RESEARCH NOTE

Identification of Determinant Attributes Using the Analytic Hierarchy Process

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This article develops a new approach, using information available in the intermediate and final phases of the analytic hierarchy process, to explicitly identify which attributes or criteria are determinant in making a choice among several given alternatives. The approach parallels that used in the popular direct dual questioning determinant attribute (DQDA) analysis, which has been widely used in marketing applications. Using the hierarchical structure and pairwise comparisons, the combined relative priorities of the criteria are compared with the relative priorities of the choice alternatives to compute determinance scores. These values are the basis for identifying which of the criteria are both important and different across alternatives (i.e., determinant). This new approach overcomes the potential ambiguities of traditional direct dual questioning methods. Moreover, the approach is easily extended to include decision hierarchies with multiple levels of attributes and subattributes.

Identification of determinant attributes, introduced by Myers and Alpert (1968), is among the most critical issues in choice theory and consumer behavior. Since Alpert's (1971) comparison of methods, there have been a number of multiattribute methods developed for evaluating sets of alternative choices. One such approach is the analytic hierarchy process (AHP) developed by Saaty (1977). The information available in the structure of a decision hierarchy used in the AHP provides a basis for identifying determinant attributes that has not yet been exploited. In this article, we use the information in the AHP to develop a procedure for identifying determinant attributes in the selection of an alternative from a given choice set.

Identification of the attributes that directly influence the selection of one alternative from a given set of alternatives has been investigated extensively, particularly with regard to consumer and buyer behavior. Myers and Alpert (1968) introduced the concept of "determinant attributes" associated with the selection of a product or service by consumers. Simply stated, given a set of decision alternatives (a choice set), determinant attributes are those attributes that are perceived to strongly contribute to the choice among the alternatives. Myers and Alpert recognized that although certain attributes may be important, unless there are differences among the alternatives with respect to those attributes, the attributes generally will not play a significant role in the selection process and thus are not considered determinant.

Alpert (1971) compared several determinant attribute analysis techniques and found strong support for the direct dual questioning determinant attribute (DQDA) approach. Subsequently, DQDA has gained acceptance in marketing research applications (e.g., Anderson, Cox, and Fulcher 1976; Bearden 1977; Martin and Winteregg 1989; Sinclair and Stalling 1990). The DQDA approach first aims to

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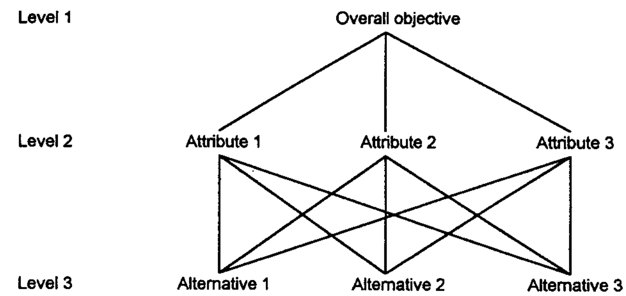
identify "importance" ratings for a set of attributes, then to measure "difference" ratings among the alternatives with respect to each attribute. A composite measure of the importance and difference ratings is then used to identify those attributes that are determinant in making a selection among the decision alternatives. An inherent limitation in DQDA is the number of attributes that can be evaluated meaningfully.

The AHP is a ratio-scaled method used primarily to assist a decision maker in evaluating alternatives (Saaty 1977, 1980). It is particularly useful when the attributes and/or the decision alternatives are considered intangible or there is a high level of subjectivity involved (as in the case of evaluating attributes in a consumer choice situation). When a multiattribute decision problem is structured as a hierarchy with the overall objective (or focus) at the highest level, the alternatives at the lowest level, and criteria or attributes at intermediate levels, the AHP yields estimates of the relative priority of the various elements on each level of the hierarchy. Synthesizing the hierarchy results in overall priorities for the alternatives. The AHP has emerged as a popular, easy-to-use decision-aiding tool with many applications in diverse areas (Golden, Wasil, and Harker 1989; Vargas and Whittaker 1990; Wasil and Golden 1991; Wind and Saaty 1980; Zahedi 1986). Many of these applications deal with the traditional problem of selecting from among a set of alternatives, but some extend the use of the AHP to new areas (e.g., Sharp 1987; Sinuany-Stern 1988). These applications illustrate the maturity of the AHP and its appropriateness for extension beyond traditional applications.

There have been numerous applications of the AHP to decision problems in marketing. Wind and Saaty (1980) examined various marketing applications of the AHP. Whipple and Simmons (1987) used AHP to evaluate the effect of the decision maker's gender in making microcomputer vendor selections. Javalgi, Armacost, and Hosseini (1989) used the AHP to examine bank selection decisions by consumers. Dyer et al. (1988) examined a wide spectrum of marketing problems using the *Expert Choice* (Decision Support Software 1983) software package. Most of these applications of the AHP focused exclusively on what alternative should be selected.

The application of determinant attribute analysis is not so much concerned with what is the preferred choice as much as it is with what attributes actually determined the choice for that given set of alternatives. Inherent in the structure of the AHP hierarchy and priorities is the opportunity to identify those attributes that are determinant in choosing among the alternatives. In this article, we exploit that structure to develop a procedure for explicitly identifying determinant attributes in the context of an AHP decision hierarchy. We suggest that our proposed approach may help to remove some of the apparent ambiguities in DQDA. An important aspect of this approach is the possibility of handling a large number of attributes. Unlike DQDA, in which all attributes are considered simultaneously, AHP allows for structuring the attributes hierarchically, thereby reducing the size of the set of attributes to be considered at one time. Moreover, attributes can be aggregated and determinance can be estimated for higher level attributes. In the following sections, we further describe AHP and DQDA, develop a methodology for identifying determinant attributes using AHP, compare AHP-DA and DQDA, and illustrate the new approach.

FIGURE 1
An Elementary Decision Hierarchy



THE ANALYTIC HIERARCHY PROCESS

The AHP, developed by Saaty (1977, 1980), involves three basic elements: (1) describing a complex decision problem as a hierarchy, (2) using pairwise comparisons to estimate the relative importance of the various criteria on each level of the hierarchy and compute the priority of each criterion, and (3) synthesizing the resulting priorities over all levels to develop an overall evaluation of the decision alternatives. Hierarchies are basic to the human way of breaking reality into manageable segments (Newell, Shaw, and Simon 1958). Conceptually, a decision problem consists of various levels representing the focus (objective), the attributes (criteria) and/or subattributes, and the decision alternatives.

Identification of the decision hierarchy is the key to success in using AHP. The attributes considered in the dual questioning determinant attribute analysis can represent a criterion level, and the elements of the choice set can represent the lowest level of the decision hierarchy. A graphical representation of a simple hierarchy using these levels is illustrated in Figure 1.

For each level in the decision hierarchy, AHP requires the decision maker to provide the relative importance of each attribute (with respect to the focus) and the relative preference for each decision alternative (with respect to each attribute). In particular, AHP uses pairwise comparisons to estimate the relative importance (preference) of each pair of elements of a given level with respect to each element in the preceding level of the hierarchy. Each expressed preference is an estimate of the ratio of the priorities or weights of the compared elements. AHP uses an eigenvector approach to compute the estimates of the priorities of elements based on the pairwise comparisons.

The priorities at each level, normalized to sum to one, are used to weight the priorities at lower levels in the hierarchy and then are aggregated across the alternatives to obtain an overall preference rating for each decision alternative. With respect to each pairwise comparison matrix, the computed priorities are referred to as local priorities. When weighted by priorities from higher levels, the priorities are termed global priorities. The use of the eigenvector approach provides the capability to measure the consistency of a decision maker's judgment and, therefore, encourages the decision maker to revise judgments as necessary. (See Zahedi [1986] for a more detailed, nontechnical overview of AHP.)

AHP first requires that a decision problem be structured as a hierarchy. Saaty (1986) and Harker and Vargas (1987) described the axioms underlying the AHP that must be satisfied in order for a dominance hierarchy to exist and the above procedures to be valid. One of the most actively discussed aspects of the AHP, the condition of rank reversal, is associated with the violation of these assumptions. Specifically, when the priorities at a given level depend on the particular elements of the hierarchy at a lower level (violation of independence axiom), changing any of the lower level elements results in a change of priorities at the higher level, affecting the synthesized priorities for the decision alternatives. Saaty identified a hierarchy containing this type of dependency as a "system with feedback" and recommended using a "supermatrix" approach to estimate overall priorities of the alternatives. Belton and Gear (1983) and Schoner and Wedley (1989) have proposed other methods for accounting for this dependence. Schoner and Wedley used the term "referenced AHP," which explicitly provides a means for using referenced comparisons. Schoner and Wedley indicated that the "referenced AHP" and the "supermatrix" approach yield the same results. Recently, Saaty (1993) and Forman (1993) have also introduced an "ideal" mode comparison that provides a reference point and eliminates the rank reversal problem. In the present determinant attribute analysis, we assume that when dependence is not an issue, a traditional dominance hierarchy is used, and when dependence occurs, a hierarchical representation is used with referenced AHP or an equivalent system to estimate the priorities.

DETERMINANT ATTRIBUTE ANALYSIS

Numerous approaches have been developed in decision theory, psychology, and marketing to identify determinant attributes affecting attitudes, perceptions, and/or choice behavior. These include variants of direct elicitation approaches (Alpert 1971), conjoint measurement methods (Green and Wind 1973), information display board approaches (Jacoby 1975), and various indirect elicitation methods such as open-ended questioning techniques (Fishbein and Ajzen 1975) and Thurstone's pairwise comparison techniques (Thurstone 1959). Alpert (1971) compared three alternative methods for identifying determinant attributes, including both direct and indirect questioning under single and dual questioning structures, and a multiple regression model with overall preference as the dependent variable. He developed strong support for the use of the direct dual questioning approach. It has been used to identify determinant attributes in bank selection (Anderson, Cox, and Fulcher 1976), in store patronage (Bearden 1977), for store choice among the elderly (Lumpkin, Greenberg, and Goldstucker 1985), and for selection of siding products in residential construction (Sinclair and Stalling 1990). All these studies examined the determinant attributes across different market segments, and appropriate statistical approaches were used with the direct dual questioning results to perform the segmentation.

Various other approaches incorporating indirect questioning or observation have also been used to identify importance and determinance of attributes. Comparative studies have largely been contradictory and generally pointed to a lack of convergence among the different methods. This has led to the concern that different techniques may measure different aspects of the concept of importance or determinance, suggesting that more than one approach may be needed to explicate different facets of determinant attribute analysis (Martin and Winteregg 1989). In this article, we are not concerned with a broad comparison of different methods. Rather, we propose a new approach to explicitly identify determinant attributes that results in a superior measure of determinance by reducing the potential ambiguity associated with traditional DQDA in obtaining the importance and difference measures, and to extend the opportunity for comparing large numbers of attributes.

The analysis methodology used for direct dual questioning follows that developed by Myers and Alpert (1968) and Alpert (1971). Consider a set of n attributes and a choice set consisting of m choices. For each attribute, a respondent must specify the importance (x) of that attribute using a 5-point categorical scale (e.g., 1 = *not important* to 5 = *extremely important*), which is treated as an interval scale in the DQDA algorithm. With respect to each attribute, a respondent must identify how much difference (y) there is among the m alternatives in the choice set using another 5-point categorical scale (e.g., 1 = *no differences* to 5 = *extreme differences*), again treated as an interval measure. The determinance score for each of the n attributes is computed as the product of the importance score and the difference score (xy). The average determinance score over all respondents can be computed directly for each attribute. In order to identify the determinant attributes, a common approach involves comparing the average determinance score for each attribute with the mean determinance score over all attributes. Those attributes that have mean scores significantly higher than the overall mean are considered determinant using a .05 level of significance (Alpert 1971; Anderson, Cox, and Fulcher 1976; Lumpkin, Greenberg, and Goldstucker 1985). Sinclair and Stalling (1990) modified the procedure by using normalized determinance scores for each respondent to reduce interrespondent variability. This obviously affects the identification of which attributes are determinant.

In the usual DQDA approach, the attributes are evaluated with respect to their importance on an individual basis, with no specified frame of reference. There may be some implicit comparison basis for evaluation, generally known only to the respondent. With a large number of attributes, this may impose a heavy burden on the respondent. Often, the attributes can be grouped into categories that can be evaluated with respect to their importance. This grouping could reduce the work involved in evaluating the importance of the attributes. Classical approaches to DQDA, however, do not take advantage of such grouping possibilities. Furthermore, different respondents will have different bases for their comparisons. Evaluating the differences among the alternatives in the choice set is typically accomplished by asking how different the entire choice set is with respect to a particular attribute. Because the individual decision alternatives are not compared with one another (e.g., on a pairwise basis), it is not clear what meaning a particular response to the above question conveys. This ambiguity is generally not resolved in the classical DQDA framework. The frame of reference ambiguity is partially addressed by Sinclair and Stalling (1990) by normalizing individual determinance scores.

The basic idea in the dual questioning approach is to separately identify the importance of each attribute, evaluate the degree of differences among the elements of the choice set with respect to each attribute, and then combine these results in a meaningful way that permits the isolation of those attributes that are determinant in reaching a decision. Our AHP-DA approach explicitly identifies the determinant attributes through an improved procedure that not only incorporates, in more detail, the differences among the alternatives, but also provides a logical procedure for considering large numbers of attributes and for considering multiple levels of attributes.

IDENTIFICATION OF DETERMINANT ATTRIBUTES USING THE AHP (AHP-DA)

Determinance is the combined effect of importance and difference and is a characteristic of the attributes with respect to a particular choice set (alternatives). Within AHP, the global priorities of the alternatives exactly represent the effects of determinance. With regard to the attributes, however, the priorities only represent importance measures, even in the case of referenced AHP. The question of interest here is which of the attributes are determinant in selecting among the particular alternatives. To address this question, it is necessary to measure the differences among the attributes with respect to the final selection among the alternatives. The AHP-DA approach uses the importance results (priorities) from the AHP as well as a difference measure based on the priorities of the alternatives to explicitly estimate determinance. This approach is illustrated for a three-level decision hierarchy consisting of an objective, attributes, and decision alternatives as depicted in Figure 1. This hierarchy is exactly the decision structure used by DQDA. The AHP-DA approach emulates the DQDA approach, computing importance scores, difference scores, and finally, determinance scores.

The following notation is used for the three-level problem. Let a_i represent the normalized priority of the ith attribute, $i = 1, \ldots, n$, and let p_{ij} be the normalized local priorities of the jth alternative with respect to the ith attribute, $i = 1, \ldots, n$, $j = 1, \ldots, m$. The priorities are usually normalized such that

$$\sum_{i=1}^{n} a_i = 1, \tag{1}$$

and

$$\sum_{j=1}^{m} p_{ij} = 1, i = 1, \ldots, n. \tag{2}$$

The values of the a_i are similar to the importance scores in DQDA, with the difference being that they are ratio-scaled and the DQDA importance scores are interval-scaled. The a_i will be used as the importance scores in AHP-DA. The pairwise comparisons and resulting priorities for the alternatives provide a means to estimate the differences among the alternatives with respect to each attribute. If there were no differences with respect to attribute i, then $p_{ij} = 1/m$ for all j because all m alternatives would be equally preferred. When all m alternatives are not equally preferred, a measure of their average similarity effect is the geometric mean of the local priorities (because the priorities are ratio-scaled measures). Let g_i be the average similarity effect for the ith attribute. Then

$$g_i = \left(\prod_{j=1}^{m} p_{ij} \right)^{1/m}, i = 1, \ldots, n. \tag{3}$$

The maximum value of g_i is $1/m$, which occurs when all alternatives are equally preferred. Thus, the g_i values measure similarity. Because we are interested in differences, we propose a difference score that measures the deviation from a no-difference situation, namely the difference between $1/m$ and g_i. Let y_i be the difference score for the ith attribute. Then

$$y_i = (1/m - g_i), i = 1, \ldots, m. \tag{4}$$

At this point, we have a_i, the importance score for the ith attribute, and y_i, the difference score for the alternatives with respect to the ith attribute. The determinance score d_i is simply the product of the importance and difference scores as in DQDA:

$$d_i = a_i y_i, i = 1, \ldots, m. \tag{5}$$

Because the difference scores are typically very small, the determinance scores will be even smaller and may be normalized for computational convenience without affecting rank or other comparisons. The criterion that we use to identify the determinant attributes is similar to that used by Alpert (1971) in DQDA. Specifically, we use the sampling distribution of the determinance scores with a one-tailed significance test at the .05 level.

The AHP-DA approach provides an effective mechanism for identifying determinant attributes. In a manner similar to the traditional DQDA, the determinant attributes can be identified for different a priori or post hoc segments using the AHP-DA method. The accessibility of these segments can be assessed using conventional statistical analysis procedures. Finally, positioning strategies can be developed using the determinant attributes as well as the background characteristics of each market segment.

EXTENSION TO MULTIPLE LEVELS OF ATTRIBUTES

Often, a large number of attributes can be identified that may potentially contribute to a decision maker's perception of a product or service. It is not uncommon for this number to exceed 20 or even 30. For example, in their study of determinant attributes affecting the elderly's choice of a grocery store, Lumpkin, Greenberg, and Goldstucker (1985) used 32 attributes. In order to facilitate the communication of their results, they divided these attributes into four general categories (i.e., main attributes), each containing a subset of the attributes (i.e., subattributes). Their analyses, however, only involved the classical DQDA of the 32 subattributes considered simultaneously.

It is well known that individuals' information processing capacity diminishes when the number of attributes considered exceeds nine (Fishbein and Ajzen 1975). Furthermore, the decision maker may wish to discern the determinant attributes both at a detailed level as well as at a more general level. Therefore, in order to reduce the number of attributes considered at a given time and allow for a graded level of resolution for the attributes in determinant analysis, a hierarchical method is desirable. The classical DQDA does not provide for this type of decomposition. Our AHP-DA approach, however, provides a natural and convenient vehicle for explicitly assessing large numbers of attributes and their characterization at multiple levels.

Suppose there is a set of subattributes in the hierarchy in Figure 1 between the attribute and alternative levels. Assume that each subattribute refers to a single attribute, and for ease of illustration, suppose that there are r subattributes referring to each attribute (this means that there is a total of rn subattributes). Let s^i_{kj} represent the local priority of the jth alternative with respect to the kth subattribute belonging to the ith attribute. Then p_{ik} becomes the local priority of the kth subattribute with respect to the ith attribute. If one is interested in identifying the determinant subattributes, one simply computes the priority (importance) of each subattribute as $a_i p_{ik}$ (global priority of the kth subattribute) and uses this value in place of a_i in equation (5), where s^i_{kj} replaces p_{ij} in equation (3) for computing the similarity effect. If, on the other hand, one is interested in identifying which attributes are determinant, the subattribute level must be collapsed onto the alternatives by letting $p_{ik}\, s^i_{kj}$ replace p_{ij} in equation (3). The resulting similarity scores are used to compute the difference and determinance scores.

COMPARISON OF DQDA AND AHP-DA

An important difference between the DQDA approach and the AHP-DA approach for identifying determinant attributes involves the focus and choice of scale. The AHP-DA approach develops the priorities after comparing the attributes on a pairwise basis using a ratio scale. DQDA develops importance measures examining the attributes in isolation using an interval scale with an unspecified basis for comparison. Both AHP-DA and DQDA evaluate the choice set with respect to each attribute to incorporate the effect of differences among the elements in the choice set. Again, there are important distinctions between the two approaches. AHP-DA compares each decision alternative on a pairwise basis with respect to each attribute to determine the relative priority for each alternative in the context of each attribute. DQDA considers the choice set as a whole and estimates the level of differences (e.g., on a scale of 1 to 5) among the elements in the choice set with respect to each attribute. The more detailed level of comparison using the AHP-DA approach obviously entails more work on the part of the decision maker as the numbers of attributes and alternatives increase.

DQDA results may be affected by problems in the use of the scales and the structure of the questions. In particular, at the importance level, there is no firm point of reference. In addition, Teas and Dellva (1985) expressed the concern that respondents may not distinguish the difference between attribute importance and choice set differences when rating an attribute on an importance scale. For example, one respondent may view the importance question in isolation, whereas another may incorporate the observation of no differences among the choice set and therefore conclude that the attribute is not important.

Another aspect of DQDA that may lead to ambiguity is the manner in which the differences among the elements in the choice set are interpreted. Are the differences based on the best and worst, or are they based on how the alternatives cluster or not—despite the range? For example, if a respondent says that the alternatives are very different with respect to a given attribute, it is not clear whether one alternative is very different from all others or every alternative is different from every other alternative. This aspect of DQDA has not been discussed in the literature. Our AHP-DA approach overcomes both of these problems by using pairwise comparisons throughout. There is always a basis for comparison, and all the decision alternatives in the choice set are evaluated explicitly.

In the DQDA approach, the analysis usually involves a sample of respondents. The determinance scores are calculated for each individual, and the arithmetic mean of those individual scores is the overall determinance score for the given attribute. Using the AHP-DA approach, aggregation of individual perceptions occurs at the judgment level. In order to aggregate the judgments of a group of individuals, the collective judgment itself must satisfy the reciprocal property. Aczel and Saaty (1983) have demonstrated that the geometric mean of the set of individual judgments satisfies this property. Therefore, in the previous development, the relative priorities can be considered the results of individual judgments or the results of using the geometric mean of the pairwise relative importances obtained from a set of respondents.

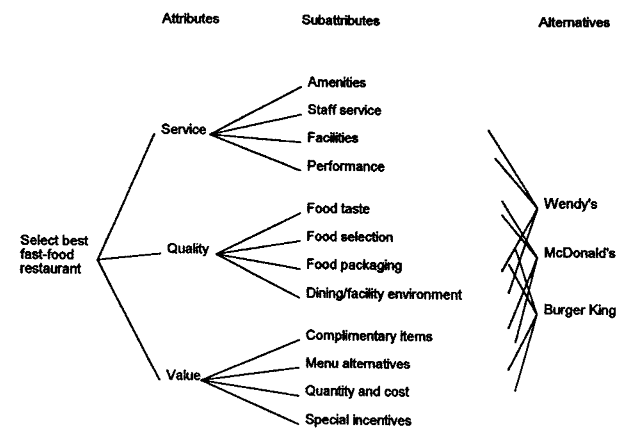
AN ILLUSTRATION AND EMPIRICAL COMPARISON

The specific advantages of the AHP-DA approach over the DQDA approach include the provision for a clear frame of reference in comparing attributes and in comparing alternatives, making comparisons on the basis of preference or importance only and not having the potentially confusing task of evaluating both importance and difference, the possibility of considering large numbers of attributes, and the extension to multiple levels of attributes. A direct comparison of the methods should focus on the latter elements in designing the empirical structure. In particular, we use a multilevel hierarchy. Because DQDA can only address the lowest level subattributes, we have limited the number of attributes considered to 12. Extension to larger numbers is obvious. For comparing the methods, however, we wanted to determine if the two methods would yield similar results under conditions where DQDA is reliable (lower number of attributes). Martin and Winteregg (1989) noted the importance of product purchase familiarity within the respondents in comparing alternative attributes. We have developed a product evaluation illustration and a respondent set that ensures that this criterion is satisfied.

The example involves the selection of a fast-food restaurant from three dominant restaurants: Wendy's, McDonald's, and Burger King. Development of the attributes was based on the use of service, quality, and value as key product dimensions (attributes) in the fast-food restaurant industry. Specific subattributes were developed by means of focus group interviews. The hierarchical representation of the attributes and subattributes is displayed in Figure 2.

The comparison between the two methods was made using a questionnaire administered to two convenience samples consisting of 21 graduate students in engineering management at the University of Central Florida (UCF) and 22 graduate students in the Master of Business Administration program at Marquette University (MU). All of the UCF graduate students were full-time employees at the Kennedy Space Center, and most of the MU graduate students were full-time employees at various Milwaukee-area companies. The UCF sample included 11 men and 10 women; the MU sample included 14 men and 8 women. Both groups purchased food from a fast-food restaurant almost once a week. Seven respondents in the UCF sample were married, and eight respondents in the MU sample were married. Both groups had a reasonably even experience with all the restaurants. The relative percentages of

FIGURE 2
Fast-food Restaurant Selection Decision Hierarchy



time that the UCF respondents patronized the three restaurants are Wendy's, 38 percent; McDonald's, 27 percent; and Burger King, 35 percent. The percentages for the MU respondents are Wendy's, 28 percent; McDonald's, 45 percent; and Burger King, 27 percent. Only three of the UCF respondents had children, and only two of the MU respondents had children. Because the two samples were very similar, the analysis was conducted aggregating their responses.

The questionnaire was organized in three sections. One section included the DQDA comparison, asking the respondents to evaluate the importance of each of the 12 subattributes (included in Figure 2) on a 1-5 scale, then asking the respondents to evaluate the differences among the alternatives on a 1-5 scale. A second section included the AHP questions that involved pairwise comparisons of the subattributes and attributes using the standard AHP scale (Saaty 1980). The AHP comparisons were completed starting at the bottom of the hierarchy to minimize the potential for rank-reversal problems and to ensure maximum use of internal references. The third section included the patronage question and demographic data. On half of the questionnaires, the DQDA section preceded the AHP section; the order was reversed on the other half of the questionnaires.

RESULTS

The DQDA results are included in Table 1. The arithmetic means (for the 43 respondents) of the importance score and difference score for each attribute are included, along with the average determinance score (formed as the product of the importance and difference score for individual respondents). The mean determinance score is 7.81, with a standard error of 1.03. Using Alpert's (1971) approach, the critical determinance score for identifying those attributes that are determinant is 9.50. Consequently,

TABLE 1
Fast-food Restaurant Dual Questioning Attribute Determinance Data

Subattribute	Importance Score	Difference Score	Determinance
Service			
Amenities	2.21	1.84	4.19
Staff service	3.40	2.30	7.93
Facilities	2.79	2.23	6.30
Performance	3.33	2.58	8.74
Quality			
Food taste	4.30	3.40	14.67[a]
Food selection	3.58	3.21	11.70[a]
Food packaging	1.74	1.93	3.47
Dining/facility environment	2.74	2.35	6.53
Value			
Complimentary items	2.09	2.14	4.72
Menu alternatives	3.58	3.09	11.35[a]
Quantity and cost	3.79	2.56	9.95[a]
Special incentives	1.88	2.02	4.12

Subattribute mean determinance score = 7.81
Subattribute determinance score standard error = 1.03
Critical value of subattribute determinance score = 9.50

a. Determinant subattribute.

four subattributes—food taste, food selection, menu alternatives, and quantity and cost—are deemed determinant in selecting a fast-food restaurant from the given alternatives. The respondents were also asked to report their preference for the three restaurants using a forced choice (constant sum) scale. The resulting preferences are Wendy's, 39 percent; McDonald's, 31 percent; and Burger King, 30 percent.

The complete decision hierarchy for this problem is illustrated in Figure 2. The AHP questionnaire using this hierarchy included a total of 57 pairwise comparisons over all levels. The geometric means of the relative importances using Saaty's (1980) 9-point scale were used with the eigenvector method to compute the local priorities at each level of the hierarchy. The local priorities of the attributes with respect to the goal of selecting the best fast-food restaurant (a_i, $i = 1, 2, 3$), the local priorities of the four subattributes with respect to each attribute (p_{ik}, $i = 1, 2, 3$; $k = 1, 2, 3, 4$), and the local priorities of the three alternatives with respect to each subattribute (s^i_{kj}, $i = 1, 2, 3$; $k = 1, 2, 3, 4$; $j = 1, 2, 3$) are included in Table 2. In addition, the geometric mean of the relative priorities for each attribute, g_i, the difference score, y_i, and the determinance score, d_i, for each subattribute are computed and displayed in Table 2. The mean determinance score is 0.00172 and the standard error of the determinance scores is 0.000983. The critical determinance score is 0.003328 and, consequently, three subattributes—food taste, food selection, and menu alternatives—are identified as determinant in selecting among the given three restaurants.

Table 2 also includes the results of identifying the determinant attributes at the level above the subattributes. The determinance scores are service, .00032, quality, .01407, and value, .00127. Clearly, a statistical test is not called for with three attributes. The results are evident. Quality is the key consideration. Not only is quality high in importance (.55), but the difference score for quality is more than 5 times as large as that for value and 15 times as large as that for service. In this case, both the perceived difference in quality and the importance of this characteristic combine to make quality the determinant attribute.

DISCUSSION

The results of the two approaches are compared in Table 3. The ranking for the importance and the determinance scores for the subattributes using both approaches are included. Both DQDA and AHP-DA identified the same three subattributes (food taste, food selection, and menu alternatives) as determinant. DQDA identified a fourth subattribute (quantity and cost) as determinant, but this subattribute was not identified by AHP-DA. The rankings seem to diverge, but the Spearman rank correlation of .64 was significant at $p = .015$. The comparison provides a measure of support for the reliability of AHP-DA. Recall that we chose an example with a modest number of subattributes so that the DQDA results would be a good basis for evaluating the AHP-DA results. In addition, AHP-DA provided higher level determinance scores for the attributes. The result showing a significant determinance effect for quality is not obvious from the DQDA results in Table 1. An additional benefit of the AHP-DA approach is the ability to examine the effects of individual alternatives in the determinance evaluation. For example, reviewing the data in Table 2 for the determinant attributes clearly shows that Wendy's is in the superior position. This information is not available from DQDA. Finally, DQDA does not yield any information regarding the overall preferences for the alternatives. The AHP-DA approach, however, does provide that information, which is the primary result from the application of the AHP. In this case, the relative priorities for the restaurants are Wendy's, .46; McDonald's, .24; and Burger King, .30. Recall that the average preferences based on direct elicitation were Wendy's, .39; McDonald's, .31; and Burger King, .30. The AHP-DA results show a much stronger overall preference position for Wendy's and a weaker position for McDonald's.

CONCLUSIONS

It is well established that human beings, when faced with a decision-making task involving many attributes, usually base their decisions on a subset of the information available to them. Determinant attribute analysis attempts to identify this subset based on the respondents' attitudes, perceptions, or behavior. In practice, identification of the determinant attributes plays a major role in developing a marketing program with respect to segmentation and po-

TABLE 2
Fast-food Restaurant Selection AHP-DA Attribute Determinance Data

Attribute	a_i	*Subattribute*	p_{ik}	*Alternative*	s^i_{kj}	g_i	y_i	d_i
Service	.19					.3317	.0017	.00032
		Amenities	.10	Wendy's	.47	.3199	.0134	.00026
				McDonald's	.25			
				Burger King	.28			
		Staff service	.38	Wendy's	.34	.3332	.0001	.00001
				McDonald's	.34			
				Burger King	.32			
		Facilities	.19	Wendy's	.39	.3304	.0029	.00010
				McDonald's	.32			
				Burger King	.29			
		Performance	.33	Wendy's	.39	.3301	.0033	.00020
				McDonald's	.33			
				Burger King	.28			
Quality	.55					.3076	.0258	.01407
		Food taste	.59	Wendy's	.52	.3007	.0327	.01045[a]
				McDonald's	.17			
				Burger King	.33			
		Food selection	.24	Wendy's	.59	.2906	.0428	.00570[a]
				McDonald's	.19			
				Burger King	.22			
		Food packaging	.06	Wendy's	.33	.3332	.0001	.00000
				McDonald's	.32			
				Burger King	.34			
		Dining/facility environment	.11	Wendy's	.42	.3281	.0053	.00033
				McDonald's	.28			
				Burger King	.30			
Value	.26					.3285	.0048	.00127
		Complimentary items	.10	Wendy's	.37	.3317	.0016	.00004
				McDonald's	.30			
				Burger King	.33			
		Menu alternatives	.38	Wendy's	.59	.2917	.0417	.00338[a]
				McDonald's	.19			
				Burger King	.22			
		Quantity and cost	.19	Wendy's	.34	.3332	.0001	.00001
				McDonald's	.32			
				Burger King	.34			
		Special incentives	.33	Wendy's	.30	.3317	.0016	.00004
				McDonald's	.37			
				Burger King	.33			

Subattribute mean determinance score = .001712
Subattribute determinance score standard error = .000983
Critical value of subattribute determinance score = .003328

a. Determinant subattribute.

sitioning strategies. Most marketing research projects, both basic and applied, begin by developing a list of the attributes that are important with respect to the eventual consumer choice behavior.

Among the many approaches for identifying determinant attributes, the popular direct dual questioning approach attempts to assess the interaction of the importance of the attributes with the differences within the choice set with respect to those attributes. There are serious ambiguities, however, in evaluating the importance and differences associated with the attributes using the traditional DQDA approach. Our proposed AHP-DA approach overcomes these problems and offers a natural methodology to identify determinant attributes in the context of multiple levels of attributes. The AHP approach is easy to understand and use. *Expert Choice* (Decision Support Software, 1983), other AHP software, or simple spreadsheet models can be used to perform the basic computations with respect to importance ratings and the relative priority weights used in computing the difference scores. The computation of difference and determinance scores in equations (3)-(5) is straightforward and can easily be set up in a spreadsheet model.

TABLE 3
DQDA and AHP-DA Comparison

	Importance Score Rankings		*Determinance Score Rankings*	
Subattribute	*DQDA*	*AHP-DA*	*DQDA*	*AHP-DA*
Service				
Amenities	9	12	10	5
Staff service	5	5	6	11
Facilities	7	8	8	7
Performance	6	6	5	6
Quality				
Food taste	1	1	1[a]	1[a]
Food selection	4	2	2[a]	2[a]
Food packaging	12	9	12	12
Dining/facility environment	8	7	7	4
Value				
Complimentary items	10	11	9	8
Menu alternatives	3	4	3[a]	3[a]
Quantity and cost	2	3	4[a]	10
Special incentives	11	10	11	9

a. Determinant subattribute.

The empirical results show that DQDA and AHP-DA yield similar determinance results for a relatively small number of subattributes. AHP-DA, however, can easily handle much larger numbers of attributes and can identify determinance at various levels of attributes. The AHP-DA approach requires more work by the respondent in terms of the number of items requiring a response. On the other hand, it provides a very explicit basis for making the comparisons and removes the ambiguity in DQDA that is associated with assessing importance and differences with no explicit basis for comparison. Further analysis is needed to determine whether the benefits outweigh the added cost of using the AHP-DA approach. In the case where a decision problem is being analyzed using the AHP to determine the appropriate choice from a given set of alternatives, this approach permits identification of determinant attributes with little additional work. Comparative studies with large numbers of attributes are required to determine whether AHP-DA and DQDA will yield different results. Independent studies of this type are required to establish the viability of the approach. Finally, the AHP-DA approach should be compared with other determinant attributes techniques in terms of validity (particularly convergent validity) and reliability.

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