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A Choice Model with Systematic Structures in Decision Weights

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This article introduces a discrete choice model which incorporates a nonlinear structural adjustment to the standard utility coefficients or decision weights. The proposed model is theoretically and empirically appealing when compared to several alternative approaches, and it can be estimated by conventional maximum likelihood. Application of the proposed model in a case study shows that it outperforms two competing approaches in model fit. Given its simplicity, this model is also capable of revealing consumers' heterogeneous choices. It is shown that based on consumers' different characteristics, their product choice and its welfare implications are also potentially different.

Key words: logit models, stated choice, structural adjustment, weights

Introduction

Demand analysis using data featuring consumers' discrete choices among several alternative options has been applied widely in literature on microeconomics, marketing, and transportation research. Usually the options in question are described by their attributes, and consumers are assumed to make their preferred choices based on these attributes rather than the options per se (Lancaster, 1966). Either with choices involving actual actions or transactions, or choices based on hypothetical scenarios, the analysis of consumer behavior and demand in this context can be seen as attribute-based. Based on random utility theory, discrete choice models have been developed to accommodate this type of analysis. Among others, the logit and probit models are the most commonly used frameworks. The logit model has been especially appealing due to its simplicity.

Several variations of the basic logit model have been developed either to ease its theoretical restrictions (e.g., IIA) or to provide more insight into the nature of choices, such as heterogeneity and behavior patterns. Nested logit models, the latent class models, and the random parameter models all have been particularly popular in the discrete choice literature.

In this study, a new choice model is developed that is also based on the basic logit model but with additional structure in the decision weights. The new model is applied to a case involving consumers' stated choices for a food item. Using respondents' demographic and socioeconomic characteristics, it provides a better model fit than the basic model while maintaining the simplicity of estimation.

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In principle, the proposed model adjusts the utility coefficients (decision weights) associated with various attributes by individual respondents' characteristics, and therefore draws information not directly included in the choice alternatives. Compared with other existing approaches, the proposed model includes the following features:

- First, it allows heterogeneity, defined through exogenous variables on respondents' characteristics, in weights associated with different attributes.
- Second, each consumer's individual-specific coefficients for different attributes can be derived by matching with the individual's personal profile.
- Third, in the weighting process, only the relative magnitude—and not the signs of the coefficients—will be altered, and therefore it does not yield theoretically implausible predictions.
- Fourth, with appropriate data, the proposed approach may be extended to reveal various decision rules proposed in the literature.
- Finally, since the model has a closed form, a conventional maximum-likelihood estimation can be conveniently applied.

The new model is formally introduced in the next section and compared with several commonly applied discrete choice models. Following the theoretical discussion, the proposed model is applied to a choice experiment data set that contains Japanese consumers' purchasing intentions for vegetable oil with potential new traits. Model fit and implications are also contrasted with those of several other models. Conclusions and further extensions are offered in the final section.

Model Development and Assessment

In a conventional choice situation, the utility of individual i choosing alternative j can be specified in the following random utility model (suppressing i and j):

$$(1) \qquad U = \mathbf{X\theta} + e = X_1\theta_1 + X_2\theta_2 + \dots + X_K\theta_K + e,$$

where the X's are variables representing attributes related to each choice alternative and the θ's are unknown weights or coefficients associated with these attributes. Assuming a largest extreme value type I distribution (Hu, 2005) of the error term e, the expression yields a conditional logit (CL) choice model. Given this common framework, consumers can be observed to implicitly evaluate the relative importance of various attributes and make a choice that represents the highest utility after combining these weighted attributes. This process whereby consumers trade off the importance of various attributes is reflected by the estimation of the weighting factors $\boldsymbol{\theta}$.

In addition to the attributes themselves, the importance of factors other than $\mathbf{X}$ in consumers' choice-making has been noted by researchers. One most direct and rich pool to consider is consumers' demographic and psychometric (such as attitudes and personality) characteristics. Past research has reported the effects of these variables (Gao, Veeman, and Adamowicz, 2005; Mehta, Rajiv, and Srinivasan, 2003).

A straightforward approach for incorporating such factors into a choice model is to create interactions between these variables and the product attributes. However, as some earlier studies have shown, the demographic or psychometric characteristics alone are not very efficient in explaining consumers' choices (Cattin and Wittink, 1982); moreover, simply incorporating these interactions into a logit model is in general not satisfactory either (Vriens, Wedel, and Wilms, 1996; Fennell et al., 2003). Inclusion of these interaction terms will consume the degrees of freedom of the analysis, but usually will not provide significant estimates (Hu et al., 2006). Here, we propose to attach structural adjustments for controlling how these and other potential variables enter into the model. The structure is also consistent with the attribute weighting process.

Suppose the final utility associated with an alternative to a particular individual depends on attributes with weights decomposed into those generated from the choice tasks and those weights assigned by respondents to the attributes due to reasons not explicitly revealed in a choice occasion. In the simplest case, these reasons may be generated by respondents' demographic and psychometric differences.[1] This is consistent with the general notion of heterogeneity—i.e., different respondents, even when facing the same choice sets, may make different choices. If decision weights associated with attributes and other factors can be labeled as $\beta_1, ..., \beta_K$ and $W_1, ..., W_K$, respectively, the utility function incorporating these adjustments within decision weights may be written as:

$$U = X_1(W_1\beta_1) + X_2(W_2\beta_2) + \ldots + X_K(W_K\beta_K) + e. \tag{2}$$

The goal is to create a model which can efficiently use additional information outside the choice experiment while maintaining the property of empirical tractability and remaining simple to estimate. In a latent class model, normally no information is directly available to assign individuals into various classes. Class memberships are defined by a set of probabilities which are in turn determined by individuals' characteristics. Inspired by this approach and trying to avoid the pitfalls of incorporating interacted variables into the utility expression, we introduce a structural adjustment to the decision weights.

Suppose $P(X_k)$ can be defined as the probability that attribute X_k is being treated as the most important attribute depending on a respondent's personal characteristics. The higher the probability of attribute X_k being the most important attribute, the more important it is in the respondent's decision-making process and the larger (in absolute value) the coefficient of X_k will be in the choice model. According to this argument, the probability expression $P(X_k)$ can be used to replace the W's in the weighting process, and the indirect utility becomes:

$$U = X_1\big(P(X_1)\beta_1\big) + X_2\big(P(X_2)\beta_2\big) + \ldots + X_K\big(P(X_K)\beta_K\big) + e. \tag{3}$$

It is important to note that one does not need to identify an absolute value of the probability measures $P(X_k)$ since these probabilities only reflect the relative weights of various attributes in question. Hence, without losing generality, the *relative* probability

[1] Other factors can be considered as well, such as consumers' attitudes and perceptions related to the consumption of a product. Factors that are relevant to the choice sets themselves may also be incorporated, such as choice task complexity and decision context measures (Hu, Adamowicz, and Veeman, 2006). However, as pointed out by a referee, when incorporating choice-set specific factors, one should check the implied preferences to ensure that transitivity still holds.

of attribute X_k being the most important attribute (in other words, the relative weight of X_k) can be written into a familiar multinomial logit (ML) kernel:[2]

$$P(X_1) = \frac{1}{1 + \sum_{q=2}^{K} \exp(\alpha_q + \mathbf{D}\gamma_q)}, \tag{4}$$

$$P(X_k) = \frac{\exp(\alpha_k + \mathbf{D}\gamma_k)}{1 + \sum_{q=2}^{K} \exp(\alpha_q + \mathbf{D}\gamma_q)}, \quad k = 2, \ldots, K,$$

where vector $\mathbf{D}$ includes exogenous variables that can be used to explain this portion of the decision weight. The probability of the first attribute being the most important attribute is arbitrarily chosen to be normalized. In this expression, $P(X_k)$ ranges from zero to one. The normal property of the probabilities estimated by an ML logit model implies

$$\sum_{k}^{K} P(X_k) = 1.$$

This property may be viewed as restrictive. However, because only the relative importance of the attributes is considered, this property can be treated as a type of normalization where the portion of weights expressed in logit kernels is normalized by the sum of the total weights for each attribute. In fact, due to this normalization, any change in one weight specified in (4) will necessarily introduce changes to at least one other weight—this is consistent with the notion of *relative* weights to the relevant attributes.

The proposed model is obtained by substituting the corresponding probabilities in (4) into the utility expression in (3) and assuming appropriate distribution for the error term. Given the weight-adjusted indirect utility function, the implied ratio between two adjusted coefficients can be shown as:

$$\frac{P(X_k)\beta_k}{P(X_q)\beta_q} = \frac{\exp(\alpha_k + \mathbf{D}\gamma_k)}{\exp(\alpha_q + \mathbf{D}\gamma_q)} \frac{\beta_k}{\beta_q} = \exp(\alpha_k - \alpha_q + \mathbf{D}\gamma_k - \mathbf{D}\gamma_q) \frac{\beta_k}{\beta_q}. \tag{5}$$

The proposed model possesses theoretical and empirical advantages to several other existing methods. The first of such methods is a model that incorporates additive interaction terms between demographic/psychometric variables and the attribute variables. Specifically, a weighted attribute in the utility function $X_k\beta_k$ can be further extended into $X_k\beta_k^* = X_k b_0 + X_k\mathbf{bD}$, where $\mathbf{D}$ can be the same vector of variables in equation (4). The difference between the proposed model and this common way of including demographic/psychometric variables is analogous to the comparison between a linear probability model and a discrete choice model. Depending on the level of variables in

[2] Because this specification only takes the kernel of an ML model, there is no error term attached. One may use other formulations for these weighting structures. For example, $P(X_k) = \exp(\mathbf{D}\gamma_k)$ can be specified. This expression, however, may generate excessively large values depending on the level of $\mathbf{D}$ and the estimated parameter in γ. On the other hand, it is only the relative importance of the attributes that counts. Individual weight factors will have to be normalized to reflect the relative importance. This also explains why, even if $\exp(\mathbf{D}\gamma_k)$ or any other similar parameterization can be transformed to values between zero and one, after normalization, the multinomial logit kernel is still very general.

vector **D** and the estimated coefficient vector **b**, the most striking difference is that the combined effect of $X_k \beta_k^*$ can be either positive or negative or zero regardless of the magnitude of $X_k b_0$. For the proposed model, however, since the multiplicative weighting factor $P(X_k)$ is a probability between zero and one, the weighting process will not change the estimated sign of the estimated coefficient associated with variable X_k. This implies that the factors outside of choice tasks will only change the magnitude of the relevant importance of the attributes but not switch an attribute from desirable to undesirable or vice versa. Given the short period involved with a reasonably designed stated-choice survey, this result appears to be sensible.

Second, compared with other more advanced choice models, the proposed model's advantage resides mostly in its simplicity. In a nested logit model, factors such as the demographic variables can be used to identify the nesting structures. However, this approach often suffers from convergence problems, especially when one or more degenerated branches are specified. For a latent class model, the main difficulty remains the identification of number of classes. As a nondefinitive testing procedure, the class determination often relies on the application of nonparametric tests after estimating several models each with a different number of classes specified (Hu et al., 2004; Morey, Thacher, and Breffle, 2006). This process can be tedious, and when model specification changes (adding or deleting variables), the full set of models must be estimated again to determine the optimal number of classes.

Furthermore, since the total number of parameters to be estimated in a latent class model equals the number of classes multiplied by the number of explanatory variables, a latent class approach may quickly deplete the total degrees of freedom. Consequently, often only a handful of segments can be successfully identified. The proposed model, on the other hand, does not encounter this problem because variables included in vector **D** directly explain choices rather than merely assigning individuals to one of the few classes determined by the estimation process. Hence the proposed model may reflect various choice patterns through only a few additional parameters—a property shown in the case study detailed below.[3] This property gives the model flexibility similar to a factor or cluster analysis often seen in the marketing literature. Yet, unlike a factor or a cluster analysis, the proposed model can be easily assessed by testable hypotheses (Morey, Thacher, and Breffle, 2006).

Another flexible model is the random parameter logit (RPL) model. It offers great detail in understanding consumer heterogeneity in the choice process, and often individual-specific parameters can be produced. However, since the RPL model does not have a closed-form representation of the likelihood function, estimation generally takes a significant amount of time even given the new developments in estimation techniques. In contrast, the proposed model does have a nicely defined closed-form likelihood function, and therefore the conventional MLE is sufficient. In this model, each individual will have a different combined coefficient for each attribute, and these coefficients vary across respondents depending on their demographic characteristics. Similarly, if the denominator in the ratio considered in (5) is the weight associated with the price attribute, then (5) can be interpreted as the marginal value of attribute k. It can be seen that this marginal value is also individual-specific.

[3] This statement is certainly conditional on a fixed number of variables included in vector **D**. Each additional variable included in **D** will increase the total number of parameters to be estimated by the size of the attribute variables minus 1.

The heteroskedastic extreme value (HEV) models comprise another less popular but also interesting model group. These models recognize that the coefficients estimated in a logit model are actually the true coefficient divided by the standard error of the model (Bhat, 1995), β_k/σ, where σ is the standard error. The HEV models allow one to further parameterize the standard error (also often referred to as the scale parameter) to reveal heteroskedasticity. Using the notation in this current study, a common approach for such a parameterization is $1/\sigma = \exp(\mathbf{D}\gamma)$. Hence, in construction, the HEV model is close to the model proposed here. However, although the scale parameter can vary across individuals or choice alternatives, all attributes in an HEV model will multiply the same scale factor in determining the utility associated with a particular alternative. The proposed model, on the other hand, allows each X_k to have a different weight given by $P(X_k)$.

Finally, since there is almost no restriction on what factors may be considered in vector $\mathbf{D}$, the proposed model may be enriched by considering factors or proxies related to individuals' perceptions, cognitive abilities, or other decision-making heuristics. With appropriate data, the proposed model may reflect a variety of decision strategies, such as those investigated by Conlon, Dellaert, and Van Soest (2001); DeShazo and Fermo (2002); Gilbride and Allenby (2004); and Hu (2007). In the remainder of this article, we apply the proposed model to Japanese consumers' purchasing intentions for vegetable oil and empirically assess the model performance and implications.

Data

The data employed in this study were collected in 2004 in the area surrounding Tokyo, Japan. The original survey focused on Japanese consumers' perceptions and acceptance of vegetable oil with potential new product traits. Survey questionnaires were mailed to a large number of residents in four major cities: Tokyo, Kanagawa, Saitama, and Chiba. Of the 1,050 survey instruments mailed that are related to this study, a total of 430 completed questionnaires were returned, ultimately yielding 367 usable responses for this study. Descriptive statistics for several key demographic characteristics are reported in table 1. Of the 367 total survey respondents, 22.9% were male consumers. The average respondent age was around 57. Also, on average, the respondents had approximately 13 years of formal education and an average annual income of 6.8 million Japanese yen (about $55,000 U.S.). These variables are candidates that may enter vector $\mathbf{D}$ and be used to identify weights attached to product attribute variables.

The survey included general questions concerning consumers' attitudes and views on issues related to vegetable oil and on seven potential new traits/claims. These new features include: (*a*) low saturated fat content, (*b*) high oleic acid content, (*c*) high alpha-linoleic (AL) acid content, (*d*) high vitamin E content, (*e*) genetically modified (GM) content, (*f*) certified organic food (JAS label), and (*g*) certified functional food (FOS label). The first four nutritional attributes are presented as four possible outcomes of the nutrition content of a product. The variable representing "low in saturated fat" is omitted from the analysis to avoid multicollinearity. In addition to these nutrition content and certification claims, the survey was interested in identifying the potential performance of imported oil in the Japanese market. Therefore, another attribute introduced into the study was whether the oil is produced domestically. The selection of these attributes was determined by a series of focus group discussions and pretests prior to conducting the final survey.

Table 1. Descriptive Statistics of Demographic and Design Variables ($N = 367$)

Variable	Definition and Coding Method	Mean	Std. Dev.
MALE	Dummy variable for respondent's gender	0.229	0.420
AGE	Continuous variable for age	56.627	12.441
EDU	Continuous variable for years of education	12.842	2.058
INCOME	Continuous variable for yearly income in Japanese yen	6,806,540	3,722,617
BUYNO	Alternative specific constant for the no-choice option	0.333	0.471
OLE	Dummy variable for presence of "high in oleic acid"	0.166	0.372
ALP	Dummy variable for presence of "high in alpha-linoleic acid"	0.167	0.373
VE	Dummy variable for presence of "high in vitamin E"	0.167	0.373
GM	Dummy variable for presence of "GM content"	0.333	0.471
JAS	Dummy variable for presence of organic food label	0.167	0.373
FOS	Dummy variable for presence of functional food label	0.333	0.471
IMP	Dummy variable for being imported	0.333	0.471
PRICE	Continuous product price in Japanese yen	306.9	242.2

The core component of the survey is a repeated conjoint choice experiment using the seven nutrition content/claim attributes, the product origin (i.e., domestically produced), and the price as design variables. A fractional main-effect factorial design was adopted, creating 16 choice sets with each choice set containing three alternatives. Among these three, respondents were instructed to choose one and only one alternative. The first two alternatives are described by actual attributes and, similar to many other stated-preference surveys (e.g., DeShazo and Fermo, 2002; Hu, Adamowicz, and Veeman, 2006), the third alternative is always an option allowing the respondent to choose "none" (i.e., neither of the first two). Also following previous literature, the 16 generated choice sets were blocked into two groups each with eight sets. Each respondent then was randomly assigned to one group.

The nine variables listed in the lower section of table 1 are those that enter the experimental design, and finally the utility specification as attribute variables. It can be seen from the nature of these attributes that all but the price variable are given as binary quantities—either present or absent in a product subject to the experimental design. Price levels were predetermined (through focus group discussions and pretests) with five possible levels, ranging from 298 to 698 Japanese yen. To assist interpretation, table 1 also summarizes the definitions and descriptive statistics for these variables. It is noteworthy that these variables are summarized over all three alternatives offered in a choice set. Since the attribute levels in the "none" option choice are coded as zero, the sample average of these attributes appears to be smaller than if summarizing across only the first two alternatives in a choice set. Intuitively, the fact that mean values of the binary design variables are multiples of 1/3 (there are three alternatives in each choice set) is an indication that the experimental design was fairly balanced.

Empirical Results

The researcher's investigative interest will dictate the choice of variables to be included in vector **D** in equation (4). It is not the intent of this study to build a large model to interpret all potential impacts to choice behavior, but rather to demonstrate the potential

Table 2. Estimation Results of Three Competing Models

Variable	Basic CL Model Coefficient	Basic CL Model Standard Error	Extended CL Model with Interactions Coefficient	Extended CL Model with Interactions Standard Error	RPL Model Coefficient	RPL Model Standard Error
BUYNO	-0.974***	0.159	-0.986***	0.160	-2.640***	0.193
OLE	-0.082	0.096	0.420	0.439	-0.531	0.649
MALE			0.275	0.229	0.730**	0.333
AGE			-0.001	0.008	0.001	0.011
Std. Deviation					0.474	0.316
ALP	0.037	0.097	0.225	0.448	-0.715	0.638
MALE			0.206	0.236	0.722**	0.330
AGE			-0.004	0.008	0.009	0.011
Std. Deviation					0.273	0.287
VE	-0.297***	0.085	-0.355	0.396	-1.056**	0.523
MALE			0.294	0.203	0.768***	0.244
AGE			0.000	0.007	0.006	0.009
Std. Deviation					0.575***	0.194
GM	-1.879***	0.088	-1.521***	0.367	-4.135***	0.957
MALE			-0.149	0.191	-0.381	0.538
AGE			-0.006	0.006	0.005	0.016
Std. Deviation					2.687***	0.247
JAS	0.313***	0.091	0.982**	0.411	1.633**	0.811
MALE			0.029	0.210	0.371	0.435
AGE			-0.012*	0.007	-0.021	0.014
Std. Deviation					0.554*	0.323
FOS	0.700***	0.063	1.471***	0.292	2.131***	0.450
MALE			-0.227	0.148	-0.192	0.219
AGE			-0.013**	0.005	-0.017**	0.008
Std. Deviation					0.425**	0.178
IMP	-0.832***	0.072	-0.034	0.315	-0.866	0.738
MALE			0.354**	0.161	0.803**	0.358
AGE			-0.016***	0.006	-0.019	0.013
Std. Deviation					1.999***	0.171
PRICE/1,000[a]	-1.305***	0.265	-4.169***	0.830	-5.133***	0.396
MALE			-0.053	0.409	0.262	0.213
AGE			0.050***	0.014	-0.020***	0.007
Std. Deviation					1.328***	0.142
Log Likelihood	-2,608.839		-2,588.103		-2,095.114	
Adjusted ρ^2	0.179		0.183		0.338	

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.
[a] In order to fit a lognormal distribution, the opposite of the normalized price variable was used in the estimation. Mean and standard deviation values reported are those of the normal distribution underlying the logarithm kernel.

usefulness of the proposed model. To keep the application succinct, we elect to incorporate only two representative variables in vector **D**: *MALE* and *AGE*. The baseline conditional logit model using only product attributes as explanatory variables is the first model presented in table 2. In order to present the magnitude of the price coefficient in line with other coefficients, the *PRICE* variable was divided by 1,000 before it entered into the estimation.

Interpretation of the model results is straightforward. The option of choosing "none" (i.e., neither of the two products offered in a choice set) is associated with negative utility, suggesting Japanese consumers in general would not sacrifice the opportunity to purchase some vegetable oil. Compared with the dropped variable representing low saturated fat content, the attributes "high in oleic acid" (*OLE*) and "high in alpha-linoleic acid" (*ALP*) are not treated very differently. Nevertheless, consumers relatively less prefer a product with high vitamin E content (*VE*). In Japan, the claims of low saturated fat and high vitamin E in vegetable oil have been well-adopted since the mid-1990s, while the claims of high in oleic acid and high in AL acid are relatively new. The results here show that Japanese consumers treat these claims similarly to the low in saturated fat claim in terms of their importance in choice decisions. This finding may suggest consumers either have not fully understood the meaning of the two newer claims or they truly do not treat all three claims differently.

The comparison between saturated fat content and vitamin E content, however, is more likely to reflect a stabilized preference. Regardless, time will offer a good measure for revealing the reasons underlying these observations. Values of products that may possess GM content are strongly discounted, while the organic food claim (*JAS*) and functional food claim (*FOS*) significantly increase product desirability. These results are consistent with findings reported by other studies where the GM attribute is commonly found to be associated with negative values compared with the organic option (Lusk et al., 2005; Hu, 2006). Finally, likely due to support for domestic industry, imported oil is also less preferred by consumers compared to domestic products.

The second model in table 2 is a CL model with extended explanatory variables. These include interactions between the two demographic factors and all attribute variables excluding the variable *BUYNO*. The reason no interactions are specified for *BUYNO* will be explained below when we interpret the proposed model. The estimation results are generally in line with the baseline model. As observed from table 2, incorporating the demographic interacted variables significantly increases the model fit. However, it is also clear that many of the interaction terms do not appear to be significant, as predicted by Vriens, Wedel, and Wilms (1996) and Fennell et al. (2003).

Finally, table 2 shows the estimation results for the RPL competing model. With the exception of *BUYNO*, all variables are assumed to be randomly distributed across the sampled consumers. The coefficient of the *PRICE* variable is assumed to be lognormally distributed, while all other random coefficients are assumed to be normally distributed. The RPL model was estimated by simulated maximum likelihood with 125 draws for each iteration. This specification provides a drastic improvement to the model fit and reveals further behavioral details. A key advantage of the RPL model is the estimation of standard deviations associated with each random coefficient. In this application, standard deviation estimates for coefficients associated with *VE*, *GM*, *JAS*, *FOS*, *IMP*, and *PRICE* are all significant. These findings suggest there are unobserved heterogeneities associated with consumers' weights on these variables beyond what can be explained by the two demographic variables included.

Results of the proposed model are presented in table 3. Since the probabilistic weighting factor $P(X)$ for one of the attribute variables must be normalized for the model to be identified, this weight for the variable *BUYNO* is chosen and therefore not estimated. To maintain a consistent model specification, no interaction terms or random parameters were specified in the last two models in table 2. The proposed model has

Table 3. Estimation Results of the Proposed Model

Variable	Coefficient	Standard Error	Variable	Coefficient	Standard Error
BUYNO	-19.919**	9.716			
OLE	6.873***	1.969	*JAS*	10.805*	5.941
Constant	-8.210***	2.164	Constant	3.589***	1.575
MALE	5.933***	1.026	*MALE*	-12.883***	2.707
AGE	4.688	3.319	*AGE*	-12.214***	3.134
ALP	0.232*	0.120	*FOS*	22.416***	3.866
Constant	-1.356***	0.475	Constant	-2.035***	0.766
MALE	0.867*	0.483	*MALE*	0.466	0.558
AGE	6.789***	1.112	*AGE*	2.718*	1.418
VE	-19.486***	5.247	*IMP*	-26.934***	7.466
Constant	-3.033***	1.265	Constant	-3.343***	0.695
MALE	-12.887***	2.276	*MALE*	-0.064	0.360
AGE	3.172	2.334	*AGE*	5.152***	0.999
GM	-43.789**	17.997	*PRICE*	-13.581***	3.907
Constant	-2.664***	0.772	Constant	2.201***	0.782
MALE	0.757*	0.406	*MALE*	-0.179	0.224
AGE	4.402***	0.926	*AGE*	-2.930***	0.591
Log Likelihood = -2,575.722			Adjusted ρ^2 = 0.192		

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

significantly better model fit than either the baseline CL model or the extended CL model after adjusting for degrees of freedom.[4] This provides statistical support for the proposed model and verifies that incorporating a more plausible structure around non-attribute variables may not only contribute to the understanding of respondents' choice patterns but may also improve model performance. It is true that the proposed model has a poorer fit than the RPL model. However, the key advantage of this new model lies in its simplicity. When compared with the first two models in table 2, it can be seen that the proposed model has the best model fit while not relying on simulated maximum likelihood. Depending on the specific focus of their analysis, individual researchers must weigh the tradeoffs when deciding which model to use.

Behavioral implications of the proposed model can be observed through the marginal values associated with each attribute. As shown in equation (5), the difference between a baseline CL model and the new model lies in the extra term in front of the ratio of the two basic coefficients. If the demographic factors do not differentiate various choice behaviors across different individuals, the term in parentheses in equation (5) will be close to zero and the marginal effects suggested by the two models will be identical. Table 4 reports the marginal values of the nonprice attributes suggested by both the basic CL model and the proposed model. Standard deviations for the marginal values are calculated through simulations with 5,000 replications.

In the CL model, the largest marginal value is that of the *GM* attribute, indicating consumers would prefer to pay about 1,500 yen to avoid products with GM ingredients.

[4] Both the extended CL model and the proposed model nest the baseline CL model, and a normal LR test can be performed to test for the joint significance of the demographic variables. Nonnested likelihood-ratio tests can be conducted between the RPL model and other models.

Table 4. Estimated Marginal Values of the Nonprice Attributes: Basic CL Model and Proposed Model

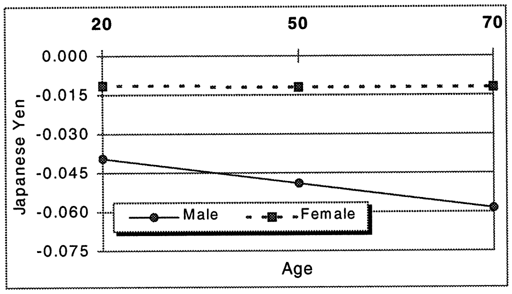
Attribute	Basic CL Model	Proposed Model					
		Male−20	Male−50	Male−70	Female−20	Female−50	Female−70
BUYNO	-759.82*	-366.94*	-889.60*	-1,638.54*	-296.29*	-717.18*	-1,319.55*
	(110.61)	(90.20)	(198.58)	(482.42)	(49.68)	(86.49)	(288.51)
OLE	-68.54	-0.04	-0.05	-0.06	-0.01	-0.01	-0.01
	(84.19)	(0.39)	(0.73)	(1.15)	(0.31)	(0.64)	(1.05)
ALP	26.51	8.53	133.98	941.86	3.33	51.52	358.54
	(77.30)	(8.08)	(105.33)	(879.48)	(2.68)	(31.13)	(261.80)
VE	-237.54*	-0.01	-0.04	-0.18	-43.20	-178.64	-618.67
	(96.39)	(0.13)	(1.17)	(5.73)	(39.50)	(59.93)	(404.97)
GM	-1,499.48*	-276.61*	-2,090.31*	-8,639.36	-134.97*	-1,007.83*	-4,133.19*
	(354.59)	(131.98)	(853.40)	(4,739.85)	(43.90)	(178.41)	(1,523.24)
JAS	249.09*	665.56	161.37	138.79	487.35	79.33	54.30
	(101.76)	(1,407.94)	(444.30)	(800.74)	(276.34)	(83.51)	(173.05)
FOS	559.25*	148.79	656.31	1,971.44	100.55*	420.78*	1,219.82*
	(144.13)	(84.90)	(339.53)	(1,463.60)	(46.12)	(82.67)	(510.53)
IMP	-662.49*	-49.60	-450.71*	-2,108.45*	-51.09*	-465.88*	-2,183.97*
	(160.53)	(27.55)	(192.62)	(1,116.25)	(18.94)	(91.32)	(782.70)

Notes: An asterisk (*) denotes statistical significance at the 5% level suggested by the confidence interval. Values in parentheses are standard deviations.

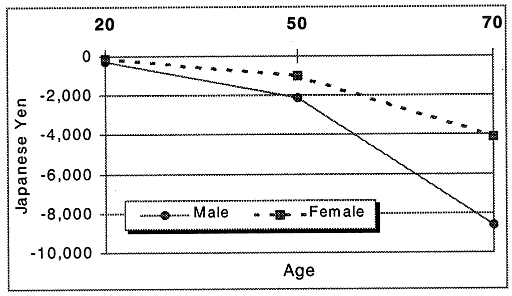
Similarly, they would be willing to pay 662.5 yen to purchase a product not produced in a foreign country (*IMP*). For the proposed model, each respondent's individual weight on each attribute and the marginal values can be calculated based on their own gender and age.

Because *AGE* is a continuous variable, to simplify the presentation, we created six consumer profiles to reflect these differences. The six profiles are male consumers at the ages of 20, 50, and 70, and female consumers at the ages of 20, 50, and 70. It can be seen that if additional explanatory variables are used in the multinomial logit kernel for the weights, the number of consumer profiles and the associated decision patterns revealed can quickly approach a large number. In contrast, no matter how many explanatory variables are included as covariates in a latent class model, the maximum number of decision rules that can be reflected is the number of classes. Increasing the number of latent classes incorporated in the estimation may simply be implausible due to the degrees-of-freedom restriction. This further demonstrates the exceptional flexibility the proposed model can provide.

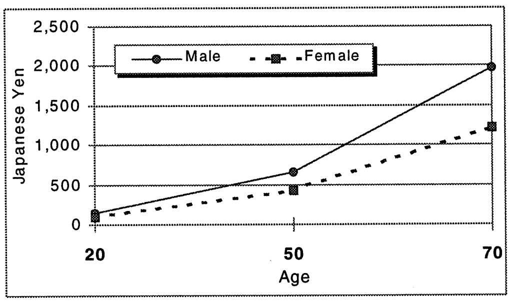
To calculate marginal values under the proposed model, the estimated parameters in equation (4) are first combined to form $P(X)$. Each of these weights are then multiplied by their corresponding element in the estimated $\boldsymbol{\beta}$ vector to form the overall attribute coefficients. The most striking result is associated with the variable *FOS*. Marginal values of *FOS* (functional food claim) are not significant across all age groups for male consumers. This shows that relative to price, the *FOS* attribute is not likely to enter the decision-making process of a male consumer. Yet, for female consumers, whether a product is claimed to be a functional food is one of the key factors determining their choice. Moreover, the importance of this factor increases as the age of a female consumer progresses.



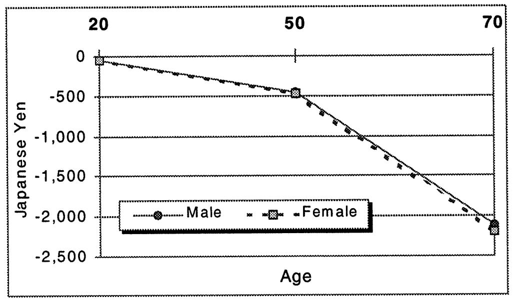
A. Marginal Value of Attribute *OLE*



B. Marginal Value of Attribute *GM*



C. Marginal Value of Attribute *FOS*



D. Marginal Value of Attribute *IMP*

Figure 1. Marginal values and implied choice behavior for sample attributes

Table 4 reports several other aspects that reveal the differences in choice behavior across different consumer profiles. For example, on the importance of the *GM* attribute, older individuals tend to place more weight on whether a product contains genetically modified ingredients, regardless of gender. However, for each age category, male consumers attach greater weight to the *GM* attribute than their female counterparts in their choice decision.

Figure 1 visually highlights some differences in consumers' decision-making processes. Four attributes were selected as illustrations: *OLE*, *GM*, *FOS*, and *IMP*. Panel A shows the marginal values associated with the attribute "high in oleic acid" (*OLE*). Although none of the marginal effects are significant for this attribute in table 4, the female consumer group does appear to assign an increasing relative importance to *OLE* compared with the price attribute in conjunction with the rise of age. For the genetically modified (*GM*) attribute (panel B), marginal values are fairly close between male and female consumers in the youngest age group. The difference accelerates with the increasing age of consumers and the attribute becomes more important for both groups. In panel C, consumers are willing to pay to purchase vegetable oil labeled as functional food (*FOS*) and, similar to the results for the *GM* attribute, the differences across male and female consumers widen when they become older. Male consumers place relatively more weight on this attribute than female consumers. In the last graph (panel D), regarding their opinions on imported oil (*IMP*), male and female consumers are very consistent in terms of the degree to which they dislike imported oil. The two curves are observed to closely overlap across all age groups. In both gender groups, the weight increases (in absolute value) with age.

Conclusions and Implications

The primary purpose of this study is to introduce a new model that reveals consumers' heterogeneity in discrete stated-preference analysis by efficiently using information outside the choice tasks themselves. This is accomplished through a structural adjustment to the decision weights (utility coefficients). By introducing the additional structured weighting factors, the proposed model avoids some problems typically associated with using interacted variables while maintaining the tractability of the functional form. The model is theoretically appealing compared to several competing models and is straightforward to estimate. The results generated also allow a sensible behavioral interpretation.

When applied to a stated-choice data set, the proposed model offers better fit than other competitive models. Although the random parameter logit (RPL) model may fit the data better than the proposed model, the simplicity in estimation associated with the proposed model significantly increases its appeal. Given its simplicity, the model is still capable of producing a great amount of information on consumers' choice behavior and heterogeneity. The case study presented here shows that, based on their individual personal characteristics, consumers reveal very different values they attach to various product attributes. The implied product choice and welfare implications are therefore potentially different.

One direct extension of the proposed model is to include additional factors to explain the weights respondents assign to various attributes. More variables may also offer greater details in characterizing each individual respondent's perception and decision strategy in further analysis of his or her behavior. The development of discrete choice analysis using either stated or revealed preference data has advanced tremendously in the past three decades. One key question has consistently been the focus in this field—*How can we better capture consumer behavior?* Advanced models and estimation techniques have been developed for this purpose and, depending on their complexity, some approaches take a significant amount of effort to implement. Perhaps another way to frame this question may be: *What approach offers the best tradeoff between better understanding consumer behavior and employing more complicated empirical models?* The current study seeks to offer some helpful insights in this regard.

Finally, the results presented in this paper are derived from a single case study. It remains to be seen if these are general results that have wide applicability. A carefully designed Monte Carlo experiment may be a rewarding way to further explore the properties of the proposed model. However, a major difficulty must be overcome by such an experiment. Specifically, if we simulate a data set with prior knowledge that different individuals attach different weights to the attributes, then the proposed model is likely to outperform the baseline CL model by assumption. A randomly generated data set may avoid this problem, but it would provide little practical usefulness in terms of comparing which model offers a better understanding of the systematic choice behavior, which does not exist in the data by assumption.

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