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A FUZZY SET PREFERENCE MODEL FOR MARKET SHARE ANALYSIS

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Consumer preference models are widely used in new product design, marketing management, pricing and market segmentation (Green and Srinivasan 1990, Wittink and Cattin 1989). The success of new products depends on accurate market share prediction and design decisions based on consumer preferences. The vague linguistic nature of consumer preferences and product attributes combined with the substantial differences between individuals creates a formidable challenge to marketing models. The most widely used methodology is conjoint analysis. Conjoint models as currently implemented represent linguistic preferences as ratio or interval-scaled numbers, use only numeric product attributes and require aggregation of individuals for estimation purposes. It is not surprising then that these models are costly to implement, are inflexible and have rather poor predictive validity not substantially better than chance, which in turn affects the accuracy of market share estimates.

A fuzzy set preference model can easily represent linguistic variables either in consumer preferences or product attributes with minimal measurement requirements (ordinal scales), while still estimating overall preferences suitable for market share prediction. This approach results in flexible individual-level conjoint models which can provide more accurate market share estimates from a smaller number of more meaningful consumer ratings. Fuzzy sets can be incorporated within existing preference model structures, such as a linear combination, using the techniques developed for conjoint analysis and market share estimation. The purpose of this article is to develop and fully test a fuzzy set preference model which can represent linguistic variables in individual-level models implemented in parallel with existing conjoint models. The potential improvements in market share prediction and predictive validity can substantially improve management decisions about what to make (product design), for whom to make it (market segmentation) and how much to make (market share prediction).

A FUZZY SET PREFERENCE MODEL

A General Preference Model

The underlying theory of conjoint measurement is that an overall preference for a product or service can be de-composed into a combination of preferences for its constituent parts (attributes such as taste and price), which are combined using an appropriate combination function. An example is a weighted sum of T attribute preferences, where the preference for alternative m is defined as

$$(1) \qquad y(m) - \sum_{i-1}^{T} (w_i \times e_i(m)) + w_0$$

where a numeric value ($e_i(m)$) is used for the linguistic evaluation of the ith attribute (e.g. "good" represented by 6 on a 1 to 7 scale). These attribute evaluations are the independent variables that are combined to calculate the dependent variable; an estimated overall preference. Crisp attribute importance weights w_i are statistically estimated using subject ratings of both attribute and overall evaluations on a separate group of "estimation" products. The weights are then used to predict overall preferences for a second group of test products ("holdouts"), which are compared to the subject's actual ratings to assess predictive validity in a cross-validation test.

Since the attribute evaluations given by subjects are often linguistic terms on a labelled rating scale,

a preference model should represent linguistic preferences accurately. The combination function should be appropriate for linguistic variables, producing an overall linguistic preference. Since the meaning of linguistic terms also varies among subjects, it is particularly important to use individual-level models. The appeal of using fuzzy sets in preference models comes from representing linguistic variables in a mathematical structure that closely corresponds to subject preferences.

Fuzzy Sets and Linguistic Variables

Fuzzy sets are a good representation for the uncertainty or vagueness inherent in the definition of a linguistic variable (Zadeh 1975). Linguistic variables are prevalent in describing products ("large") and in expressing preferences ("somewhat good"). Since conjoint analysis is based on preferences, a fuzzy set preference model is uniquely suited to this situation. Consumer ratings such as "good" are inherently vague, with a gradient of membership as to which other ratings belong, and a lack of sharp boundaries between ratings. Combinations of ratings, 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).

Fuzzy sets are defined for each of the 7 linguistic ratings on a Likert scale. The domain variable for these sets is a numeric subjective evaluation on a 0 to 100 scale. Seven subjective evaluations (0-100) are anchored to linguistic terms as prototypes, with 6 additional evaluations assigned as crossover points and 2 additional endpoints, for a total of 15 domain elements in each set. The rating 75 might be prototypical (i.e. have a membership of 1.0) of the set "good" for example. The fuzzy sets for the linguistic terms good and very good are shown in Figure 1. The sets are graphed for subjective ratings above 50, where they have the highest membership. The fuzzy set "good" is shown as: { (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 fuzzy set definition, nor of any measurement properties beyond ordinality in the underlying subjective evaluations.

The Fuzzy Set Preference Model

A fuzzy set preference model is developed to represent linguistic ratings (e_i *(m)*) in the vector preference model. This new model is, in effect, a "fuzzified" vector conjoint model from Equation 1. Subject ratings are represented by the fuzzy set definition for the linguistic term applicable to each rating (e.g. "good" for 6), instead of the number associated with the rating (1-7). These fuzzy sets are combined in a linear preference model using attribute weights in a manner similar to the combination of "crisp" (non-fuzzy) numbers in the vector model. The inputs to the fuzzy conjoint model are the fuzzy sets defined for 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

$$ (2) \qquad \mu_{B'}(y_j,m) = \sum_{i=1}^{T} \frac{w_i}{\sum_{k=1}^{T} w_k} \times \mu_{A_i}(x_j,m) $$

where $\mu_{A_i}(x_j,m)$ is the membership degree of the subject's linguistic rating A_i for the *ith* attribute of product m for domain element 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 calculated set B' 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

evaluations from 0 to 100. The crisp 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. There are no assumptions about interval or ratio scale properties, avoiding the need for extensive diagnostic procedures which are often required by crisp preference models. 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 a conjoint scenario using a rating scale. The membership values for each linguistic term $\mu_{Ai}(x_j,-)$ can be pre-specified or can be based on an elicitation procedure which obtains set parameters from each subject. Since an accurate ordering of overall evaluations is sufficient for choice prediction, the minimal measurement requirements of the fuzzy conjoint model are well suited to preference data.

THE TEST OF FUZZY AND CRISP CONJOINT MODELS

Hypotheses

The purpose of this research is to test the fuzzy conjoint model, both in terms of predictive validity and market share estimation. 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. Two specific hypotheses tested are:

H1: The fuzzy conjoint model will predict the first choice and even more of the ordered sequences of choices of more subjects than the crisp vector conjoint model.

H2: Improvements in predictive validity should be related to the representation of vagueness in product attributes and fuzzy set definitions.

Experimental Design

The experimental design has two main factors: the product category, which varies within subject, and the vagueness of the attribute information, which varies according to the linguistic or numeric attributes selected by each subject. Vagueness is defined as the number of linguistic attributes selected, ranging from 0 to n, where n is the number of attributes in the stimulus design. Since most products have some characteristics that are linguistic, it is important to permit the subject to select this type of attribute. The experimental design allows both fuzzy and crisp conjoint models to be implemented from the same subject ratings of full profile stimuli collected in a computer-assisted conjoint task.

A key component of the experimental design in conjoint analysis is the stimulus design, which specifies a small number of combinations of attribute levels designed to permit effective estimation of crisp conjoint parameters (attribute weights). A total of 24 hypothetical stimuli are used in this

experiment to provide 18 estimation stimuli and 6 cross-validation holdout stimuli on which to test each model at an individual level. Since the fuzzy conjoint model does not require estimation and does not use regression analysis or other statistical techniques, the 18 estimation stimuli are only necessary to estimate the crisp conjoint model. The 6 holdout stimuli are designed to be realistic, requiring trade-offs between attributes (no dominated alternatives).

Product Categories

Two product categories are tested in this research, 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. Some product attributes in any category are naturally vague and linguistic. For a pizza, taste, quality and consistency are attributes 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.

Measurement

The measurement scale used for attribute and overall preferences is a Likert scale labelled with 7 linguistic terms representing 3 positive, 3 negative and 1 neutral evaluation. The linguistic terms 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 to the conjoint models (Equations 1 and 2). For the fuzzy set model, membership values are assigned to the 15 elements of each of the 7 fuzzy sets based on either experimental data and expert assessment (pre-defined) or based on each subject's response to an interactive set definition module in the conjoint analysis software. The later technique has been implemented successfully (Willson 1991), demonstrating that preference models can obtain fuzzy set parameters from ordinary subjects with relative ease. The results in this paper use only pre-defined set definitions in order to assess the success of the model separate from the issue of interactively defining individual sets. The same pre-defined sets have been used in all research involving the fuzzy conjoint model to allow an overall assessment across product categories, subject types and preference model implementations.

Experimental Procedures

The preference experiment is administered by custom written computer software given to subjects on a diskette (Willson 1991). Subjects can run the software on any IBM-compatible personal computer without any installation. 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. Volunteer subjects were recruited from marketing classes at the University of Toronto and paid $10 (CAN) for completing the study. Each product category takes about 25 minutes to complete, with the entire experiment taking 58.9 minutes on average. The software 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. Analysis software then automatically validates subject data, determining choice predictions and market shares for crisp and fuzzy set models.

Prediction Tests

Practitioners and researchers have used relatively weak prediction measures in conjoint analysis. Paired comparisons of alternatives, for example, result in prediction rates for the first choice of each pair that are only 40 percent better than chance (Currim and Sarin 1984). Relatively few results are reported for 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 to use is the number of correct ordered predictions for each subject, ranging from 0 to 6 in this research. 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. Since all models are individual-level, the prediction test is a cross-validation test using each subject's six holdout profiles, with model estimation based only on the ratings given by that subject for the 18 estimation profiles.

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 subject's actual overall evaluations are then compared to the model's calculated overall evaluation for each of the six holdout profiles in the order of preference. The comparison continues until the correspondence in ranking between subject ratings and estimated model ratings 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

$$(3) \qquad SIM\left(B'(y_j,m),B(y_j,l)\right) = 1\ /\ [\ 1 + \sqrt{\sum_{j-1}^{15} \left(\mu_{B'}(y_j,m) - \mu_B(y_j,l)\right)^2}\ ]$$

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 calculated set for product m from Equation 2. 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 the 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 provide 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 as well as 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.

Preference Model Implementation

The vector conjoint model (Equation 1) is an appropriate crisp conjoint model for comparison, since it can be "fuzzified" by using fuzzy sets for linguistic ratings and since its 4 linear parameters are easily estimated from the 18 estimation products in the stimulus design. Crisp model attribute weights are estimated using ordinary least squares regression for each subject and product separately. The fuzzy conjoint model does not need estimation in the conventional sense, but to be comparable to the crisp model, the estimation data can be used to refine the pre-defined sets for each subject. A cut-off level or alpha-cut for fuzzy set membership is found by discrete testing of the estimation ratings. The goal is to consider only the more important higher membership elements in the calculated overall fuzzy set. For each subject, the cut-off level (among 10 tested) with the highest prediction for the estimation profiles is then automatically used for the holdout profiles in the prediction test. In previous research this procedure improved the quality of predictions somewhat (longer predictions), but did not affect the number of first choice predictions.

RESULTS

Prediction

The predictive validity of the crisp and fuzzy conjoint models is presented in this section, addressing both hypotheses. The prediction measures reported in Table 1 are the percentage of subjects for which first choice is predicted, the sum of choices and weighted sum of choices measures and the mean prediction used for statistical tests. The two product categories (pizza and car) are combined to provide a sample of 50. A naive model that randomly orders the six holdout profiles is given in the first column, with the crisp vector conjoint model shown in the second column and the fuzzy conjoint model in the third column. The results show that the fuzzy conjoint model predicts the first choice of 82 percent of the subjects, compared to 50 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 crisp model results reported in the literature, with the crisp conjoint model results also very good relative to the best current models (e.g. Green 1984). Previous experiments using the fuzzy conjoint model and the pizza product add further support, with an average first choice prediction rate of 78 percent using the experimental software and 72 percent using written questionnaires over a total of 142 subjects (Willson 1991). The improvement of the fuzzy preference model over the crisp preference model increases substantially beyond first choice prediction, as reflected in the sum and weighted sum measures. The advantage increases from 64 percent for first choice prediction to 140 percent for the sum of choices and 212 percent for the weighted sum measures. The relative improvement of the fuzzy conjoint model over the naive model is even larger, ranging from 390 percent for first choice prediction to 11500 percent for the first 5 choices in order (16 percent fuzzy prediction rate versus .138 percent naive prediction rate).

The overall improvement is obtained by averaging 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 138 percent better than the crisp conjoint model overall. To conduct a statistical test of differences in predictive validity, the mean of the prediction measure for each subject is calculated as 2.16, .90 and .28 for the fuzzy conjoint model, the crisp conjoint model and the naive model respectively. On average, the fuzzy conjoint model predicts the first two choices in order from the 6 holdout profiles, an occurrence that would be expected by chance only 1 in 33 times. Comparing the mean predictions, the fuzzy conjoint model is significantly better than the crisp conjoint model with probability of error less than .0001.

To examine the second hypothesis, the effects of both the number of set elements used in defining sets and the number of vague linguistic attributes are considered. The number of non-zero elements in a fuzzy set can be varied in stages from a single element "crisp" set (one prototype element with membership 1.0) to the 15 element sets (11-14 non-zero elements) used in the prediction results. The predictive validity of the fuzzy conjoint model is tested using four variations of the same basic fuzzy set definition using 1,3,7 and 15 element sets for each of the 7 linguistic terms. The first three sizes are defined over 7 domain elements (1 element per rating on the scale), while the larger size is defined over 15 domain elements, with intermediate elements between ratings and two additional endpoint elements. The prediction results clearly demonstrate a large improvement in adding just 2 set elements to a single element set, and smaller improvements as set size increases. First choice prediction increases from 62 to 74 percent over 1 to 3 element sets, and to 82 percent for 7 and 15 element sets. Prediction means improve from 1.04 to 1.50 for 1 to 3 element sets, a significant increase ($p < .03$). Further improvements with 7 and 15 set elements are not significant, although such improvements would be very valuable in a conjoint study.

Vagueness in product information is also expected to influence model performance. A linguistic term ("medium") is certainly more vague than a numeric attribute value (price = $12.70). The number of linguistic attributes (1-3) selected by subjects provides a simple measure of vagueness which is graphed in Figure 2 according to the number of linguistic attributes selected. The results confirm that the fuzzy conjoint model performs well at all three levels of vagueness, while the predictive validity of the crisp conjoint model declines steadily as vagueness in attribute information increases. For subjects selecting one linguistic attribute, the fuzzy conjoint model has a higher mean prediction than the crisp model, although the t-value of the difference is not significant ($t=0.59$). For two linguistic attributes, the fuzzy set mean prediction is significantly higher than the crisp mean, with a t-value of 3.31 ($p < .003$), improving further for three linguistic attributes to a t-value of 3.57 ($p < .002$). This relative improvement in fuzzy conjoint predictive validity is also reflected in the correlation coefficient between vagueness and prediction, which is not significant (-.110) for the crisp conjoint model and is significant (.322, $p < .02$) for the fuzzy conjoint model. Thus the relative predictive validity of the fuzzy conjoint model improves with vagueness in attribute information, an important quality since subjects selected an average of 2.14 linguistic attributes in their top 4 attributes. The prediction improvements due to set size and linguistic attributes support the second hypothesis.

Market Share Prediction

Market share prediction is a very important component of conjoint analysis. Most conjoint studies use computer software to simulate choice and to compare estimated and actual market shares based on overall preference ratings of a cross-validation group of products (Green and Srinivasan 1990). The logit choice axiom is widely used to convert preference scores to choice probabilities. The probability of choosing a given alternative m from a choice set is given by

$$(4) \qquad P(m) - (\ e^{y(m)} \ / \ \sum_{p-1}^{6} e^{y(p)}\ )$$

where $P(m)$ is the probability of selecting product m, given a crisp preference score y (m) and a set of six hypothetical products (Batsell and Lodish 1981). The choice probabilities are averaged across subjects to estimate overall market share. Ultimately managers need to know the market share that would result from a particular attribute level, all else being equal. Preferences can be linked to the main effects of attribute levels (e.g. price) according to Equation 4 and the stimulus design. Analysis software tracks the different choices of attributes and attribute orders relative to the fixed stimulus design among subjects to calculate overall shares for attribute levels, linking these to prototype values.

For example, the average market share for holdout products with a medium level of price can be calculated for each model and compared to $13.36, the mean prototype elicited from subjects that selected the price attribute.

To estimate market shares for the fuzzy conjoint model, the overall preference must be converted to a crisp number to use in Equation 4. A weighted centroid de-fuzzification method was developed for this research. The membership value of each set element is weighted by a preference value equal to the domain variable index (1-15 for 15 element sets) and then summed for all elements and divided by 15. A crisp preference score is calculated as

$$(5) \qquad y(m) = \sum_{n=1}^{15} (\mu_{B'}(y_n, m) \times n) \ / \ 15$$

where $\mu_{B'}(y_n, m)$ is the fuzzy conjoint model output for product m from Equation 2. Market shares are given in Table 2 for the pizza (n=26) and car (n=24) product categories for the three attribute levels (labelled in terms of their evaluation as good, average or poor). All comparisons are done by subject, with the actual share computed from the subject's overall evaluations of the six holdout profiles. For all three attribute levels and both products, the fuzzy conjoint model market share correlations with the actual share are higher than the crisp model's. Four of the six fuzzy model correlations are significant at the .01 level, while none of the crisp model correlations are significant at this level and only two are significant at the .05 level.

The mean share error of the absolute difference between estimated and actual shares is also lower for the fuzzy conjoint model in every case. The average market share error is 5.09 percent for the fuzzy model and 7.64 percent for the crisp model. The crisp model estimated market shares have 50 percent more deviation from the actual share. Accurate share estimates are critical to managing existing products. For pizza, the actual share for a medium price (mean=$13.36) is 48, compared to 24 for a low and 28 for a high price level. This suggests that a price slightly above medium would be optimal. The fuzzy conjoint model would recommend a similar optimal price based on estimated shares of 32, 42 and 26 for low, medium and high price levels respectively. The crisp conjoint model estimated shares of 40, 42 and 18 (for L/M/H levels) differ substantially from the actual shares, resulting in a much lower optimal pizza price between low and medium. The more accurate fuzzy conjoint share estimates would allow a manager to charge a higher price, increasing profits without a loss in market share. Using existing methods, the fuzzy conjoint model substantially improves market share estimation and predictive validity.

CONCLUSIONS AND DISCUSSION

The results demonstrate the substantial benefits from using fuzzy sets to represent consumer ratings. The fuzzy conjoint model significantly improves predictive validity compared to existing conjoint models using identical data in a typical conjoint experiment, predicting the first choice of 82 percent of subjects. The largest improvements are for the more difficult task of predicting the ranking of preferences beyond first choice, which is reflected in the overall 138 percent improvement. The results are consistent across attributes types, product categories, administration methods, stimulus designs and 192 subjects. The underlying measurement properties of the fuzzy conjoint model require only ordinal information. Results show that both crisp and fuzzy conjoint models perform well using computer software that fully adjusts to the subject preferences and attributes. Linguistic attributes are clearly important to consumers, since subjects selected more than two, on average, among their top four attributes. The predictive validity of the fuzzy model does not decline when linguistic attributes are

present, as the crisp model does. The fuzzy conjoint model gives practitioners the flexibility to deal with linguistic attributes in an individual-level model with increasingly good predictive validity in situations in which current models are not suitable.

The results also demonstrate the value of identifying situations and subjects for which a fuzzy set preference model is most appropriate and of adapting conjoint analysis techniques to fuzzy set models (e.g. statistical estimation, hybrid models, product optimization). Vagueness measures may form an important part of a more general model relating predictive validity to subject, situation and preference model characteristics. Alternative preference models based on fuzzy production rule combinations of attribute values and approximate reasoning also show considerable promise (Willson 1991).

The results also show that the fuzzy conjoint model can be readily applied to marketing problems using automated software for data collection. The experimental software is easily used by subjects, providing all of the information needed to implement both crisp and fuzzy models in about 25 minutes of interaction per product category. Once data is collected, the fuzzy conjoint model is actually easier to implement and estimate than existing crisp models. Automated analysis software created for this research can read and verify returned data, generating preference predictions and market shares. In addition, the fuzzy conjoint model is an important module in a broader intelligent business system which combines the best fuzzy logic and management science models to provide enterprise-wide management systems. Improved market share and demand estimates from the fuzzy conjoint model would be an important input to manufacturing and distribution systems.

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TABLE 1: PREDICTION RESULTS

Prediction Measure:	Naive Model	Crisp Model	Fuzzy Model
1st choice rate:	16.67%	50%	82%
Sum of choices measure:	10.69	45	108
Weighted sum measure:	19.66	80	250
Mean prediction:	0.28	0.90	2.16
t-value of mean (fuzzy - crisp):			4.53 (p<.0001)

TABLE 2: MARKET SHARE ESTIMATES BY ATTRIBUTE LEVEL

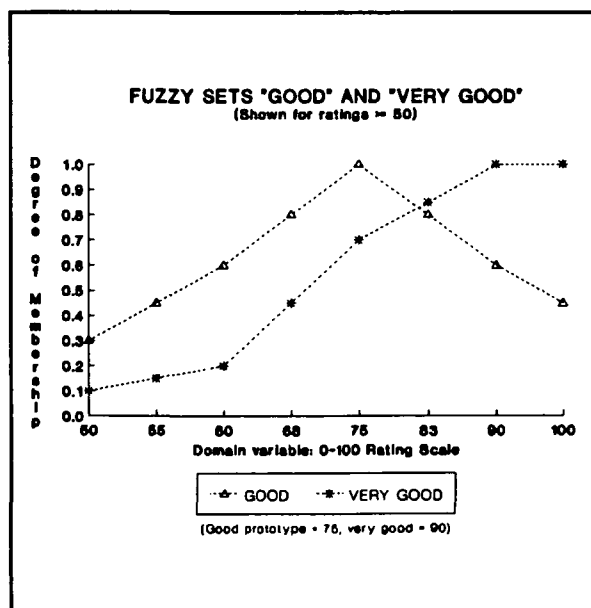| Attribute Level	Crisp Conjoint		Fuzzy Conjoint	
	Mean Abs. Share Error	Correlation W/. Actual	Mean Abs. Share Error	Correlation W/. Actual
Pizza Product:				
Good Level:	6.26	0.627	5.31	0.917[a]
Average Level:	6.02	0.828[b]	4.74	0.901[a]
Poor Level:	4.00	0.866[b]	3.32	0.906[a]
Car Product:				
Good Level:	10.34	-0.191	5.95	0.412
Average Level:	11.73	0.044	5.98	0.298
Poor Level:	7.51	0.538	5.28	0.837[a]

[a] $p < .01$. [b] $p < .05$. Abs. = Absolute Value

FIGURE 1: FUZZY SETS GOOD/VG

FIGURE 2: PREDICTION BY VAGUENESS

FUZZY SETS "GOOD" AND "VERY GOOD"
(Shown for ratings ≥ 50)

GOOD   VERY GOOD
(Good prototype = 75, very good = 90)

MEAN PREDICTION
BY NUMBER OF VAGUE ATTRIBUTES
(DV = # of correct ordered predictions)

Crisp Conjoint   Fuzzy Conjoint