A Multi-Attribute Benefits-Based Choice Model with Multiple Mediators: New Insights for Positioning

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ABSTRACT

Previous research has demonstrated that consumers evaluate products according to their perceived benefits when making a choice. This paper extends prior work by proposing a method that evaluates the degree to which multiple a priori defined benefits mediate product choices. The model is the first to consider process heterogeneity i.e., heterogeneity in how consumers perceive multiple attributes to positively or negatively impact multiple benefits simultaneously and the contribution of each benefit to product utility. The authors propose discrete choice experiments to measure holistically the link between attributes and benefits, as well as between attributes and choice, resulting in data that can be analyzed with a generalized probit model. The approach contributes to mediation research by offering an alternative to handle multiple multinomial mediators and dichotomous outcome variables. An empirical illustration of bread choices shows how consumer judgments about health and value perceptions of products mediate purchase decisions. The authors demonstrate how the method can help managers to confirm and test existing knowledge about latent benefits, including whether they explain all the variation in choice, and to consider process heterogeneity to inform market segmentation strategies.

Keywords: benefit-based choices; discrete choice experiments (DCEs); integrated choice and latent variable (ICLV) models; mediation; product positioning.

THE MEDIATING EFFECTS OF MULTIPLE BENEFITS ON CONSUMER CHOICES

Positioning is a key driver of product success, requiring that "*not only must a new product deliver the benefits the customer needs, but it must do so better than competition*" (Urban and Hauser 1993, p. 202). Marketers must anticipate how variation in their own or their competitors' product features alters consumer perceptions about the multiple benefits of each product and they must consider whether each competing benefit can mediate choices. For example, *McDonald's* have begun replacing artificial ingredients with natural ones to improve perceptions about the healthiness of their offerings; yet such changes are having a small effect on perceptions relative to the effectiveness of changing other attributes (Jargon 2018). Equally, these efforts may be futile if health is less important for customers relative to other benefits (e.g., fast service; value-for-money). In the same way that brands and features can be thought of as having a relative and holistic impact on choices from a multi-attribute perspective (McFadden 1974), so too can they be viewed as affecting a products' positioning on multiple benefits, which then act as precursors to consumer choices.

Of strategic concern is whether alterations to product features impact *multiple* perceived benefits and do so in detrimental ways. To illustrate, car manufacturers like *General Motors* and *Toyota* have to evaluate whether using innovative engine types helps position offerings with respect to environmental benefits, but negatively affects perceptions about a car's power or safety (Austin 2013). Similarly, companies offering foods such as chocolate, ice-cream, soft drinks and yoghurts have introduced 'sugar-free' options to reduce calorie content. However, each possible sugar-substitute (e.g., aspartame; stevia) may raise concerns about health risks (e.g., links with cancer) (Rogers et al. 1988). Indeed, the vice-president of *Pepsi* has attributed such risk perceptions to declining diet soda sales (Gage 2015). Companies like *Pepsi* and *Coca Cola* must also evaluate how to make such changes with an accompanying range of branding, color and front-of-pack design options, which can all affect multiple benefits and subsequently mediate choices. These considerations are further complicated when companies have incomplete knowledge about the different benefits their products deliver or when consumers differ in how they perceive attributes to impact various benefits or how they value each benefit. For example, the *Toyota Prius* initially received demand from consumers because the hybrid electric vehicles were perceived to be environmentally friendly as expected, but some consumers also saw ownership as a mechanism to improve their social status (Devinney, Auger and Eckhardt 2010).

In this research, we present a model that enables researchers to evaluate how the impact of multiple attributes on choice is mediated by multiple benefits. This model advances theoretical and methodological aspects of random utility theory and structural models of consumer choice (McFadden 1974; 1986) as well as mediation (e.g., Baron and Kenny 1986; Zhao, Lynch and Chen 2010). We allow for unobserved heterogeneity across the entire mediating process (i.e. process heterogeneity) to identify new ways aggregation bias based on consumer differences can occur in consumer choice (Hutchinson, Kamakura and Lynch 2000).

Past research has already taken significant steps to model various intermediate processes by which product attributes affect latent constructs, such as perceived benefits, which in turn can influence consumer choices (see, Dellaert et al. 2018). The resulting extensions to choice models include research in marketing that explores how product attributes affect consumer perceptions about higher-order benefits (e.g., Kim et al. 2017; Dellaert and Chorus 2015) and processes in which consumers use goal attainment potential to re-evaluate choice options (e.g., Swait, Argo and Li 2018). These models differ to the set of integrated latent variable choice models (ICLVs) that focus on attitudes and values; in such models the latent constructs are fixed at the individual level and do not vary across product attributes (e.g., Ashok, Dillon and Yuan 2002; Danthurebandara, Vandebroek and Yu 2013).

All these models overlook the degree to which latent constructs mediate consumer choice (Judd and Kenny 1981; Baron and Kenny 1986). Hence, none of the previous works allows marketing managers to adequately test whether the effect of a product feature on choice can be exclusively explained by its impact on the considered perceived benefits or whether important benefits have been left out of the analysis (e.g., Hauser and Simmie 1981). By including a direct effect capturing the remaining effect of attributes on choices, our proposed model accounts for this possibility and thus ensures that the estimated impact of benefits on choices is not biased. Additionally, some models only allow each attribute to impact one mediator exclusively at the individual consumer level or restrict the impact on the mediator to be the same sign as the impact of the attribute on choice outcomes (e.g., Kim et al. 2017). This limits managers' abilities to evaluate whether positioning strategies involving the alteration or introduction of features to change one perceived benefit also unintentionally change perceptions of non-targeted benefits. Our model enables a comprehensive understanding of mediating processes behind choice and an accurate identification of segments based on these by explicitly accounting for the simultaneous impact of attributes on different observed and unobserved benefits.

Most prior work also neglects the presence of heterogeneity in consumers' evaluation of perceived benefits and instead aggregates across individuals over one or more of these intermediate processes (e.g., McFadden and Train 2000; Swait, Argo and Li 2018). This work assumes that the latent components are uncorrelated except for when they are affected by shared product attributes. It disregards that perceived benefits might be driven by underlying correlated components, limiting the ability to consider halo effects and unobserved consumer inferences. Finally, prior works that explicitly measure the latent constructs do so using rating scales, focusing on individual level constructs (e.g., Ashok, Dillon and Yuan 2002). This prevents managers from understanding and forecasting how changes in multiple product features (e.g., pricing; new ingredients; communications on packaging) drive positioning on multiple dimensions (e.g., health, value) and choice outcomes in relative terms.

In this paper, we propose a benefits-based choice model to examine how changes to product features affect perceived benefits that are of interest to the researcher or manager and whether such changes affect consumer choices. The model addresses the above limitations by simultaneously: i) accounting for and testing the extent to which *multiple* perceived benefits mediate the impact of features on choice; ii) including a direct effect of attributes on choice to account for the possibility that the list of included benefits is not comprehensive thereby ensuring the evaluation of mediation is not based on biased parameter estimates; iii) allowing for unobserved heterogeneity across *both* perceived benefit formation and the impact of benefits on choice (i.e. process heterogeneity), as well as correlation between the unobserved components affecting latent benefits; and iv) using discrete choice experiments (DCE's) to operationalize the reflective measures of each latent benefit, thus utilizing their advantages beyond their application to multi-attribute choices (Louviere et al. 2000). Our model allows the effect of multiple attributes on multiple perceived benefits to be compared against brand-based forms of positioning (e.g., Bhat and Reddy 1998; Fuchs and Diamantopoulos 2010). Our approach offers an alternative to the recently published benefit- (Kim et al. 2017) and goal-based models (Swait, Argo and Li 2018) that derive latent goals or benefits from the structure of the data; our model instead is useful to test, confirm and compare the importance of benefits that have been a priori selected by the manager or researcher.

By proposing a mediation model that handles multiple mediators and choice outcomes with multinomial measures, which can be estimated simultaneously, we also make a strong contribution to the growing body of literature examining multiple competing mediators (Preacher and Hayes 2004; Hayes 2009; Zhao, Lynch and Chen 2010) including models involving categorical / dichotomous measures (Iacobucci 2012; Hayes and Preacher 2014). Allowing effects to be heterogeneous across the stages of mediation, we offer an alternative to measure process heterogeneity that enables managers to identify segments beyond moderated mediation (Fairchild and MacKinnon 2008; Preacher, Rucker and Hayes 2007).

The remainder of the paper is as follows. First, we detail how our work is positioned against prior works that have utilized latent variables to elaborate upon the 'black box' of consumer choices (McFadden 1986) and against models of mediation (Judd and Kenny 1981).

Second, we introduce our DCE-based approach to operationalize the benefit-based model and the accompanying mathematical representation of the model. Third, we provide an empirical application of the approach and illustrate the strategic insights it generates. Finally, we discuss our contribution to understanding market positioning, anticipated extensions and applications.

LATENT VARIABLES IN MODELS OF CONSUMER CHOICE

In his seminal paper on choice models, McFadden (1986) described different types of latent factors that influence consumers' choices, constituting a 'black box' of processes for researchers (see Figure 1). He noted that one set of latent factors that shapes preferences are the attitudes or values of the decision-maker, which can be formatively measured by fixed individual-level indicators, such as socioeconomic characteristics (Diamantopoulos, Riefler and Roth 2008). These factors can also be measured using reflective indicators, often via ratings scales, described as attitudinal inventories by McFadden. Models of this type have been used to further insights into consumer choices in marketing (e.g., Ashok et al. 2002; Danthurebandara et al. 2013) and in transportation (e.g., Bahamonde-Birke and Ortúzar 2014; Bolduc and Alvarez-Daziano 2010; Kløjgaard and Hess 2011; Paulssen et al. 2014).

Figure 1 about here

McFadden (1986) also highlights that attributes drive consumers' perceptions, which can affect choices. In this case, the value of the latent perception varies at the product-specific level, not the individual level. More recently, Dellaert et al. (2018) distinguished between research examining how attributes affect product benefits (e.g., Kim et al. 2017) and goal-based decisions (e.g., Swait et al. 2018). The current research focuses on how attributes drive perceptions about product benefits consistent with a benefit-based discrete choice model.

The next section highlights our distinction from previous works in benefit- and goal-based choice models. One distinction is that our model allows testing for mediation to reveal the extent to which the effect of attributes on choice occurs via their impact on perceived benefits (Baron and Kenny 1986). To enable such a test, we allow attributes to indirectly influence choices via perceived benefits, but also to directly impact choices (see dotted line in Figure 1). Another distinction is that we account for unobserved consumer heterogeneity across all of these effects (i.e., process heterogeneity). Finally, we differ in how we operationalize our reflective measure of a product's perceived benefits using DCEs (see dotted box in Figure 1).

Benefit- and Goal- Based Choice Models

In this section, we review our work in the context of previous benefit- and goal-based choice models. Table 1 presents an indicative list of this research against our model with respect to their inability to test for multiple mediation, their limited consideration of consumer heterogeneity and the way the latent construct is measured (if at all). The table also includes some contrasting papers that focus on attitudes and values, whereby socio-demographics rather than attributes are formative measures of the latent variable (e.g., Ashok et al. 2002).

Table 1 about here

Allowing attributes to formatively impact multiple latent constructs: To understand drivers of positioning, managers must anticipate how changes to attributes of their products and those of their competitors can affect multiple perceived benefits. Forecasts must assess changes to consumer perceptions about focal benefits that management may be deliberately targeting, but also must extend to non-focal benefits that may be (unintentionally) affected. For example, a bread manufacturer may highlight its flour as 'unbleached'; consumers may perceive the product to be healthier as intended, but they may infer that sourcing this ingredient negatively affects its value for money. The necessity to allow attributes to affect multiple benefits is supported by works in positioning and perceptual mapping, with brands shown to influence several benefits simultaneously (Lilien and Rangaswamy 1998; Steenkamp et al. 1994).

An important characteristic of our proposed model is that we allow each product attribute to influence multiple constructs. This contrasts, for example, Oppewal et al. (1994) who group large numbers of attributes into mutually exclusive sets, which consumers then evaluate in a summarized form to determine their effect on choice. In their empirical model of transport choice, Walker and Ben-Akiva (2002) map each attribute onto only one latent variable. Kim et al. (2017) consider how attributes have a decreasing marginal impact on benefits, but restrict the impact to one benefit per attribute for each individual. A further restriction of the model proposed by Kim et al. (2017) is that the aggregate (over individuals) impact of an attribute on any benefit is restricted to be the same sign as its impact on overall choice. Our model instead allows the formative impact on each benefit to be independent of any other effect. This enables managers to examine cases where an attribute such as brand positively impacts one benefit, but negatively affects another (Lilien and Rangaswamy 1998). Swait, Argo and Li (2018), and Arentze, Dellaert and Chorus (2015), are noteworthy exceptions in allowing each attribute to affect consumers' ability to attain multiple goals or contribute to multiple benefits differently.

Accounting for process heterogeneity in impact of formative variables: Researchers have to account for consumer heterogeneity not only when modeling the impact of benefits on choice, but also to describe differences in the formation of consumer perceptions about product benefits, as the latter is particularly useful for segmentation (e.g., Urban and Hauser 1993). Prior research neglects this issue. For example, Swait et al. (2018) modeled how attributes affect consumers' ability to attain goals, but do not account for heterogeneity with respect to how each attribute affects a competing goal. For example, consumers were described to differ on the value placed on the goal labeled 'keeping up with new technology', but their model assumed all consumers agreed upon which brands and features allowed them to achieve this.

Correlation between unobserved components of latent constructs: We differ from previous models involving latent, product-specific constructs, by accounting for unobserved correlation between the latent variables. Correlations may be present for different reasons, such as when consumers make unobserved inferences (e.g., healthy foods represent poor value) or exhibit halo effects (e.g., Choi and Springston 2014) in response to the latent variable assessment task. Correlations can also occur because omitted variables can affect multiple benefit dimensions simultaneously. Table 1 lists two papers that consider relationships between latent factors, but in the context of attitudes. Specifically, Ashok et al. (2002) accounted for correlation between attitudes in their SEM-based binary choice model. Paulssen et al. (2014) examined the effect of values on attitudes; neither accounted for correlations among the value constructs nor among the attitudinal constructs.

Reflective measures of latent variables: Previous research incorporating latent variables into choice models either explicitly observes reflective measures of the latent variables based on prior research or management input (e.g., Danthurebandara, Vandebroek and Yu 2013; Walker and Ben-Akiva 2002) or infers the latent variables based on underlying structures of the data (e.g., Elrod and Keane 1995; Kim et al. 2017; Swait, Argo and Li 2018). Whereas the latter approach is exploratory in nature and requires additional steps after model estimation to interpret the latent variables that the models detect, our proposed model follows the former stream of research with the aim of confirming and testing existing knowledge about the latent variables, including whether they capture all variation in choices. However, our operationalization deviates from previous works: Rather than using a series of rating scales (e.g., Walker 2001), which are susceptible to response style bias (Baumgartner and Steenkamp 2001), we employ a DCE-based task to determine how attributes drive holistic evaluations of an alternative's perceived benefits. Specifically, we ask respondents to nominate which one product out of a set of competing alternatives performs best on a perceived benefit of interest.

Using DCEs to measure latent benefits overcomes several limitations of using rating scales: First, separately measuring how each attribute affects perceptions does not reveal how respondents make trade-offs between attribute levels when forming perceptions. For example, using a series of separate rating scales such as those presented in Figure 2, a respondent may indicate that: wholemeal breads are healthy; breads labeled low GI are healthy; and *Tip-Top*-branded breads are healthy. However, it is unclear how consumers use (i.e., weight) combinations of attribute levels to formulate a holistic evaluation of the "healthiness" of a product. Our DCE-based approach is useful to capture these types of judgments (see Figure 3).

Figure 2 and Figure 3 about here

A second limitation of rating scales is that they often lack a suitable benchmark, making the task cognitively difficult. For instance, judging the healthiness of a nine-grain bread may be challenging if done without reference to another type of grain. This may mean that consumers will report upon the perceived benefits of an attribute differently if asked to do so one-at-a-time relative to choice situations in which they evaluate features relative to others (Hsee 1996). Finally, the number of rating scales to obtain information on each attribute-benefit combination can be large. For example, examination of how each of the 40 attribute levels considered in our empirical illustration alters two benefits requires 80 rating-scale questions. This contrasts with the efficiency of collecting trade-off information using our DCE-based approach.

Direct and indirect effects of attributes allowing testing for mediation: As discussed, previous models have accounted for attributes as being formative predictors of a latent variable of interest, which in turn are used to explain the latent utilities used by consumers to make observable product choices. In this regard, attributes have an indirect impact on choice through a (mediating) latent variable of interest. One path often overlooked is the direct effect that the attribute has on utility (e.g., Hauser and Simmie 1981); however, its inclusion is required to test for the extent to which each included perceived benefit mediates choice outcomes (Baron and Kenny 1986). This direct path provides insight into the suitability of the a priori selected benefits. If it is significant for a product attribute, then the benefits examined do not explain all variation in consumers' choices and there eithers exist other, not yet included benefits that drive choices or the product attribute has an idiosyncratic impact on choice. As noted, Walker and

Ben-Akiva (2002) allowed some, but not all, attributes to affect both a latent variable of interest and the utility component directly. Thus, while it was possible to test for the significance of the mediating effect of these few attributes via the latent variable of interest, the authors offered no such method or test. We now elaborate on current models of mediation, as well as the necessary extensions we offer to examine benefit-based mediated choices.

Mediation Analysis and Multinomial Indicators

Mediation exists when a predictor – in this case, product features – affects a dependent variable (choice) indirectly through at least one intervening variable (perceived benefits). The value of mediation analysis to researchers is in providing "*a story about a sequence of effects that leads to something*" (Kenny 2008, p. 2). In the present context, we use it to understand the mediating process by which product features can affect choices directly, but also indirectly via their impact on judgments about perceived benefits. To facilitate the comparison, a representation of the standard mediation model is presented on the left hand side of Figure 4 (Baron and Kenny, 1986, p. 176; Hayes 2009, p. 409; Zhao et al., 2010, p. 198) which captures the relevant equations first offered by Judd and Kenny (1981). A representation of our framework with corresponding parameters is shown on the right hand side of Figure 4.

Figure 4 about here

First, standard mediation models explore the process underlying c', which captures the predicted effect of a variable X on an outcome variable Y (see, Figure 4A). In a choice context, we are interested in the potential mediating processes behind γ'_k, the impact of a product feature, x_k, on the latent utility of an option, U^c. Rather than observe U^c, we instead observe y^c, a dichotomous variable indicating whether an option is judged to have the highest utility among all other options in the choice set. The marginal utility of attribute k, γ'_k, can thus be viewed as a total effect consistent with the interpretation of c' in standard mediation models.

Second, mediation analysis examines how a total effect can be broken down into a set of indirect effects and a direct effect. In the simple mediation model (Figure 4B), the indirect effect is defined as the product ab, where a is the impact of X on an observable mediating variable, M, and b is the impact of the mediator on the outcome variable. The direct effect, c, captures the remaining impact of X on Y after accounting for the indirect effect with $c'=c+ab$. By evaluating the significance of these parameters, conclusions about the occurrence of complete/full mediation ($ab \neq 0$; $c=0$) or partial mediation ($ab \neq 0$; $c \neq 0$) can be determined. In a choice context, we investigate α_k, the effect of attribute k on a latent perceived benefit, M^*. However, due to our proposed DCE-based operationalization, we observe only a multinomial indicator, y^{M^*}, that denotes whether an option maximizes the perceived benefit relative to other options. Further, our model simultaneously investigates β, the impact of the latent component associated with the mediating outcome (i.e., M^*) on overall latent utility (i.e., U^c). The indirect effect of attribute k on latent utility is therefore equal to the product of α_k and β. Since the effects relate to relationships between (unobservable) continuous rather than dichotomous variables, the total effect can be written as $\gamma'_k=\gamma_k+\alpha_k\beta$, where γ_k refers to the direct effect of an attribute on utility. Subsequently, models that fail to account for the direct effect (essentially implying a restricted model of $\gamma_k=0$) will lead to biased estimates of the indirect effects.

Third, researchers can also consider multiple mediating variables (Hayes 2009). In a model with two mediating variables, as shown in Figure 4C, the total effect is equal to the sum of the direct effect, c, and the two indirect effects (i.e., $c'=c+a_1b_1+a_2b_2$). This allows researchers to investigate cases where the overall effect of X on Y may be insignificant even though the intervening mediating effects are significant and the direct effect is not (e.g., $a_1b_1>0$; $a_2b_2<0$; $c=0$). In a choice context, the comparable extension involving two mediators allows the total effect of an attribute k on latent utility to equivalently be expressed as $\gamma'_k = \gamma_k + \alpha_k^1\beta^1 + \alpha_k^2\beta^2$. That is, in both cases, total effects can be expressed in terms of a single direct effect and sum of each indirect effect of interest.

Finally, cases involving more than one independent variable and more than one mediator, the effect of any one variable on an outcome variable can be evaluated using the same approach. For example, when there are two independent variables and two mediators as shown in Figure 4D, the total effect c'_1, which predicts the impact of attribute X_1 on Y, can be expressed as the sum of the indirect effect on Y via a first mediator ($a_{11}b_1$), the indirect effect via a second mediator ($a_{12}b_2$), and the direct effect of X_1 (c_1). Our choice model extends the mediation framework to consider how multiple attributes impact multinomial choices through multiple mediators in a similar way. More generally, our model allows the recognition that the marginal utility of any attribute (γ'_k) is equivalent to the sum of all indirect effects of an attribute ($\Sigma\alpha_k^m\beta^m$) and direct effects (γ_k). That is, $\gamma'_k = \gamma_k + \Sigma\alpha_k^m\beta^m$.

In the next section, we show how our benefits-based choice model can be operationalized using extensions of the RUT framework. This enables us to allow for process heterogeneity, i.e., heterogeneity in the set of indirect and direct effects across consumers and parameters that capture potential correlations between mediating benefits. Our proposed model of benefit-based choices thereby contributes to previous works in mediation by allowing for multiple mediators and choice outcomes measured by multinomial indicators as follows.

While most applications of mediation analysis involve constructs being measured by continuous variables, as summarized in Table 2, several authors offer methods to handle cases in which the independent, mediator or outcome variables are categorical (e.g., Hayes and Preacher 2014; MacKinnon and Dwyer 1993). To perform mediation tests in these cases, regression coefficients for direct and indirect path effects are standardized after estimation. Since we model the impact of the underlying continuous latent mediating variables on latent utility, we require no posterior standardization of scales for mediation testing. Further, the term "categorical" in the mediation literature has referred to solutions suitable for contexts involving binary rather than multinomial outcomes (e.g., Iacobucci 2012) and rely on models that are restricted in their ability to independently parameterize the description of a base option (e.g., Maydeu-Olivares and Böckenholt 2005; Temme et al. 2008). Our model exhibits neither of these restrictions and thus enables researchers to investigate mediation in cases involving multinomial choices as well as forced choice scenarios (e.g., retail stock-outs). Further, we permit each attribute to impact multiple benefits at the individual level, not just one mediating construct; so our model extends the works focused on multiple mediators and approaches that do not account for unobserved heterogeneity (e.g., Preacher and Hayes 2004; 2008). Instead, we allow for heterogeneous direct and indirect effects across both the perception formation stage and stage by which benefits impact choice, offering new insights for managers about segmentation.

Insert Table 2 about here

A CHOICE MODEL OF PERCEIVED BENEFITS AND MEDIATED CHOICES

The structure of our benefits-based choice model specified below can be summarized as follows. First, each attribute has a direct impact on latent utility and impacts multiple latent benefits indirectly, offering the ability to test for multiple mediating effects. Second, the model allows for correlations between the unobserved components of the latent benefits. Third, additional to a regular choice task where consumers reveal their most preferred options, latent benefits are evaluated holistically using a second discrete choice task in which respondents nominate which option performs best on each dimension (i.e., perceived benefit) of interest. Fourth, consumers may differ with respect to the degree: a) attributes affect each latent benefit; b) each latent benefit affects overall utility; and c) each attribute affects utility directly.

More formally, let X_{int} be the vector of attributes of alternative *i, i=1,..,J,* that respondent *n, n=1,…,N,* faces in choice set *t, t=1,..,T*. Further, let y_{int} be an indicator variable, taking the value 1 if alternative *i* is chosen and 0 otherwise. In line with the random utility framework, we assume that latent utility, U_{int}^{C}, of an alternative *i* as judged by person *n* in choice set *t*, is a function of a systematic component, V_{int}', and a random component, $\varepsilon_{int}' \sim N(0, I_J)$ with

I_J being the (JxJ)–identity matrix. The utility of a choice option is specified to be a linear function of the features describing each alternative (X_{int}) such that:

(1) $$U_{int}^{C} = X_{int}\gamma_n' + \varepsilon_{int}',$$

where γ_n' is a vector of unknown parameters (i.e. a set of total effects). The systematic component may also include exogenous characteristics of the consumer and interaction effects.

Following the tradition of ICLV models, we assume that the utility of each alternative is affected by a set of latent variables, M_{int}^{*}, pertaining to unobservable attitudes of the individual and/or perceived benefits of the alternative judged by the individual (Ben-Akiva et al. 2002b; McFadden 1986). Consistent with mediation models, the utility function can be written as:

(2) $$U_{int}^{C} = X_{int}\gamma_n + M_{int}^{*}\beta_n + \varepsilon_{int}^{C},$$

where γ_n and β_n are parameters to be estimated and ε_{int} is a random component. Allowing for multiple mediating terms (m=1, …, $\mathcal{M}$) and denoting this construct M^{*m}, we assume that:

(3) $$M_{int}^{*m} = X_{int}\alpha_n^{m} + \varepsilon_{int}^{m} = V_{int}^{m} + \varepsilon_{int}^{m},$$

with α_n^{m} a Kx1 vector of parameters capturing the impact that changes in the product attribute levels have on each latent perception. ε_{int}^{m} is assumed to be normal distributed with correlation structure further specified below. Applying RUT to this mediating choice, we observe the choice of alternative i in the mediator task m, $y_{int}^{m} = 1$, if $M_{int}^{*m} \geq M_{jnt}^{*m},\ \forall j \in \{1,\ldots,J\}\backslash\{i\}$. The overall choice utility U_{int}^{C} of the alternative is then:

(4) $$U_{int}^{C} = X_{int}\gamma_n + \sum_{m=1}^{\mathcal{M}}\beta_n^{m}M_{int}^{*m} + \varepsilon_{int}^{C} = V_{int}^{C} + \sum_{m=1}^{\mathcal{M}}\beta_n^{m}V_{int}^{m} + \sum_{m=1}^{\mathcal{M}}\beta_n^{m}\varepsilon_{int}^{m} + \varepsilon_{int}^{C},$$

with γ_n a Kx1 vector of unknown parameters, and β_n^{m} unknown scalars that capture the impact of latent dimension m on overall choice. Again, ε_{int}^{C} is assumed to be a normal distributed error term with correlation structure defined as follows.

Let $\varepsilon_{nt} = \{\varepsilon_{1nt}^{1},\ldots,\varepsilon_{Jnt}^{1}, \varepsilon_{1nt}^{2},\ldots,\varepsilon_{Jnt}^{2},\ldots,\varepsilon_{1nt}^{\mathcal{M}},\ldots,\varepsilon_{Jnt}^{\mathcal{M}}, \varepsilon_{1nt}^{C},\ldots,\varepsilon_{Jnt}^{C}\}^{T}$, then we assume that ε_{nt} follows a normal distribution with mean 0 and covariance Ω, where:

$$\Omega = \begin{pmatrix} I_J & \rho^{12} I_J & \cdots & \rho^{1\mathcal{M}} I_J & O_J \\ \rho^{12} I_J & I_J & \cdots & \rho^{2\mathcal{M}} I_J & O_J \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \rho^{1\mathcal{M}} I_J & \rho^{2\mathcal{M}} I_J & \cdots & I_J & O_J \\ O_J & O_J & \cdots & O_J & \rho I_J \end{pmatrix}, \tag{5}$$

with O_J a (JxJ)–zero matrix, ρ^{ml} reflecting the correlation between the utility of mediator m and mediator l, and ρ defined as $\rho = 1 - \sum_{m=1}^{\mathcal{M}} \beta^m (1 + \sum_{m'=1, m' \neq m}^{\mathcal{M}} \beta^m \beta^{m'} \rho^{mm'})$.[1] Thus, we assume that the error terms are uncorrelated over time, alternatives and individuals, but correlated across mediators[2].

We stack all joint outcomes of interest and thus obtain:

$$U_{nt} = \begin{pmatrix} M_{1nt}^{*1} \\ \vdots \\ M_{Jnt}^{*1} \\ \vdots \\ M_{1nt}^{*\mathcal{M}} \\ \vdots \\ M_{Jnt}^{*\mathcal{M}} \\ U_{1nt}^{C} \\ \vdots \\ U_{Jnt}^{C} \end{pmatrix} = \begin{pmatrix} V_{1nt}^{1} \\ \vdots \\ V_{Jnt}^{1} \\ \vdots \\ V_{1nt}^{\mathcal{M}} \\ \vdots \\ V_{Jnt}^{\mathcal{M}} \\ V_{1nt}^{C} + \sum_{m=1}^{\mathcal{M}} \beta_n^m V_{1nt}^m \\ \vdots \\ V_{Jnt}^{C} + \sum_{m=1}^{\mathcal{M}} \beta_n^m V_{Jnt}^m \end{pmatrix} + \begin{pmatrix} \varepsilon_{1nt}^{1} \\ \vdots \\ \varepsilon_{Jnt}^{1} \\ \vdots \\ \varepsilon_{1nt}^{\mathcal{M}} \\ \vdots \\ \varepsilon_{Jnt}^{\mathcal{M}} \\ \varepsilon_{1nt}^{C} + \sum_{m=1}^{\mathcal{M}} \beta_n^m \varepsilon_{1nt}^m \\ \vdots \\ \varepsilon_{Jnt}^{C} + \sum_{m=1}^{\mathcal{M}} \beta_n^m \varepsilon_{Jnt}^m \end{pmatrix} = V_{nt} + \tilde{\varepsilon}_{nt}, \tag{6}$$

where:

$$\tilde{\varepsilon}_{nt} = \begin{pmatrix} \tilde{\varepsilon}_{1nt}^{1} \\ \vdots \\ \tilde{\varepsilon}_{Jnt}^{1} \\ \vdots \\ \tilde{\varepsilon}_{Jnt}^{\mathcal{M}} \\ \vdots \\ \tilde{\varepsilon}_{Jnt}^{\mathcal{M}} \\ \tilde{\varepsilon}_{1nt}^{C} \\ \vdots \\ \tilde{\varepsilon}_{Jnt}^{C} \end{pmatrix} = \begin{pmatrix} 1 & \cdots & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & & & & & & & & \\ 0 & & 1 & & & & & & & \\ \vdots & & & 1 & & & & & & \\ 0 & & & & 1 & & & & & \\ \vdots & & & & & 1 & & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \beta_n^1 & 0 & 0 & \cdots & \beta_n^{\mathcal{M}} & 0 & 0 & 1 & 0 & 0 \\ 0 & \beta_n^1 & 0 & \cdots & 0 & \beta_n^{\mathcal{M}} & 0 & 0 & 1 & 0 \\ 0 & 0 & \beta_n^1 & \cdots & 0 & 0 & \beta_n^{\mathcal{M}} & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_{1nt}^{1} \\ \vdots \\ \varepsilon_{Jnt}^{1} \\ \vdots \\ \varepsilon_{Jnt}^{\mathcal{M}} \\ \vdots \\ \varepsilon_{Jnt}^{\mathcal{M}} \\ \varepsilon_{1nt}^{C} \\ \vdots \\ \varepsilon_{Jnt}^{C} \end{pmatrix} = R_n \begin{pmatrix} \varepsilon_{1nt}^{1} \\ \vdots \\ \varepsilon_{Jnt}^{1} \\ \vdots \\ \varepsilon_{Jnt}^{\mathcal{M}} \\ \vdots \\ \varepsilon_{Jnt}^{\mathcal{M}} \\ \varepsilon_{1nt}^{C} \\ \vdots \\ \varepsilon_{Jnt}^{C} \end{pmatrix}, \tag{7}$$

and $\tilde{\varepsilon}_{nt} \sim N(0, \widetilde{\Omega}_n)$ with $\widetilde{\Omega}_n = R_n \Omega R_n^T$. The probability of the observed set of choices is then:

$$\Pr\left(y_{i^1 nt}^{1} = 1, \ldots, y_{i^{\mathcal{M}} nt}^{\mathcal{M}} = 1, y_{i^C nt}^{C} = 1\right) = \int_{\tilde{\varepsilon}_{nt} \in B_{\{i^1, \ldots, i^{\mathcal{M}}, i^C\}nt}} \phi(\tilde{\varepsilon}_{nt})\, d\tilde{\varepsilon}_{nt}\,. \tag{8}$$

where ϕ refers to the pdf of the normal distribution with mean 0 and covariance $\widetilde{\Omega}_n$ and

[1] See Web Appendix 1 for full details of the model estimation and justification of this choice of ρ.

[2] Note that it is not possible to allow for both a link between the mediating utility and the choice utility and a correlation in the error term between these two utilities as the model would not be identified.

$$\tilde{B}_{\{i^1,\dots,i^{\mathcal{M}},i^C\}nt} = \{\tilde{\varepsilon}_{nt} \text{ s.t.} (V^1_{i^1nt} + \tilde{\varepsilon}^1_{i^1nt} > V^1_{j^1nt} + \tilde{\varepsilon}^1_{j^1nt}, \forall j^1 \neq i^1) \land \dots$$

$$(V^{\mathcal{M}}_{i^{\mathcal{M}}nt} + \tilde{\varepsilon}^{\mathcal{M}}_{i^{\mathcal{M}}nt} > V^{\mathcal{M}}_{j^{\mathcal{M}}nt} + \tilde{\varepsilon}^{\mathcal{M}}_{j^{\mathcal{M}}nt}, \forall j^{\mathcal{M}} \neq i^{\mathcal{M}}) \land \dots \tag{9}$$

$$(V^C_{i^Cnt} + \textstyle\sum_{m=1}^{\mathcal{M}} \beta^m_n V^m_{i^Cnt} + \tilde{\varepsilon}^C_{i^Cnt} > V^C_{j^Cnt} + \sum_{m=1}^{\mathcal{M}} \beta^m_n V^m_{j^Cnt} + \tilde{\varepsilon}^C_{j^Cnt}, \forall j^C \neq i^C)\}.$$

Equation (8) shows that our mediating model reduces to a multivariate probit model with a particular covariance matrix. Our model could be estimated in two stages by first estimating the models pertaining to the mediators (i.e., Equation 3) and then incorporating these estimates into the model pertaining to overall choice (i.e., Equation 4). While sequential procedures are easier to implement and previously used in ICLV models (e.g., Morikawa et al. 2002; Temme, Paulssen and Dannewald 2008), they produce consistent, but not efficient, estimates as compared to a simultaneous estimation of both equations (Bahamonde-Birke and Ortúzar 2014; Bolduc and Alvarez-Daziano 2010; Fu and Juan 2017). Hence, it is preferable to estimate the model simultaneously using for example the GHK simulator (e.g., Geweke et al. 1994).

Consumer heterogeneity can be accounted for in several ways in our model. The researcher can, for example, investigate how the value of each attribute is moderated by observable characteristics that describe an individual decision-maker. These interactions can be included with respect to the formation of perceptions or use of these perceptions in choice. This allows the exploration of moderated mediating effects (Preacher, Rucker and Hayes 2007; Hayes 2009). Another approach is to allow for unobserved consumer heterogeneity using a continuous or discrete distribution of preferences. Popular examples of these distributions and associated estimation techniques are a discrete distribution (Kamakura and Russell 1989), estimated via the expectation maximization (EM) algorithm (e.g., Train 2009), or a multivariate normal distribution, estimated using simulation (e.g., McFadden and Train 2000) or Bayesian estimation techniques (Burda, Harding and Hausman 2008).

In the next section, we illustrate the value of accounting for heterogeneity beyond its typical application to preferences (i.e., differences in γ_n'). We instead consider process heterogeneity, which arises due to differences across consumers with respect to the role of attributes in both forming perceptions about benefits of alternatives (i.e., α_n^m) and in how much each benefit is used by each consumer in their product choices (i.e., β_n^m). A series of simulations, presented in Web Appendix 2, confirms that the proposed model is able to recover these parameters under various scenarios. This includes cases with different combinations of significant versus non-significant direct and indirect effects, cases with competing mediation, cases with high levels of correlation between attributes and mediators and cases where only one rather than multiple observations is available per respondent. We also illustrate the bias that arises if researchers do not account for direct effects in mediating choice models.

EMPIRICAL ILLUSTRATION

The empirical example illustrates the operationalization of the proposed mediating choice model in a typical market research setting. The application demonstrates the framework's appeal for managers to assess and to forecast which attributes drive perceptions about a product's benefits and how these affect consumer choices. We first present a model that assumes judgements about perceived benefits and their impact on choices are homogenous across consumers. We then relax this assumption to show how managers can understand that latent segments may be present because consumers differ in: i) how they use attributes and brands to judge the perceived benefits of alternatives; and/or ii) how perceived benefits mediate their choices. We conclude this section with a discussion of predictive model fit.

We conducted an online survey of 265 adult grocery shoppers who evaluated bread options described by brand and several product features, including type of flour, advertised claims (e.g., low GI; enriched with omega 3), seeds, grains, vitamins, minerals, expiry date, loaf size, shelf and unit price. The attributes of each option were determined by a completely randomized design (Cox and Cochran 1953) to investigate higher-order effects; for parsimony, the results presented focus on main effects only. After screening and providing information about prior purchases, respondents undertook a DCE with eight choice sets nominating their most preferred bread, evaluating three breads on each occasion. After further questions about purchases, respondents viewed the same sets of breads and nominated which performed best on healthiness and value for money. These sets were presented on a second separate occasion to eliminate any impact that the mediating task would have on a respondent's preferences in the first DCE task measuring the impact of each attribute on utility (i.e., total effects).

Survey respondents lived in the same capital city, were equally split between genders, and were 52 years of age, on average. All had purchased bread from a supermarket retailer in the last fortnight, with purchases dominated by supermarket varieties (34%); the remainder were led by brands appearing in the experiment, including *Helga's* (23%), *Abbott's* (11%) and *Tip-Top* (10%). More than half (52%) had purchased wholemeal breads in the previous fortnight as compared to 35% who had bought white varieties and 10% who had bought unbleached varieties. Having screened out those with dietary requirements (e.g., allergies), only one percent of respondents reported to regularly purchase gluten-free breads. Around half (48%) of the respondents purchased one loaf, with an average of 1.7 loaves bought. Many regularly bought breads at a discounted price (42%), at an average of 19% off the shelf price.

Mediating Model without Unobserved Heterogeneity

Results relating to total effects (standard discrete choice model): The first model examines how changes in bread attributes affect utility (see estimates of γ'in Table 3). This total effects model (i.e., without mediators) is the standard discrete choice model as per Equation 1. The results show the dominance of the *Helga's* brand and preference for wholemeal varieties, regardless of whether the flour is unbleached; gluten-free varieties are strongly rejected. Brand and flour type dominate other considerations, including various key claims such as whether a product is promoted as being low GI, high fiber or is 'stone-milled'. Respondents preferred breads that were larger, cheaper and had a longer expiration date.

Insert Table 3 about here

Effects of attributes on perceived benefits (perceptual formation stage): The proposed mediating benefits-based choice model disentangles the aforementioned results to provide insight into how each feature drive perceptions with respect to health and value benefits (see estimates of α^{Health} and α^{Value} in Table 3). For example, *Abbott's* is perceived to be relatively healthy, but is poorly positioned in terms of value; the reverse is true for supermarket brands. The results can be examined in terms of how any attribute level simultaneously drives the perceived benefits of alternatives on multiple positioning dimensions. In Figure 5, each attribute level's impact on health perceptions (α^{Health}) is plotted against the same attribute level's impact on value perceptions (α^{Value}). This perceptual map shows the strong positioning of *Helga's* in terms of health, supermarket brands in terms of value and the weakness of *MightySoft* on both dimensions. Perceptions of value are associated with longer shelf life, larger weights and lower shelf prices. The dominance of brands and flour type in shaping perceptions is apparent when compared against the impact of adding ingredients (e.g., vitamins; minerals) or the advertised absence of others (e.g., no artificial flavors).

Insert Figure 5 about here

Mediating effects (indirect effects): A strategic advantage of the model is being able to evaluate whether variation in perceived benefits explain variation in choice. Table 3 reveals that the impact of both mediators on choice (β^m) are positive and significant; breads perceived as healthier and better value for money are more likely to be chosen. Table 3 also shows that the correlation, ρ^{HV}, between the unobserved components that drive perceived healthiness and perceived value for money is significant ($p < .01$). This correlation might be due to a halo effect, such as respondents believing that unhealthy breads offer poor value. It could also arise because of respondent bias, such as a decision heuristic in which some respondents nominated the same alternative as maximizing both benefits.

All model parameters are estimated on the same scale (see definition of Ω). Thus, we can obtain the marginal indirect effect of each attribute level with respect to each perception by calculating the product of the two stages (i.e., the impact of the attribute level on the latent mediator, α, and the impact of the mediator on latent utility, β). Consistent with models of mediation involving continuous measures (Judd and Kenny 1981), the total effect (γ') is equal to the sum of the direct effect (γ) and the two indirect effects ($\alpha\beta$). The indirect effect estimates and test of their significance (based on simulating the standard errors) appear in Table 3.

Consistent with definitions of *complete* mediation (Baron and Kenny 1986), several attribute levels have a significant total and mediation effects and insignificant direct effect. For example, the overall significant total effect of *traditional stone-milled* is explained entirely by the indirect mediating effects with no remaining significant direct effect. Similarly, claims in the form of *low GI* and *high fiber* mediate choices completely via perceptions on health. Several cases of *partial mediation* also occur. For example, the significant preference for *wholemeal wheat* is explained by a significant set of positive indirect effects with respect to health and value, but a significant direct effect indicates remaining unexplained effects.

Competing mediation effects (beyond complete and partial mediation): The results highlight interesting cases involving a mixture of positive and negative indirect effects. For example, the total effects model indicates that *wheat (white)* flour has no significant impact on utility relative to other flour types. Examining the process by which this non significance arises reveals a set of significant, but contrasting mediating effects: breads made with *wheat (white)* flour are negatively perceived with respect to health, but well positioned with respect to value. We label such cases *competing mediation* effects.

By showing that one mediating effect can cancel out the impact of another opposing mediating effect resulting in a non-significant total effect, our results support the assertions of

Zhao, Lynch and Chen (2010), who suggest that the exploration for mediation does not necessarily require a significant total effect (c.f., Baron and Kenny 1986). The outcome is analogous to other cases of aggregation bias, which highlight how incorrect conclusions can be made about how non-significant effects arise as a result of not accounting for competing effects relating to unobserved heterogeneity (Hutchinson, Kamakura and Lynch 2000).

Extensions to Account for Process Heterogeneity

The model discussed above assumes that consumers have homogeneous preferences, form perceptions about benefits using product features in the same way and are identical in terms the extent that each benefit affects their choices. Several opportunities exist to explore process heterogeneity to offer insights beyond preference heterogeneity. First, consumer segments may differently judge the perceived benefits of an attribute level. For example, one segment may perceive *Helga's* to be healthy while another may not, but both may agree on the extent that health benefits should determine choices. In this case, we would expect to see differences in α across segments, but not differences in β. Second, two segments may agree on *Helga's* health benefits, but differ with respect to the emphasis each places on health relative to value in their choices. In this case, α would be identical across segments, but differences would appear in β. Of course, the two cases may occur simultaneously, with heterogeneous perceptions about the benefits that an attribute delivers and varying importance of these benefits for product choice.

The following analyses illustrate the insights our model can provide when using a discrete parameter distribution with two underlying latent segments based on process heterogeneity. We used the EM algorithm to estimate segment size and the associated parameters. In contrast to the total effects model where segments are based solely on choice outcomes, latent segments from the mediator model can be derived based on differences in perceptions, as well as overall choices. Segmentation based on the total effects model will better predict choices, whereas segmentation using our mediator model will better predict the joint outcomes relating to both outcomes reflecting the process by which choices are made (i.e., perceived benefits) and choice outcomes.

The latent segment mediator model classified respondents into segment 1 (59% of respondents) or segment 2 based on a posteriori membership probabilities, with 91% of respondents having a probability of at least 90% for being in one segment. Examining whether differences in perceptions and preferences can be explained by scale differences instead (Swait and Louviere 1993), we tested and rejected the hypothesis that the two segments only differ with respect to the error variability in their choices ($p < .001$).

Table 4 reports the parameter estimates of the corresponding mediator models for the two segments (a full set of results is presented in Web Appendix 3). As captured by estimates of β^n, these segments differed in the weight they place on perceptions of health over value in their choices, with segment 1 using both perceptual dimensions equally and segment 2 being a health-conscious segment that disregards value in choices. Estimates of α^m reveal further insights into how product attribute levels are differently perceived on each of these two dimensions. For example, those in segment 1 perceive *supermarket brands* to represent good value, but be relatively less healthy, leading to a neutral evaluation of these brands in choice. Members of segment 2 similarly perceive *supermarket brands* to be less healthy, but represent poor value, resulting in negative evaluations of these brands in their overall choices. Both segments share similar views about brands with respect to health perceptions, but segment 1 view all non-supermarket brands as offering poor value.

Insert Table 4 about here

The latent segments also illustrate how aggregation bias can occur, resulting in non-significant effects (Hutchinson, Kamakura and Lynch 2000). For example, as discussed, the aggregate results indicated the non-significance of the parameter estimate for *wheat (white)* bread. However, the total effect estimates for each latent segment explains this non-significance:

segment 1 has a positive preference for *wheat (white)* bread, while segment 2 has a significant negative preference. Further, both segments agree that this flour type is poor relative to other flour types when judged on health. However, they disagree in relation to perceptions of value: segment 1 believes products with wheat flour offer value for money, while segment 2 does not. This illustrates the merit in our model to detect that opposing preferences occurring across latent segments may be explained by differing perceptions.

We also explore whether differences exist across the segments with respect to various sociodemographic and behavioral variables. The two segments do not differ with respect to gender (p = .499) or average age (p = .408), but differ in their shopping habits (see Table 5). Members of health-conscious segment 2 are less likely to buy more than one loaf per trip (p < .05), but more likely to shop at least once per week (p <. 10) and make purchases carefully (p < .10). They have a higher purchase rates of gluten-free (p <. 01) and sourdough breads (p <. 10).

Insert Table 5 and Table 6 about here

Model Comparisons

Using the above model specifications, we report the associated in-sample and predictive fits in Table 6. We used six tasks for model calibration and two tasks for evaluating predictive performance. The predicted utilities using an aggregate standard choice model (Model I) are equivalent up to simulation error to estimates from the aggregate mediating-benefits choice model (Model II). This is because the sum of the direct and indirect effects equates to the total effects of the standard choice model as per Equation 1 and 2; in turn, there is no difference in both in-sample and predictive fit performance between Model I and II.

In Table 6, we further consider model fit when accounting for consumer heterogeneity in two ways. First, we estimated a standard model that accounts for *preference* heterogeneity via two latent preference segments (Model III). The modal memberships emerging from this model were then used to estimate two separate (one for each segment) benefits-choice models and the results subsequently summarized (Model IV). Model III and Model IV produce equivalent results relating to in-sample and predictive fit following the same explanation as above, however, Model IV provides additional insights into *why* these differences in preference across the segments arise with respect to multiple mediating processes.

Second, we estimated our proposed mediator model to allow for two latent segments based on unobserved heterogeneity across *all* parameter estimates (i.e., γ,α,β,ρ; see Model V), thereby sourcing membership from *multiple* forms of heterogeneous effects (i.e., direct and indirect effects, rather than total effects only). It detects heterogeneity to maximize the likelihood of choice outcomes, but also simultaneously maximizes the $\mathcal{M}$-likelihoods associated with the chosen benefits. This model underperforms on measures of in-sample and predictive fit pertaining to choice outcomes only (see Model III vs Model V), but offers superior predictions of the judgements of perceived benefits, as well as the judgments of benefits and choice combined (see Model IV vs. V). Taken together, the proposed mediator model offers superior insights into the idiosyncratic mediating process (i.e., *process heterogeneity*) and overarching joint outcomes of judgements of perceived benefits and choice.

DISCUSSION AND FUTURE RESEARCH

Summary and Methodological Contributions

We introduced a benefit-based choice model allowing researchers to investigate whether the effects of multi-attributes on choice are mediated by multiple perceived benefits. The method enables researchers to: a) test whether benefits influence choice (via the significance of the indirect effects, β); b) assess whether these comprehensively describe choices or whether important benefits have been left out (via the direct effects, γ); c) confirm or project the positioning of brands and features against competitors on these dimensions (via the indirect effects, α); and, d) evaluate the overall impact of brands and attributes on choice (via the total effects, γ'). The researcher can investigate unobserved heterogeneity across all these effects.

The model disentangles the total effects presented in standard choice models via a series of multiple, possibly competing, indirect effects as other researchers have considered (see, Dellaert et al. 2018). By allowing each attribute to have both a direct and set of indirect effects on choices, we are the first to propose and test the extent by which perceived benefits mediate choice. In contrast to models that consider that an attribute exclusively impacts a single latent benefit (e.g., Oppewal et al. 1994) or in a way that the impact must be positively correlated with overarching preferences (Kim et al. 2017), we allow and provide evidence that each attribute can independently impact multiple perceived benefits at the individual level. Our model and empirical application also presents an important contrast against choice models that account for preference heterogeneity (Train 2009) and to describe process heterogeneity with respect to how perceptions may form differently across consumers (e.g., Dellaert et al. 2018; Swait et al. 2018).

Our proposed model offers several methodological advantages relative to the multiple indicators causes model and SEM-based frameworks considering mediation (Jöreskog and Goldberger 1975; Preacher and Hayes 2008; Temme et al. 2008). Our model is able to: be estimated simultaneously; avoid rescaling of estimates for mediation analysis; handle multiple categorical mediators and multinomial choice outcomes; allow for moderated mediators; and, consider forced choice scenarios. Our empirical results also reinforce that mediation effects may be present even when total effects are not significant (Zhao, Lynch and Chen 2010).

Our approach involves collecting additional data to be included as a reflective measure of the latent dimension as performed in other studies utilizing hybrid choice models (e.g., Daly et al. 2012). However, our DCE-based approach recognizes that consumers form overarching perceptions of each product on various latent dimensions using all attributes simultaneously. Our approach offers all the advantages associated with DCEs, including the recognition of trade-offs made by consumers, ability to consider interactions among attributes and avoidance of rating-scale biases (Baumgartner and Steenkamp 2001). Those familiar with DCEs can readily adapt their implementation and gather the additional information required. For example, the same experimental design and online user interface can be re-used, requiring an alteration of the choice task to focus on perceived benefits.

Our method aims to confirm and test how the impact of attributes on benefits mediate choices, with the selection of benefits to examine made a priori by the researcher or manager. These benefits may be derived from different sources: Researchers can rely on prior literature or suitable theory to propose testable hypotheses about mediating effects. In managerial settings, benefit dimensions may be sourced from: internal or competitor positioning statements; past or planned advertising claims; preceding research (e.g., focus groups; perceptual mapping exercises; new product development teams); or analysis of secondary sources (e.g., product reviews). Our method therefore differs to exploratory models that require additional steps after model estimation to interpret the latent variables detected (e.g., Elrod and Keane 1995; Kim et al. 2017; Swait, Argo, and Li 2018).

Our method is well equipped to consider forecasting of perceptions and choice when market data is not available (e.g., new or emerging markets) or where there are high levels of correlation in the presentation of features (e.g., a brand is always offered with a particular ingredient) (Louviere, Hensher and Swait 2000). The method thus allows companies and regulators to anticipate the combined impact of market or government induced changes on perceptions and choice, such as a push to disclose nutritional information on products and in-store menus using several mechanisms (e.g., health star ratings; colored panels) or via price tariffs (e.g., 'sugar tax') (Dunford et al. 2017). This could help determine whether negative perceptions exist, targeted consumers care little about a benefit relative to others or whether brand dominates perceptions and choices (Rogers et al. 1988; Russell 2018).

Empirical Findings and Managerial Contributions

In practice, the method allows managers to compare perceptions and their impact on choice across brands (e.g., to see if *Helga's* is perceived as healthier and/or chosen over

Abbott's) and features (e.g., to see if mixed wholegrains are perceived as healthier or preferred over mixed grains). It allows relative comparisons to be across perceptual dimensions (e.g., to see if *Helga's* performs better on health than value). Managers can identify which features impact certain dimensions more than others (e.g., whether brand influences health perceptions more than key claims or flour type), allowing valuable comparisons regarding the drivers of positioning from a holistic, multi-attribute, multi-brand perspective. Each of these comparisons can also be considered in terms of potential heterogeneity to guide segmentation strategies.

Our empirical results indicate that brands cannot exclusively focus on one point of differentiation, a question considered by other researchers (e.g., Bhat and Reddy 1998; Fuchs and Diamantopoulos 2010). We find that while brands can be well positioned on one benefit-dimension, their utility can be undermined by perceptions on other dimensions. Our results also indicate that positioning strategies must consider the role of product features and not just branding activities; this indicates how managing positioning can be problematic when using the same brand across product lines. Nonetheless, we found that brands dominated the shaping of perceptions about the benefits of an alternative more so than product attributes, as highlighted in other studies (e.g., Graeff 1997; Vriens and Hofstede 2000).

Our research contributes to and extends works that focus on determining how brands are perceived on various dimensions and how this can enable identification of market structures. This includes methods based on means-end-chains to identify attribute-benefit connections (e.g., Herrmann and Huber 2000; Hofstede et al. 1999), factor-analytical approaches to identify market structures (Elrod and Keane 1995), multidimensional scaling applied to brand proximity ratings to develop perceptual maps, and discriminant analysis of attribute-brand ratings to identify dimensions to group or differentiate among brands (e.g., Huber and Holbrook 1979). Our approach differs by establishing a quantifiable link between attributes, benefits and choices by observing consumer trade-offs among these dimensions, reflecting their relative importance. Quadrant analysis and importance-performance analysis (e.g., Lynch, Carver and Virgo 1996;

Martilla and James 1977), as well as product-attribute utility-based models (Gwin and Gwin 2003), provide similar insights by visualizing the correlation and disconnections between attribute-importance and brand-performance. However, our model does not require respondents to provide the weights that link attributes to perceptions one-at-a-time. Instead, we estimate these by observing the result of trade-offs between different features.

The empirical results highlight that our account of consumer heterogeneity – beyond differences based on preferences (Train 2009) or weighting of benefits (Swait et al. 2018) – provides valuable insights for consumer segmentation. Whereas cluster analysis of part-worths from conjoint tasks identify segments based on links between attributes and preferences (e.g., Johnson, Ringham and Jurd 1991), we indicate that differences can be present with respect to how perceived benefits form and how benefits shape preferences among alternatives. For example, we identified a health-conscious segment that perceived products with omega 3 or pumpkin seeds offered no health-benefits, but the other segment placing value on both health and value benefits did. This insight highlights that alternative reasons may explain preference heterogeneity and, in response, managers may employ different promotion strategies for each segment to alter perceptions or benefit importance.

Limitations and Future Research

Our proposed method provides opportunities for extensions given its foundations in random utility theory. For example, the model could use different methods to explore heterogeneity and differences in error variability (Hess and Rose 2012). It may also incorporate cross-effects between alternatives via flexible error correlations or by altering the systematic component as per a mother logit framework (Timmermans et al.1991). Our approach could be modified to handle contexts with many alternatives (e.g., Fader and Hardie 1996) or use other estimation approaches (e.g., Bolduc and Alvarez-Daziano 2010). Similarly, researchers could explore alternative model specifications to include attitudes and values (Ashok et al. 2002) or nonlinear effects to consider satiation of an attributes' contribution to benefits (Kim et al. 2017).

The DCE method to measure perceived benefits could also be modified, for example by eliciting both the best and worst alternatives or by ranking on a given dimension of interest to obtain more information (Marley and Pihlens 2012). Researchers could additionally explore perceptions about barriers to choice (Burke et al. 2014). While the choice sets in our study were based on a completely randomized design, alternative designs could reduce the possible confound between effects relating to individual differences and experimental design. Similarly, we presented an identical DCE task to measure perceptions after the choice task, so there is scope to explore variations in survey structure, including eliciting both tasks simultaneously or using separate experimental designs for the two tasks. Such variations may reduce correlation between the unobserved components of the latent constructs. In addition, there may be opportunities to combine data from various sources following similar approaches utilizing both revealed and stated preference data (e.g., Ben-Akiva et al. 1994; Hensher and Bradley 1993). For example, a manager could observe market behavior and collect information on perceived benefits of market and hypothetical offerings to test for their mediating effects on choices.

Beyond product positioning, we anticipate applications of the model in other research settings where mediating effects are of interest. For example, it would be useful to explore mediation in group decision-making, where choice outcomes can be influenced by competing effects (Arora and Allenby 1999). These could relate to differences about the perceived benefits of some attributes (e.g., disagreement in households about the healthiness of breads made with unbleached flour relative to other flours) or differences in the relative importance of benefits (e.g., disagreement about preferences for healthier products over those offering value).

The approach also provides the opportunity to revisit previous studies of mediation, but in the context of choices with multiple attributes and multiple mediators (Mackinnon and Dwyer 1993). For example, Cian et al. (2014) showed that logo dynamism impacted attitudes toward the brand via the mediating effect of engagement. It would be worthwhile for managers to observe how such effects impact product choices alongside other competing logo and front-of-pack elements, as well as exploring other potential mediators, such as complexity or novelty. Similarly, researchers have discussed consumer perceptions about price information and promotion bundles (e.g., cash back; points) (e.g., Cheng and Cryder 2018). Our model could offer insights into consumer heterogeneity inherent in the holistic perceptions of product value and quantify how these mediate choice. In addition, the model could offer insights into how such pricing strategies improve inferences about perceived product value, but also negatively affect perceptions about product quality, and whether these perceptions differ across consumers in how they impact choices (Rao and Monroe 1998; Zeithaml 1988).

The model presents opportunities to break down the process behind the impact of features of interest reported in past choice studies. For example, Auger et al. (2003) examine the value of ethical attributes (e.g., child labor) against product features using a traditional DCE-based approach. Researchers could use our method to evaluate whether a lack of demand for ethical attributes occurs because social benefits are not as important as functional benefits, or instead, whether consumers are skeptical and perceive that ethical attributes do not deliver the ethical benefits as intended. Similarly, it would be valuable to review previous choice studies that have considered preference heterogeneity, to understand whether the differences arise due to heterogeneity in perceived benefits and/or use of benefits in choice. For example, Mueller et al. (2010) identified five clusters of wine consumers based on preferences for label information (e.g., history, food pairing) and price; our method could reveal whether differences between segments arise due to the perceived benefits inferred from the label information (e.g., taste; value) or differences in the relative importance of each benefit. The model is therefore useful in many settings as it offers a deeper understanding of diverse forms of heterogeneity regarding how multiple features impact multiple perceived benefits and mediate choices.

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TABLE 1: COMPARISON OF HYBRID CHOICE MODEL STUDIES INVOLVING PRODUCT ATTRIBUTES

			Formative Component (Stage 1)						
Exemplary studies	**Context**	**Label of LVs**	**Attributes of alternatives affect LV**	**Same attribute affects multiple LVs**	**Account for unobserved heterogeneity in attribute-LV path**	**Correlation between LVs**	**Reflective measure of LV**	**Same attribute affects utility directly & indirectly**	**Test of mediation**
Oppewal, Louviere, and Timmermans (1994)	Marketing (retailing)	Constructs	Summative form only	No	No	No	Sub-tasks (DCEs; budget allocation)	No	No
Ashok, Dillon, and Yuan (2002)	Marketing (services)	Attitudes	No	n.a.	No	✓	Ratings	No	No
Walker and Ben-Akiva (2002)	Transport	Attitudes & values	Some, but not all	No	No	No	Ratings	Some, but not all	No
Danthurebandara, Vandebroek, and Yu (2013)	Marketing (cell phones)	Attitudes	No	n.a.	No	Causal	Ratings	No	No
Paulssen et al. (2014)	Transport	Values & attitudes	No	n.a.	No	Causal	Ratings	No	No
Arentze, Dellaert, and Chorus (2015)	Transport	Benefits	✓	✓	No	No	open-ended (mental maps)	No	No
Kim et al. (2017)	Marketing (cameras;B2B)	Benefits	✓	Not at individual level	✓	No	n.a.	No	No
Swait, Argo, and Li (2018)	Marketing (cameras)	Goals	✓	✓	No	No	n.a.	No	No
Our study	**Marketing (bread)**	**Benefits**	✓	✓	✓	✓	**DCE-based**	✓	✓

TABLE 2: COMPARISON OF STUDIES INVOLVING DEVELOPMENT OF MODELS WITH MEDIATING LATENT VARIABLES

		Indicator Items/Measures				
Exemplary studies	**Contribution/purpose**	**Independent variable(s) X**	**Mediating variable(s) M**	**Dependent/ variable Y**	**Multiple mediators**	**Simultaneous estimation**
Judd and Kenny (1981)	Describes process of mediation	continuous	continuous	continuous		
Baron and Kenny (1986)	Outlines conditions to test for complete and partial mediation	continuous	continuous	continuous		
MacKinnon and Dwyer (1993)	Method to standardize regression coefficients to correct scale differences for categorical variables	continuous or binary	continuous	binary		
Preacher and Hayes (2004; 2008)	Process to include multiple mediators	continuous	continuous	continuous	✓	
Preacher, Rucker and Hayes (2007)	Process to include moderated mediating effects	continuous	continuous	continuous		
Iacobucci, Saldanha and Deng (2007)	Simulations to examine SEM or regression approaches under depending on multiple mediators	continuous	continuous	continuous	✓	✓
Diamantopoulos, Riefler and Roth (2008)	Advancing formative measurement models	continuous	continuous	continuous	✓	
Zhao, Lynch and Chen (2010)	Alternative process/conditions to test for mediation (no significant total effect)	continuous	continuous	continuous	✓	
Iacobucci (2012)	Extensions to deal with binary mediators/DV	continuous	continuous or binary	continuous or binary		
Hayes and Preacher (2014)	Process to include categorical independent variable	multinomial	continuous	continuous		
Our study	**Introduce mediator with multinomial reflective indicator to model multinomial choice outcome**	**Continuous or multinomial**	**multinomial**	**multinomial**	✓	✓

TABLE 3: TOTAL EFFECTS AND IMPACT OF ATTRIBUTES ON MEDIATORS (AGGREGATE RESULTS)

	Total Effect	Perceived Benefits		Total Indirect		Direct
	γ'	α^{Health}	α^{Value}	$(\alpha\beta)^{Health}$	$(\alpha\beta)^{Value}$	γ
Abbott's	.086***	.228***	-.081***	.072***	-.027***	.040
Helga's	.384***	.514***	.090***	.163***	.029***	.190***
Tip-Top	-.142***	-.198***	-.126***	-.062***	-.041***	-.039**
MightySoft	-.215***	-.199***	-.267***	-.063***	-.087***	-.064**
Supermarket brand	-.112***	-.346***	.384***	-.109***	.125***	-.127***
Wheat (white)	.036	-.292***	.117***	-.092***	.039**	.090***
Wholemeal wheat	.408***	.357***	.393***	.113***	.128***	.167***
Unbleached wheat (white)	.047**	-.162***	.117***	-.051***	.038***	.059***
Unbleached wholemeal wheat	.277***	.365***	.373***	.116***	.122***	.040
Gluten free	-.767***	-.269***	-.999***	-.086***	-.326***	-.355***
Traditional stone-milled	.055**	.106***	-.019	.033***	-.006	.029
Low GI	.058**	.127***	.001	.040***	.000	.018
High fiber	.064***	.141***	.009	.045***	.003	.017
No added sugar	.005	.108***	.042**	.035***	.014**	-.042*
Low salt	.000	.100***	-.039**	.032***	-.013**	-.019
98% Fat Free	-.009	.085***	-.009	.027***	-.003	-.033
Enriched omega 3	.040*	.095***	.045**	.030***	.014**	-.004
No flavors etc.	.038*	.194***	.043**	.062***	.014**	-.037*
Low carb	.023	.079***	-.004	.025***	-.002	.000
No seeds	.035	-.131***	-.051***	-.041***	-.017***	.093***
Mixed seeds (with linseed)	.052**	.079***	.014	.025***	.004	.021
Mixed seeds (with pumpkin)	-.052**	.073***	-.041**	.023***	-.013**	-.061***
Mixed seeds (with poppy)	-.034	-.022	.078***	-.007	.026***	-.053***
No grains	-.030	-.153***	-.039**	-.048***	-.013***	.032
Mixed grains	-.011	.032**	.029*	.011**	.009**	-.030
Mixed wholegrain	.040*	.121***	.011	.038***	.003	-.002
Added niacin, vitamins E & B6	-.027	.104***	.005	.033***	.002	-.062***
Zinc and iron	.025*	.106***	.018	.034***	.006	-.015
Expires in 1 day	-.223***	-.076***	-.097***	-.024***	-.032***	-.168***
Expires in 3 days	.027	.024	-.009	.007	-.003	.023
Expires in 5 days (i.e., fresher)	.197***	.052***	.105***	.017***	.035***	.145***
Size (per 100g)	.124***	.054**	.281***	.017*	.091***	.016
Price ($)	-.338***	.014	-.911***	.004	-.298***	-.050
		Health	**Value**			
Impact of mediator on choice (β^m)		.318***	.326***			
Correlation between mediators (ρ^{HV})			.590***			

Significant terms indicted by */**/*** for effects are .10/.05/.01 levels.

TABLE 4: TOTAL EFFECTS AND IMPACT OF ATTRIBUTES ON MEDIATORS — TWO PREFERENCE CLASSES

	Segment 1 (59%)						Segment 2 (41%)					
	Total	**Perceived benefits**		**Total indirect**		**Direct**	**Total**	**Perceived benefits**		**Total indirect**		**Direct**
	γ'	α^{Health}	α^{Value}	$(\alpha\beta)^{Health}$	$(\alpha\beta)^{Value}$	γ	γ'	α^{Health}	α^{Value}	$(\alpha\beta)^{Health}$	$(\alpha\beta)^{Value}$	γ
Abbott's	.052*	.318***	-.281***	.092***	-.083***	.043	.137***	.100***	.068**	.067***	.000	.069***
Helga's	.143***	.400***	-.353***	.115***	-.104***	.130***	.721***	.704***	.490***	.477***	.003	.240***
Tip-Top	-.152***	-.290***	-.361***	-.083***	-.107***	.038*	-.135***	-.079***	.053*	-.053***	.000	-.082***
MightySoft	-.084***	-.149***	-.326***	-.043***	-.096***	.055**	-.388***	-.247***	-.220***	-.168***	-.001	-.220***
Supermarket brand	.041	-.279***	1.321***	-.080***	.389***	-.266***	-.335***	-.477***	-.390***	-.324***	-.002	-.007
Wheat (white)	.209***	-.284***	.522***	-.082***	.154***	.137***	-.163***	-.289***	-.095***	-.194***	-.001	.031
Wholemeal wheat	.395***	.307***	.531***	.088***	.156***	.151***	.504***	.426***	.479***	.289***	.003	.212***
Unbleached white	.150***	-.159***	.470***	-.046***	.139***	.056	-.090*	-.192***	-.169***	-.131***	-.001	.041
Unbleached w/meal	.371***	.385***	.655***	.111***	.193***	.068***	.151***	.350***	.244***	.237***	.002	-.086***
Gluten free	-1.125***	-.249***	-2.177***	-.072***	-.642***	-.411***	-.402***	-.294***	-.459***	-.200***	-.003	-.198***
Trad. stone-milled	.047**	.111***	-.041*	.032***	-.012*	.027	.077**	.104***	.047*	.071***	.000	.006
Low GI	.069***	.138***	-.075***	.040***	-.022***	.050**	.035	.117***	.046*	.079***	.000	-.045*
High fiber	.068***	.137***	-.060**	.039***	-.018***	.047**	.066**	.150***	.080***	.103***	.000	-.037
No add sugar	.044*	.135***	.017	.039***	.005	-.002	-.038	.080***	.079***	.054***	.000	-.093***
Low salt	.053**	.121***	-.088***	.035***	-.026***	.044*	-.065**	.077***	.033	.052***	.000	-.117***
98% fat free	.000	.059**	-.107***	.017**	-.032***	.014	-.022	.143***	.079***	.097***	.000	-.120***
Enriched omega 3	.034	.139***	.067***	.040***	.020**	-.028	.049*	.043	.051**	.030	.000	.020
No flavors etc.	.051**	.219***	-.042*	.063***	-.012*	-.001	-.001	.161***	.094***	.110***	.001	-.111***
Low carb	.037	.084***	.002	.024***	.000	.010	.008	.099***	.032	.068***	.000	-.060**
No seeds	.049**	-.178***	-.077***	-.051***	-.022***	.123***	.020	-.072***	-.043*	-.048***	.000	.068***
with Linseed	.073***	.080***	.017	.023***	.005	.045**	.023	.065***	-.014	.044***	.000	-.021
with Pumpkin	-.016	.111***	-.031	.032***	-.009	-.038*	-.081***	.036	.016	.024	.000	-.104***
with Poppy	-.106***	-.013	.091***	-.004	.027***	-.129***	.037	-.029	.041*	-.020	.000	.057**
No grains	-.074***	-.241***	-.057***	-.070***	-.017***	.012	.026	-.054**	-.024	-.037**	.000	.064***
Mixed grains	-.022	.057***	.057***	.017***	.017***	-.054***	-.007	.005	.026	.004	.000	-.011
Mixed wholegrain	.095***	.184***	.000	.053***	.000	.042**	-.019	.050**	-.001	.034**	.000	-.053**
Niacin, vit. E & B6	-.016	.141***	.011	.041***	.004	-.060***	-.036	.052**	.000	.034**	.000	-.070***
Zinc & iron	.016	.152***	.048**	.044***	.014**	-.042*	.033	.039*	.000	.027*	.000	.007
Expires in 1 day	-.299***	-.060***	-.188***	-.017***	-.056***	-.227***	-.139***	-.086***	-.081***	-.058***	-.001	-.081***
Expires in 3 days	.091***	.012	.050**	.004	.015**	.073***	-.051*	.026	-.044*	.018	.000	-.068***
Expires in 5 days	.209***	.048**	.139***	.014**	.041***	.154***	.190***	.060***	.125***	.040***	.001	.148***
Size (per 100g)	.172***	.054*	.610***	.016*	.180***	-.024***	.066***	.054**	.077***	.037**	.001	.029***
Price ($)	-.539***	-.020	-2.152***	-.005	-.634***	.102	-.188**	.049	-.091**	.033	-.001	-.221**
		Health	**Value**					**Health**	**Value**			
Mediator impact (β^{m})		.287***	.295***					.678***	.004			
Correlation (ρ^{HV})			.269**						.865***			

Significant terms indicted by */**/*** for effects are .10/.05/.01 levels.

TABLE 5: SOCIO-DEMOGRAPHICS AND BUYING BEHAVIOR OF LATENT SEGMENTS

	Segment 1	Segment 2	Test of Difference
Individual-level measure	**Mean^**	**Mean**	**p-value**
Female	52%	48%	.499
Age (years)	53	52	.408
Shops at least once per week	46%	56%	.094*
Regularly purchases gluten-free bread	1%	14%	.000***
Regularly purchases sourdough bread	15%	23%	.088*
Has to consider selection carefully	38%	49%	.100*
Buys more than one loaf per trip	58%	44%	.029**

^ Represents mean proportion or numeric mean of measure; Significant terms indicted by */**/*** for effects are .10/.05/.01 levels.

TABLE 6: MODEL FIT COMPARISONS

		Base^	Model I	Model II	Model III	Model IV	Model V
Outcomes model reports on:		-	Choice	Benefits & Choice	Choice	Benefits & Choice	Benefits & Choice
Heterogeneity based on:		-	None	None	Preference (γ')	Model III	All parameters
Estimated terms:		-	γ'	γ;α;β;ρ	γ'	γ;α;β;ρ	γ;α;β;ρ; ns
Product Choices:	LL	-1933.558	-1564.29	-1564.60~	-1304.78	**-1302.12**~	-1510.60
	HRI	.333	.407	.408	.500	**.505**	.427
	HRO	.333	.408	.409	.457	**.457**	.414
Perceived Benefits:	LL	-3867.115	-	-2997.39	-	-2893.71	**-2666.59**
	HRI	.333	-	.426	-	.456	**.496**
	HRO	.333	-	.430	-	.432	**.462**
Joint outcomes:	LL	-5800.673	-	-4236.32	-	-3940.62	**-3805.59**
	HRI	.037	-	.112	-	.145	**.149**
	HRO	.037	-	.112	-	.126	**.134**

Note: ^ The base case refers to predicting J^M perceived benefit outcomes and J choice outcomes in each set. Joint outcomes refers to (J^{M+1}) observable outcomes.
~Model I and II are equivalent in predicting choices (without preference heterogeneity); Model III and IV are equivalent in predicting choices (segments based on Model III).
LL = log-likelihood of model; HRI= probabilistic hit rate for in-sample sets; HRO= probabilistic hit rate for hold-out sample.

FIGURE 1: STRUCTURAL MODELS OF CHOICE (ADAPTED FROM McFADDEN 1986)

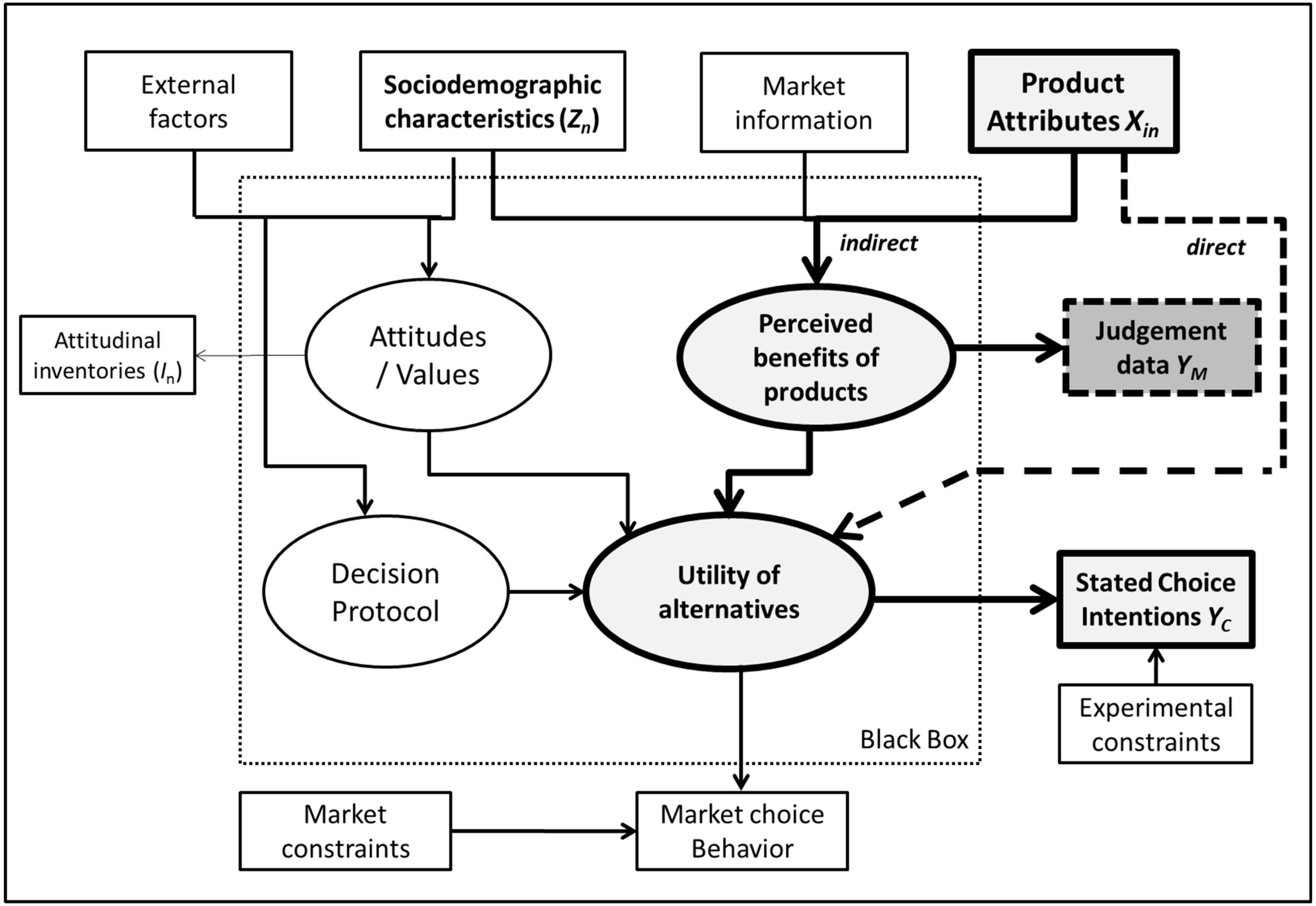

FIGURE 2: EXAMPLE OF RATING-SCALE BASED ON REFLECTIVE MEASURE OF LATENT PERCEPTIONS

Ratings scale approach:

Rate each on brand on a scale of healthiness?

	Unhealthy				Healthy
Abbott's	1	2	3	4	5
Helgas	1	2	3	4	5
Tip Top	1	2	3	4	5
MightySoft	1	2	3	4	5
Supermarket Brand	1	2	3	4	5

Rate each flour type on a scale of healthiness?

	Unhealthy				Healthy
Wheat (White)	1	2	3	4	5
Wholemeal Wheat	1	2	3	4	5
Unbleached Wheat (White)	1	2	3	4	5
Unbleached Wholemeal Wheat	1	2	3	4	5
Gluten Free	1	2	3	4	5

Rate each of the following claims on a scale of healthiness?

	Unhealthy				Healthy
Traditional Stone milled	1	2	3	4	5
Low GI	1	2	3	4	5
High Fibre	1	2	3	4	5
No add sugar	1	2	3	4	5
Low salt	1	2	3	4	5
98% Fat Free	1	2	3	4	5
Enriched Omega 3	1	2	3	4	5
No flavors etc.	1	2	3	4	5
Low Carb	1	2	3	4	5

...

FIGURE 3: EXAMPLE DCE-BASED REFLECTIVE MEASURE OF LATENT PERCEPTIONS

	Option A	Option B	Option C
Brand:	Helgas	Tip Top	MightySoft
Flour type:	Wheat (White)	Unbleached Wheat (White)	Wholemeal Wheat
Product claim:	Low GI	High Fibre	No add sugar
	Enriched Omega 3	No artificial flavors	High Fibre
Seeds	No seeds	Mixed seeds (with Linseed)	Mixed seeds (with Pumpkin)
Grains	No grains	Mixed grains	Mixed grains
Added Vitamins	Vitamins E & B6	No added vitamins	Vitamins E & B6
Minerals	Zinc and Iron	No added minerals	Zinc and Iron
Expiry date	Expires 1 day from now	Expired 3 days from now	Expired 5 days from now
Size	650g	700g	800g
Price	$3.20	$3.40	$3.40

Which of the above represents the *healthiest* option?

[ ] A [ ] B [ ] C

Which of the above represents the *best value for money*?

[ ] A [ ] B [ ] C

FIGURE 4: COMPARISON OF MEDIATION MODELS

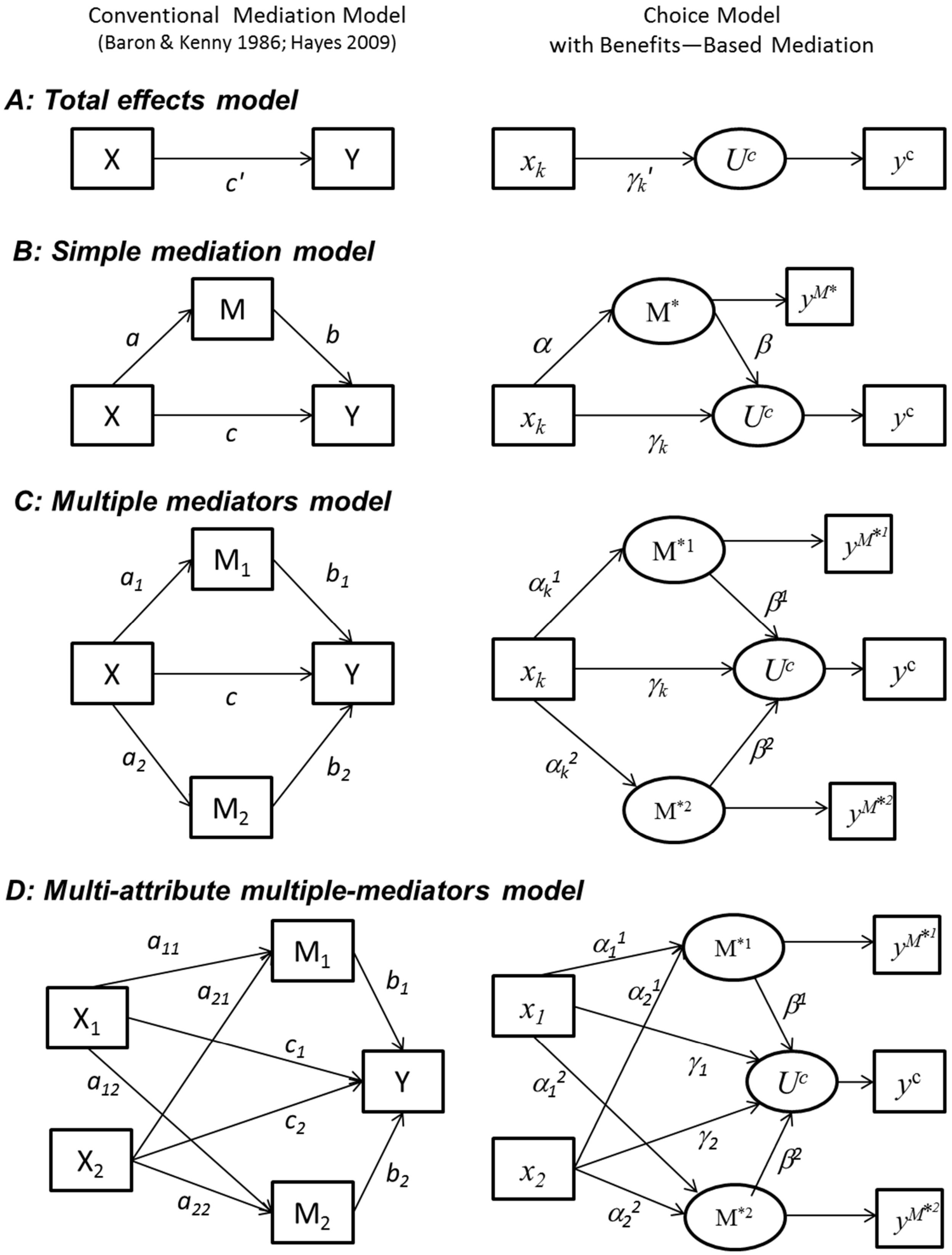

FIGURE 5: RELATIVE PERCEIVED POSITIONING OF BRANDS AND FEATURES (VALUE VERSUS HEALTH)