STATED PREFERENCE APPROACHES TO TRANSPORTATION AND LAND USE PLANNING: AN OVERVIEW

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1. INTRODUCTION

There are various ways of predicting the likely effects and feasibility of transportation and land use and land development plans. If it is realised, however, that ultimately these effects depend on how users or consumers react to such plans, the success and relevance of any prediction will largely depend on the accuracy of the model that is used to predict consumer response (preference, choice, adaptation) to these plans.

Traditionally, models of spatial choice behaviour have relied on observations about how people behave in real markets. In the 1960s and 1970s, the models that were developed to represent these observations were typically based on social physics, such as the gravity and entropy-maximising models. Concepts borrowed from physics were used to predict destination and route choice. In the 1980s, as a result of progress in statistics in the area of discrete multivariate analysis and in random utility theory in economics, these social physics models were gradually replaced by discrete choice models, especially with the multinomial and nested logit model. It was argued that these models had a sound theoretical basis. Observed choice behaviour was interpreted in terms of some underlying utility function and utility-maximising behaviour.

However, if one takes a more critical stance, it is doubtful that observed behaviour in many domains truly reflects individual preferences. Space not only offers opportunities but also imposes constraints on individual behaviour. For example, while people may prefer an attractive shopping centre at close distance, in reality some people may need to travel a considerable distance to visit such a centre. The longer travel time does not represent their preference; they have no choice. Hence, in many domains, observed choice patterns reflect some unknown mixture of individual preferences and spatial constraints, and consequently, not only the theoretical underpinnings of models derived from such data is questionable, their application as a forecasting tool is also limited as transport and land use policies will typically change spatial structure, implying that observed correlations between spatial structure and spatial behaviour can strictly speaking not be used validly.

Some scholars therefore started to explore the possibility of asking respondents directly about their preferences. One way of eliciting consumer preferences is to construct attribute profiles that combine the attribute levels of interest. Originally, this approach became known as axiomatic conjoint measurement. It represented a means of identifying the nature (linear versus multiplicative) of the function that is used to arrive at overall judgements. Later, statistical analyses were used to decompose the overall preference measured for the attribute profiles into the contributions of the attribute levels. This approach was therefore called conjoint analysis or decompositional preference models.

Pioneers who explored the application of this approach include Green and Srinivasan (1978) in marketing, Louviere (1979) in geography, Timmermans (1980) in retailing, Lieber (1979) in migration research, and Knight and Menchik (1976) in housing research. Although Louviere and Timmermans and that co-workers published some working papers and little known articles about transportation applications in the late 1970s (Louviere and Wilson, 1978; Timmermans and Overduin, 1981), it was not before the 1990s that this approach became popular in transportation research as stated preference analysis, and many applications followed.

The label "stated preference" is unfortunate as it does not emphasize the quintessence of the approach. Moreover, as we will discuss in the remainder of this paper, many alternative methods of eliciting consumer preferences have been suggested in the literature. These methods can be distinguished between algebraic and non-algebraic approaches. Common to algebraic approaches is that preferences are represented in terms of an algebraic equation. In contrast, non-algebraic approaches represent preferences in terms of a set of condition variables and Boolean expressions (if … then-rules).

In the next session, the essentials of these different modelling approaches will be discussed. The discussion is best viewed as an introduction to the various modelling approaches. More advanced topics are not discussed. First, we will discuss alternative algebraic approaches. This is followed by a discussion of some non-algebraic approaches.

2. MODELLING APPROACHES

2.1 Algebraic approaches

Algebraic preference and choice models have in common the assumption that choice alternatives consist of bundles of attributes. An individual's overall evaluation (satisfaction, preference, utility, etc) of a choice alternative is assumed to be the result of a cognitive integration process in which an individual combines his or her evaluations of the alternative's attribute levels according to some algebraic function or combination rule. The various modeling approaches can be differentiated in terms of the way in which the nature of this integration process is uncovered and the measurement of its components. At least three approaches can be identified: compositional models, decompositional or conjoint models and hybrid models.

2.1.1 Compositional models

The compositional approach typically assumes that the overall evaluation of a multi-attribute choice alternative can be arrived at by combining evaluations associated with the attribute levels of that choice alternative and the subjective importance weights which an individual attaches to the various attributes according to a researcher defined and untested combination rule. Consequently, this approach involves measuring *separately* and *explicitly* an individuals' evaluation of perceived attribute levels and subjective importance weights.

Several combination rules may be used to describe the way in which these part-worth utilities and importance weights are combined to arrive at some overall evaluation. For example, a linear additive rule assumes that the overall evaluation of a choice alternative can be computed by summing the self-explicated attribute evaluations weighted by the subjective importance. Thus,

$$U_i = \sum_k w_k E_{ik}$$

where,

U_i is the overall utility of choice alternative i;

w_k is the explicitly measured importance weight of attribute k;

E_{ik} is the evaluation of choice alternative i on attribute k.

Such a linear combination rule represents a compensatory decision process in the sense that a low evaluation of some attribute may at least partially be compensated by a high evaluation of one or more other attributes.

Another example is a multiplicative combination rule, in which the attribute evaluations are multiplied. Weights appear as exponents. Because a low score of say zero on one attribute implies that the overall evaluation will also be equal to zero, regardless of the evaluations of the other attributes, a multiplicative function is capable of depicting noncompensatory behavior. The multiplicative model can be expressed as:

$$U_i = \prod_k E_{ik}{}^{w_k}$$

Other specifications are possible. In addition, one could use weighted or normalized versions. Unweighted versions assume that importance weights are implicitly included in the evaluations of the attribute levels. Normalized weights normalize the attributes evaluations and importance weights by dividing them by their respective means.

Note that compositional model have primarily been used to estimate preference or evaluation function. In principle, however, they can also be used to predict choice behaviour by formulating a choice rule, which links preference (evaluation, satisfaction, utility) to overt choice. Different rules of this nature have been suggested in the literature (e.g. Timmermans and van der Heijden, 1984). For example, one can assume that the choice alternative with the highest evaluation score is invariably chosen. Alternatively, a multinomial logit model can be assumed.

2.1.2 Decompositional or conjoint model

The term stated preference analysis as used in transportation research typically refers to this modeling approach. As the term suggests, decompositional preference models decompose the measured preference or utility for a multi-attribute choice alternative into the part-worth utilities of the attribute levels that make up the choice alternative, according to some pre-specified combination rule. The vast majority of models assume that a linear additive model is used for this integration process. The model can then be expressed as:

$$U_i = \mu_0 + \sum_k \sum_l^{L_k - 1} u_{kl} x_{ikl}$$

U_i is an individual's overall utility for choice alternative i;

μ_0 is the utility of the base alternative;

u_{kl} represents the derived part-worth utility of level l of attribute k;

x_{ikl} is a coded variable representing level l of the k-attribute.

In order to arrive at an unbiased estimate of these part-worth utilities, experimental designs are used. The properties of the design that is used should allow one to estimate the model of interest.

Developing a conjoint preference model involves the following steps. First, the attributes influencing the problem of interest should be elicited. This can be done on the basis of a literature review, factor listing, repertory grids, focus group and many other methods. Some of these attributes will be selected because they have a high impact on preference formation or choice; others will be selected because they are relevant from a policy point of view.

The choice of the number of attributes influences the complexity of the experimental design and therefore respondent burden. Ceteris paribus, a larger number of attributes implies a larger number of attribute profile and/or choice sets, increasing the time it takes to complete the experimental task. Moreover, a larger number of attributes means a longer time to appreciate the description of the choice alternatives. In the transportation literature, there is a tendency to use a small number of attributes. If, however, this would unrealistically reduce the complexity of the problem under investigation, this rule of thumb only has negative effects.

Secondly, each attribute should be defined in terms of a set of attribute levels. Often, the attribute levels are dictated by reality. Quantitative attributes, however, should be discretisized. The levels should be realistic and span the domain of interest. Moreover, if one wishes to estimate a non-linear utility function, the number of attribute should at least be equal to three. Another consideration is that five or more levels often create problems in terms of constructing an economical experimental design.

Having decided on the number of attributes and the attribute levels, these are combined according to some experimental design to create attribute profiles. If all possible combinations of attribute levels are used, a full factorial design is used. In most cases, however, the number of resulting attribute profiles would be overwhelming, and hence a fractional factorial design is typically used. If one assumed that all interaction effects are negligible, the smallest orthogonal fraction can be used to estimate a main-effects only linear additive model. One should realize however that the interaction effects of these designs are typically not independent from the main effects, implying that if interaction effects do occur in the response patterns they are confounded with the main effects. Some, mostly larger design, allow the estimation of some first order interaction effects.

Originally, these models were used to estimate preference functions. When used to predict choices, the estimated preference functions were linked with some choice rule as discussed above for the compositional models. However, this practice does not allow one to test the choice rule. Louviere and Woodworth (1983) therefore suggested to estimate choice models from the experimental design data. To estimate such decompositional or conjoint choice models, the attribute profiles need to be placed into choice sets. Several design strategies to construct such designs have been suggested (Louviere and Timmermans, 1990a). If a multinomial logit model is used, one can construct the choice sets at random. In contrast, if the IIA-property of the MNL model needs to be tested one should create an orthogonal overall design, in which the attributes within and between choice alternatives are orthogonal. The IIA-property states that the probability of choosing a particular choice alternative is independent of the composition of the choice set. Over the last couple of years, the construction of experimental designs have received a new impulse, exploring the possibility to construct efficient designs with particular properties. The discussion of this work is however beyond the scope of this paper.

Next, one has to decide on the presentation of the attribute profiles and response format/experimental task. In most studies, attribute profiles are presented verbally. Sometimes, however, visualization may be a better means of capturing the meaning of an attribute level. There is also some work on using virtual reality to allow people to appreciate the meaning of an attribute profile (Dijkstra, et al, 2003). When the goal is to estimate a preference function, the attribute profiles can either be ranked or rated. When the aim is to estimate a choice model, respondents are invited to choose in each choice set the alternative they like best, or to allocate some fixed resources (money, trips, etc) to the choice alternatives in each choice set.

Finally, given these responses, the preference function can be estimated. The choice of statistical method depends on the nature of the response data. If the attribute profiles were ranked, some multidimensional scaling is strictly speaking the best method to derive the parameters of the preference/utility function. If the profiles were rated in terms of overall preference, multiple regression analysis can be used. If choice data were obtained, procedures for estimating discrete choice models can be applied (see Louviere and Timmermans, 1990a for an overview). The data need to be properly coded before applying the appropriate statistical method. Each attribute with L levels is coded in terms of L-1 indicator variables. Choice alternatives can be coded in a similar way. Different coding schemes can be used. Dummy coding means that the value of the indicator variable, corresponding to the attribute level is coded as one, while all other indicator variables are equal to zero. One attribute level (the base) is coded as zero across all indicator variables. Effect coding implies that the base is coded as –1 on all indicator variables. One can also use orthogonal coding schemes. The overall goodness-of-fit of the model are not influenced by the coding scheme that is used. The interpretation of the estimated parameters and the t-tests however depends on the chosen scheme. When dummy coding is used, the parameters pick up differences between the corresponding attribute levels and the base level, and the t-test indicates whether this difference is significant. In contrast, effect coding picks up differences with the mean and the t-tests indicate whether the part-worth utility of the corresponding attribute level is significantly different from the mean utility, which is represented by the intercept of the regression equation. Orthogonal scheme picks up contract between attribute levels.

Over the years, much progress has been made in refining and elaborating this modeling approach. It goes beyond the present paper to discuss all these developments. I will however briefly discuss some developments that have widened the possible application of these models.

3. COMPLEX CHOICE BEHAVIOR

This term has been use to indicate that many attributes influence the choice behavior under investigation. The use of a fractional factorial design will generate too many profiles or choice sets to be realistically completed by an individual respondent. To handle this problem of information overload, Louviere (1984) introduced the method of hierarchical information integration. He assumed that when faced with complex decisions, individual will first classify the attributes into higher order decision constructs, evaluate each higher order construct separately and then trade-off their evaluations of these higher order constructs to arrive at an overall preference. Consistently with this theory, he suggested to create a separate orthogonal, fractional factorial design for each decision construct and an additional bridging experiment that varies the evaluations of the higher order decision constructs. Later, Timmermans (1989; see also Louviere and Timmermans, 1990b) generalized this method to the case of choice as opposed to preference. In this case, the bridging experiment is a choice design.

One of the problems with this approach is that the assignment of attributes to higher order constructs cannot be tested. Moreover, as individual respondents do not complete all, but typically one subdesign and the bridging experiment, they do not know what to assume about the other decision constructs. Oppewal, Louviere and Timmermans (1994), therefore, suggested the method of integrated choice experiments. In this case, summary construct evaluations of the remaining higher order decision constructs are added to the design varying the attribute levels of a specific higher order decision construct.

Another way of reducing information overload is to use pairwise conjoint analysis (Wang et al, 2001). In this case, attribute levels are varied in pairs and respondents need to assume that all other attribute levels are the way they are now. The advantage of this approach is that respondent burden is further reduced. However, the base alternative now varies between respondents.

4. FROM INDIVIDUAL TO GROUP MODELS

Conjoint preference and choice models typically represent individual choice behavior. While this may be realistic in many cases, choices such as vacation choice and housing choice are probably group/family decisions. The logic behind hierarchical information has been used in a slightly different way to build group utility and choice models. Timmermans, et al (1992) modeling the residential/job choice decision of dual-earner household, suggested to develop an experiment for each construct for each family member separately, and a bridging experiment to arrive at a joint choice. This bridging experiment used the evaluations of the various constructs for each spouse. To take advantage of the positive properties of integrated experiments, this design strategy was later applied by Molin, et al (1999). In addition, rather than having individuals responding to experiments, they had groups/families completing all tasks, implying that any negotiation may be better reflected in the response patterns. Comparative analyses suggested that indeed the latter approach generated the best predictive results (Molin, et al, 2001).

5. CONTEXT-SENSITIVE MODELS

Conjoint preference and choice models typically estimate context-invariant preference and choice models, implicitly assuming that the context does not exert any influence on people's preference and choice behavior. For situations where this may be a too rigorous assumption, Oppewal and Timmermans (1991) indicated how context-sensitive models can be built. First, an orthogonal fractional factorial design is constructed, varying the condition states that define the context. The choice sets or attribute profiles are then nested under this design. Finally, the effects of the condition states are represented in terms of interaction effects between the condition states and the attribute levels.

5.1 Hybrid models

The third approach is called the hybrid modeling approach. This approach is an amalgamation of the measurement procedures associated with the other two approaches. The approach requires an individual to rate both the overall evaluation for the choice alternatives and an evaluation of the attribute levels characterizing the choice alternative. Unlike the compositional model, the importance weights are not explicitly measured but are estimated using multiple regression analysis. The overall evaluation constitutes the dependent variable in the regression, while the evaluations of the attribute of the choice alternatives constitutes the independent variables. Three specifications have often been used: the linear model, the multiplicative model and the addilog model, which can be expressed respectively as:

$$U_i = \beta_0 + \sum_k \beta_k E_{ik}$$

$$U_i = \prod_k \beta_0 E_{ik}{}^{\beta_k}$$

$$U_i = \beta_0 + \sum_k \beta_k \log E_{ik}$$

The parameters of the multiplicative models can be easily obtained by taking the natural logaritm on both sides of the multiplicative equation. The addilog model was suggested on the basis of empirical evidence, which suggested that an individual's perception of differences in physical stimuli is proportional to the logarithm of the difference and not the distance itself.

5.2 Non-algebraic approaches

The above algebraic models use mathematical equations to represent and predict preferences and choices. In addition to these models, some qualitative, Boolean approaches have been suggested in the literature. The express preference formation and choices in terms of a set of logical conditions that need to be satisfied to generate a particular preference or choice. I will focus the discussion on decision nets and decision tables.

5.2.1 Decision nets

Basically, decision nets represent a structured interview, which aims at disentangling individuals' decision making processes. Individuals are requested to identify the attributes that influence their decisions of interest. Then, they are invited to explicate the levels of each of these attributes at which they would no longer consider the choice alternative (rejection-inducing attribute). They can also indicate that they would still consider the alternative, if it would meet their criteria on all other attributes, or if this attribute would be compensated by better scores on one or more of the other attributes (trade-off attribute). Timmermans and van der Heijden (1987) applied this modelling approach to the study of recreational behaviour. It has also found increasing application in housing studies (e.g., Op 't Veld, et al, 1987). Figure 1 presents an example

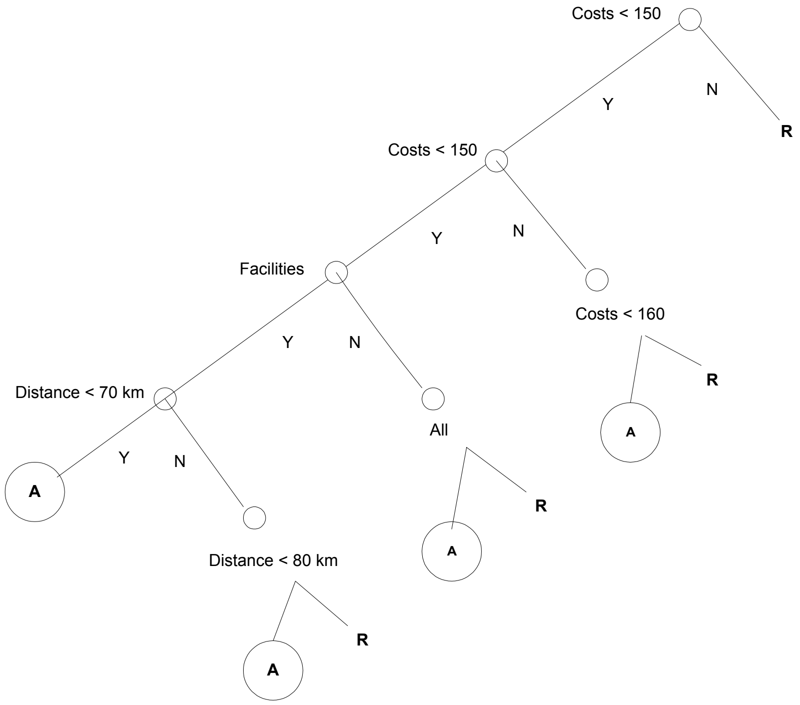

Figure 1. Example of a decision net. (Source: Timmermans and van der Heijden, 1987)

Most studies only attempted to identify the attributes of interest and their role in the decision making process. This results in a decision net describing the nature of the decision-making process under investigation, and assists in identifying constraints, trade-off dimensions, etc. If one wishes to use decision nets for prediction, the implied logical conditions need to be represented. Expert systems and Prolog or Lisp constitute natural environments for this kind of analysis. By using the qualitative conditions as rules in such systems, actual behaviour can in principle be simulated. This involves testing whether a particular choice alternative meets the conditions represented by the system. In some cases, some additional ad hoc rules may be required to perform a complete simulation that will result in a single choice.

5.2.2 Decision tables

Decision tables were initially introduced over three decades ago, primarily as a method in software engineering for structuring computer programmes (McDaniel, 1970; Montalbano, 1974).

It was found that, as a formalism, DTs were very well-suited to describe and analyse problems that contain procedural decision situations which are characterised by a set of influential conditions, the state of which determines the execution of a set of actions (CODASYL, 1982). Later on, several other important application domains such as manual decision-making, system analysis and design, representation of complex texts, verification of knowledge bases, and knowledge acquisition emerged (Vanthienen and Dries, 1992, 1994). In recent years, the potential of DTs as a conceptual modelling language for representing qualitative and complex knowledge have been investigated (Lucardie, 1994; Arentze *et al*., 1996).

Formally, a decision table (DT) is "a table that represents the exhaustive set of mutually exclusive conditional statements within a pre-specified problem area " (Verhelst, 1980). It displays the possible actions that a decision-maker can follow according to the outcome of a number of relevant conditions. The *condition set* consists of all the relevant conditions or attributes (inputs, premises or causes) that have an influence on the decision-making process. The *condition space* specifies all possible combinations of *condition states* of a condition. The number of possible condition states is unlimited, at least in theory. It could range from one to any desired number. However, the more condition states used, the more complex the decision table structure will be. The *action set* contains all the possible actions (outputs, conclusions or consequences) a decision-maker is able to take. The *action space* contains the categorizations of all the possible *action states* of an action. The number of possible action states is also unlimited.

Each column of the decision table thus specifies a rule that will lead to a particular action (type of behavior or preference. Figure 2 below presents an example.

Centry supply action							
C1	Number of supermarket outlet	None	one				More than one
C2	M2 gross floor space of the supermarket	-	< 700	700 – 800		> 800	-
C3	All fresh products are available	-	-	no	Yes	-	-
A1	Expand floor space of supermarket	-	X	-	-	-	-
A2	Open large supermarket	X	-	-	-	-	-
A3	Open complimentary specialty stores	-	-	X	-	-	-
		R1	R2	R3	R4	R5	R6

Figure 2. Decision table for centre supply actions (Source: Arentze, 1999).

As a rule, conditions (or attributes) and actions have to be unambiguous, relevant and realistic to the decision-maker. All condition recurrences, as well as all complementary conditions, should be avoided. Conditions that depend upon other conditions should separately be treated, and ranked in such a way that dependent conditions follow independent conditions. In respect to the categorisation of the conditions, two important logical requirements must be fulfilled: *exhaustivity* and *exclusivity*. Exhaustivity means that the DT must account for all possible states that a condition is able to take. The exclusivity requirement refers to the fact that each combination of condition states has to be included in one and only one column of the DT. Therefore, an important property of using decision tables is that the condition states are mutually exclusive but jointly form an exhaustive set. Other formalisms, including decision trees, do not necessarily guarantees these properties, which may cause problems.

Decision tables can be used to simulate behavior. An example is the Albatross model (Arentze and Timmermans, 2000), which is based on decision tables. Traditionally, these rules were deterministic or crisp. As part of this project, however, probabilistic rules were developed. Alternatively, fuzzy rules can be used (Wets, 1998). Also, as part of this project, Arentze and Timmermans (2003) developed a method to assess the impact of each rule on the final outcome.

Originally, the rules are extracted from interviews. However, more recently, rule-inducing algorithms have been applied to extract the rules from empirical data. This process is similar to the estimation of the parameters of algebraic models.

3. CONCLUSIONS AND DISCUSSION

In this paper, I have briefly discussed the essentials underlying some approaches to modelling consumer preference and choice. Each of these approaches has particular advantages and drawbacks. A researcher can take these into considerations when choosing a particular approach. Table 1 gives an overview.

Within the set of algebraic models, the main advantage of compositional approaches is their ease of use. They have been criticised for their lack of theoretical underpinnings, but critics often meant that they cannot be derived from random utility theory. Compositional model are, however, consistent with several attitude theories and theories in social psychology. Researchers have considerable flexibility in specifying the preference function as the choice is not restricted by statistical or methodological considerations. This is however also the weakness of these models. Assumptions are not rigorously tested. Moreover, the predictive performance of the compositional modelling approach has been shown weak compared to conjoint preference models (e.g. Akaah and Korgaonkar, 1983; Timmermans, 1987). This is likely due to the fact that respondents do not have to make trade-offs and hence have difficulty in understanding what to assume about the other attributes. Because parameters are not estimated, individual levels can be developed.

Table 1. Overview.

Component	Compositional	Conjoint	Hybrid	Decision tree	Decision table
Overall utility	Calculated	measured	measured	elicited	Elicited or induced from data
Attribute evaluations	measured	estimated	measured	------	------
Importance weights	measured	implicit	estimated	------	-------
Combination rule	assumed	tested	tested	multiple rules	multiple rules
Level of aggregation	individual level	mostly aggregate; sometimes individual	individual or aggregate	individual	individual

The main advantage of conjoint models is that the assumed preference and choice models can be rigorously tested. There is also consistent evidence that these models outperform the compositional and hybrid models. On the other hand, except for small “toy” problems, preference and choice models with a realistic number of attributes can only be estimated at the segment or aggregate level, implying that it is more difficult to incorporate heterogeneity.

Also, the number of attribute levels is usually restricted. There is now increasing awareness that the variation in the attribute levels may influence the scale parameter of the estimated multinomial logit model and thereby the prediction of real world choice behavior (Louviere, et al, 2002), leading to recent stream of methodological research.

The advantages and disadvantages of hybrid models are somewhere in between. Individual-level models can be developed. They seem to have a reasonable predictive performance. They are however less rigorous.

The main advantage of rule-based models over the algebraic models is that of flexibility. Some behavioural mechanisms such as thresholds and equivalence are difficult to incorporate into algebraic models. Many different kinds of assumptions are needed to simulate behavior. This may also be the disadvantage of this approach. It lacks the theoretical and analytical rigor of the conjoint models. Moreover, it does not have an error theory, implying that one either relies on the measurements or makes ad hoc non-testable assumptions. If decision rules are derived from interview protocols, the question is whether subjects indeed are capable of reproducing their decision-making process.

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