice of each alternative allows them to achieve their higher order needs, consumers can evaluate the attractiveness of different courses of action. Therefore, consumers' mental representations of decision problems include attributes of the choice alternatives that they face and connect these attributes to higher order benefits that reflect the consumer's own personal needs (Gutman 1982; Liberman, Trope and Wakslak 2007; Newell and Simon 1972; Reyna and Brainerd 1995).

Importantly, inherent cognitive constraints restrict the size and complexity of consumers' mental representations of complex decision problems (Beach and Mitchell 1987; Johnson-Laird 2001; Loewenstein 2001). Therefore we propose that, akin to information search theory (Hauser, Urban and Weinberg 1993; Meyer 1981; Moorthy, Ratchford and Talukdar 1997; Weitzman 1979), additional decision components (i.e., attributes and benefits) are taken into account in a mental representation only if the expected gains of evaluating alternatives on these components outweigh the cognitive costs of doing so. We formalize this process in a utility theory-based model of the cognitive activation of different components of consumers' mental representations of decisions. The activation model reflects consumers' latent utility for alternatives in the decisions. More specifically, the consumer's utility function drives the selection of attribute and benefit components (and their links) such that cognitive activation in the mental representation depends on whether variations in the level of a decision component have a strong enough impact (i.e., above the individual's mental cost threshold) on the decision outcome to warrant its inclusion in the consumer's mental representation of reality. This conceptualization allows us to formally model the connection between selective mental representations and consumers' decision utilities. Thus, we can simultaneously model the consumer utility function, the attributes and benefits that consumers consider in making their choices, and consumers' mental connections between decision alternatives and different attributes and benefits.

The model and empirical analysis also contribute to marketing practice by introducing a new approach for researchers and marketing managers to obtain deeper insights in consumers' attribute and benefit utilities. The approach is especially useful in the context of consumer decisions between complex alternatives but only few possibilities to observe variations in supply and demand the market (e.g., because the supply and demand are highly stable such as with many consumer shopping center choices or health care facility choices). In such cases it is difficult to estimate choice models directly from market data and also hard to conduct conjoint choice experiments because no well-informed a priori selection of attributes can be made (Louviere, Hensher and Swait 2000). The approach that we propose provides a new method to obtain a utility-based quantification of attribute and benefit importances in such circumstances. It also expands on other approaches to elicit consumers' attribute and benefit importances that do not integrate the importances in a utility theory framework and therefore are easily integrated in a model of consumer choice (Dellaert, Arentze and Timmermans 2008; Gutman 1982; Reynolds and Gutman 1988; Ter Hofstede, et al 1998; 1999).

CONSUMERS' MENTAL REPRESENTATIONS OF DECISIONS

A mental representation of a decision problem is a reduced cognitive representation of reality that consumers can use to evaluate the alternatives from which they choose. For reasons of cognitive efficiency, mental representations tend to include only the most relevant knowledge that is needed for the decision task at hand. This central property of mental representations has been well-documented in research on human reasoning and memory representation and learning (e.g., Beach and Mitchell 1987; Johnson-Laird 2001; Reyna 2012).

The evaluation of possible courses of actions in a decision task requires that besides activation of knowledge about relevant features of decision alternatives, knowledge about meaningful (functional) relationships between alternatives and the individual's own needs are also included in the mental representation. Without knowledge about such relationships, a consumer's choices would be disconnected from his or her own needs. With additional knowledge about consequences of the available alternatives the ability to discriminate between alternatives increases and the risk of making a decision with a lower level utility outcome decreases. However, there is also cognitive effort involved in making a decision and this effort increases as the complexity of the mental representation expands to capture additional knowledge.

We theorize that a consumer's cognitive construction of a mental representation is the result of an (implicit) trade-off between the gain of information about the consumer's choice outcome preferences and the costs of mental effort. This process is akin to information search theory where additional information sources are inspected in order of expected return and only if the expected gain of inspecting them is greater than the costs of inspection (Hauser, et al. 1993, Meyer 1981; Moorthy, et al. 1997; Weitzman 1979). More specifically, we propose that components are included in the mental representation of a decision based on their expected return in evaluating decision alternatives on the component and only when the gains of including the component in the evaluation outweigh the cognitive costs of the additional evaluation. Note that this structure implies that since need activation, available alternatives, and external conditions can differ across situations, mental representations are likely to be temporary structures that are specifically activated in the context of a given choice problem.

To formally model knowledge activation in mental representations of decisions we structure this knowledge as a means-end belief network that link choice alternatives in different domains, on the one hand, to outcomes on the consumer's need dimensions on the other. Schematically, we represent such a means-end belief network in multiple layers. We distinguish between attributes that describe decision alternatives in detail ("what is chosen") and benefits that connect alternatives' attributes to the consumer's underlying personal needs ("why it is chosen") (Gutman 1982; Liberman et al. 2007; Myers 1976; Newell and Simon 1972; Reyna and Brainard 1995). Thus, attributes relate to directly observable characteristics of the alternatives (e.g., price, travel time) or the situational context in which the consumer operates (e.g., weather conditions) while benefits describe the impact of the attributes on the consumer's underlying needs (e.g., convenience or fun). Attributes and benefits are interrelated because the value of an attribute to the consumer lies in how it affects the benefits that are of relevance to the consumer.

This structure defines three knowledge-based mappings that connect the decision alternatives in the different choices that can be made to the consumer's latent decision utility. The first mapping describes the consequences of selecting a *decision alternative* of a given choice set in terms of the *attributes* that the alternative provides. In this first mapping it is not yet evident how choosing an alternative affects the fulfillment of the consumer's more basic needs. Therefore the second mapping relates attributes to the set of underlying *benefits* that reflect the consumer's underlying needs. The third mapping finally connects realized benefit outcomes (that can be positive or negative) to the consumer's *utility* function for decision alternatives. The utility of each benefit depends on how well each benefit outcome fulfills the consumer's underlying internal needs.

Typically, benefits are influenced by multiple attributes that may come from more than one decision alternative. This implies that decision domains, attributes and benefits need not be strictly nested but that they may follow a structure in which cross-over connections exist between the components of the different decision domains across the attribute and benefit evaluation layers. The activation in the mental representation then depends on how these connections affect consumers' decision utility, but activation per se is not one-to-one indicator of utility. Figure 1 graphically illustrates how in a complex choice involving two decision domains the attributes and benefits could be connected in a consumer's mental representation. In particular, at the benefit level the value of Benefit 2 is jointly determined by Attributes 2, 3 and 5. These attributes in turn depend on the consumer's choice of alternative in decision domain A (Attributes 2 and 3) and decision domain B (Attribute 5). This structure clearly illustrates that the cognitive activation of each attribute and benefit in the mental representation depends on how these components jointly affect consumer utility through the overall network structure.

- INSERT FIGURE 1 ABOUT HERE –

A UTILITY THEORY-BASED MODEL OF MENTAL REPRESENTATIONS OF COMPLEX DECISIONS

Mental representations are temporary contextually dependent structures, and in this section our aim is to model the activation of attributes, benefits and their functional relationships in the mental representation as taken from the broader causal knowledge of an individual. Earlier research introduced different approaches to how attribute-benefit relationships can be integrated in consumer choice models (Arentze, et al. 2014; Ashok, et al. 2002; Chandukala, et al. 2011; Dellaert and Stremersch 2005; Luo, et al. 2008). However, here we show that utility models can also be derived directly from mental representations of decisions.

The intuition behind the approach is that the activation of a decision component in a mental representation involves an implicit cognitive trade-off between mental costs and the expected preference-information gains of different evaluations of decision domain-attribute-benefit (DAB) chains. This represents an implicit evaluation of the extent to which a choice of an alternative within a decision domain (D) determines the level of consumer benefit (B) that is achieved because of the fact that an attribute (A) is realized by selecting the alternative. The utility model that we develop depends on the gains and costs of evaluating candidate DAB chains for inclusion in a mental representation. More specifically, we first formalize consumers' cognitive activation of decision components in mental representations in line with recent research (Arentze, et al. 2014). Then, we extend this model by deriving specific expressions for the decision utility of attributes and benefits based on the observed mental representation.

In the model, the gains of activating a given DAB chain in a mental representation are tightly coupled to the utilities of the different choice alternatives. Therefore a basic element of the model concerns the composition of these utilities (McFadden 1986). The utility component of an attribute-benefit combination obtained from a given choice alternative is given as:

$$V_g^{ij} = r_{ij}(X_{jg}) \tag{1}$$

where X_{jg} is the level of attribute j achieved by selecting alternative g, r_{ij} is an evaluation of the extent to which this attribute level matches the desired outcome for benefit i and V_g^{ij} is the resulting utility value. In case the choice problem involves multiple decision domains, alternative g refers to a particular combination of choices (e.g., location and transport mode).

The gain of including a DAB chain evaluation in the mental representation is conceptualized as the expected utility differences that the chain reveals if all choice alternatives are evaluated on the attribute-benefit combination in the chain. Formally this is expressed as:

$$Z_{ijk} = s_{jk}^{DA} \cdot D(V_\bullet^{ij}) \tag{2}$$

where k is an index of decision domain, Z_{ijk} is the expected gain of evaluating DAB chain ijk, D is a measure of dispersion (i.e., range), $V_\bullet^{ij}$ is a vector of utility values across all alternatives for attribute-benefit relation ij and s_{jk}^{DA} is the individual's subjective assessment of how much of the total variation on the attribute (and hence the utility for attribute-benefit relation ij) across decision domains should be attributed to decision domain k.

The true utility values $V_{\bullet}^{ij}$ are not known a priori to the individual. The assessment of the *D* term is based on an individual's knowledge about the world and about his or her own needs. In this respect, a key distinction must be made in the knowledge structure between the individual's knowledge about causal influences that allow the individual to assess the impact of (possible) choice outcomes on need fulfillment (*s*), and the individual's knowledge about his or her own current needs as they are activated in the current decision situation (α). We extend equation 1 as follows to reflect this underlying structure:

$$V_g^{ij} = \alpha_i \cdot s_{ij}^{AB} \cdot r'_{ij}(X_{jg}) \tag{3}$$

where α_i is the activation of benefit *i* based on the individual's own needs, s_{ij}^{AB} is the (causal) influence of attribute *j* on benefit *i* and r' is the evaluation value. In equation 3, r' represents a standardized value for *r* that allows us to identify the utility scale of the DAB chain based on the activation value $\alpha_i \cdot s_{ij}^{AB}$. The standardization is performed such that:

$$D[r'(X_{j\bullet})] \equiv 1 \tag{4}$$

where *D*, as before, is a measure of dispersion and $X_{j\bullet}$ is a vector of outcomes of the alternatives on attribute *j*. Now a solution for the total gain *Z* can be derived. Substituting definition (3) in (2) gives the following expression for Z:

$$Z_{ijk} = s_{jk}^{DA} \cdot D(\alpha_i \cdot s_{ij}^{AB} \cdot r'_{ij}[X_{j\bullet}]) \tag{5}$$

Rewriting gives:

$$Z_{ijk} = \alpha_i \cdot s_{ij}^{AB} \cdot s_{jk}^{DA} \cdot D(r'_{ij}[X_{j\bullet}]) \tag{6}$$

Substituting definition (4) for the last term on the right-hand-side then gives:

$$Z_{ijk} = \alpha_i \cdot s_{ij}^{AB} \cdot s_{jk}^{DA} \tag{7}$$

So, the gain of including a certain DAB chain in the mental representation is a multiplicative function of benefit activation and the strengths of the links in the chain that connect the decision domain to the benefit. In line with what one would expect intuitively, this formulation implies that the gain is zero if the benefit has zero activation or if the decision has no consequences for attaining the benefit. Using cognitive reflection, a subject has access to all these elements: benefit activation (α) is directly observable as a current state of internal needs (e.g., an individual feels like going out), whereas assessment of link strengths between attributes and benefits (s_{ij}^{AB}), and between decision and attribute (s_{jk}^{DA}) are based on a subject's causal knowledge of the domain (e.g., knowing that location choice for a shopping trip generally has a strong impact on travel time). In sum, causal knowledge in combination with introspection on the own subjective state allows an individual to assess the gain of including a given DAB chain in his mental representation for making decisions. We exploit this property in our data collection for the empirical test of the model.

The cost component (C) takes into account the mental effort involved in using the mental representation to determine likely outcomes of action alternatives (memory retrieval, inference, judgment, etc.). The cost is assumed to be constant across DAB chains. Equation (7) and the cost component together determine the activation of DAB chains in the mental representation. More specifically, a DAB chain *ijk* is activated in the mental representation only if the gain of including this chain in the mental representation exceeds the costs. This is expressed in the inclusion condition:

$$Z_{ijk} > C. \tag{8}$$

Deriving the Marginal Utility of Attribute and Benefits

As we do not observe the choices that consumers make, we need to derive the utility of the attributes and benefits in the consumer decision utility function from the mental representation model's estimates. As a starting point we take the typical expression of systematic utility in a consumer choice model for any alternative *g*:

$$V_g = \sum_{j \in J} \beta_j \cdot X_{jg} \tag{9}$$

where *J* is the set of attributes considered for the decision, β_j is a marginal utility of attribute *j* and X_{jg} is the value of alternative *g* on attribute *j*. This equation represents a mapping of the attribute outcomes of a choice on utility outcomes. Additionally, when choice outcomes are considered at the level of benefits, the following equation applies:

$$V_g = \sum_{i \in I} \beta_i \cdot B_{ig} \tag{10}$$

where *I* is the set of benefits considered for the decision, β_i is the marginal utility of benefit *i* and B_{ig} is the value of alternative *g* on benefit *i*.

We are interested in deriving marginal utilities β for each of the two formulations above from the mental representation model as this provides us with a new method to determine the utility impacts of attributes and benefits as an alternative to traditional choice-based analyses and that furthermore allows for a direct utility-based valuation of benefits based on mental representation data only. The necessary derivations can be accomplished as follows.

Note that in the mental representation model the systematic utility of a decision alternative g is given by the sum over the utilities of the DAB chains in which it is present (see Equation (3)):

$$V_g = \sum_{ij \in I \times J} V_g^{ij} = \sum_{j \in J} \sum_{i \in I} \alpha_i \cdot s_{ij}^{AB} \cdot r'_{ij}(X_{jg}) \tag{11}$$

where r'_{ij} refers to a transformation of X such that the scale of the value range is equal to one and a larger transformed value is preferred to a smaller value (the preference direction is positive). To relate this formulation to its more traditional utility counterparts in Equations (9) and (10), we use the definition:

$$r'_{ij}(X_{jg}) = \Delta_{ij} \cdot X'_{jg} \tag{12}$$

where Δ_{ij} represents the sign of the preference value of attribute i regarding benefit j ($\Delta_{ij} \in \{-1,1\}$) and X'_{jg} is the value of X_{jg} standardized for dispersion (i.e., $X'_{jg} = X_{jg} / D(X_{j\bullet})$). Substituting (12) in (11) gives:

$$V_g = \sum_{j \in J} \sum_{i \in I} \alpha_i \cdot s_{ij}^{AB} \cdot \Delta_{ij} \cdot X'_{jg} \tag{13}$$

This can be rewritten as:

$$V_g = \sum_{j \in J} X'_{jg} \cdot \sum_{i \in I} \alpha_i \cdot s_{ij}^{AB} \cdot \Delta_{ij} \tag{14}$$

A marginal utility corresponding to β in Equation (9) can now be defined in terms of the mental representation model by relabeling $\sum_{i \in I} \alpha_i \cdot s_{ij}^{AB} \cdot \Delta_{ij}$ as the coefficient of X in Equation (14):

$$\beta'_j = \sum_{i \in I} \alpha_i \cdot s_{ij}^{AB} \cdot \Delta_{ij} \tag{15}$$

In this equation β'_j is equivalent to the marginal utility of attribute j where the attribute is standardized based on the range of the attribute scores in the choice set. An unstandardized form of the coefficient such as contained in Equation (9) can be obtained as:

(16) $$\beta_j = \frac{1}{D(X_{j\bullet})} \cdot \sum_{i \in I} \alpha_i \cdot s_{ij}^{\mathrm{AB}} \cdot \Delta_{ij}$$

Theoretically the sign Δ_{ij} of the impact of each attribute on each benefit cannot be derived from the mental representation directly because activation of a decision component in the mental representation is driven by the size of its (positive or negative) impact, but not its sign. However, the assessment of these signs can typically be determined by the researcher based on objective knowledge of the domain (e.g., travel time has a negative effect on a benefit to save time). If this is not the case, additional questions can be included in the mental representation elicitation process to determine the direction of the relationships.

An analogue derivation provides the marginal utilities of the benefits as expressed in Equation (10). First, note that the mental representation model allows us to derive benefit scores of alternatives (B_{ig}) from the alternatives' attribute scores as:

(17) $$B_{ig} = \sum_{j \in J} s_{ij}^{AB} \cdot \Delta_{ij} \cdot X'_{jg}$$

For the derivation of marginal utilities we again use Equation (14). This time it is useful to reverse the order of summating utility components and first aggregate over attributes and next over benefits, that is, by reordering the summation terms we obtain:

(18)
$$V_g = \sum_{i\in I} \sum_{j\in J} \alpha_i \cdot s_{ij}^{\mathrm{AB}} \cdot \Delta_{ij} \cdot X'_{jg}$$

This can be rewritten as:

(19)
$$V_g = \sum_{i\in I} \alpha_i \cdot \sum_{j\in J} s_{ij}^{\mathrm{AB}} \cdot \Delta_{ij} \cdot X'_{jg}$$

Substituting (17) in (19) gives:

(20)
$$V_g = \sum_{i\in I} \alpha_i \cdot B_{ig}$$

Combining with Equation (10) provides:

(21)
$$\beta_i = \alpha_i$$

This result implies that the estimates of the benefit activation parameters α_i are in principle estimates of the marginal utilities of benefits β_i. However, to be able to interpret the mental representation model estimates of the benefit activation values as utilities further constraints need to be applied. This is necessary to guarantee that the sums of the link strength values per benefit (equation 22) and per attribute (equation 23) are identical (otherwise utility parameters for the different benefits are not identically scaled in the utility V_g).

(22)
$$\sum_j s_{ij}^{AB} = 1 \quad \forall i$$

(23)
$$\sum_k s_{jk}^{DA} = 1 \quad \forall j$$

Since, in the mental representation model there is no inherent mechanism to guarantee that these constraints are met we impose them as follows. First, we identify α_i, s_{ij}^{AB} and s_{jk}^{DA} as the model parameter values where the constraints given by equations (22) and (23) are met, and α'_i,

$s_{ij}'^{AB}$ and $s_{jk}'^{DA}$ as an estimated set of parameters when these constraints are not imposed. Since both sets of parameters capture the same data and model structure, the following identity condition must hold:

$$\alpha_i \cdot s_{ij}^{AB} \cdot s_{jk}^{DA} = \alpha_i' \cdot s_{ij}'^{AB} \cdot s_{jk}'^{DA} \tag{24}$$

Next, expressions can be derived for α_i and s_{ij}^{AB} that are used in the attribute and benefit utility related equations (15) and (21).

To obtain an expression for α_i we consider the sum of the activated links across all DAB chains that include benefit *i*:

$$\sum_{jk} \alpha_i \cdot s_{ij}^{AB} \cdot s_{jk}^{DA} = \sum_{jk} \alpha_i' \cdot s_{ij}'^{AB} \cdot s_{jk}'^{DA} \tag{25}$$

Rewriting gives:

$$\alpha_i \cdot \sum_j \left(s_{ij}^{AB} \cdot \sum_k s_{jk}^{DA} \right) = \alpha_i' \cdot \sum_j \left(s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA} \right) \tag{26}$$

Since the sum constraints hold for the set of parameters α_i, s_{ij}^{AB} and s_{jk}^{DA}, combining this with equations (22) and (23) results in:

$$\alpha_i = \alpha_i' \cdot \sum_j \left(s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA} \right) \tag{27}$$

Thus, based on estimated values of the benefit activations and link strengths in the mental representation model we have derived the value of α_i that corresponds to the marginal benefit utility defined in equation (21).

Continuing on this result we can also derive an expression for s_{ij}^{AB} as follows. Substituting equation (27) in equation (24) gives:

$$\alpha_i' \cdot \left(\sum_j \left(s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA} \right) \right) \cdot s_{ij}^{AB} \cdot s_{jk}^{DA} = \alpha_i' \cdot s_{ij}'^{AB} \cdot s_{jk}'^{DA} \tag{28}$$

Summating the activation of DAB chains across all decision variables *k* leads to:

(29)
$$\sum_k \alpha_i' \cdot \left(\sum_j \left(s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA}\right)\right) \cdot s_{ij}^{AB} \cdot s_{jk}^{DA} = \sum_k \alpha_i' \cdot s_{ij}'^{AB} \cdot s_{jk}'^{DA}$$

Rewriting gives:

(30)
$$\alpha_i' \cdot \left(\sum_j \left(s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA}\right)\right) \cdot s_{ij}^{AB} \cdot \sum_k s_{jk}^{DA} = \alpha_i' \cdot s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA}$$

By dividing by α_i' on both sides of the equation and using equation (23) this reduces to:

(31)
$$\left(\sum_j \left(s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA}\right)\right) \cdot s_{ij}^{AB} = s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA}$$

This can be rewritten as:

(32)
$$s_{ij}^{AB} = {s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA}} \Big/ {\sum_j \left(s_{ij}'^{AB} \cdot \sum_k s_{jk}'^{DA}\right)}$$

This equation now can be inserted in equation (15) to calculate the link strength values based on the estimated values in the mental representation model.

Thus, we have derived how based on the observation of consumers' mental representations of decisions combined with the estimation of a utility driven model of the cognitive activation of mental representation components, we can obtain expressions for consumers' attribute and benefit utilities. Note that we do not need to observe choice data to estimate the mental representation model, and hence to decompose the attribute and benefit utilities of the decision alternatives into. We empirically illustrate the different steps of the proposed process (from data collection, mental representation model estimation, to calculation of the utilities) in the next section.

EMPIRICAL ILLUSTRATION FOR MENTAL REPRESENTATIONS OF SHOPPING DECISIONS

Data on consumers’ mental representations of shopping location decisions were elicited in a dedicated online survey. We present the results of the estimation of the mental representation model and demonstrate how they are used to decompose the utility of different attributes and benefits of the shopping location alternatives. This provides insights in the relative importance of the different attributes and benefits in the consumer decision.

Data

Online data were collected through a survey in which participants were presented with a shopping decision problem and their mental representations of this decision problem were elicited. The survey protocol used a laddering style approach aimed at revealing attributes and benefits and the causal relationships between them. This method follows the logic of iteratively tracing DAB chains where the online questioning system uses a pre-defined list of attributes and benefits for respondents to indicate which attributes and benefits they had in mind when thinking about the decision. This protocol closely resembles previously applied procedures in hard laddering (Russell et al. 2004) and the association pattern technique (APT) (Ter Hofstede et al. 1998), but deviates in that it does not elicit consumers’ underlying values as these are stable across decisions (Wendel and Dellaert 2005).

To develop the survey protocol, first face-to-face interviews were conducted with a small number of respondents (n=6) to generate an initial list of attributes and benefits that was exhaustive for the participants in the interviews. Next, a pilot study (n=139) was conducted with the on-line tool where this initial attribute and benefit database was tested and extended based on open-ended responses. These steps allowed us to select the most relevant set of attributes and benefits for the actual online interface that fully automated the elicitation and processing of consumer responses. Thus, large-scale data collection of consumer mental representations at relatively low costs was supported with the additional advantage of eliminating possible influences and biases of a human interviewer.

Experimental task. In the decision problem presented in the study, respondents were asked to plan a trip for shopping for daily groceries on a usual workday. To avoid reliance on existing shopping routines a hypothetical city was presented in the experiment and respondents were asked to imagine that they had recently moved to this city to take on a new job. The lay-out of the city was shown on a map and the respondent was asked to imagine that he or she had recently moved to that city where he or she had started a new job. The planning of the shopping trip required choices of shopping location, as well as time of shopping and transport mode. The available options for each of these choices were pre-defined and explained to the respondents. The alternatives included a supermarket, a corner store and a weekly open-air market at specifically indicated distances from home and work place. The possible times of shopping were: during lunch break at work, directly after work, or in the evening. Transport mode options consisted of bicycle, bus and car. Respondents were instructed to imagine the following decision setting: “You are working an eight hour working day with a flexible starting time and can take a lunch break of maximally one hour. All shopping locations of interest are accessible by bicycle, car and busses that run regularly. Traveling between locations is possible on direct routes with travel times of 10 minutes. One of three different scenarios was presented to each respondent based on random allocation. There was a base scenario as well as two others that varied in terms of the uncertainty of the availability of products in the different stores and the level of traffic congestion and in terms of the time frame (now vs. in the future) in which the hypothetical choice was set. For expositional clarity we combine the data across the three scenarios in the empirical illustration. This does not affect the principle structure guiding the empirical illustration of the proposed approach.

Sample. Individuals who participated in the survey were recruited from a nationwide panel representative for the Dutch population. Considering the nature of the choice task, only members of the panel that possessed a driving license and were aged between 18 and 60 years could participate. Within this group a subset of respondents were selected at random from the panel. This resulted in a sample of 594 respondents. The average age of the respondents was 43.1 years old, 55% were female, 83% were living with a partner, 60% had one or more children living at home, and 35% had earned a bachelor's degree or higher.

Econometric Analysis of Mental Representations

Econometric model. The observations obtained for participants' mental representations consist of a collection of DAB chains elicited from each individual. Benefit evaluations, link strengths, and mental costs in the model are unobserved to the researcher and need to be estimated. We formulate the model of a participant *n*'s mental representation within a random-utility framework allowing for individual heterogeneity in mental costs. To do so, we first define the random utility function for activation of a DAB chain in the mental representation:

$$U_{ijk}^{n} = Z_{ijk} - C \ + \varepsilon^{n} + \varepsilon_{ijk}^{n} \qquad \forall (i, j, k) \in I \times J \times K \tag{33}$$

where *n* is an index of the individual, *U* is the utility of DAB chain *ijk*, *Z* and *C* are as before, perceived gains and costs of activating the DAB chain in the mental representation, ε^{n} is an individual specific error component that reflects amongst others unexplained variation in mental costs and ε_{ijk}^{n} is an overall error component, *I* is an exhaustive set of benefit variables, *J* is an exhaustive set of attribute variables and *K* is an exhaustive set of decision domains for the choice task and setting considered.

Based on utility-maximizing behavior, the probability of observing a DAB chain *ijk* in case of participant *n* is defined as:

(34)
$$\Pr[(i,j,k)\in MR_n] = P(U_{ijk}^{n} > 0)$$

Now, the gain component is parameterized as follows:

(35)
$$Z_{ijk} = \alpha_i \cdot \exp(\lambda_{ij}^{AB}) \cdot \exp(\lambda_{jk}^{DA})$$

where *α*'s are parameters related to benefit activation, and λ^{AB} and λ^{DA} are parameters of link strengths. Exponents of strength parameters, *λ*, are used so that strength values have positive signs for an unrestricted value range of the parameter. The mental cost component is specified as:

(36)
$$C = \theta$$

where *θ* is a parameter representing an average value of (cognitive) costs of evaluating DAB.

To handle the multi-level error component structure a mixed logit model is used. In the mixed logit the overall random error component (ε_{ijk}^{n} in equation 33) is assumed to be iid Gumbel distributed, whereas the individual-specific component (ε^{n}) can be simulated based on any assumed distributional form. We apply a normal distribution in the estimation. The probability of activation of a DAB chain is written as:

(37)
$$P(ijk \mid \varepsilon^{n}) = P_{ijk}^{n} = \frac{\exp(Z_{ijk} - C_{ijk} + \varepsilon^{n})}{1 + \exp(Z_{ijk} - C_{ijk} + \varepsilon^{n})}$$

Furthermore, the likelihood of an observed mental representation of a given individual *n* is defined as:

$$L(MR_n) = \int_{\varepsilon^n} \prod_{(i,j,k)\in MR_n} P_{ijk}^n \cdot \prod_{(i,j,k)\notin MR_n} (1 - P_{ijk}^n) \cdot d\varepsilon^n \tag{38}$$

The first product term represents the joint probability of all the activated DAB chains and the second product term that of all the non-activated DAB chains, both are integrated over the distribution of the individual-specific error term.

These mental representation-based estimates are then used to derive the utilities of the attributes and benefits of the different alternatives (see equations 15 and 21). To obtain an error scale invariant value of the relative importance of different attributes and benefits from the utilities we can calculate the ratio of all other parameters to the parameter for one commonly observed attribute (typically price or travel time). This allows us to rank the attributes and benefits scale free in their order of impact on the consumer's decision and to calculate willingness to pay or willingness to spend time for each attribute (Lanscar, Louviere and Flynn 2007).

Estimation. For the estimation, we set the minimum for Attribute-Benefit (AB) and Decision domain-Attribute (DA) links for inclusion in the model to an occurrence probability of p=0.05 in our sample (this corresponds to a minimum frequency of 30 occurrences for the total of 594 respondents). 108 AB links and 41 DA links meet this minimum. After also omitting zero-strength links this leads to a set of DAB chains of 196. Thus, for every individual we have 196 observations of yes/no occurrence for DAB chains as the basis for the likelihood function given by equation (38). The 196 chains include 24 attributes, 18 benefits and 3 decision domain variables[1]. Normalization involves that for each benefit B the strength of one AB link is set to one and for each attribute A the strength of one DA link is set to one (See Appendix A). Thus, the number of link strength parameters to be estimated equals 90 (= 108 – 18) on the level of AB links and 17 (= 41 – 24) on the level of DA links. Arbitrarily, the link with the highest frequency was taken as base for both AB and DA link groups. The non-linear optimization model NLM in R was used to find the values of the parameters that maximize the loglikelihood function. For the agent-error term a normal distribution was assumed and simulation was based on 250 draws.

Results

Mental representation model. The estimation results for the activation of components in the participants' mental representations are presented in Tables 1 to 3. Table 1 provides the detailed estimation results for benefit activation, mental costs and the individual error component; Table 2 the estimates for the strengths of the AB links; and Table 3 the estimates for the strengths of the DA links. Compared to the null model (i.e., the model where all benefit and link parameters are set to zero and the mental cost parameter is set to its base value) the loglikelihood improved from -80,039 to -45,001. The adjusted rho-square of 0.436 indicates a satisfactory goodness-of-fit.

- INSERT TABLES 1-3 ABOUT HERE -

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[1] Situational attributes are also allowed in the model (e.g., weather) and are included in the estimation as an evaluation chain with a situational attribute in the middle position of the chain (i.e., a DSB chain where S is a situational variable). Such a chain is not structurally different from a DAB chain, but there is a difference in the nature of the first link in the chain in that a DS link does not represent a causal link with a decision variable but a link that indicates if attribute S is considered with respect to benefit B in the context of decision D. In addition, we also allow for a decision domain to have a direct influence on a benefit without an intermediating attribute. This is captured by chains of the form DB.

In the mental representation model we find that there is considerable variation in activation between benefits, that mental costs are significant in the model, and that there is also significant variation between consumers in terms of the general level of component activation as reflected by the significance of the individual error component (Table 1). The estimation results for the AB link strength parameters are presented in Table 2 and show for each benefit which attributes drive that benefit (shown are the values after the exponential transformation ($s = \exp[\lambda]$)). We find that benefits vary strongly in terms of the number of attributes that are linked to them. On the one extreme, benefits such as ease of travelling and time-savings have many attribute connections (10 and 12 respectively). On the other extreme, benefits such as attractiveness of the shopping environment, safety of travelling, and taste experience only have two or three attributes connected to them. The *t*-values that are shown refer to a *t*-test of difference from one (i.e., the link strength at which the base level was set). Finally, the estimation results for the DA link strengths demonstrate which attributes individuals consider for each decision domain (Table 3). We find that as expected many attributes are activated for more than one domain. For example, in the mental representation the available time to shop is activated for the shopping time choice as well as the shopping location choice, and the number of bags to carry is a activated for all three choices (shopping time, shopping location and transport mode).

Attribute and benefit utilities. The results of the mental representation model provide the input for deriving the utility values of the benefits and attributes of the different shopping alternatives. These utilities are presented from high to low in Tables 4 and 5 for benefits and attributes respectively. We find that the five benefits with the highest utility values in the shopping decision were: time savings, ease of travelling, relaxation, ease of shopping and shopping pleasure. This implies that these benefits are the ones that are most valuable to the participants in the survey that can be provided by a shopping location. It is important to note that the order of benefit utilities does not correspond one-on-one with the order observed in the activation model (Table 1). The reason for this difference is that the fact that the sum constraints are imposed in deriving the benefit utilities (equations 22 and 23). They correct for the fact that the impact of a benefit on utility is not only a function of the benefit activation alone (which is estimated in the mental representation model), but also of the number and strength of the links that the benefit has with various attributes. This implies that a relatively low benefit activation level may still have a relatively large utility impact and vice versa. From a retailer's perspective it is interesting to see that at least two of the top five benefits that consumers look for are related to the shopping experience itself (e.g., ease of shopping and shopping pleasure) and not to time or transport. The other three of the top benefits are more composite in nature, in that they are related to combinations of decisions (e.g., time savings or relaxation).

When we look at the attributes, we find that the attributes that most strongly affect consumers' decisions are: crowdedness in the store, travel time, road congestion, departure time flexibility of the transport mode, and accessibility of the store. These attribute utilities cannot be observed in the mental representation estimates in Tables 1 to 3 but are necessary to provide key insights for retailers on what could be promising changes in their service offering to increase consumer utility. Interestingly, for retailers we find that at the attribute level, a reduction in the hassle of travelling to the store (e.g., travel time, road congestion) seems to have to the strongest potential to affect consumers' shopping decisions.

- INSERT TABLES 4 AND 5 ABOUT HERE –

DISCUSSION

This paper introduces a utility theory-based model of consumers' mental representation of attribute-benefit relationships. The results of the empirical application of the proposed approach demonstrate how the utility of attributes and benefits of choice alternatives can be decomposed from individuals' mental representations of decisions. Whereas previous research on consumer choice models and attribute-benefit relationships focused on including attribute-benefit relationships in models of consumer choice (e.g., Arentze, et al. 2014; Ashok, et al. 2002; Chandukala, et al. 2011; Dellaert and Stremersch 2005; Luo, et al. 2008), our research provides a formal framework that allows for the activation of mental representation components to be quantified in a way that is consistent with utility-based theory of decision making (McFadden 1986; Johnson-Laird 2001). Therefore we can derive attribute and benefit utilities from the mental representation model. This utility-based approach also distinguishes our work from more descriptive quantitative approaches of modeling mental representations (Ter Hofstede et al. 1999) because it provides a formalization of the process that drives the selective activation of components in the mental representation based on mental costs and that is also consistent with utility theory.

Managerial Implications

The proposed methodology represents a new opportunity to marketing managers and marketing researchers to bridge what are typically qualitative insights on the basis of means-end chain or laddering research with quantitative insights based on conjoint choice experiments or choice models. The new method and model are likely to be most useful in market conditions where supply is relatively complex, highly stable over time, and narrow in terms of the number alternatives that any given customer will consider (e.g., shopping centers, recreational attractions, and healthcare facilities). These conditions restrict the possibility to determine the relative importance to consumers of the different aspects of these fixed alternatives by using traditional choice models. In such cases, the proposed approach based on mental representations provides a viable way to generate in-depth insights about consumer benefit needs and attribute preferences that can be quantified in terms of consumer decision utility.

Thus the approach can help generate ideas for marketing improvements. In particular, the areas of new product development and marketing communications offer promising applications. In recent years consumers have increasingly come to expect ever more tailored communications and offers from firms to match their own individual needs (Wind and Rangaswamy 2001). These developments make it critical for firms to understand how consumers think about decisions to better match the consumer's own unique needs (Griffin and Hauser 2003). Our approach may be applied particularly fruitfully when little opportunity exists to present consumers with many hypothetical scenarios to explore which attributes best match their individual benefit needs. Some examples, where this could be relevant include the design of websites to match consumer information needs (Hauser et al. 2009), or the sales of customized products in a way that fits the consumer's individual needs (Randall, Terwiesch and Ulrich 2007).

In marketing communications, the growing number of marketing messages that consumers receive also provides firms with fewer opportunities to captivate consumers. In these instances communications that focus on the key elements in consumers' mental representation of decisions are likely to enhance conceptual and perceptual fluency and hence information and product acceptance (Lee and Labroo 2004; Novemsky et al. 2009). In addition, based on the cognitive activation of causal links revealed in the models, communication tools could be designed to help consumers deal with conditions where they are exposed to so much information that they cannot easily extract meaning out of it. This approach can help consumers to find the most relevant information in available data (most impactful DAB chain), and provide a method for comparing and processing different kinds of information (Murray and Häubl 2008). A promising application of the modeling approach could be in mobile decision support, where consumers only have a small screen available and are likely to wish to have access very quickly to only the most important information to help them make a choice (e.g., when they are travelling or browsing in a store). Firms can use the model introduced in this research to provide information that makes the bottom line of choosing different alternatives clearer to consumers, thereby helping them to make better decisions with lower effort (Reyna 2012).

Limitations and Future Research

Some limitations of the present research are also worth noting along with opportunities for future research. First, although we allow for differences in mental costs between consumers through the random parameter specification of the model, it would be worthwhile to also look for more systematic sources of differences between mental representations of different consumers. For example, the level of a consumer's expertise with respect to a decision may affect their mental representation of the decision (Alba and Hutchinson 1987), or consumers' psychological distance to the decision outcome may affect their mental representation structure (Trope and Liberman 2010). Future research could address such systematic variations between consumers.

Second, in our research we presented respondents with realistic but hypothetical decision tasks. This provided us with control and was helpful to rule out unobserved differences in choice contexts between respondents. However, it is also important to investigate how consumers' mental representations of real-world decisions could best be measured. On the one hand, such mental representations may be simpler than those found in our research because habit formation may imply that fewer relevant components are taken into account in real-world decisions by consumers. On the other hand, real-world based mental representations may be more elaborate because decision consequences may be greater in real-world decisions and more contingencies may need to be taken into account, which both could lead to more detailed mental representation structures. Taken together, these conflicting influences suggest that consumer heterogeneity in mental representations of real-world decisions is likely to be greater than that observed in the current study.

Third, the mental representations that we analyzed were static in that we only observed mental representations at one moment in time. It would be valuable to extend the findings from this study to applications where dynamic updating of mental representations may take place (e.g., when consumers are introduced to a new shopping environment and learn to shop more efficiently in this environment over time). We consider this to be an especially promising extension to the current framework because in many instances consumer mental representations of decisions will evolve over time and this may significantly affect the choices that consumers make. We hope that this study provides a valuable starting point for such future research.

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FIGURE 1 SCHEMATIC ILLUSTRATION OF A MENTAL REPRESENTATION OF A CONSUMER CHOICE SPANNING TWO DECISION DOMAINS

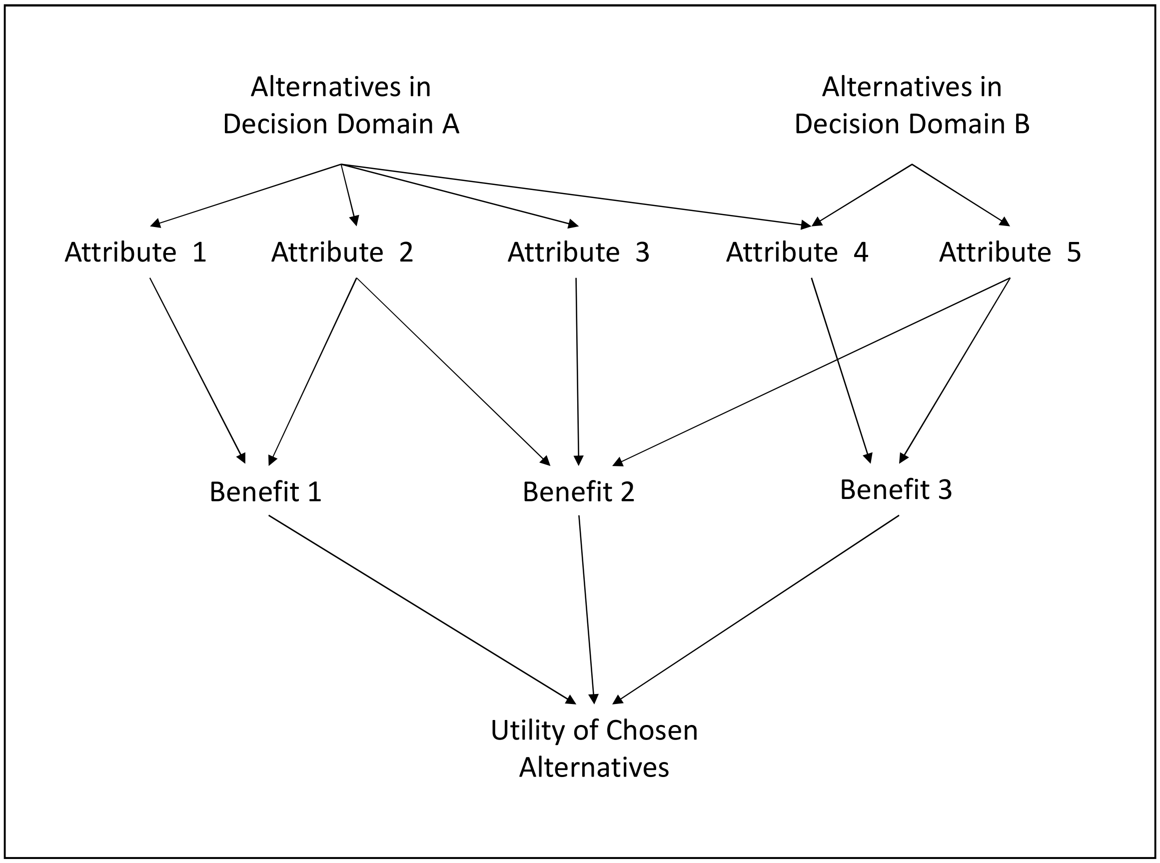

TABLE 1 MENTAL REPRESENTATION MODEL: BENEFIT ACTIVATION, MENTAL COSTS AND INDIVIDUAL ERROR COMPONENT ESTIMATES

Benefits	*parameter*[§]	*t-value*
ease of travelling	4.54	53.40
diversity in product choice	4.41	46.40
time savings	4.22	49.91
travel comfort	3.92	43.19
ease of shopping	3.66	61.21
shopping success	3.62	39.71
financial savings	3.48	31.60
shopping comfort	3.43	36.01
shopping pleasure	3.26	33.01
health	3.21	26.55
taste experience	2.94	22.42
safety of travelling	2.52	19.59
attractiveness of the shopping environment	2.50	18.11
relaxation	2.34	20.17
mental ease	2.20	16.55
environmental protection	1.99	10.75
travel pleasure	1.94	33.83
fitness/wellbeing	1.92	14.48
mental costs	2.29	57.18
individual-error component	0.72	38.59

[§] all parameters significant at $p <.001$ level

TABLE 2 MENTAL REPRESENTATION MODEL: ATTRIBUTE-BENEFIT LINK STRENGTH ESTIMATES

Benefits	*Attributes*	*Value*	*t-value*£
ease of travelling	number of bags to carry	1	
	capacity of the transport mode	0.89*	-5.74
	simplicity of the travel route	0.85*	-7.95
	travel time	0.85*	-8.71
	accessibility of the store	0.83*	-8.13
	departure time flexibility of the TM	0.81*	-9.49
	road congestion	0.77*	-11.52
	weather	0.75*	-11.63
	time to find a parking lot	0.71*	-12.63
	requires physical activity	0.63*	-10.48
diversity in product choice	available range of goods	1	
	price level of the assortment	0.87*	-6.18
	size of the shopping location	0.82*	-7.79
	crowdedness in the store	0.71*	-11.82
time savings	required time to shop	1.02	1.16
	travel time	1	
	accessibility of the store	0.99	-0.75
	crowdedness in the store	0.93*	-3.95
	leisure time	0.89*	-5.09
	departure time flexibility of the TM	0.86*	-6.83
	familiarity with the shopping location	0.82*	-7.43
	road congestion	0.82*	-8.88
	time to find a parking lot	0.81*	-8.79
	simplicity of the travel route	0.77*	-10.38
	size of the shopping location	0.71*	-9.29
	weather	0.62*	-11.52
travel comfort	number of bags to carry	1	
	weather	0.94*	-2.96
	capacity of the transport mode	0.89*	-4.54
	departure time flexibility of the TM	0.83*	-7.03
	accessibility of the store	0.81*	-6.86
ease of shopping	available time to shop	1.20*	8.06
	accessibility of the store	1.02	0.78
	crowdedness in the store	1.01	0.67
	required time to shop	1.01	0.22
	opening hours	1	
	number of bags to carry	1.00	-0.36
	familiarity with the shopping location	0.98	-1.11

	atmosphere in the shopping location	0.95	-1.94
	available range of goods	0.95*	-2.22
	size of the shopping location	0.90*	-4.28
shopping success	available range of goods	1.14*	6.76
	available time to shop	1.05*	2.51
	opening hours	1	
	size of the shopping location	0.93*	-2.86
	familiarity with the shopping location	0.91*	-3.45
	required time to shop	0.89*	-4.12
	crowdedness in the store	0.87*	-5.45
	accessibility of the store	0.87*	-4.77
financial savings	price level of the assortment	1.21*	8.48
	parking costs	1	
	costs for petrol	0.92*	-2.92
	travel costs	0.88*	-3.85
	familiarity with the shopping location	0.76*	-6.16
	durability of products bought	0.76*	-6.22
shopping comfort	crowdedness in the store	1	
	familiarity with the shopping location	0.91*	-3.20
	available range of goods	0.88*	-4.17
shopping pleasure	crowdedness in the store	1	
	atmosphere in the shopping location	0.97	-1.18
	available time to shop	0.89*	-4.06
	familiarity with the shopping location	0.84*	-4.56
	accessibility of the store	0.81*	-5.21
	available range of goods	0.79*	-5.36
	weather	0.77*	-6.89
	time to find a parking lot	0.73*	-7.69
	parking costs	0.67*	-8.69
health	durability of products bought	1	
	requires physical activity	0.92*	-2.45
	weather	0.80*	-5.86
taste experience	durability of products bought	1	
	available range of goods	0.85*	-3.50
safety of travelling	number of bags to carry	1	
	simplicity of the travel route	0.91*	-2.35
	road congestion	0.87*	-3.37
attractiveness of the shopping environment	atmosphere in the shopping location	1	
	size of the shopping location	0.91	-1.94
	accessibility of the store	0.90*	-2.06
relaxation	leisure time	1.11*	3.03
	requires physical activity	1.07	1.88

	required time to shop	1.03	0.65
	crowdedness in the store	1.02	0.54
	weather	1.00	0.07
	travel time	1	
	atmosphere in the shopping location	0.97	-0.75
	simplicity of the travel route	0.95	-1.25
	road congestion	0.95	-1.40
	departure time flexibility of the TM	0.90*	-2.18
	accessibility of the store	0.90*	-2.11
	number of bags to carry	0.86*	-2.98
mental ease	departure time flexibility of the TM	1.05	1.29
	accessibility of the store	1.01	0.18
	familiarity with the shopping location	1.01	0.18
	time to find a parking lot	1	
	weather	0.94	-1.47
	simplicity of the travel route	0.90*	-2.33
environmental protection	costs for petrol	1	
travel pleasure	number of bags to carry	1.24*	8.22
	departure time flexibility of the TM	1.23*	7.58
	road congestion	1.21*	4.39
	travel time	1.09*	2.90
	capacity of the transport mode	1.01	0.22
	weather	1	
	accessibility of the store	1.00	-0.07
fitness/wellbeing	number of bags to carry	1.01	0.17
	travel time	1	
	required time to shop	1.00	-0.01
	weather	0.97	-0.55

[£] t-test of difference from one; * significant at p< .05

TABLE 3 MENTAL REPRESENTATION MODEL: DECISION-ATTRIBUTE LINK STRENGTH ESTIMATES

Attributes	*Decisions*	*Value*	*t-value*[£]
available time to shop	timing of shopping	1	
	shopping location	0.90*	-5.51
departure time flexibility of the TM	transport mode	1	
	timing of shopping	0.81*	-9.55
accessibility of the store	shopping location	1	
atmosphere in the shopping location	shopping location	1	
	timing of shopping	0.82*	-7.14
crowdedness in the store	timing of shopping	1	
	shopping location	0.92*	-6.18
size of the shopping location	shopping location	1	
familiarity with the shopping location	shopping location	1	
price level of the assortment	shopping location	1	
available range of goods	shopping location	1	
time to find a parking lot	timing of shopping	1	
	shopping location	1.00	-0.09
capacity of the transport mode	transport mode	1	
travel costs	transport mode	1	
costs for petrol	transport mode	1	
parking costs	transport mode	1	
	shopping location	0.96	-1.64
	timing of shopping	0.92*	-2.80
opening hours	shopping location	1.04*	2.82
	timing of shopping	1	
simplicity of the travel route	transport mode	1	
	shopping location	0.98	-1.14
leisure time	timing of shopping	1	
requires physical activity	transport mode	1	
travel time	transport mode	1	
	shopping location	0.92*	-4.87
	timing of shopping	0.91*	-5.80
road congestion	transport mode	1	
	timing of shopping	0.94*	-2.60
		0.83*	-6.67
Situational attributes			
weather	transport mode	1	
	timing of shopping	0.84*	-8.39
	shopping location	0.81*	-9.55

number of bags to carry	transport mode	1	
	timing of shopping	0.78*	-14.41
	shopping location	0.75*	-15.55
required time to shop	timing of shopping	1	
durability of products bought	timing of shopping	1	

£ t-test of difference from one; * significant at the p <.05 level

TABLE 4 MARGINAL UTILITIES: BENEFITS

Benefits	*Utility*	*Willingness to Travel*[§] *(in minutes travel time)*
time savings	114.9	63.0
ease of travelling	109.0	59.8
relaxation	100.2	54.9
ease of shopping	91.5	50.2
shopping pleasure	73.5	40.3
travel pleasure	69.6	38.1
shopping success	61.8	33.9
travel comfort	51.0	28.0
mental ease	45.6	25.0
financial savings	42.7	23.4
fitness/wellbeing	37.8	20.7
safety of travelling	32.4	17.8
diversity in product choice	27.1	14.9
health	22.2	12.2
shopping comfort	21.2	11.6
attractiveness of the shopping environment	17.4	9.5
taste experience	9.7	5.3
environmental protection	4.3	2.3

[§] Base range for travel time based on travel times presented to participants in the shopping decision.

TABLE 5 MARGINAL UTILITIES: ATTRIBUTES

Attributes	*Utility*	*Willingness to Travel*[§] *(in minutes travel time)*
crowdedness in the store	-73.0	40.0
travel time	-73.0	40.0
road congestion	-67.3	36.9
departure time flexibility of the transport mode	54.7	30.0
accessibility of the store	50.0	27.4
simplicity of the travel route	46.8	25.7
time to find a parking lot	-37.3	20.4
atmosphere in the shopping location	36.0	20.3
familiarity with the shopping location	35.4	19.4
available time to shop	34.8	19.1
available range of goods	33.0	18.1
parking costs	-27.3	15.0
opening hours	24.2	13.3
capacity of the transport mode	15.9	8.7
requires physical activity	14.3	7.8
price level of the assortment	-12.8	7.0
leisure time	11.1	6.0
costs for petrol	-9.6	5.2
size of the shopping location	5.4	2.9
travel costs	-5.1	2.8
Situational attributes		
weather	108.2	59.4
number of bags to carry	-94.1	51.6
required time to shop	-26.9	14.7
durability of products bought	15.1	8.3

[§] Base range for travel time minutes based on travel times presented to participants in the shopping decision.

APPENDIX A – MODEL IDENTIFICATION

The total number of (basic) parameters to be estimated in the mental representation model (equation 33) is equal to $|I|$ α-terms + $|I| \times |J|$ s^{AB}-terms + $|J| \times |K|$ s^{DA}-terms + 1 costs parameters ($|I|$ is the number of benefits, $|J|$ is the number of attributes and $|K|$ is the number of decision domains). However, only $|J|$ - 1 BA-strength values are free to choose for each benefit and only $|K|$ - 1 DA-strength values are free to choose for each attribute (as the sums are given and fixed). In the estimation we set one BA-strength value for each benefit and one DA-strength value for each attribute to a fixed value and estimate the remaining values against these preset values. Arbitrarily, we set the strength values of the base links to unity. Given this setting, the estimated values of each alpha parameter represents the activation value of the arbitrary base-line chain, i.e., the DAB chain where the DA and AB link are the chosen base link.