# Assessing the Importance of Apple Attributes: An Agricultural Application of Conjoint Analysis

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The use of conjoint analysis in assessing consumers' preferences for attributes is demonstrated with the apple as an example. Conjoint analysis may be used to estimate the importance of attributes and attribute levels through decomposition of consumers' ranking of alternative attribute combinations. It is shown that conjoint analysis provides results that may not be obtained from a survey where respondents are asked to directly state their assessment of the importance of attributes.

The "marketing concept" holds that to meet organizational goals, a firm must determine the needs and wants of its consumers and then deliver products and services that satisfy those needs and wants more efficiently than its competitors (Kotler). In today's agriculture, with its advances in plant breeding, crop management, and post-harvest handling, producing and delivering products that appeal to consumers should be easier than in the past. An important task is to determine, with some reasonable degree of precision, what consumers want. Several marketing research techniques have been developed to increase understanding of consumers' preferences. This paper illustrates the use of conjoint analysis in assessing consumers' preferences for the attributes of an agricultural product. The benefit of using conjoint analysis is emphasized by comparing its results in analyzing the importance to consumers of apple attributes with those results obtained with the use of a survey.

## Overview of Conjoint Analysis

Conjoint analysis finds theoretical support in economics in the approach to consumer theory proposed by Lancaster. This approach suggests that consumers derive utility not from goods themselves, but rather from the attributes or characteristics that the goods possess.

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The basic principle underlying conjoint analysis is that a product is composed of attributes (e.g., size) and that each attribute may have two or more levels (e.g., small, medium, large). Consumers' preferences for products are assessed by estimating the importance of product attributes to consumers. Respondents are presented stimuli comprised of alternative combinations of attribute levels and asked to rank or rate these alternatives. Using any of several methods, the relative importance of each attribute is estimated given the ranking or rating data. The estimation technique assigns to each attribute level a value called part-worth that indicates the relative importance of that level to the respondents. The measure of the importance of an attribute is then derived from the range of the part-worths over the levels of that attribute. By summing the part-worths for various combinations of attribute levels, one can find the total worth or value of a product to consumers (Green and Srinivasan; Green and Tull).

The early literature on conjoint analysis estimated part-worths for each individual respondent. This approach leads to high predictive validity, which is defined as how well the part-worths estimated from an individual's (or group's) responses can predict the same individual's (or group's) ranking or rating of a different set of combinations of the attributes specified in- the conjoint study. Nonetheless, the results of individual-level analysis may be difficult to analyze and understand when the number of respondents is large. Some studies estimated average part-worths for all respondents. The results of this method are easy to explain, but because they are averages, their predictive validity is lower than the individual-level approach (Moore). More recently, several methods have been proposed in an effort to provide results that have high predictive validity and, at the same time, are very useful to marketing managers who want to identify consumer segments to which they can tailor their marketing efforts. Today 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 part-worths (Green and Helsen). Kamakura has proposed a procedure that clusters respondents with similar responses and then estimates the part-worths using pooled data within each cluster. Other developments pertaining to conjoint analysis were reported in Wittink and Cattin.

## **Determination** of **the** Important **Apple Attributes**

The research task is to determine the attributes consumers seek when they buy apples. Such information is often collected through surveys where consumers are asked to directly state their preferences for attributes. Conjoint analysis appears to be a better way of obtaining this type of information because conjoint analysis has the advantage of providing more useful results than ordinary surveys. To underscore this point, the usefulness of apple attributes obtained from a consumer survey is compared with that obtained with the use of conjoint analysis.

A random sample of 208 apple consumers was interviewed in a shopping mall. They were asked to provide demographic information and responses to several survey questions, as well as to participate in a conjoint analysis study, the details of which will be discussed in a later section. For the survey portion of the interview, respondents were asked to assess the importance of the following attributes: size, color, flavor (i.e., whether the apple is tart or sweet), crispness, and price. A preliminary interview of several consumers conducted beforehand revealed that they consider these attributes in their apple purchasing decisions. In the survey, each attribute was rated as very important, somewhat important, or not important.

### *Survey Results*

The results are show in Table 1. It appears, given the frequency distribution of responses, that consumers consider size, color, flavor, and crispness as very important attributes and price as not important. This information, however, does not tell us the relative importance of attributes. Is flavor, for example, the most important attribute because the greatest number of consumers said it was very important? If so, how important is flavor relative to crispness or to size? If an apple has the desired flavor, will consumers not mind so much if it is not crisp?

**Table 1. Importance of Selected Apple Attributes to Consumers, as Directly Reported by 208 Respondents**

| | Degree of Importance | | | |
|---|---|---|---|---|
| Attribute | Very Important | Somewhat Important | Not Important | Total |
| | | *Pen* | *•en!* | |
| Size | 38 | 33 | 30 | 100[a] |
| Color | 61 | 21 | 18 | 100 |
| Price | 26 | 28 | 46 | 100 |
| Crispness | 89 | 6 | 5 | 100 |
| Flavor | 96 | 2 | 1 | 100[a] |

[a] The actual total does not equal 100 because of founding.

It could be argued that if the desired information is relative importance of attributes, then the respondents should have been asked to rank the attributes according to importance. Although such an approach could produce an ordinal ordering of the attributes, it still could not provide a measure of how much more important an attribute is relative to others.

Such a measure is useful because it will allow growers to make strategic decisions related to apple production. For example, given a particular cultivar or variety, the larger the apple, the greater the likelihood that it will be less crisp. The issue confronting an apple grower who wishes to provide maximum satisfaction to consumers is whether to produce large apples and sacrifice some crispness, or ensure crispness first and foremost. Will consumers prefer a large apple that is slightly soft to a medium apple that is very crisp? The answer rests upon knowing how much more important size is relative to crispness. This type of information may be obtained with the use of conjoint analysis.

### *Use of Conjoint Analysis*

An apple was defined in the conjoint study as having the five attributes that consumers assessed in the survey: size, color, price, crispness, and flavor. Each of these attributes has either two or three levels, as shown in Table 2. The levels for size, color, crispness, and flavor represent the characteristics of apples normally found in supermarkets. The levels for the attribute price reflect the range

**Table 2. Attributes and Levels Used in the Apple Conjoint Study**

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

of prices in supermarkets in the seacoast region of New Hampshire at the time of the study (July 1988). The data collection method used is the full-profile approach (Green and Srinivasan), 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—a number that is too large 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 number of combinations is chosen. Addelman developed several basic plans for generating orthogonal arrays for different numbers of attributes and attribute levels. The plan that applies to this particular case contains 18 combinations, which are shown in Table 3.

Eighteen stimulus cards were prepared; each card contained a combination of attributes from the orthogonal array. A sample card is shown in Figure 1. The 208 respondents who were interviewed in the survey were also asked to rank the eighteen combinations using 1 and 18 to indicate highest and lowest preference, respectively. Ranking data provided by the respondents were analyzed with the use of ordinary least squares (OLS) regression. Wittink and Cattin found that OLS is an appropriate estimation method in conjoint analysis. The regression model used to estimate the part-worths is

where $Y_{in}$ is the rank assigned by the nth respondent to the Ah combination in the orthogonal array; fJ$_0$ is the intercept term; Pi, $p_2$, • • • » Ps are the regression coefficients; $X\backslash_{in}$ and $X_{2in}$ denote the level of the attribute size in the fth combination; $X_{3in}$ and $X_{4in}$ denote the level of the attribute color; $X_{5in}$ and $X_{6in}$ denote the level of the attribute price per pound; $X_{7in}$ denotes the level of the attribute crispness; $X_{Kin}$ denotes the level of the attribute flavor; and $e_{in}$ is a random error term.

The *Xs* are expressed as dummy variables with the use of effects coding (Cohen and Cohen). For the three-level attributes (size, color, and price), the coding is (— 1, - 1) for the first level, (1,0) for the second level, and (0, 1) for the third level. For the two-level attributes (crispness and flavor), the first and second attributes are coded (- 1) and (1), respectively. For example, for the second com-

**Table 3. Orthogonal Array of Combinations of Apple Attributes**

| | Attributes | | | | |
|---|---|---|---|---|---|
| Number | 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 | Sweel |
| 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 |

**Figure 1. A Sample Card Showing a Combination of Apple Attributes Evaluated by Respondents in the Conjoint Study**

*SIZE*
Large
*COLOR*
Uniformly red
*PRICEILB.*
$0.99
*CR1SPNESS* Crisp
*FLAVOR* Tart

bination shown in Table 3 (i.e., small, green, $0.897 lb., crisp, and tart), the predictor variables were specified as follows: $X$\ = - 1, $X_2$ = - 1, $X_3$ — 1, $X_4 = 0$, $X_5 = 1$, $X_6 = 0$, $X_7 = -1$, and $X_8 = 1$.

The specification of the regression model indicates that average part-worths are to be estimated. Although the use of this approach leads to lower predictive validity than the other procedures cited previously, it allows for easy explanation of the basic method of estimating part-worths and interpretation of the conjoint analysis results. The dummy-variable regression presented here is an integral part of the conventional and Kamakura approaches, except that they estimate either individual or cluster-level part-worths. Furthermore, interpretation of the part-worths obtained with the use of the more recent approaches is similar to that discussed in this paper.

## Conjoint Analysis Results

The regression coefficients are shown in Table 4. The part-worths are estimated from the regression coefficients. The second column of Table 5 indicates the derivation of the part-worth for each attribute level.

Because respondents were asked to rank the various combinations of attributes from 1 to 18, with 1 representing the most preferred combination, the raw part-worth that has the lowest value indicates the most important level of an attribute to the consumer (Table 5). To make interpretation of the values more intuitively appealing, the estimated part-worths for each attribute were adjusted so that the least-desired level has a part-worth equal to zero, and the most-preferred level has the highest

**Table 4. Estimated Regression Coefficients**

| Variable | Estimate |
|---|---|
| Intercept | 10.35[a] |
| | (122.40) |
| $X_1$ | -0.59[a] |
| | (-5.51) |
| $X_2$ | -0.71" |
| | (-6.64) |
| $X_3$ | 1.16" |
| | (10.90) |
| $X_4$ | -0.33[a] |
| | (-3.06) |
| $X_5$ | -0.19[b] |
| | (-1.75) |
| $X_6$ | 0.63[a] |
| | (5.87) |
| $X_7$ | 1.99" |
| | (24.78) |
| $X_8$ | 0.56[a] |
| | (7.02) |
| $K^2 = .21$ | *F* Ratio - 121.782 |

Note: The ( ratios are shown in parentheses.
[a] Statistically significant at a = .01 level.
[b] Statistically significant at a = .10 level.

adjusted part-worth. This was accomplished by getting the absolute value of the difference between each raw part-worth and the part-worth of the least-desired level. To illustrate, for the price/lb. attribute, the adjusted part-worths for the $0.79, $0.89, and $0.99 levels were derived, respectively, as follows: 9.91 - 10.98 | = 1.07; | 10.16 -10.98 = 0.82; and | 10.98 - 10.98 | = 0. It may also be seen in Table 5 that, consistent with economic theory, the respondents prefer a lower price to a higher price.

Tests were run to determine whether, for each attribute, the estimated part-worths are significantly different from each other. The resulting / statistic for each null hypothesis and the conclusion for each test are shown in Table 6. The tests reveal that for all attributes except size, the estimated part-worths are significantly different from others. For the attribute size, we are unable to reject the null hypothesis that the estimated part-worth for medium is equal to the part-worth for large. Nevertheless, the part-worths for medium and large differ statistically from the part-worth for small.

Knowing the part-worths allows the determination of the total worth to consumers of different attribute combinations, even of those that are not included in the orthogonal array. The most preferred combination of attributes is represented by an apple that is large, red, priced at $0.79/lb., crisp, and sweet. The total worth (i.e., the sum of the attribute-level part-worths) of this combination is 2.01 + 1.99 + 1.07 + 3.98 + 1.12 = 10.17. This combination is not found in the orthogonal

**Table S. Attribute-Level Part- worths**

| Attributes and Levels | Expressed in Terms of Regression Coefficients | Estimated Part- worths | Adiusted Part- worths |
|---|---|---|---|
| Size | | | |
| Small | Po - P, - $P_2$ | 11.65 | 0 |
| Medium | Po + Pi | 9.76 | 1.89 |
| Large | Po + Pi | 9.64 | 2.01 |
| Color | | | |
| Uniform red | Po - P3 - P4 | 9.52 | 1.99 |
| Uniform green | Po + Pi | 11.51 | 0 |
| Red-green combination | Po + P4 | 10.02 | 1.49 |
| Price/lb. | | | |
| $0.79 | P« - $P_5$ - 36 | 9.91 | 1.07 |
| $0.89 | Po + Ps | 10.16 | 0.82 |
| $0.99 | Po + P6 | 10.98 | 0 |
| Crispness | | | |
| Crisp | Po - PT | 8.36 | 3.98 |
| Mealy | Po + PT | 12.34 | 0 |
| Flavor | | | |
| Sweet | Po - Pa | 9.79 | 1.12 |

array. Of the combinations shown in Table 3, combination 13—medium, red, $0.79/lb., crisp, and sweet—has the highest total worth (10.05).

*Importance of Attributes*

In conjoint analysis the measure of the importance of an attribute is derived by obtaining the difference between the part-worth of the most-desired level and the part-worth of the least-desired level. Since the adjusted part-worth of the least-desired level is equal to zero, the importance weight for an attribute is measured by the adjusted part-worth of the most-desired level. For example, the importance weight for the color attribute is 1.99 (Table 5). This value is then compared with those for other attributes; the greater the importance weight, the more important the attribute. To make importance comparisons easier, the attribute importance values were also expressed in terms of percent. Crispness is the most important attribute, followed equally by size and color. The least important attributes are flavor and price. The attribute importance weights are shown in Table 7.

It must be stressed that the derived importance of attributes is dependent on the levels of each attribute. Different levels (say, $0.69, $1.59, and $2.49) of the price/lb. attribute, for example, will

**Table 6. Tests of Hypothesis that for Each Attribute, Each Estimated Part-worth (EPW) Is Significantly Different from Others**

| Attribute | | Null Hypothesis*t* Statistic | |
|---|---|---|---|
| Size | $EPW_{small} = EPW_{medium}$ | or ($P_0$ - p, - $p_a$ = 9.76) | 13.84* |
| | $EPW_{small} = EPW_{,argf}$ | or (Po - P, - $P_2$ = 9.64) | 14.72* |
| | $EPW_{m\cdot,Jilim} = EPW_{largf}$ | or($p_c$, + p, = 9.64) | 0.65** |
| Color | $EPW_{reif} = EPW_{greea}$ | or($p_0$ - p, - $p_4$ = 11.51) | 14.69* |
| | $EPW$^ = $EPW_{reti\cdot Sffei,}$ | or ($p_($, - p, - $p_4$ = 10.02) | 3.75* |
| | $EPW_{KrefH} = EPW_{reti\cdot grffit}$ | or ($p_0$ + p-, = 10.02) | 10.96* |
| Price/lb. | *EPWw* $_7$, = $EPW_{K\ K9}$ | or($p_{(1}$ - p, - P«, = 10.16) | 1.85* |
| | *EPWw.n* = $EPW_{K99}$ | or ($p_{()}$ - ps - P,, - 10.98) | 7.87* |
| | *EPWw.M = EPWsa.w* | or (p«, + p, - 10.98) | 6.01* |
| Crispness | $EPW_{,,isp}$ = *EPW ,,,..,,,* | or($p_0$ - $P_7$ = 12.34) | 41.29* |
| Flavor | $EPW\_{mfrl} = EPW_{tan}$ | or(po - $p_H$ = 10.91) | 11.68* |

* **Reject //o at a = .05 significance** level, 3,735 degrees **of freedom. ** Unable to** reject ***fi****$_{()}$* **at a -** .10 significance **level,** 3,735 **degrees of freedom,**

**Table 7. Relative Importance of Apple Attributes Based on the Estimated Part-worths**

| Attribute | Importance | Percent |
|---|---|---|
| Size | 2.01 | 20 |
| Color | 1.99 | 20 |
| Price/1 b. | 1.07 | 11 |
| Crispness | 3.98 | 39 |
| Flavor | 1.12 | 11 |
| Total | 10.17 | 100* |

* The actual total does not equal 100% because of rounding.

likely result in a different estimate of attribute importance (Moore).

The conjoint analysis results confirm the survey findings that consumers do not give much importance to price, at least when price is within the range of apple prices normally found in stores at the time of the study. Conjoint analysis reveals, however, that flavor is not as important as may be inferred from the survey results that show flavor as the attribute most often rated as very important by respondents.

## Usefulness of the Conjoint Analysis Results

Knowledge of the relative importance of attributes and their levels will help growers in managing apple production. The results show that crispness is the critical attribute; it is almost twice as important as either size or color. This suggests that the apple growers' strategic priority should be to produce crisp apples. Ignoring other attributes but size and crispness, a crisp, large apple will have a total worth of 3.98 + 2.01 = 5.99. If the consumer is offered instead an apple that is crisp but small, the worth of that apple to the consumer is 3.98. There is a loss of 2.01 because of the size change from large to small. If a large, but mealy, apple is presented to the consumer, the worth of that apple would be 2.01. There would be a 3.98 decline in worth compared to the first apple because the consumer is getting a fruit that is mealy, not crisp. Given these choices, (1) crisp and large, (2) crisp and small, and (3) mealy and large, the consumer would prefer most the first apple, and the second apple Would be preferred over the third. The loss in total worth associated with not getting a large apple is considerably less than that associated with not getting a crisp apple.

The conjoint analysis results may also be used in making pricing decisions. Among the attributes included in the conjoint study, price is the least important. This suggests that consumers may not mind paying a higher price provided they get the crisp, large, red, and sweet apple that they want.

Retailers may also use price to increase the total worth of the apple that they sell if one or more of the desired levels are not available. For example, suppose that the retailer sells uniformly red apples for $0.99/lb. The total worth of this combination (ignoring the other three attributes) is 1.99 + 0 = 1.99. Suppose that the next shipment is composed of red-green fruit. If the retailer sells these apples for $0.99/Ib., the total worth to consumers will be 1.49 + 0 = 1.49. Consumers are not going to find the combination of not uniformly red apples and a high price as attractive as the red-and-$0.99/ Ib. combination. The retailer may, however, encourage consumer purchases by reducing the price to $0.79/lb. This action increases the worth of the apple to 1.49 + 1.07 = 2.56.

The above are just two examples of what could be done with information obtained with the aid of conjoint analysis. Among the other reported uses of conjoint analysis by marketing research firms are new-product identification, market segmentation, advertising, distribution, competitive analysis, and product repositioning (Wittink and Cattin).

There are many potential applications of conjoint analysis in today's agriculture. One example that comes to mind is assessing the importance to consumers of food safety. For example, the concern for food safety has increased the production of organically grown food. However, produce that are grown truly chemical-free may not look as visually appealing as produce grown under the traditional manner. Through conjoint analysis, the importance of appearance vis-a-vis the chemical-free attribute may be determined.

## Summary and Conclusion

This paper demonstrated the application of conjoint analysis in assessing the apple attributes that are important to consumers. It was also shown that conjoint analysis provides information that may not readily be elicited from respondents when they are asked in a survey to state their attribute preferences. Conjoint analysis estimates measures of importance of each attribute level. These measures are useful in making production and marketing decisions. The conjoint analysis results allow firms to make trade-offs in making products available to consumers and still offer products that provide consumer satisfaction.

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