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Extended Framework for Modeling Choice Behavior

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Abstract

We review the case against the standard model of rational behavior and discuss the consequences of various "anomalies" of preference elicitation. A general theoretical framework that attempts to disentangle the various psychological elements in the decision-making process is presented. We then present a rigorous and general methodology to model the theoretical framework, explicitly incorporating psychological factors and their influences on choices. This theme has long been deemed necessary by behavioral researchers, but is often ignored in demand models. The methodology requires the estimation of an integrated multi-equation model consisting of a discrete choice model and the latent variable model system. We conclude with a research agenda to bring the theoretical framework into fruition.

Key words: Rationality, behavioral decision theory, psychological factors, latent constructs, choice modeling

Introduction

This paper is concerned with fundamental aspects of modeling choice behavior. We begin with a review of the case against the standard model of rational behavior and discuss the consequences of various "anomalies" of preference formation and choice behavior. We then present an extended theoretical framework and corresponding modeling methods designed to incorporate fundamental psychological insights into empirical choice models. We conclude with suggested research directions.

Rational Behavior[1]

Rational behavior, in the broad meaning of behavior that is sensible, planned, and consistent, is believed to govern market behavior. However, rationality has been given a much more specific meaning in the classical theory of consumer demand perfected by Hicks and Samuelson. In Simon's words, "The rational man of economics is a maximizer, who will settle for nothing less than the best" (Simon, 1959). While this model of consumer behavior dominates demand analysis, there is a long history of questioning its behavioral validity and seeking alternatives.

Behavioral Decision Theory (BDT) had its origins in the von Neumann and Morgenstern (1947) treatise on choice under uncertainty and game theory. This work had two major impacts: (a) it made formal, axiomatic analysis fashionable in economics and psychology, and (b) it invited laboratory experimentation to test the descriptive validity of the axioms. In the following decades, behavioral evidence against the rational model has been accumulating.

Choice behavior can be characterized by a *decision process*, which is informed by perceptions and beliefs based on available information, and influenced by affect, attitudes, motives, and preferences. *Perceptions* are the cognition of sensation. *Affect* refers to the emotional state of the decision-maker and its impact on cognition of the decision task. *Attitudes* are defined as stable psychological tendencies to evaluate particular entities (outcomes or activities) with favor or disfavor. *Motives* are drives directed toward perceived goals. *Preferences* are comparative judgments between entities. Under certain technical conditions, including completeness and transitivity, preferences can be represented by a numerical scale, or *utility*. The *cognitive process* for decision-making (DM) is the mental mechanism that defines the cognitive task and the role of perceptions, affect, attitudes, motives and preferences in performing this task to produce a *choice*.

Economics and psychology have radically different views of the D-M process. First, the primary focus of psychologists is to understand the nature of the decision elements, how they are established and modified by experience, and how they determine behavior. The primary focus of economists is on the mapping from information inputs to choice. Preferences, or values, are treated as primitives of the analysis, and the decision process as a black box. Second, psychological views of the D-M process are dominated by ideas that behavior is local, adaptive, learned, dependent on context, mutable, and influenced by complex interactions of perceptions, motives, attitudes, and affect. The *standard model* in economics is that consumers behave *as if* information is processed to form perceptions and beliefs (*perception-rationality*); preferences are primitive, consistent, and immutable (*perception-rationality*); and the typical cognitive process is preference maximization, given market constraints (*process-rationality*).

Accumulating behavioral evidence against the standard model indicates that consumers may be wired differently than what economic rationality posits. While the consumer's wiring may produce market behavior patterns that in many cases can be approximated well by the standard model, when we approach the consumer from a different angle, asking direct questions about beliefs or values, we find alarming deviations from the standard model.

Rationality and the Standard Model

The standard model of perception, preference, and process rationality is associated with one-way flows from perceptions and tastes to the cognitive task of preference maximization. This view of rationality is virtually irrefutable until one starts to restrict and codify the manner in which preferences shift with experience in subsequent choice occasions. A theory of aggregate demand, which looks only at the distribution of outcomes, handles individual preference volatility in the same way that it handles heterogeneity in preferences across individuals; see McFadden (1981, 1997b). Stochastic rationality is sufficient to accomplish major objectives of demand analysis, while avoiding some of the invariance properties in restrictions and codification of the standard model that are refuted experimentally. Unfortunately, stochastic rationality cannot explain cognitive anomalies that correspond to shifts in the distribution of preferences, nor is it immune to experimental refutation. For example, it implies the potentially refutable *regularity property* that a choice probability cannot rise when the choice set is expanded.

Systematic failures of rationality do not necessarily imply a total rejection of the standard model. Because we can never measure all the aspects of the complex life-course of consumer choices, we are never sure whether what appears to be irrational behavior in some limited time window is not part of an overarching rationality, a grand strategic design. Moreover, the standard model is viewed as a practical approximation. As such, the model is not expected to work perfectly, and evidence against the approximation is not necessarily evidence against the fundamentals of demand analysis. Perhaps this is a sensible way to approach aggregate demand analysis, but it may blind us to behavioral evidence that challenges rationality at a more fundamental level.

The Psychology of Decision-Making

Psychology has various theories and techniques for studying the D-M *process*, including decision latencies, information search, and verbal reports (before, during, and after decisions are made), and has accumulated a large body of experimental evidence. The leading research paradigm has been the focus of Tversky and Kahneman on experimental study of *cognitive anomalies*: circumstances in which an individual exhibits surprising departures from rationality. The studies show that individuals faced with decision-making tasks in carefully constructed experimental settings often exhibit behavior that is inconsistent with the rational model hypothesis (see, for example, Tversky and Kahneman, 1974). Decision-makers have trouble handling information and forming perceptions consistently, use D-M heuristics that can fail to maximize preferences, and are too sensitive to context to satisfy rationality postulates.

Such experimental results have not been codified into a "standard model" for BDT, and many psychologists would argue it is not possible or useful to construct such a model. Nevertheless, it is possible to identify some of the major features of the psychological view of D-M. The central element is the *process* by which the cognitive task is defined and elements such as perceptions and attitudes enter. Attitudes and affect are major factors in determining motivation and the structuring of the cognitive task. Attitudes and affects also influence perceptions. Finally, there may be feedback, from process and choice to attitudes and perceptions, as the decision-maker reconciles and rationalizes trial choice. Preferences may play a role in the psychological view, as does maximization, but they compete with other heuristics for defining and solving the cognitive task.

Psychologists make a sharp distinction between attitudes and preferences. In this view, attitudes are multi-dimensional, with no requirement of consistency across attitudes. Preferences are viewed as constructed from more stable attitudes by a context-dependent process that determines the prominence given to various attitudes and the tradeoffs among them; see Payne et al. (1993) and Kahneman et al. (1998).

Choice tasks are distinguished by their complexity and familiarity, from quick and largely "automatic" or impulsive decisions on the one hand to complex, "planned" decisions on the other; see Ajzen (1991), Gärling (1992), Gärling and Gillholm (1998). An example of an automatic decision is choosing to change lanes when driving. An example of a planned decision, which may also contain impulsive elements, is choice of occupation, where the alternatives must be elicited or created, and the task requires problem-solving to clarify attributes and goals. Psychologists emphasize the importance of affect on decisions, with emotion not only inducing impulsive decisions, but also coloring perceptions; see Loewenstein (1996).

There may be feedback from the D-M process to perceptions, particularly through affect and attitudes, with perceptions becoming an instrument to facilitate the cognitive D-M process. Svenson (1992, 1998) describes a D-M process in which simple heuristics are used to produce a preliminary choice, using *markers* and *editing* to simplify and group information. The decision-maker then engages in a process of differentiating the test choice from the alternatives through an internal dialogue. The ambiguity about tastes is resolved so that features where the test choice has an advantage are emphasized, through sharpening of perceptions of the favorable attributes of the test choice and unfavorable attributes of alternatives, and through restructuring of the choice situation by adding or resurrecting alternatives. There may also be consolidation of perceptions following choice, to reduce dissonance and promote development of rules and principles for future decisions.

Psychologists use the terms *reason-based* or *rule-driven* to refer to behavioral processes that override cost-benefit calculations, relying instead on principles or analogies to guide choice; see Prelec (1991). There is nothing in rule-driven behavior *per se* that is inconsistent with the view of the rational consumer; rules may simply facilitate the consumer's life-course strategic preference maximization. This could be true even if rule-driven behavior is apparently inconsistent with the standard model. However, strategically optimal behavior will appear tactically sub-optimal precisely when the purpose of strategy is to avoid tactical decisions that have *long-run* implications.

How deeply do cognitive anomalies infect market behavior and how much of the standard demand analysis can be preserved? The answers will depend critically on how rationality fails. It is possible that the standard model of rationality works well in some circumstances, where repetition and the experience of market rewards train consumers to adopt behavior rules that are consistent with rationality. It is also possible that consumers conform to the rational model at some points in the decision process but not in others. (See Camerer (1997), Rabin (1998), and Thaler (1991) for excellent surveys of BDT.)

Theoretical Framework

The crux of the theoretical framework presented in Figure 1 is the D-M process that generates an outcome from a set of optional ones or an intention to implement such a choice. In accordance with Payne et al. (1993), the D-M process is defined as a sequence of mental operations used to transform the initial state of knowledge into a final *goal* state of knowledge.

In our theoretical framework, we do not attempt to develop a detailed description of the D-M process. However, we note that the process varies across:

- Decision problems (e.g., simple vs. complex, well-defined vs. ill-defined, quantitative vs. qualitative, risky vs. risk-free, reversible vs. irreversible outcomes);
- Contexts (e.g., degree of time pressure);
- Social situations (e.g., degree of accountability, group vs. individual decision); and
- Individuals (degree of cognitive capacity, degree and type of prior knowledge, affective state, degree of motivation).

Therefore, it is necessary to unravel the black box and incorporate the sources of process variations to better predict the outcomes.

We posit factors which affect the D-M process, and thereby, the outcome. We identify five general psychological factors, represented by the ellipses in Figure 1, which affect the D-M process. The figure follows the convention of depicting a path diagram where the ellipses represent *unobservable* (i.e., latent) constructs, while rectangles represent *observable* variables. The arrows from the ellipses to the rectangles, labeled as *indicators*, represent the measurements needed to quantify and characterize the latent constructs. The relevance of the latent psychological factors in the D-M process is considered below.

Humans adapt to changing external and internal environment while aiming to achieve goals such as survival, well being, or pleasure. Extensive research has revealed how individuals cognitively represent such goals and how they are prioritized (Schwartz, 1992).

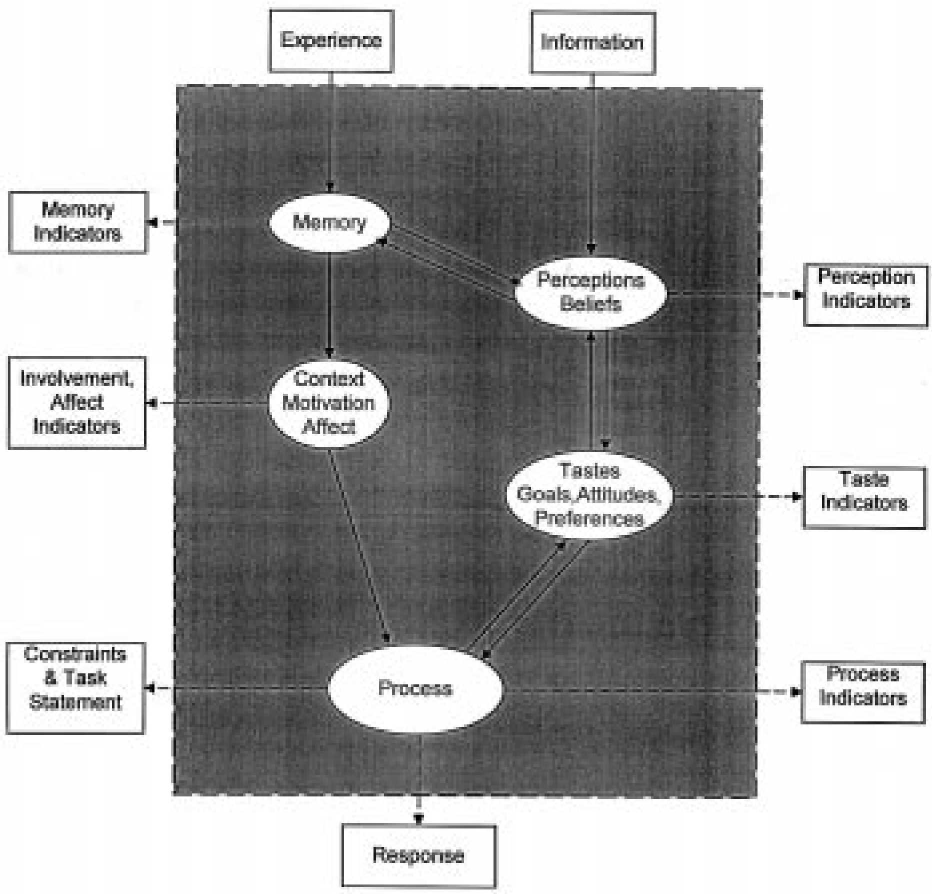

Figure 1. Theoretical Framework for Modeling Choice Behavior.

Cognitively, goals are represented hierarchically (Kahle et al., 1986). In such hierarchies, higher-order goals are assumed to be more stable than lower-order goals. We assume that individuals strive to achieve higher-order goals that we refer to as *tastes or values*. An important component of the D-M process is to evaluate the different outcomes of the optional courses of action relative to tastes (Lindberg et al., 1989). We assume that this stage of the D-M process is always present unless the process is completely rule-based in which case outcomes are ignored[2]. It has been found that automatic processing is frequently goal-driven to the same extent as deliberate processing (Bargh and Barndollar, 1996). On the other hand, a shallow process may result in an outcome that is less likely to achieve the goal compared to an outcome from a deeper process (Messick, 1993).

Individual's motivational and affective states have been demonstrated to have profound effects on the D-M process. A decision may for some reason be perceived to be less important, in which case an individual would be less motivated to invest in the required effort (Payne et al., 1993). Such motivational and affective states are characterized by varying degrees of arousal and hedonic tone (Mano and Oliver, 1993; Russell et al., 1989). A positive affect has been shown to promote a negative risk attitude, whereas arousal is directly related to shallow processing (Isen, 1987). Influences of transient affective and motivational states may seem largely unpredictable, however, it should be realized that situational factors are important in inducing affects. Similarly, the value and reversibility of outcomes are likely to affect motivation and involvement.

The framework also takes into account human cognitive limitations. Such cognitive limitations are well known and documented (e.g., Newell and Simon, 1972). However, humans are also known to have a remarkable ability to overcome such limitations through practice. A notable exception to this is a decision-making situation where an easily understood feedback is absent (Camerer and Johnson, 1991). The cognitive limitations are reflected in the speed with which information is processed as well as in the amount and type of information processed. Input to the D-M process consists of information about alternative courses of action as well as information about situational constraints. If memory or decision aids are unavailable and/or time pressure exists, working memory capacity is sometimes overtaxed. Changes in the D-M process should be viewed as an adaptive response to such overloads (Payne et al., 1992).

As seen in Figure 1, the D-M process is also assumed to influence beliefs through experience and memory. At least some of the so-called "biases" are better understood as adaptive changes of the D-M process (Gigerenzer and Goldstein, 1996; Gärling et al., 1997). Reference point or framing and anchoring effects, which distort evaluations of alternatives, may reflect maladaptive perceptual-like judgment components of the D-M process, instead of biases (Tversky and Kahneman, 1992). Although these effects are strikingly consistent, a recent meta-analysis shows that they may be rather weak (Kühberger, 1998). Research findings from applying process tracing techniques suggest that tentative choices may be made in the D-M process (Montgomery and Svenson, 1989). Such tentative choices change beliefs (Festinger, 1957; Janis and Mann, 1977; Montgomery, 1983; Svenson, 1992). Specifically, evaluations of a tentative choice appear to increase the likelihood that it will be chosen later. It is possible that these kinds of distortions reflect cognitive limitations when involvement is particularly high, thus may constitute still another example of adaptive failures.

Modeling the Theoretical Framework[3]

The objective is to explicitly model the D-M process depicted in Figure 1. The model needs to include relationships that quantify the attitudes, perceptions and other psychological constructs, explain how they are formed, and thereby, influence choices.

The methodology presented is an integration of latent variable models, which aim to quantify unobservable constructs, with discrete choice models, resulting in a rigorous theoretically grounded methodology for explicitly including psychological factors in choice models. It incorporates indicators provided by responses to survey questions related to attitudes, perceptions, motivation, memory and decision protocol to aid in estimating the model. A simultaneous estimator can be used, which results in latent variables that provide the best fit with the information provided by both the choice and the indicators of the latent variables.

Notation. The following notation is used:

X	observed variables, including
	S characteristics of the individual
	Z_i attributes of alternative i
X^*	latent (unobservable) variables, including
	S^* latent characteristics of the individual
	Z_i^* latent attributes of alternative i as perceived by the individual
I	indicators of X^*
	(e.g., responses to survey questions related to attitudes, perceptions, etc.)
	I_s indicators of S^*
	I_{z_i} indicators of Z_i^*
U_i	utility of alternative i
U	vector of utilities
y_i	choice indicator; equal to 1 if alternative i is chosen and 0 otherwise
y	vector of choice indicators
α, β, γ	unknown parameters
η, ε, υ	random disturbance terms
Σ_η, Σ_ε, Σ_υ	covariances of random disturbance terms

The modeling framework shown in Figure 2 consists of two components: a choice model component and a latent variable model component. As in the previous section, the figure uses the convention of depicting a path diagram where ellipses represent *unobservable* (i.e., latent) constructs, while rectangles represent *observable* variables.

As with any random utility choice model, the individual's utility U for each alternative is assumed to be a latent variable, and the observable choices y are *manifestations* of the underlying utility. A dashed arrow representing a *measurement equation* links the unobservable U to its observable indicator y. Solid arrows representing *structural equations* (i.e., the cause-and-effect relationships that govern the D-M process) link the observable and latent variables (X, X^*) to the utility U.

It is possible to identify a choice model with limited latent variables using only observed choices and no additional indicators (e.g., Elrod, 1998). However, it is quite likely that the information content from the choice indicators will not be sufficient to empirically identify the effects of individual-specific latent variables. Therefore, indicators of the latent variables are used for model identification, which leads us to the latent variable portion of the combined model.

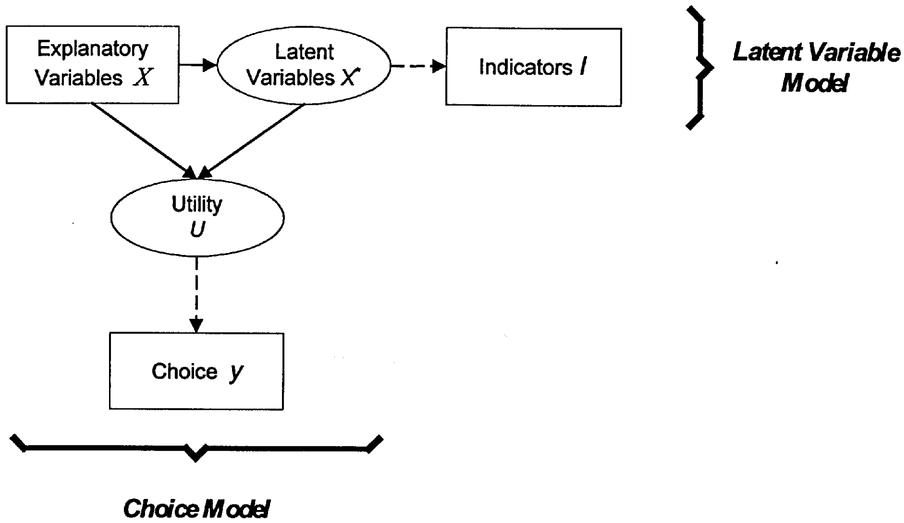

Figure 2. Integrated Choice and Latent Variable Model.

The top portion of Figure 2 is a latent variable model. Latent variable models are used when we have available indicators for the latent variables X^*. Indicators could be responses to survey questions regarding, for example, the level of satisfaction with or importance of attributes, level of adherence to a decision protocol, alternatives considered, etc. The figure depicts such indicators I as manifestations of the underlying latent variable X^*, and the associated measurement equation is represented by a dashed arrow. A structural relationship links the observable causal variables X (and potentially other latent endogenous variables X^*) to the latent variable X^*.

The integrated choice and latent variable model explicitly incorporates the latent variables that influence the choice process. Structural equations relating the observable explanatory variables X to the latent variables X^* captures the behavioral process of formation of the latent variables. While the latent constructs are unobservable, their effects on indicators are observable. The indicators allow identification of the latent constructs and also contain information, thus potentially provide for increased efficiency in model estimation. Note that the indicators do not directly influence the behavior. That is, the causal relationship goes *from* the latent variable *to* the indicator, and the indicators are only used to measure the underlying causal relationships (the solid arrows). Consequently, the indicators are typically used only in the model estimation stage and not in model application.

As described earlier, the integrated model is composed of two parts: a discrete choice model and a latent variable model. Each part consists of one or more structural equations and one or more measurement equations. Specification of these equations and the likelihood function follow.

Structural Equations

For the latent variable model, we need the distribution of the latent variables given the observed variables (and, potentially, other latent variables), $f_1(X^*|X;\gamma,\Sigma_\eta)$. For example:

$$X^* = h(X;\gamma) + \eta \tag{1}$$

This results in one equation for each latent variable. For the choice model, we need the distribution of the utilities, $f_2(UX, X^*;\ \beta,\ \Sigma_\varepsilon)$. For example:

$$U = V(X, X^*;\ \beta) + \varepsilon \tag{2}$$

Note that the random utility is decomposed into systematic utility and a random disturbance, and the systematic utility is a function of both observable and latent variables.

Measurement Equations

For the latent variable model, we need the distribution of the indicators conditional on the values of the latent variables, $f_3(I|X, X^*;\ \alpha,\ \Sigma_\upsilon)$. For example:

$$I = g(X, X^*;\ \alpha) + \upsilon \tag{3}$$

This results in one equation for each indicator. These measurement equations usually contain only the latent variables on the right-hand-side. However, they may also contain individual characteristics or any other variable determined within the model system such as the choice indicator. In principle, such parameterizations capture systematic response biases when the individual is providing indicators. For example, in a brand choice model with latent product quality (Z^*), one may want to include the choice indicator (y_i) for the chosen brand, for example, $I_r = \alpha_{1r} Z_i^* + \alpha_{2r} y_i + \upsilon_r$ for each indicator r of latent product quality Z_i^*. This would capture any exaggerated responses in reporting the perceived quality of the chosen brand, perhaps caused by justification bias.

For the choice model, we express the choice as a function of the utilities. For example, assuming utility maximization:[4]

$$y_i = \begin{cases} 1, & \text{if } U_i = \max\limits_j \{U_j\} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Note that $h(\cdot)$, $V(\cdot)$, and $g(\cdot)$ are functions, which are currently undefined. Typically, the functions are specified to be linear in the parameters, but this is not necessary. Also note that the distribution of the error terms must be specified, leading to additional unknown covariance parameters. These parameters often include numerous restrictions to both simplify the model and aid model identification.

Integrated Model

The integrated model consists of equations (1) to (4). Equations (1) and (3) comprise the latent variable model, and equations (2) and (4) comprise the choice model. From equations (2) and (4) and an assumption about the distribution of the disturbance, ε, we can derive $P(y|X, X^*; \beta, \Sigma_\varepsilon)$, the choice probability conditional on both observable and latent explanatory variables.

Likelihood Function

In order to use maximum likelihood techniques to estimate the parameters, we must write the likelihood function. The most intuitive way to create the likelihood function for the integrated model is to start with the likelihood of the choice model portion without considering the latent variables. The likelihood from a choice model without latent variables is simply:

$$P(y|X; \beta, \Sigma_\varepsilon) \tag{5}$$

This choice model can be one of any number of forms, e.g., logit, nested logit, multinomial probit, and can include a combination of different choice indicators such as stated and revealed preferences.

Now we add the latent variables. Once we hypothesize the unknown latent constructs, X^*, the associated distribution, and independent (for simplicity) error components (η, ε), the likelihood function is then the integral of the choice model over the distribution of the latent constructs:[5]

$$P(y|X; \beta, \gamma, \Sigma_\varepsilon, \Sigma_\eta) = \int_{X^*} P(y|X, X^*; \beta, \Sigma_\varepsilon) f_1(X^*|X; \gamma, \Sigma_\eta) dX^* \tag{6}$$

We introduce indicators to improve the accuracy of estimates of the structural parameters. Assuming, for simplicity, the error components (η, ε, v) are independent, the joint probability of the observable variables y and I, conditional on the exogenous variables X, is:

$$\begin{aligned} & f_4(y, I|X; \alpha, \beta, \gamma, \Sigma_\varepsilon, \Sigma_v, \Sigma_\eta) \\ & \quad = \int_{X^*} P(y|X, X^*; \beta, \Sigma_\varepsilon) f_3(I|X, X^*; \alpha, \Sigma_v) f_1(X^*|X; \gamma, \Sigma_\eta) dX^* \end{aligned} \tag{7}$$

Note that the first term of the integrand corresponds to the choice model, the second term corresponds to the measurement equation from the latent variable model, and the third term corresponds to the structural equation from the latent variable model. The latent variable is only known to its distribution, and so the joint probability of y, I, and X^* is integrated over X^*.

For simplicity of exposition of the modeling approach, we restricted the attention to latent constructs that are captured through *continuous* latent variables. Latent constructs such as choice sets considered, sensitivity to alternative attributes, decision protocols, and so on can be captured through latent classes, and latent class choice models have been adopted in such situations (see, for example, Boccara (1989), Gopinath (1994), Ben-Akiva et al. (1998)). Prototypical applications of the modeling approach can be found in Boccara (1989), Morikawa (1989), Gopinath (1994), Bernardino (1996), Börsch-Supan et al. (1996), Morikawa et al. (1996), and Polydoropoulou (1997).

The three case studies in Ben-Akiva et al. (1998) illustrate how psychometric data can be used in choice models to improve the definition of attributes and to better capture taste heterogeneity. They also demonstrate the flexibility and practicality of the methodology, as well as the potential gain in explanatory power and improved specifications of discrete choice models. The dimensionalities of the likelihoods in each of the three case studies were small enough such that numerical integration was feasible and preferred over simulation based estimation techniques. Several practical lessons were learned from the three case studies. First, in terms of the measurement equations (*eq. 3*), having a sufficient number of indicators relevant to the latent variable under consideration, as well as variability among the indicators is critical. Second, for the structural equations (*eq. 1*), it can be difficult to find good causal variables (X) for the latent variables. In some cases, it is difficult to even conceptually define good causal variables, that is, cases in which there are no good characteristics of individuals or observable attributes of the alternatives that sufficiently explain the latent attitudes and/or perceptions. However, quite frequently, even if one can define good causal variables, these types of data have not been collected. To address both of these issues, it is critical for the successful application of this methodology, to clearly think about the behavioral hypotheses behind the choices, then develop the framework, and *then* design a survey to support the modeling effort.

Research Agenda

We identify several areas for further research in order to enrich choice analyses following the theoretical and modeling frameworks described in the previous sections. The focus of the research agenda is the development of modeling and measurement methods that incorporate decision mechanisms manifested in BDT research. We will use as examples two such mechanisms—preference construction and rule-driven behavior—to identify major research needs. In most circumstances we will not be able to directly observe how decision-making actually "happens." Rather, we will only observe indicators from which we might infer which behavioral decision mechanism was used. Thus, research is needed (a) to construct and measure suitable indicators that permit inference on the underlying behavioral decision mechanism, and (b) to model how to link such indicators, the latent constructs, and observed stated or revealed choices.

Measurement of indicators of latent constructs

Taking Figure 1 as the guide to developing future models, it is quite clear that one needs methods for measuring various indicators of the underlying factors of the D-M process.

These include not only indicators of the perceptions of the choice alternatives but also indicators on how an individual processes information and her attitudes and values. Measures of perceptions are generally obtained through ratings of the alternatives on a set of attributes; the list of attributes is usually developed in a preliminary study such as a focus group. Specific items on the process naturally depend on the situational context. It is important that these measures be developed at the individual level and elicited through a survey. A good source for various measurement scales is the handbook by Bearden, Netemeyer, and Mobley (1993). The scales on involvement and information processing, values, innovation, and general attitudes may be of particular interest in demand analyses.

While process tracing and physiological measures such as eye movement or heart rate may be useful in indicating decision processes in an experimental setting, most surveys, given cost considerations, will have to rely on traditional questionnaire and interview techniques. Carefully designed, interactive experiments can help shed light on how process and preferences interact in producing responses (Delquié, 1997). The feedback between observation and decision is an open research question. For instance, how do we elicit process information without influencing the process itself? If we want to test for rule-driven behavior, suggesting a list of rules to choose from may influence the rules that will subsequently be employed. Here again however, clever experimental designs may allow testing hypotheses about process with minimal interference, for example by comparing the outcomes of closely related tasks as in Casey and Delquié (1995).

Modeling

We need to find computationally tractable models that incorporate the various latent constructs characterizing behavioral decision elements. Examples of such latent constructs are the extent to which preferences need to be constructed rather than recalled from memory, and the extent to which choices are derived by a rule (heuristic) rather than by systematic evaluation of all available alternatives.

In order to keep models tractable and to reduce their dimensionality, it is also helpful to be able to impose more structure on the very general scheme of Figure 1. For this, we need to understand whether some of the elements in Figure 1 have a unidirectional structure, e.g., whether there is a fixed order of the processes of preference construction and choice determination. Most probably, we will find only conditional ordering. Thus, we need to search for background variables, such as familiarity with the decision problem, that permit imposing structure on Figure 1.

A related modeling task is the search for appropriate indicators that help us branch into simpler model segments, e.g., a rule-driven decision branch versus a branch that models decisions generated by systematic evaluation. Arguably, rule-driven decisions require simpler models at the last stage of Figure 1 than models that incorporate the complexity of the full choice set.

Finally, an important modeling issue is identification. Specifically, we need to understand whether we can obtain sufficiently many and precise indicators for each of the latent constructs. In the absence of such indicators, we will not be able to disentangle the structure of the black box in Figure 1. Such a lack of structural identification would hamper our ability to understand the latent behavioral decision mechanisms and cognitive processes in depth; however, it would not reduce the predictive capabilities of the model as long as all relevant indicators are included in the model.

Empirical Work

The framework presented in this paper and the modeling methods are very general and are consistent with a wide range of model specification. Hence, there is a need to develop and empirically test competing hypotheses. We need to evaluate whether the inclusion of elements derived from BDT research improves the predictive capability of choice models by evaluating choice problems with and without indicators that measure characteristics of process, preference construction, attitudes, etc. This will be most usefully done in the context of specific decision problems, such as consumer brand or travel mode choice.

Early attempts to adopt the modeling framework and to incorporate a subset of the decision elements represented in Figure 1, indicate that the theoretical framework and the methodology are promising areas of investigation. These results show that the goodness of fit improves, the latent constructs play a significant role, and the behavioral representation is more complete. Rigorous validation tests must now be performed, including tests of forecasting ability and performance comparisons with models of simpler formulations.

Practical applications of these models with more than a handful of latent constructs also call for further development and testing of integration methods based on simulation.

Conclusion

This paper outlines a view of how to augment extant choice modeling frameworks, survey data and discrete choice methods to explicitly capture in practical empirical models the insights into the decision-making process available from behavior decision theories and research. Prototypical applications of these ideas have already been conducted; see Börsch-Supan (1996) and Ben-Akiva et al. (1998). However, there are numerous issues concerning psychological choice theories, their modeling and measurement that ought to be the focus of future research.

Notes

1. This section is based on McFadden (1997a).
2. It is likely that the response achieves desired goals since most rules (e.g., social or personal norms) enforced by groups or internalized in the socialization process serve exactly this purpose.
3. This section borrows heavily from Ben-Akiva et al (1998).
4. Other non-compensatory decision-protocols can be accommodated through latent constructs which capture the decision protocols potentially adopted by individuals (see Gopinath (1994), Ben-Akiva et al. (1997)).

5. If the latent constructs represent categorical constructs such as choice set considered and decision protocol adopted, the integral is replaced by a summation over the distribution of the latent constructs.

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