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AN EXPERIMENTAL METHODOLOGY FOR A FUZZY SET PREFERENCE MODEL

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A flexible fuzzy set preference model first requires appropriate methodologies for implementation. Fuzzy sets must be defined for each individual consumer using computer software, requiring a minimum of time and expertise on the part of the consumer. The amount of information needed in defining sets must also be established. The model itself must adapt fully to the subject's choice of attributes (vague or precise), attribute levels and importance weights. The resulting individual-level model should be fully adapted to each consumer. The methodologies needed to develop this model will be equally useful in a new generation of intelligent systems which interact with ordinary consumers, controlling electronic devices through fuzzy expert systems or making recommendations based on a variety of inputs. The power of personal computers and their acceptance by consumers has yet to be fully utilized to create interactive knowledge systems that fully adapt their function to the user.

Understanding individual consumer preferences is critical to the design of new products and the estimation of demand (market share) for existing products, which in turn is an input to management systems concerned with production and distribution. The question of what to make, for whom to make it and how much to make requires an understanding of the customer's preferences and the trade-offs that exist between alternatives. Conjoint analysis is a widely used methodology which de-composes an overall preference for an object into a combination of preferences for its constituent parts (attributes such as taste and price), which are combined using an appropriate combination function (Green 1984). Preferences are often expressed using linguistic terms which can not be represented in conjoint models. Current models are also not implemented an individual level, making it difficult to reach meaningful conclusions about the cause of an individual's behavior from an aggregate model. The combination of complex aggregate models and vague linguistic preferences has greatly limited the usefulness and predictive validity of existing preference models. A fuzzy set preference model that uses linguistic variables and a fully interactive implementation should be able to simultaneously address these issues and substantially improve the accuracy of demand estimates. The parallel implementation of crisp and fuzzy conjoint models using identical data not only validates the fuzzy set model but also provides an opportunity to assess the impact of fuzzy set definitions and individual attribute choices implemented in the interactive methodology developed in this research. The generalized experimental tools needed for conjoint models can be also be applied to many other types of intelligent systems.

FUZZY SETS AND PREFERENCE MODELS

Fuzzy Sets and Linguistic Variables

The most important consideration in developing a preference model is to select an appropriate representation for preferences. Likert rating scales are the most commonly used measurement scales in conjoint analysis studies (Wittink & Cattin 1989). Since preferences are measured on a labelled rating scale, a representation is needed for linguistic ratings such as "good" and "somewhat good". Fuzzy sets are a good representation for the uncertainty or vagueness inherent in the definition of a linguistic variable (Zadeh 1975), such as a rating of a product (e.g. somewhat good). Since conjoint analysis is based on preferences, a fuzzy set preference model is uniquely suited to this domain. Consumer ratings such as "good" are inherently vague, with a gradient of membership as to which other possible ratings belong, and a lack of sharp boundaries between ratings. Combinations of preferences, such as "good price AND somewhat good taste", are also expected to be fuzzy, in that classical logic does not adequately describe the combination operator "AND" (Turksen 1986). There has been substantial research in cognitive psychology in general, and categorization in particular, confirming that fuzzy sets are a good representation for linguistic variables. Conceptually, there is agreement on the gradient thesis and the concept of typicality in natural categories and fuzzy set theory (e.g. McCloskey and Glucksberg 1978). For preference models, fuzzy sets can be defined for the linguistic preferences on any labelled rating scale. A Likert scale labelled with 7 linguistic terms (very poor,...,very good) requires a fuzzy set definition for each of the 7 linguistic terms.

Fuzzy Set Measurement

Fuzzy sets representing preference ratings can be defined either on an individual basis or an aggregate basis. The proposed experimental methodology can obtain and refine fuzzy set parameters (prototype and crossover values) interactively and apply these values to an algorithm for generating individual fuzzy set membership values. Fuzzy sets should ideally be determined on a completely individual basis using interactive software. If this is not practical, membership values may be also pre-defined based on expert assessment or analysis of previous values. Both approaches are useful and are tested in this research. The domain variable for all fuzzy sets is a numeric subjective evaluation on a 0 to 100 scale (100 is best). Seven subjective evaluations (0-100) are anchored to the linguistic terms on the Likert scale and are treated as prototypes. Six additional evaluations are assigned as crossover points and two additional evaluations are added as endpoints, creating a total of 15 domain elements. The rating 75 might be prototypical (i.e. have a membership of 1.0) of the set "good" for example, while 80 might represent the crossover value or point where an evaluation becomes "very good" instead of "good". The transition or crossover domain value is given a membership of .50, corresponding to a point of maximum entropy in a set. For each set there are 3 membership values directly derived from subject responses (prototype and adjacent crossovers). The remaining membership values for the 15 domain elements are assigned to each set based on the slope of the line segment connecting the prototype and crossover elements and their position on the 0-100 domain variable.

In order to study the effect of using a fuzzy set representation for subject ratings, four types of fuzzy sets are used. The crisp number for a rating is essentially a one element set with the prototype having membership of 1.0. A 7 element set is defined by omitting the crossover membership values between prototypes. The 15 element set just described is the main form of measurement used in this research, while a 29 element set is also created by assigning intermediate membership values between existing elements. This provides 1, 7, 15 and 29 element sets on which to assess the impact of the fuzzy set representation and to determine an appropriate set size. An example of a pre-defined set for each of these four sizes is shown in Figure 1, along with an example of an elicited set for a particular subject. The support for the 15 element set "good" in Figure 1 is: { (32,0.05), (40,0.10), (45,0.20), (50,0.30), (55,0.45), (60,0.60), (68,0.80), (75,1.0), (83,0.80), (90,0.60), (100,0.45) }. There are no assumptions about a functional form, a distribution or an axiom such as additivity in the definition, nor of any measurement properties beyond ordinality in the underlying subjective evaluations.

Fuzzy Set Preference Models

It is not enough to have a good representation for preferences, since a model must estimate an overall preference for an object based on the preferences of its constituent attributes. The combination of linguistic preferences and the parameters associated with this function are a key component of any preference model. With fuzzy sets as attribute evaluations, a valid method of combining fuzzy sets must be found to produce an overall fuzzy set preference. The most effective and simplest crisp combination function, the vector model, will be used. The vector model uses an importance weighted sum of attribute evaluations, where each estimated attribute importance weight is multiplied by the attribute evaluation and summed across attributes to calculate an overall evaluation. The same approach can be used with fuzzy sets, given measurement support for the operations involved.

The fuzzy set conjoint model represents linguistic ratings in the weighted sum structure of the vector preference model. The fuzzy conjoint model uses the same consumer ratings as conventional conjoint models to allow direct comparisons of the effect on predictive validity. Subject ratings are represented by the fuzzy set definition for the linguistic term, instead of the number associated with the rating ("good" instead of 6). These fuzzy sets are combined in a linear preference model using crisp attribute importance weights similar to the combination of crisp numbers in the vector model. The inputs to the fuzzy conjoint model are the fuzzy sets defined for the linguistic terms of each attribute rating ($e_i\,(m)$). The membership of each domain element y_j in the calculated overall preference set ($\mu_{B'}(y_j,m)$) for product m is defined as

$$\mu_{B'}(y_j,m) - \sum_{i-1}^{T} \frac{w_i}{\sum\limits_{k-1}^{T} w_k} \times \mu_{A_i}(x_j,m) \tag{1}$$

where $\mu_{Ai}(x_j,m)$ is the membership degree of the subject's linguistic rating A_i for the *ith* attribute of product m for domain value x_j, w_i is a crisp attribute importance weight (1-7), and T is the number of attributes. For example, the membership of the domain element "good" in the overall set is the weighted sum of the membership of the domain element "good" in each of the attribute evaluation sets. The attribute and overall evaluation domain variables x and y are both subjective evaluation scores from 0 to 100 anchored to the identical 7 linguistic terms and their intermediate crossover points. The weight w_i is a directly elicited subject rating of the attribute's importance from 1 to 7. Attribute importance weights are normalized to produce an overall fuzzy membership value between 0 and 1. The overall preference is a convex linear combination of fuzzy sets representing attribute evaluations.

The fuzzy conjoint model requires only ordinal measurement of the fuzzy sets representing attribute and overall evaluations. The fuzzy conjoint model and a general class of fuzzy set models (including approximate reasoning using min/max norms) have been proven to preserve monotonic weak ordering of inputs through fuzzy operations (Turksen 1991). The membership function must only establish a weak order relation, that of being connected, transitive and bounded. Given such a structure, Turksen has proven that there exists an ordinal scale for the convex linear combination of fuzzy sets. The fuzzy conjoint model requires only ordinal attribute evaluations, which are easily obtained in conjoint analysis using a rating scale. Since an accurate ordering of overall evaluations is sufficient for choice prediction, the minimal measurement requirements of the fuzzy conjoint model are suitable for preference data.

Experimental Methodology

The individual fuzzy preference model requires an effective implementation, based on a sophisticated interactive computer program. For a product preference study for a given product category, the methodology must provide a wide range of attributes and attribute types from which the subject can pick, and then adjust the values and presentation of these attributes according to subject preferences. The individual options offered by the software are described in Table 1. Attributes and values are routinely pre-assigned in existing conjoint models, making it possible that the attribute is not important to the subject or that the values chosen are not meaningful or distinct (e.g. all 3 pre-specified levels appear low or high), invalidating the data from that subject and distorting the results in aggregate models. The interactive adjustment to the subject, independent of the model, is critical to successfully understanding preferences and provides important advantages. Each subject is treated as completely independent of all others, yet can be combined, as needed, in a bottom-up rather than top-down process. For example, the effect of price on preferences can be examined for all subjects for which price is an important attribute. Since only a few attributes are actually important to each subject, model complexity can also be reduced from the set of all possible attributes to only a few attributes for each subject. The combination of a good representation for ratings, a model which can use such a representation and an appropriate individual-level implementation can realize the full potential of preference models.

THE TEST OF THE FUZZY PREFERENCE MODEL

Experimental Design And Objectives

The objective of this research is to test a suitable implementation for the fuzzy conjoint model, considering the effect on predictive validity relative to the crisp model. The predictive validity is measured in a cross-validation test for first choice prediction and for longer ordered sequences of preferences from among test stimuli. The experimental design should permit both the fuzzy and crisp conjoint models to be properly implemented at an individual-level, with sufficient estimation and holdout stimuli for a strong test of predictive validity. The experimental procedures should take advantage of computer software to fully adjust the attributes and values to be most appropriate for each subject. The results should also provide convincing evidence about potential applications of fuzzy set preference models and of the interactive methodology outside of conjoint analysis.

The experimental design allows the fuzzy and crisp models to be implemented from identical data, subject ratings of hypothetical products based on combinations of general attribute levels. The attributes and exact value of attribute levels are obtained from each subject by the computer software that administers the experiment. A key component of the experimental design is the stimulus design, which specifies a small number of combinations of general attribute levels (e.g. low/medium/high) designed to permit statistical estimation of crisp conjoint model parameters. Since the fuzzy conjoint model does not require estimation or other statistical techniques such as regression analysis, estimation stimuli are only necessary for the crisp conjoint model. Individual-level models require that all estimation and test (or holdout) stimuli be presented to each subject. A set of 9 stimuli, each having 4 attributes with 3 levels can provide a statistical estimate of the main effects of the 4 attributes on the dependent variable (Addelman 1962). An addition 9 estimation stimuli represent additional combinations and provide sufficient degrees of freedom for crisp estimation procedures. In addition to 18 estimation stimuli, 6 unique holdout or cross-validation stimuli are used which are realistic tests for the models, forcing subjects to trade-off values of attributes (no dominated alternatives).

Two product categories are tested, with each subject completing the conjoint experiment for the delivered pizza and compact car categories. For the pizza category, subjects are to pick a large, 4 item pizza to order for home delivery. For the car category, subjects are instructed to rate cars they are given information on in order to select a few to test drive. Almost any type of product or service could be tested, as long as it could be described to subjects using a computer screen in words or pictures. Some product attributes in any category are naturally vague and linguistic. For a pizza, taste, quality and consistency are described with linguistic terms. For the car category, linguistic attributes such as acceleration (adequate, moderate, strong) and interior space (limited, somewhat roomy, roomy) are provided. Subjects select their four most preferred attributes from a pre-tested set of equal numbers of linguistic and numeric attributes. In addition to subject-specific attribute selection, the software further customizes the levels of all numeric attributes to each subject. For example, the price values used in product displays are directly elicited from each subject. The software combines a general stimulus design specifying attribute level combinations with a subject-specific set of attributes and attribute values to provide a unique and meaningful set of alternatives for each subject.

Experiment Implementation

The experiment is implemented using custom-written computer software given to subjects on a diskette that can be run on any IBM-compatible personal computer. The software provides all of the information needed, validating responses and recording data and monitoring information on the distribution diskette, which is returned by the subject. The software is run at any time, without the need for supervision or written instructions. The program describes the product category, obtains the attributes and prototypical values for each subject and then presents hypothetical combinations of these values according to the stimulus design. Subjects rate the products based on the information presented, with the software providing help and carefully logging all subject responses and times for subsequent analysis. The measurement scale used for all subject preference ratings is a Likert rating scale labelled with 7 linguistic terms representing 3 positive, 3 negative and 1 neutral evaluation. The linguistic terms for the scale responses are: very poor (1), poor (2), somewhat poor (3), neutral (4), somewhat good (5), good (6) and very good (7). The subject is instructed to pick the linguistic term that best represents his or her evaluation and to respond using the corresponding number (1-7). This labelled scale makes it possible to use either numbers or fuzzy set definitions for the corresponding linguistic terms as inputs.

In order to implement the fuzzy set model, membership values must be defined for the 15 elements of each of the 7 fuzzy sets representing preference ratings. These values can be assigned based on subjective assessment (identical pre-defined sets for all subjects) or defined interactively using computer software, with both methods reported in the results. The automated set elicitation technique has been implemented successfully in previous experiments (Willson 1991) and is based on a modified reverse rating procedure (Turksen 1991). The subject is asked for the prototype values ("What rating best represents good?") of each of the 7 sets on the underlying 0-100 domain variable. The 6 crossover values ("At what value (0-100) does good become very good?") are then elicited between adjacent ratings, for a total of 13 parameters for the set definition algorithm. The interactive software carefully validates all responses, displays a partition of the domain variable and offers opportunities to change and refine values. The set elicitation procedure takes about 5 minutes to complete on average. Each complete product category takes 25 minutes to complete, making it possible to implement two categories with each subject without excessive demands on the subject. Volunteer subjects were recruited from an undergraduate subject pool at the University of Toronto and were given course credit for successful participation in the experiment. This test involved 70 subjects who took 64.05 minutes on average to complete the entire experiment (2 product categories each).

Model Implementation and Testing

The experimental software provides relatively clean validated data from subjects. The data files are simply copied to a computer for use by the analysis software that implements the preference models. Specially written analysis modules automatically analyze subject data, determining choice predictions for crisp and fuzzy models. Other analyses can be done on the extensive monitoring data to determine how long subjects spent on each component of the experiment and how much assistance was required during the experiment, both important validation issues. The subject data can be automatically analyzed and input into other management systems, providing updates of demand estimates. This experimental and analytical software has been extensively refined based on previous experiments. The crisp vector conjoint model is implemented by estimating 4 attribute weight parameters using the ratings (implicit attribute and explicit overall evaluations) from the 18 estimation profiles. These crisp weights are estimated using ordinary least squares regression for each subject and product separately. The fuzzy conjoint model uses the estimation data to refine the pre-defined sets for each subject.

Once the models are implemented, a method of comparing predictive validity is needed. The success of a model in predicting the ranking of overall preferences is the most important criteria. The task is to predict the ranking of the 6 holdout profiles based on the attribute evaluations for these profiles. The subject's actual overall evaluation is the dependent variable to predict. Marketing practitioners and researchers have used relatively weak prediction measures (e.g. prediction of top product from a pair), with few tests of prediction among multiple alternatives, and even then only the rate of prediction for the top ranked alternative. Green (1984) reports that the best first choice prediction rate among current conjoint models is 53 percent for 4 holdout products. A stronger prediction measure developed in this research is the number of correct ordered predictions for each subject, ranging from 0 to 6 (6 holdout stimuli). Due to a promotion, advertising or inventory situation, a consumer could easily purchase a second or third choice product, particularly if preferences are relatively close together. Thus it is important to consider more than just the "hit rate" for first choice.

To determine prediction for a subject, the attribute evaluations of each holdout profile are used together with any estimated parameters to predict the subject's overall evaluation. The overall evaluations are then compared to the model's calculated overall evaluation for each of the 6 holdout profiles in the order of ranking until the correspondence in ranking is broken. For the crisp models, the procedure uses the calculated crisp preference scores ($y\ (m)$) and the subject's overall evaluations. For the fuzzy conjoint model, a fuzzy similarity measure is used to calculate the sum of the Euclidean distance between corresponding elements in the calculated and actual fuzzy sets, without first de-fuzzifying either set. The formula for the similarity of two sets is

$$(2) \qquad SIM(B'(y_j,m), B(y_j,l)) - 1 / [\, 1 + \sqrt{\sum_{j-1}^{15} (\, \mu_{B'}(y_j,m) - \mu_B(y_j,l)\,)^2}\ ]$$

where $B(y_j,l)$ is the fuzzy set for linguistic term l (subject's actual overall evaluation) and $B'(y_j,m)$ is the fuzzy conjoint model output for product m. The squared difference of the degree of membership of the jth element of each set is summed for all elements in the two sets. The square root of this sum added to 1 and then divided by 1 defines the similarity measure. The similarity is computed for product m to each of the 7 possible linguistic terms l. The similarity score ranges from 0 to 1 and provides only ordinal information, which is sufficient to determine prediction.

To predict a subject's product preference, the most similar set must be the set representing the subject's actual overall evaluation. For the *nth* highest overall evaluation, the calculated preference score should be the *nth* highest among the six holdout profiles. If the top rated product has an overall evaluation of good, then the calculated fuzzy set from the fuzzy conjoint model must be most similar to good, compared to any of the other fuzzy sets. The prediction measure (0-6) for each subject for both crisp and fuzzy models is then aggregated across subjects in three summary measures along with the mean. The number of subjects with first choice predicted, the sum of the prediction measure and the weighted sum ($n(n+1)/2$ where n is the number of correct ordered predictions) are reported in results and averaged as an overall comparison.

RESULTS

Prediction Results

The predictive validity of the crisp and fuzzy preference models is measured in terms of first choice prediction (%), the sum and weighted sum measures, the average of these three and the mean prediction by subject. All of these measures are reported in Table 2 for the crisp conjoint model and for the fuzzy conjoint model using 7,15 and 29 element pre-defined sets and using individually elicited sets with 15 elements (see Figure 1 for examples). The two product categories (pizza and car) are combined to provide a sample of 139 (1 product was incomplete). A naive model that randomly orders the 6 holdout profiles is also used to put the results in perspective. The prediction results will be discussed in this section for the standard 15 element pre-defined sets (column 3 of Table 1), with the different set sizes and elicited sets discussed in the following two sections.

The results show that the fuzzy conjoint model predicts the first choice of 76 percent of the subjects, compared to 48 percent for the crisp model and 17 percent for the naive model. This rate of first choice prediction from six holdouts is much higher than results reported in the literature. The crisp conjoint model, however, is still very good relative to the naive model and to the best current methods (e.g. Green 1984), which manage at best only similar prediction rates using much more complex models and aggregate estimation. Previous experiments using the fuzzy conjoint model and the pizza product add further support to these results, with an average first choice prediction rate of 78 percent over three previous tests (Willson 1991).

The prediction advantage of the fuzzy conjoint model over the crisp model increases substantially beyond first choice prediction, as reflected in the sum and weighted sum measures. The advantage increases from 58 percent for first choice prediction to 95 percent for the sum and weighted sum measures. The percentage of subjects for which the first n choices are correctly predicted declines quite slowly in the fuzzy conjoint model compared to the crisp conjoint model. The relative advantage over the naive model is even larger, starting with a 358 percent improvement in first choice prediction and increasing to 5700 percent for the first 5 choices in order. The overall improvement percentage is the average of the fuzzy conjoint model improvement over the crisp model for the first choice, sum of choices and weighted sum measures. The fuzzy conjoint model is 82.6 percent better than the crisp conjoint model overall. Comparing the mean prediction of the fuzzy conjoint model (FC-15) and the crisp conjoint model, the fuzzy conjoint model predicts the first two choices in order on average from the six holdout profiles, an event that would be expected by chance only 1 in 33 times. Comparing the mean predictions, the fuzzy conjoint mean is significantly better at 1.892 than the crisp conjoint mean of 0.971 with probability of error less than .001.

Fuzzy Set Definitions

The number of elements used to define the pre-defined fuzzy sets is expected to influence the predictive validity of the fuzzy conjoint model, with more elements increasing prediction to a point and then providing little additional improvement. With 7 linguistic terms providing 7 anchored subjective evaluations (prototype of each set with membership 1.0), there are 3 useful fuzzy set sizes to consider; 7, 15 and 29 elements. The 7 element sets have membership values only for prototype elements in the sets, while 15 element sets add crossover membership elements between prototypes and 29 element sets add an additional intermediate element between each of the 15 elements. The prediction for the three set sizes is given in Table 2 in the second, fourth and fifth columns. Predictive validity improves significantly using 15 element sets compared to 7 element sets, but much less so between 15 and 29 element sets. First choice prediction increases 6 percent from 7 to 15 elements and not at all using 29 element sets. The improvements are larger for longer sequences of prediction, as indicated by the 11 and 19 percent improvements in the sum and weighted sum measures respectively from 7 to 15 elements. The overall advantage over the crisp model increases from 63 percent with 7 element sets to 83 percent with 15 element sets and to 85 percent with 29 element sets.

The mean prediction measure is used to test for significant differences in the results (t-value and its significance given in Table 2). All three set sizes of the fuzzy conjoint model are better than the crisp conjoint model at a high level of significance (.001). The different set sizes can be compared to each other to see if the additional elements improve prediction significantly. The mean prediction using 15 and 29 element pre-defined sets is higher than the 7 element results, but at a lower level of significance (.05). The 29 and 15 element results are not statistically different. The results suggest that it is important to have an adequate number of set elements in defining membership in sets representing preference ratings. Clearly 7 element sets are not yet sufficient to represent ratings, with only one element covering each rating. Simply representing the crossover elements between adjacent sets using a total of 15 elements is sufficient to achieve very high levels of predictive validity, with little improvement gained by adding an additional 14 elements. This result is a strong confirmation of the notion of minimally sufficient measurement in defining fuzzy sets.

Experimental Implementation

This section examines the results of the fuzzy conjoint model using elicited set definitions determined interactively. The predictive validity of the fuzzy conjoint model using the elicited set definitions is shown in the third column of Table 2 (FC-EL). The results are somewhat better than the 7 element pre-defined sets and somewhat worse than the 15 element sets. Compared to the crisp results, the elicited results are 65 percent better overall, with a first choice prediction rate of 74 percent, a 54 percent improvement. The mean prediction of 1.712 is 76 percent better than the crisp mean, a difference significant at the .001 level. The large improvement over the crisp model and the comparable results to the pre-defined sets are a strong indication of the value of eliciting fuzzy set information from subjects. Using individual-level models it is most desirable to be able to also have individual fuzzy set definitions, and to do so easily and with a minimal loss of predictive validity compared to aggregate methods. This simple set elicitation procedure involving only 13 parameters for all 7 sets and requiring only 5 minutes appears to meet this goal. The subjects in this research are not told about fuzzy sets and do not examine graphed sets or refine membership functions. This is an important criteria for the future use of fuzzy set methods in management and with consumers, who can not be expected to use engineering-oriented set definition software.

One final aspect of the results is the success of the fully interactive experimental method implemented using computer software. Earlier tests of the crisp and fuzzy models using identical 15 element pre-defined sets and the pizza product allow a direct comparison of the effect of using the interactive methodology. The first two tests of the fuzzy conjoint model used written questionnaires with only pre-assigned attributes and attribute values and otherwise identical rating scales and data. The fuzzy conjoint model results improve using the experimental software. The average first choice prediction rate for all written tests is 71.5 percent, compared to 76 percent for the computerized studies (Willson 1991). Extensive analysis of subject comments and responses demonstrates that subjects can easily use the preference software without the need for prior training, providing meaningful responses sufficient to implement both fuzzy and crisp models from their preference ratings. This is a clear demonstration that fuzzy sets and linguistic preferences can be easily obtained from subjects in an automated methodology based on interactive computer software. The result is a fuzzy conjoint study that is easier to implement and requires fewer subjects than existing crisp conjoint methods, providing much better information for management at a lower cost.

CONCLUSIONS & DISCUSSION

The results clearly demonstrate the improvements due to an appropriate preference representation and an individual-level model implemented with fully adaptive computer software. The prediction improvement over existing models in a realistic comparison test using identical data is 83 percent, with the largest improvements for the more difficult task of predicting longer sequences of choices. The first choice prediction rate of 76 percent for 6 holdout products is much higher than crisp model, while the crisp model equals the best results in the literature. The results also demonstrate the value of using a fully interactive computer program to implement individual-level models, adjusting attribute choices and values to each subject. Individual fuzzy set definitions can be obtained from any subject in a few minutes with large improvements in predictive validity compared to crisp models. Since the fuzzy preference model does not require statistical estimation, it much easier to implement. The adjustment of attributes and values to each consumer improves both crisp and fuzzy set models enough for the crisp model to surpass existing aggregate models with only individual estimation. Since all subjects selected at least one linguistic attribute (2 on average) in their top 4 choices, it is important to accommodate both numeric and linguistic information in a preference model. The fuzzy model output provides information on each individual's preferences and how attribute values are traded-off. Optimal product(s) can be customized to particular market segments, created by grouping similar individuals together. The resulting aggregate market segment will be based on meaningful interpretations of the behavior of individual consumers, unlike existing approaches which rely on imaginary aggregates of consumers.

The success of the fuzzy set elicitation procedure (compared to crisp results and pre-defined sets) may have important implications for many types of intelligent systems. Almost any fuzzy expert system that involves individual tastes or perceptions (picture quality, microwave cooking, car performance) can benefit from the individual definition of fuzzy sets used in the inference process. The machine intelligence expected in the next generation of consumer products will require an ability to individually adapt to consumer preferences for attributes and to differences in the definition of linguistic terms. It is hard to imagine an optimal television picture or microwave cooking cycle in the abstract, without regard to a particular individual's preferences. A microwave should interact with an individual to learn what "well-done" means and to learn when this degree of cooking is desired. A television picture controller must consider the particular visual characteristics of its viewers, such as relative colour sensitivity and particular picture preferences (e.g. strong or weak flesh tones). Such intelligent devices can directly utilize the methods demonstrated in this research to improve performance and ultimately to better adapt the characteristics of the product to its user.

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TABLE 1: INDIVIDUAL-LEVEL MODEL OPTIONS

Option	Adjustment to each subject
Attribute Types	Both numeric and linguistic attributes must be available (e.g. linguistic acceleration OR numeric engine horsepower for a car)
Attributes	Only the most important attributes should be used, selected by the subject from a larger list of possible product attributes
Attribute Order	Attributes used in order of importance as ranked by subject
Attribute Values	Attribute values customized for each subject to ensure relevance. (E.g. elicit low/medium/high prices from the subject)
Fuzzy Set Definition	Individually elicit fuzzy set parameters from each subject (prototypes and crossovers) to define their fuzzy sets

TABLE 2: PREDICTION RESULTS

Prediction Measure:	Crisp	FC-7	FC-EL	FC-15	FC-29
1st choice rate:	48.2%	71.9%	74.1%	76.3%	76.3%
Sum of choices measure:	135	236	238	263	267
Weighted sum measure:	287	470	471	559	567
Overall % Advantage (fuzzy/crisp):		62.6%	64.7%	82.6%	84.5%
Mean prediction:	0.971	1.698	1.712	1.892	1.921
t-value of mean differences:					
FC-__ - Crisp		0.73 [a]	0.74 [a]	0.92 [a]	0.95 [a]
FC-__ - FC-7			0.01	0.19 [b]	0.22 [b]
FC-29 - FC-15					0.03

[a] $p < .001$. [b] $p < .05$. [c] $p < .10$. FC-7/15/29 = Fuzzy Conjoint with 7/15/29 element pre-defined sets, FC-EL = Fuzzy Conjoint using 15 element elicited sets.

FIGURE 1: FUZZY SETS FOR "GOOD"