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Benefits Sought by Apple Consumers

by

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INTRODUCTION

Consumers generally show preferences for specific varieties of apples. Manalo (1989) found that the most popular varieties in New Hampshire are McIntosh, Red Delicious, Granny Smith and Cortland. Another survey revealed that Connecticut consumers prefer McIntosh and Red Delicious (Leonard and Wadsworth 1989). The purpose of this study is to increase understanding of such consumer preferences. An assumption is made that consumers look for specific attributes when they buy apples, and that a variety represents a combination of attributes that they like. The research task then is to find out the attributes that are important to consumers.

Traditionally, information on the attributes that consumers consider important are obtained from them through surveys. In this study, the importance of attributes was determined with the use of another procedure called conjoint analysis. This method is considered to yield results that are more reliable and useful than those that are obtained by asking respondents directly to identify the attributes they prefer (Mullet 1983).

OVERVIEW OF CONJOINT ANALYSIS

The basic principle underlying conjoint analysis is that a product is composed of attributes and that each attribute may have two or more levels. Consumers' preferences for products are assessed by estimating the importance to consumers of product attributes. Respondents are presented stimuli representing variations of the product, *i.e.*, alternative combination of attribute levels, and asked to rank or rate these alternatives. Using any of several estimation techniques available, the relative importance of the attributes are computed given the ranking or rating data. The estimation technique will assign a value called utility or part-worth, to each level of each attribute. The part-worth indicates the relative importance of that attribute level to the respondents. The measure of the importance of an attribute is then derived from the range of the part-worth values over the levels of that attribute. By summing up the part-worth values for various combinations of attribute levels, one can find the total value or utility of a product to consumers (Green and Srinivasan 1978; Mullet 1983).

The use of conjoint analysis has increased since the first paper describing its application to marketing problems appeared in 1971. A 1982 survey by Cattin and Wittink showed widespread use of conjoint analysis among marketing research firms for purposes like new product identification, pricing, market segmentation, advertising and distribution. A follow-up survey seven years later showed the applications widening in scope to include competitive analysis and repositioning along with the five uses found in the first study (Wittink and Cattin 1989).

Theoretical Basis

Conjoint analysis finds theoretical support in economics in the approach to consumer theory introduced by Lancaster (1966). This approach suggests that consumers derive utility not from goods themselves but rather from the attributes or characteristics that the goods possess. The model may be represented as follows:

Maximize $U(z)$

subject to $px \leq k$

with $z = Bx$

$z, x \geq 0$

where $U(z)$ is an ordinal preference function; z is a vector of characteristics; p is a vector of prices; x is a vector of goods; k is income; and B is the consumption technology matrix that transforms the goods x into the characteristics z.

As Ratchford (1975) pointed out, Lancaster assumed that z is given and investigated how people react to varying prices or characteristics. In conjoint analysis the characteristics or attributes are also predetermined, and consumers' reactions to changing characteristics are assessed.

Data Collection

There are two alternative data collection methods in conjoint analysis: (1) the trade-off procedure and (2) the full-profile approach. With the former, respondents are asked to evaluate only two attributes at a time; with the latter, respondents are asked to rank or rate combinations of levels of all attributes specified in the conjoint study. Green and Srinivasan (1978) discuss the strengths and weaknesses of both methods. The most widely used procedure today is the full-profile approach; application of the trade-off procedure is very low and appears to be declining (Wittink and Cattin 1989).

Estimation Procedures

There are a number of estimation procedures used in conjoint analysis. Those cited in the literature include MONANOVA, LINMAP, logit, and ANOVA or ordinary least squares (OLS) regression using dummy variables. It appears that dummy-variable regression is the method most often used. The validity of using this method in estimating part-worths was described by Wittink and Cattin in 1981. In this method, effects-type coding is used, instead of the usual dummy-variable coding normally used in econometric studies. In other words, if a factor has three levels, the coding is (1, 0) for the first level, (0, 1) for the second level and (-1, -1) for the third level (Cohen and Cohen, 1983). OLS regression is run with the preference ratings or ranks as dependent variables and the effects codes, signifying presence or absence of the various levels of the specified attributes, as the predictor variables.

The conventional conjoint analysis approach is to estimate part-worths for each individual and then, with the use of cluster analysis, group respondents based on the similarity of their estimated part-worths. An area of emphasis in the conjoint-analysis literature is on improving its predictive accuracy which refers to how well the estimated part-worths from a sample's responses can predict the same respondents' ratings or ranking of a different set of attribute-level combinations. Hagerty (1985) suggested using Q-type factor analysis to improve predictive accuracy. Responses (ratings or ranks) are standardized and then transformed using optimal weights obtained from a Q-type factor analysis of the response data. Given the transformed responses, the part-worths are estimated using OLS. Kamakura (1988) proposed clustering respondents with similar responses and then, with the use of OLS, estimating the part-worths using pooled data within each cluster. An assessment found that there is not much difference in predictive accuracy among the conventional, Hagerty and Kamakura approaches (Green and Helsen 1989).

For this paper the Kamakura approach was followed for its intuitive appeal, its ease of application and the usefulness of its output. Kamakura's procedure is discussed in the following section.

The Kamakura approach. Assume that J is the number of stimulus profiles used in the conjoint experiment, S is the number of benefit segments under consideration, K is the number of parameters to be estimated for each segment, and N is the sample size. The equation for the preference functions for each of the N individuals is

$$\mathbf{Y} = \mathbf{XBG} + \mathbf{E}$$

where $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_N]$, a JxN matrix containing the ranking or rating vectors for each of the N individuals;

$\mathbf{X}$ = a JxK matrix containing dummy variables representing the different levels of the various attributes;

$\mathbf{B} = [\mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_N]$, a KxS matrix containing the regression intercept and preference weights for the S segments

$\mathbf{G} = [\mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_N]$, a SxN matrix of boolean vectors $\mathbf{g}_i$ defining the cluster membership for each subject *i*. The S-vector $\mathbf{g}_i$ contains a value of 1 in the row corresponding to the segment assigned to the individual *i* and 0 otherwise; and

$\mathbf{E} = [\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_N]$, a JxN matrix containing random errors.

In this representation each individual has a preference function and all members of a particular segment have the same preference function.

Once **G** is known, the preference functions for the given number of segments can be estimated using OLS:

$$\mathbf{B} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}\mathbf{G}'(\mathbf{G}\mathbf{G}')^{-1}$$

It has been demonstrated that the highest predictive accuracy is attained when a preference function is derived for each respondent (Moore 1980). It may be expected, therefore, that a solution with a certain number of clusters will include some error due to bias and estimation of a misspecified model, and hence provide a lower predictive accuracy. The task then, given a certain number of segments, is to determine the allocation weights, *i.e.*, the components of matrix **G**, such that the reduction in predictive accuracy is minimized; in other words, finding the elements of matrix **G** that lead to lowest unavoidable prediction error.

Kamakura showed that the lowest unavoidable prediction error for a given number of segments is attained by the allocation matrix **G** such that

$$\max_{(\mathbf{G})} \operatorname{tr} [\mathbf{G}'(\mathbf{G}\mathbf{G}')^{-1}\mathbf{G}\mathbf{D}]$$

where $\mathbf{D} = \mathbf{Y}'\hat{\mathbf{Y}}$

$\hat{\mathbf{Y}}$ = estimated preference ratings based on individual level part-worths.

Kamakura used an agglomerative clustering algorithm to find the **G** that satisfies the above objective.

Kamakura developed a computer program, named *The Segmenter*, that clusters respondents into segments and estimates the preference part-worths for each segment. The program also estimates, for a given number of segments, a predictive accuracy index (PAI), which is defined as "the proportion of variance (of the preference ratings) expected to remain unexplained if the segment-level functions are used to predict the respondents' ratings for a holdout set of stimuli" (page 161). The higher the level of aggregation, *i.e.*, smaller number of clusters, the higher the PAI. As will be demonstrated later, the PAI may be used to determine the appropriate number of segments to retain.

ANALYSIS OF PREFERENCES OF APPLE CONSUMERS

The main objective of this study is to determine the benefits or attributes consumers seek when they buy apples. Because of the great diversity among consumers, it is hypothesized that they value the various attributes differently. On the assumption that the hypothesis is true, this study therefore aims more specifically to (1) segment apple consumers according to attributes they consider important and (2) identify the common characteristics of the members of each segment. Research results may be used to improve the efficiency in fulfilling the needs of the various market segments.

An apple was defined in this study as having five attributes: size, color, price, crispness and flavor. Each of these attributes has either two or three levels as shown in Exhibit 1.

The data collection method used is the full-profile approach, where respondents are asked to evaluate a set of stimuli representing alternative combinations of all five attributes. With three attributes each with three levels, and two attributes each with two levels, there are 108 possible attribute combinations - too large a number for respondents to evaluate and rank. This problem was solved by the use of a special experimental design called an orthogonal array, in which only a subset of the total member of combination is chosen. Addelman (1962) developed several basic plans, depending on the number of attributes and attribute levels, for generating orthogonal arrays. In this study the appropriate orthogonal array contains eighteen combinations which are shown in Exhibit 2.

Eighteen stimulus cards were prepared; each card contained details about each of the five attributes. Respondents were asked to rank the eighteen combinations using 1 and 18 to indicate highest and lowest preference, respectively. Respondents were also asked to provide demographic information and other data including varietal preferences and apple attributes they consider important. Interviews were conducted in a shopping mall in Newington, New Hampshire. Ranking data provided by 185 respondents were analyzed with the use of *The Segmenter*, the estimation algorithm developed by Kamakura.

Exhibit 1. Attributes and levels used in the apple conjoint study

Size	Color	Price/lb.
1. Small	*1. Uniformly red*	*1. $0.79*
2. Medium	*2. Uniformly green*	*2. $0.89*
3. Large	*3. Red-green combination*	*3. $0.99*
Crispness	**Flavor**	
1. Crisp	*1. Sweet*	
2. Mealy	*2. Tart*	

Exhibit 2. Orthogonal array of combinations of apple attributes

Combination no.	Size	Color	Price/lb.	Crispness	Flavor
1	Small	Red	$0.79	Crisp	Sweet
2	Small	Green	0.89	Crisp	Tart
3	Small	Red-green	0.99	Mealy	Sweet
4	Medium	Red	0.89	Mealy	Tart
5	Medium	Green	0.99	Crisp	Sweet
6	Medium	Red-green	0.79	Crisp	Sweet
7	Large	Red	0.99	Crisp	Tart
8	Large	Green	0.79	Mealy	Sweet
9	Large	Red-green	0.89	Crisp	Sweet
10	Small	Red	0.99	Mealy	Sweet
11	Small	Green	0.79	Crisp	Tart
12	Small	Red-green	0.89	Crisp	Sweet
13	Medium	Red	0.79	Crisp	Sweet
14	Medium	Green	0.89	Mealy	Sweet
15	Medium	Red-green	0.99	Crisp	Tart
16	Large	Red	0.89	Crisp	Sweet
17	Large	Green	0.99	Crisp	Sweet
18	Large	Red-green	0.79	Mealy	Tart

Conjoint Analysis Results

To determine the number of segments to retain, Kamakura suggested using either of two methods: (1) plotting the predictive accuracy index (PAI) against the number of clusters, and choosing the number of segments associated with the portion of the plot that shows an elbow; and (2) in cases where there is no clear elbow, choosing the last number of segments that contributes to a significant decline in the PAI. A plot of the predictive accuracy indices (Figure 1) shows no clear elbow and therefore it was concluded that the appropriate number of clusters is five because of the minor decline in the PAI as the number of segments is increased from five to six. The predictive accuracy index with five segments is 0.572. This may be interpreted as follows: supposing that the respondents interviewed for this study were asked to evaluate a different set of combinations of attributes, and the estimated part-worths from their earlier responses were used to predict their rankings of the alternatives in the second set, then 57% of the variance of the second set of preference rankings would remain unexplained.

Table 1 shows the estimated part-worths for each segment. Recall that respondents were asked to rank stimuli from 1 to 18, with 1 representing the most preferred combination of attributes. As a result, the part-worth that has the lowest value indicates the most important level of an attribute to the consumer. For example, under Segment 1 and the attribute color, green with part-worth equal to -0.17 is the most preferred, followed by red-green (-0.01) and red (0.17).

Relative importance of attributes. In conjoint analysis the measure of the importance of an attribute is derived by obtaining the absolute value of the difference between the part-worth of the most desired level and the part-worth of the least desired level. For example, given the part-worths under Segment 1 in Table 1, the importance weight for the attribute color is

Figure 1. Predictive Accuracy Index by Number of Segments

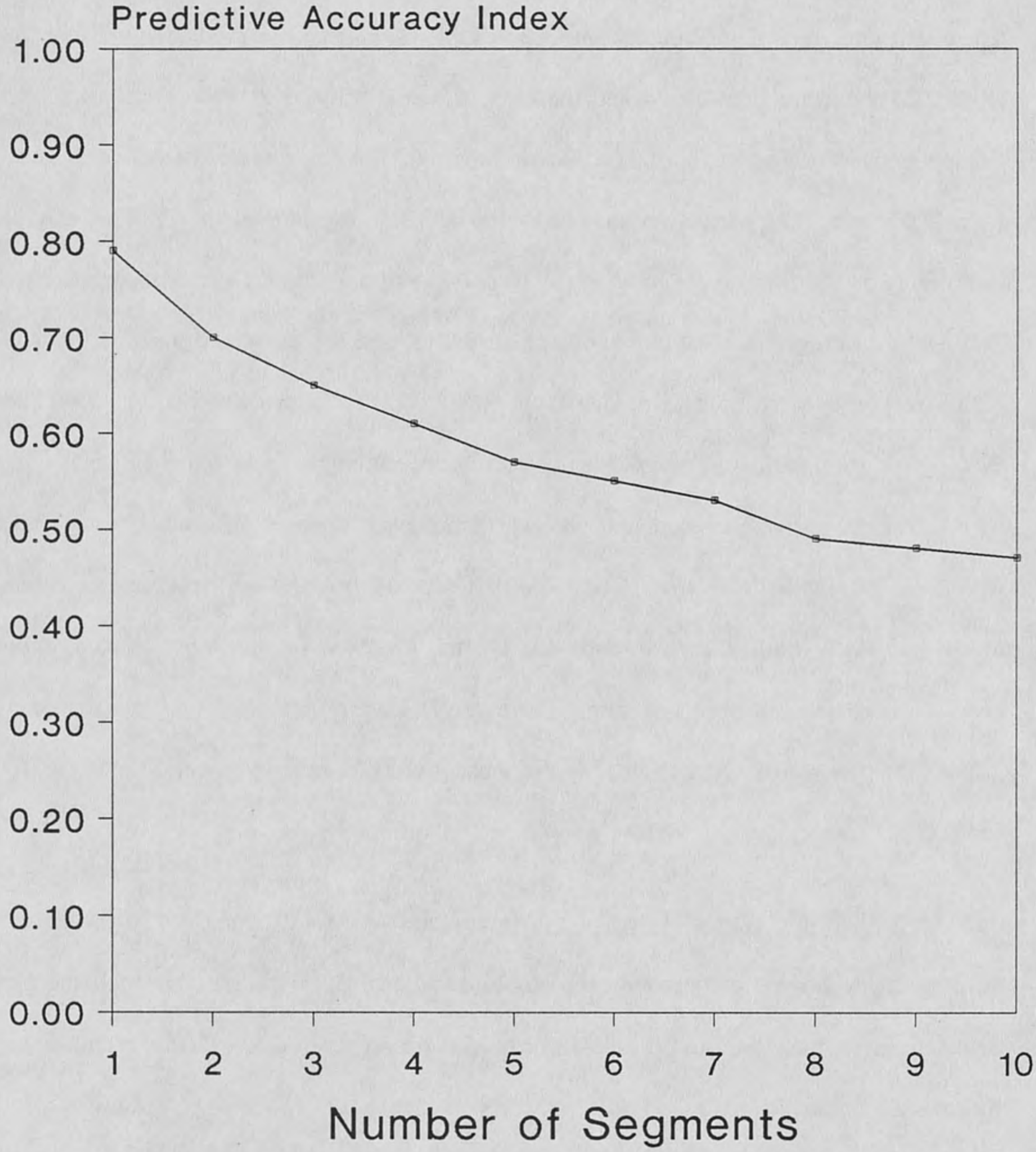

Table 1. Estimated attribute-level part-worths, by segment

Attributes and Levels	Segments 1	2	3	4	5
			Part-worths		
Size					
1. Small	0.03	0.42	0.24	-0.25	0.97
2. Medium	0.04	-0.24	-0.14	0.09	-0.09
3. Large	-0.07	-0.18	-0.10	0.16	-0.88
Color					
1. Red	0.17	-0.15	-0.40	-0.08	-0.16
2. Green	-0.17	0.26	0.47	0.05	0.28
3. Red-green	-0.01	-0.11	-0.07	0.03	-0.12
Price/lb.					
1. $0.79	0.04	-0.06	-0.14	-0.24	-0.04
2. $0.89	-0.01	0.02	-0.09	-0.10	-0.01
3. $0.99	-0.04	0.04	0.22	0.34	0.05
Crispness					
1. Crisp	-0.68	-0.66	-0.17	-0.07	-0.06
2. Mealy	0.68	0.66	0.17	0.07	0.06
Flavor					
1. Sweet	-0.04	0.24	0.14	-0.09	0.09
2. Tart	0.04	-0.24	-0.14	0.09	-0.09

Predictive accuracy index = 0.572

Table 2. Derived importance weights of the apple attributes, by segment

Attributes	Segments 1	2	3	4	5
Size	0.11	0.66	0.38	0.41	1.85
Color	0.34	0.41	0.87	0.13	0.44
Price/lb.	0.08	0.10	0.36	0.58	0.09
Crispness	1.36	1.32	0.34	0.14	0.12
Flavor	0.08	0.48	0.28	0.18	0.18
Segment size	27	62	52	29	15

$|-0.17 - 0.17| = 0.34$. This derived value is then compared with those for other attributes within the same segment; the greater the derived value, the more important the attribute. The attribute importance weights, as well as the segment sizes, are shown in Table 2.

Determining Segment Membership

The logit model. The next step is to determine how members of one segment differ in their demographic characteristics from those of other segments. The procedure used was logit analysis for categorical variables (SAS CATMOD procedure) because the independent variables: sex, New Hampshire residence status, household size, education, age and income, were measured either on a nominal or ordinal scale (Agresti and Finlay 1986). The dependent variable is membership in a particular segment z ($z = 1, 2, \ldots, 5$) and has two levels: (1) membership in segment z, and (2) membership in other segments. The levels of the independent variables are shown in Table 3.

The model was specified as follows:

$$\ln \frac{(\pi_{ijklmn})}{(1 - \pi_{ijklmn})} = \mu + \phi^S{}_i + \phi^R{}_j + \phi^H{}_k + \phi^E{}_l + \phi^A{}_m + \phi^Y{}_n \qquad \text{(Model I)}$$

where π is the proportion of segment z members among respondents possessing levels i, j, k, l, m, and n of sex, New Hampshire residence status, household size, education, age and income, respectively;

μ is the estimated mean of the logits for all combinations of the independent variables

ϕ is the effect on the logit of being classified in the specified level (designated by the subscript) of a particular independent variable (designated by the superscript)

S is sex $(i = 1, 2)$

Table 3. Levels of independent variables used in assessing preference for apple varieties

Variable	Levels
Sex	1. Male
	2. Female
New Hampshire residence status	1. Resident
	2. Nonresident
Household size	1. One member
	2. Two members
	3. Three members
	4. Four members
	5. Five members
	6. Six members
	7. More than six members
Education	1. 11th grade or less
	2. High school graduate
	3. Technical/trade school
	4. Some college
	5. College graduate
	6. Some postgraduate work
	7. Postgraduate degree
Age	1. Under 20 years
	2. 20-29 years
	3. 30-39 years
	4. 40-49 years
	5. 50-59 years
	6. Over 59 years
Annual Income	1. Under $10,000
	2. $10,000-14,999
	3. $15,000-24,999
	4. $25,000-34,999
	5. $35,000-49,999
	6. Over $49,999

R is New Hampshire residence status $(j = 1, 2)$

H is household size $(k = 1, 2, \ldots, 7)$

E is education $(l = 1, 2, \ldots, 7)$

A is age $(m = 1, 2, \ldots, 6)$

Y is income $(n = 1, 2, \ldots, 6)$

The goodness of fit of Model I to the data was assessed with the likelihood ratio statistic. Then the presence of association between the dependent variable and each of the independent variables was determined. Any variables that appeared to affect membership in segment z were used as independent variables in a second logit model, again with membership in segment z as the dependent variable. The presence of association between the dependent and independent variables were again assessed and individual parameters were analyzed.

Results. The results show that some of the independent variables influence membership in Segments 1, 4, and 5 and that none of those variables affects membership in Segments 2 and 3. Tables 4 and 5 imply that age affects membership in the first segment, and that, more specifically, the probability of membership in Segment 1 increases when respondents belong to the 30-39 and 40-49 age groups. Membership in Segment 4 is influenced by income level (Table 6). It is concluded from Table 7 that the probability of membership in Segment 4 increases when the respondent's income is within the $15,000-24,999 or $25,000-34,999 range. Table 8 shows that membership in the fifth segment is affected by age. The probability of membership in Segment 5 increases when the respondent's age is below 20 years (Table 9).

As seen in Table 2, the second segment, with sixty-two members, and the third segment, with fifty-two members, represent the largest clusters of consumers. It may be concluded from

Table 4. Analysis of variance for the model with membership in Segment 1 as the dependent variable

Source	Degrees of Freedom	Chi-square	P value
Intercept	1	46.67	0.0001
Age	5	10.75	0.0567
Likelihood Ratio	168	128.29	0.9900

Table 5. Analysis of individual parameters for the model with membership in Segment 1 as the dependent variable

Parameter	Estimate	Standard Error	Chi-square	P value
μ	-2.043*	0.299	46.67	0.0001
$\phi^{A}_{Under\ 20}$	0.539	0.705	0.58	0.4448
$\phi^{A}_{20\text{-}29}$	0.218	0.494	0.19	0.6590
$\phi^{A}_{30\text{-}39}$	0.826*	0.444	3.46	0.0629
$\phi^{A}_{40\text{-}49}$	1.126*	0.427	6.94	0.0084
$\phi^{A}_{50\text{-}59}$	- 0.902	0.889	1.03	0.3107
$\phi^{A}_{Over\ 59}$	- 1.808*	0.877	4.25	0.0394

* Significant at at least $\alpha = 0.10$ significance level
A stands for age.

Table 6. Analysis of variance for the model with membership in Segment 4 as the dependent variable

Source	Degrees of Freedom	Chi-square	P value
Intercept	1	43.25	0.0001
Income	5	9.91	0.0780
Likelihood Ratio	168	140.92	0.9368

Table 7. Analysis of individual parameters for the model with membership in Segment 4 as the dependent variable

Parameter	Estimate	Standard Error	Chi-square	P value
μ	- 1.959*	0.298	43.25	0.0001
$\phi^{Y}_{Under\ \$10,000}$	- 0.238	0.911	0.07	0.7938
$\phi^{Y}_{\$10,000\text{-}14,999}$	0.087	0.688	0.02	0.8989
$\phi^{Y}_{\$15,000\text{-}24,999}$	0.743*	0.444	2.80	0.0940
$\phi^{Y}_{\$25,000\text{-}34,999}$	1.099*	0.418	6.90	0.0086
$\phi^{Y}_{\$35,000\text{-}49,999}$	0.013	0.464	0.00	0.9772
$\phi^{Y}_{Over\ \$49,999}$	- 1.704*	0.879	3.76	0.0524

* Significant at at least $\alpha = 0.10$ significance level
Y stands for income.

Table 8. Analysis of variance for the model with membership in Segment 5 as the dependent variable

Source	Degrees of Freedom	Chi-square	P value
Intercept	1	55.47	0.0001
Age	5	12.18	0.0324
Likelihood Ratio	168	90.90	1.0000

Table 9. Analysis of individual parameters for the model with membership in Segment 5 as the dependent variable

Parameter	Estimate	Standard Error	Chi-square	P value
μ	-2.552*	0.343	55.47	0.0001
$\phi^{A}_{Under\ 20}$	1.992*	0.616	10.46	0.0012
$\phi^{A}_{20\text{-}29}$	-1.004	0.896	1.25	0.2628
$\phi^{A}_{30\text{-}39}$	-0.975	0.896	1.18	0.2770
$\phi^{A}_{40\text{-}49}$	-0.975	0.896	1.18	0.2770
$\phi^{A}_{50\text{-}59}$	0.355	0.698	0.26	0.6117
$\phi^{A}_{Over\ 59}$	0.606	0.494	1.50	0.2203

* Significant at at least $\alpha = 0.10$ significance level
A stands for age.

the results of the logit analysis that membership in either of these segments cuts across the independent variables specified in the model.

Discussion and Comments

For the first segment, crispness is the most important attribute. The derived importance weights (Table 1) also show that, to this segment, the other attributes are relatively unimportant[1]. The combination of attributes that brings the highest worth to these consumers is represented by an apple that is crisp, green, large, sweet and priced at $0.99/lb. The total worth of this combination is -1.0 which is obtained by adding the part-worths associated with the above attribute levels (i.e., -0.68 + -0.17 + -0.07 + -0.04 + -0.04, respectively). It may also be seen that this segment prefers a higher price to a lower price, which is not consistent with typical consumer behavior. This seems to imply, however, that these consumers are willing to pay a high price as long as they get a crisp apple. Compared to consumers belonging to other age groups, those who are thirty to forty-nine years old are more likely to belong to this group.

Crispness is also the most important attribute to the second segment. The next important attributes in descending order are size, flavor, color and price. To these consumers, price (at least in the range specified in the conjoint experiment) appears to be not a major concern. This group prefers apples that are crisp, medium, tart, red and priced at $0.99/lb.

[1]Wittink *et. al.* (1981) suggested that relative attribute importance may not be compared across attributes with different levels particularly when responses are in the form of rank orders. Their conclusion supports the argument of Currim *et. al.* (1981) that the derived importance weights of three-level attributes are greater than those of two-level attributes. In this study, two-level attributes are compared with three-level attributes because the results show that the derived importance weights of the two-level attributes are not consistently smaller than those of the three-level attributes.

Color is the most important attribute to the third segment, which prefers red apples. The second most important attribute is size, followed by price, crispness and flavor. The ideal apple to these consumers is one that is red, medium-sized, priced at $0.79/lb, crisp and tart.

Consumers who belong to the fourth segment are price-conscious and thus, prefer the lowest-priced apples. Size also appears to be relatively important, while flavor, crispness, and color appear to be relatively less important. The combination that this group prefers most features the following attribute levels: a $0.79/lb. price, small, sweet, crisp and red. Consumers with annual incomes ranging from $15,000-34,999 have the highest probability of belonging to this segment.

The fifth segment, which is most likely to be comprised of teen-aged people, considers size as the most important attribute. More specifically, these consumers like large apples. Color is relatively less important, and flavor, crispness and price appear to be even less important than size. This segment likes large red apples that are tart, crisp, and priced at $0.79/lb.

The above results support the earlier hypothesis that consumers value the specified apple attributes differently. Nevertheless there are two results that are consistent across segments. Although only Segments 1 and 2 (comprising 48% of 185 respondents) consider crispness as the critical attribute, all consumer groups prefer crisp over mealy apples. Furthermore, there is no segment that considers flavor as most important. Considering all groups, this attribute ranks no higher than third in importance.

As to the use of conjoint analysis, the experience in this study reveals that, at first glance, this research method appears easy to apply because the procedure is relatively straightforward. The validity of the results, however, depends on how well the respondents do their evaluation of the alternatives. In this study, respondents were asked to evaluate eighteen alternative combinations of attributes, and though many respondents were deeply involved in the task, some appeared to give their choices very little thought. It is very important therefore to make sure that respondents' rating or ranking of the alternatives truly represents their preferences. Part of the problem is that many respondents find the evaluation task difficult particularly if they have to consider a large number of combinations. In response to this practical constraint, variations of the traditional conjoint analysis method used in this study have been developed. Wittink and Cattin (1989) discussed these methods, as well as other developments and issues concerning the use of conjoint analysis in marketing research.

The acceptance of conjoint analysis as a research method is evidenced by its widespread adoption in business marketing research today. Its popularity is likely to increase because of the availability of personal computer software that helps researchers design conjoint experiments and estimate part-worths.

REFERENCES

Addelman, Sidney. "Orthogonal Main-Effect Plans for Asymmetrical Factorial Experiments." *Technometrics* 4 (February 1962): 21-46.

Agresti, Alan and Barbara Finlay. *Statistical Method for the Social Sciences*, 2nd. ed. San Francisco: Dellen Publishing, Co., 1986.

Cattin, Philippe and Dick R. Wittink. "Commercial Use of Conjoint Analysis: A Survey. *Journal of Marketing* 46 (Summer 1982): 44-53.

Cohen, Jacob and Patricia Cohen. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 2nd ed. Hillsdale, NJ: Lawrence Earlbaum Associates, Inc. 1983.

Currim, Imran S., Charles B. Weinberg and Dick R. Wittink. "Design of Subscription Programs for a Performing Arts Series." *Journal of Consumer Research* 8 (June 1981): 67-75.

Green, Paul E. "On the Design of Choice Experiments Involving Multifactor Alternatives." *Journal of Consumer Research* 1 (September 1974): 61-68.

_______ and Wayne S. DeSarbo. "Additive Decomposition of Perceptions Data Via Conjoint Analysis." *Journal of Consumer Research* 5 (June 1978): 58-65.

_______ and Kristiaan Helsen. "Cross-Validation Assessment of Alternatives to Individual-Level Conjoint Analysis: A Case Study." *Journal of Marketing Research* 26 (August 1989): 346-50.

_______ and Vithala R. Rao. "Conjoint Measurement for Quantifying Judgmental Data." *Journal of Marketing Research* 8 (August 1971): 355-63.

_______ and V. Srinivasan. "Conjoint Analysis in Consumer Research: Issues and Outlook." *Journal of Consumer Research* 5 (September 1978): 103-23.

_______ and Yoram Wind. "New Way to Measure Consumers' Judgments." *Harvard Business Review* 53 (July-August 1975): 107-17.

Hagerty, Michael R. "Improving the Predictive Power of Conjoint Analysis: The Use of Factor Analysis and Cluster Analysis." *Journal of Marketing Research* 22 (May 1985): 168-84.

Kamakura, Wagner A. "A Least Squares Procedure for Benefit Segmentation with Conjoint Experiments." *Journal of Marketing Research* 25 (May 1988): 157-67.

Lancaster, Kelvin J. "A New Approach to Consumer Theory." *Journal of Political Economy* 74 (1966): 132-57.

Leonard, Robert L. and James J. Wadsworth. *Consumer Preferences: A Guide to Connecticut Apple Marketing.* University of Connecticut Food Marketing Policy Center Research Report No. 4, Storrs, 1989.

Manalo, Alberto B. "*Preferences of Apple Consumers in the New Hampshire Seacoast.*" New Hampshire Agricultural Experiment Station Report No. 120, Durham, 1989.

Moore, William L. "Levels of Aggregation in Conjoint Analysis." *Journal of Marketing Research* 17 (November 1980): 516-23.

Mullet, Gary M. "Using Customer Preferences to Design Products." *Business* (Oct.-Dec. 1983): 27-32.

Ratchford, Brian T. "The New Economic Theory of Consumer Behavior: An Interpretive Essay." *Journal of Consumer Research* 2 (September 1975): 65-75.

Wittink, Dick R. and Philippe Cattin. "Alternative Estimation Methods for Conjoint Analysis: A Monte Carlo Study." *Journal of Marketing Research* 18 (February 1981): 101-6.

_______ and _______. "Commercial Use of Conjoint Analysis: An Update." *Journal of Marketing* 53 (July 1989): 91-96.

_______, Lakshman Krishnamurthi and Julia B. Nutter. "Comparing Derived Importance Weights Across Attributes." *Journal of Consumer Research* 8 (March 1982): 471-74.

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