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USING ANALYTIC HIERARCHIES FOR CONSUMER RESEARCH AND MARKET MODELING

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Abstract. Strategic planning, product design and marketing decisions often require a thorough understanding of consumers' preferences and choice behaviors. This paper describes the use of the Analytic Hierarchy Process (AHP) for eliciting preferences by questionnaire. Using AHP, consumers can comfortably provide quantitative measures of numerous, diverse and intangible influences on their choices. The preference scores are on a ratio scale and can be used directly in a power model of choice that can be used to evaluate hypothetical products and analyze marketing strategies. In a medical application, the choice model accurately predicted behaviors and helped guide design of improved treatments.

Keywords. Analytic hierarchy process; choice modeling; consumer research.

I. INTRODUCTION

Consumer preferences are a key input to resource allocation, product planning, and marketing mix decisions. Consumers' evaluations of products and services may involve diverse considerations such as cost, effectiveness, convenience, and safety. In some cases, the relevant aspects are difficult to define precisely, and the corresponding preferences difficult to measure and quantify. In such cases, it may be difficult to use conventional preference elicitation techniques such as conjoint measurement, multidimensional scaling, multiattribute utility estimation, and direct assessment. This paper describes a technique that is particularly useful when preferences depend on diverse and intangible concerns.

Understanding consumer preferences helps organizations:

- Determine how well current products or services are fulfilling people's needs
- Discover trends and changes in customers' needs over time
- Identify and evaluate new opportunities for products and services
- Formulate ways to get new programs utilized more quickly.

Aside from their use in product design and evaluation, preference measures may also be useful as part of a service itself, for example, to monitor customers' needs and regularly adjust the service accordingly. The resulting service provides a high degree of flexibility and responsiveness.

An example of an area in which preferences are particularly important but difficult to measure is in the health care field. Often, the success of medical interventions depends not only on altering the physical health of the patient, but also on changing their <u>perceptions</u> of their physical health. Researchers have demonstrated that the two may not coincide. For example, occupational recovery following a mild heart attack is determined largely by perceived health status, family pressures, and doctor concerns rather than by objective medical status or prognosis (Dennis et al., 1986a; Davidson et al., 1979). Perceptions can impede the success of therapies and behavior change programs and must be addressed when designing and evaluating them.

Preference measures are not only useful for product planning and evaluation, but are essential to quantitative market analysis. A logical and defensible market analysis program involves several important steps:

1. Identifying what product characteristics matter most to consumers (e.g., price and waiting time)
2. Depicting each actual or hypothetical product as a combination of these characteristics
3. Modeling how consumer choices depend on their values for product characteristics
4. Eliciting consumer preferences for each product characteristic
5. Using the model and data to project market share for competing products.

The methodology described in this paper can be used in the first and fourth steps. The technique employs the Analytic Hierarchy Process (AHP), an approach developed by T.L. Saaty (1980) to help individuals rate objectives and prioritize alternatives.

In the next section, we describe how AHP can be used to measure preference by written survey. Section III presents a healthcare application. Section IV summarizes the results and insights we gained from this exercise. We conclude by comparing this approach with others and suggesting possible extensions.

II. METHODS

The Analytic Hierarchy Process is helpful in structuring and analyzing complex decisions involving numerous, diverse, and intangible influences (Saaty, 1980). The approach has been used in a variety of applications, including management-level market planning and strategizing (Wind and Saaty, 1980).

The preference scores are derived from a series of pairwise comparisons. The respondent assigns a score between 1 and 9 that expresses the relative preference for (or importance of) one aspect over the other. The resulting weights are on a ratio scale. AHP also provides a measure of the consistency of a respondent's scores relative to that of a set of random responses. For example, if a set of scores has a consistency ratio of 0.1, the responses are ten times more consistent than if they had been generated randomly. A poor consistency ratio indicates that the respondent may have been inattentive or uninformed.

Analytic Hierarchies as a Survey Technique

AHP has typically been used interactively: the analyst guides the individual who may change responses to achieve acceptable consistency. This adjustment of answers is not possible when using a written questionnaire. In analyzing the results, we excluded the roughly 5% of respondents whose consistency ratios exceeded 0.50. Average consistencies among the remaining respondents ranged from 0.11 to 0.23 depending upon the question.

Our questions involved up to eight aspects. Given n aspects, one must elicit $n(n-1)/2$ comparisons, or up to 28 in our case. Harker (1987) suggests procedures to reduce the number of judgments, possibly at some cost to the quality of the results. However, the number of comparisons did not seem excessive in our application.

AHP appealed to us as a survey technique for several reasons. Choices are structured in a logical hierarchy that reflects how people think, simplifying the respondent's task. The pairwise comparisons are easily understood, and the scores can be used directly in choice models. The consistency ratio indicates the reliability of the responses. Finally, by separating the influences of underlying aspects we can measure their sensitivity to design changes, advertising, and other strategies. Recently, Bahmani and Blumberg (1987) demonstrated a similar application involving consumers' product-safety concerns.

Analytic Hierarchies for Market Analysis

Market analysis models allow us to project the desirability and profitability of new products and services. Since the preferences elicited by AHP are on a ratio scale, they can be incorporated directly in the Power Model of choice (Oren et al., 1980; McFadden, 1974). This model is similar to (and can be derived mathematically from) the more common Logit model. Both models assume that in choosing from a set of alternatives, individuals pick the one they value most highly. However, there is a deviation between the <u>measured</u> values and the <u>true</u> values on which they base their selection, due to temporal effects and aspects not measured. The Power Model assumes that the true value has a Gumbel probability distribution. Given a set of N alternatives with corresponding preference scores $w_1, w_2, \ldots, w_N$, the probability of choosing the jth alternative is

$$\text{Prob}(j) = \frac{(w_j)^k}{\prod_{i=1}^{N} (w_i)^k}, \qquad (1)$$

where k is a parameter of the underlying probability distribution of the values and can be estimated by fitting the predicted choice probabilities to actual or elicited choices. If the w's are average weights for the population, then the probabilities are the market potentials for each product and the parameter k also reflects variation in the population. Notice in (1) that if k=0, then each alternative has an equal share of the market, and as k approaches infinity, the market share approaches 100% for the highest-valued alternative.

After eliciting preferences and estimating k, the market share model is complete. We can use this model to estimate how the market shares would be affected by strategies that influence the underlying preferences, as illustrated in the following application.

III. APPLICATION

We used the Analytic Hierarchy Process to obtain preference measures during a clinical trial of a new intervention for patients recovering from an uncomplicated myocardial infarction (MI). These patients were given an Occupational Work Evaluation (OWE) consisting of a treadmill test three weeks after their MI followed by a doctor's recommendation on when they can return to work, counseling by medical staff regarding their resumption of activities, and a self-directed behavior change program to encourage smoking discontinuation, dietary changes, stress reduction, and increased exercise (Dennis et al., 1986b).

A group of 201 employed men under age 60 were recruited in five hospitals in an HMO chain; 99 were randomized to receive the OWE (Intervention Group) and 102 to receive standard treatment (Usual Care Group).

Questionnaires were administered to each patient in-hospital and at five other times over the six months following their discharge. While the questions addressed a wide range of issues, those employing AHP had three main purposes:

1. To determine the importance of components of the intervention as perceived by the patient. This guided design and improvement of the intervention.

2. To measure the perceived importance of various health risks. This suggested ways to make the intervention more relevant to each patient.

3. To elicit influences on the return-to-work decision. This indicated how best to promote earlier return to work.

The next section focuses on the results obtained from these questions.

IV. RESULTS

Perceived Importance of Intervention Components

In trying to evaluate programs involving several components, it is often difficult to parcel out the influence of each component on the outcomes. The OWE combines diagnostic, therapeutic, and behavioral components in one "package". Although we could not measure the direct influence of each component, we measured their perceived importance according to the patient.

Patients rated the importance of four components of the intervention on their health recovery and return to work:

- Treadmill test
- Nurse counseling and feedback
- Physician advice
- Audiovisual (A/V) program.

This question, illustrated in Figure 1, was asked at one month and six months post-MI.

The results, summarized in Figure 2, provide patients' weights on each component. We also analyzed a set of responses obtained from 41 patients during a pilot test prior to the start of the trial, depicted as the third set of bars. From these pilot responses, we learned that the A/V program had little perceived influence with less than one-tenth that of the other components. After this, we

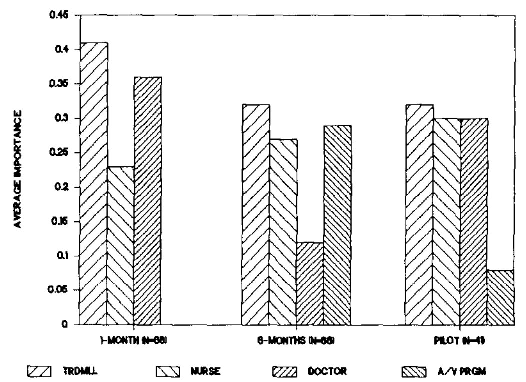

FIG. 2. Importance of Intervention Components

simplified the A/V program and promoted it more strongly. Apparently this effort paid off; by the end of the trial the average weight had increased from 0.08 to 0.29 ($p<0.0003$).

The results show that the treadmill test has the greatest perceived importance. The scores change over time: while doctors are more influential than nurses at one month, by six months the situation is reversed. This reflects the enhanced role of nurses following the initial treadmill test.

Respondents had few problems in answering these questions: 83% completed them and of these, 94% had acceptable consistency ratios. In the latter group, the average consistency was 0.12.

Finally, we are interested in how different aspects of your visit have influenced your feelings about your health and your ability to return to work. On each line below, we ask you to compare two different aspects of your visit. For each line, circle ONE number from on the side of the aspect that has influence you more as far as your feelings about your health and your return to work are concerned.

AS FAR AS MY HEALTH AND RETURN TO WORK ARE CONCERNED:

ASPECT A	A is completely more important		A is strongly more important		A is somewhat more important		A is slightly more important		A and B are equally important		B is slightly more important		B is somewhat more important		B is strongly more important		B is completely more important	ASPECT B
Taking the treadmill test	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Talking with the nurse
Taking the treadmill test	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Talking with the physician
Talking with the nurse	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Talking with the physician

FIG. 1. Question on Intervention Effectiveness

Perceptions of Health Risk Factors

While in the hospital, patients rated the importance of five risk-reducing behaviors on their recovery:

- Quitting smoking
- Reducing job stress
- Improving eating habits
- Improving physical activity
- Reducing stress at home.

These items address actual and perceived contributors to heart attack. Figure 3 depicts the average weights for these aspects, separated by smokers and nonsmokers (some nonsmokers had resumed smoking by the time of the questionnaire). As expected, smokers

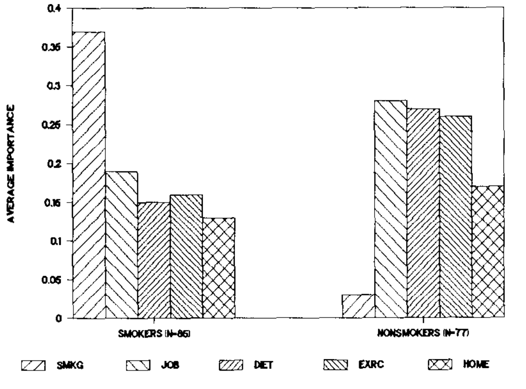

FIG. 3. Perceived Importance of Health Risks

assigned the greatest importance to quitting smoking; aside from this, the other factors received roughly equal importance. Not indicated by the average scores is the great variation between individuals. This justifies a multi-faceted intervention and suggests the value of using such ratings to tailor the intervention to individual needs.

The response rate was particularly high (greater than 95%) for the health risk questions. On average the consistency ratio was 0.18.

Influences on Return to Work

The primary goal of the OWE is to promote more rapid return to work. We used the AHP to get a detailed picture of the return-to-work decision. Based on literature and discussions with patients, we formulated eight key influences on return to work:

1. "My job satisfaction upon return"
2. "My relationship with my family"
3. "What people would think about me"
4. "My recreational and leisure time activities"
5. "My future financial situation"
6. "My health"
7. "My employer's attitudes about my returning"
8. "What my doctor recommends."

The questionnaire expresses these aspects neutrally; different patients may prefer earlier or later return as far as one aspect alone is concerned. The questionnaire elicits, first, the importance of each aspect in the return-to-work decision, and second, for each aspect, the relative strength of preference for each of three return-to-work times:

- One month post-MI ("Early")
- Three months post-MI ("Nominal")
- Six months post-MI ("Delayed").

This two-level hierarchy is depicted in Figure 4.

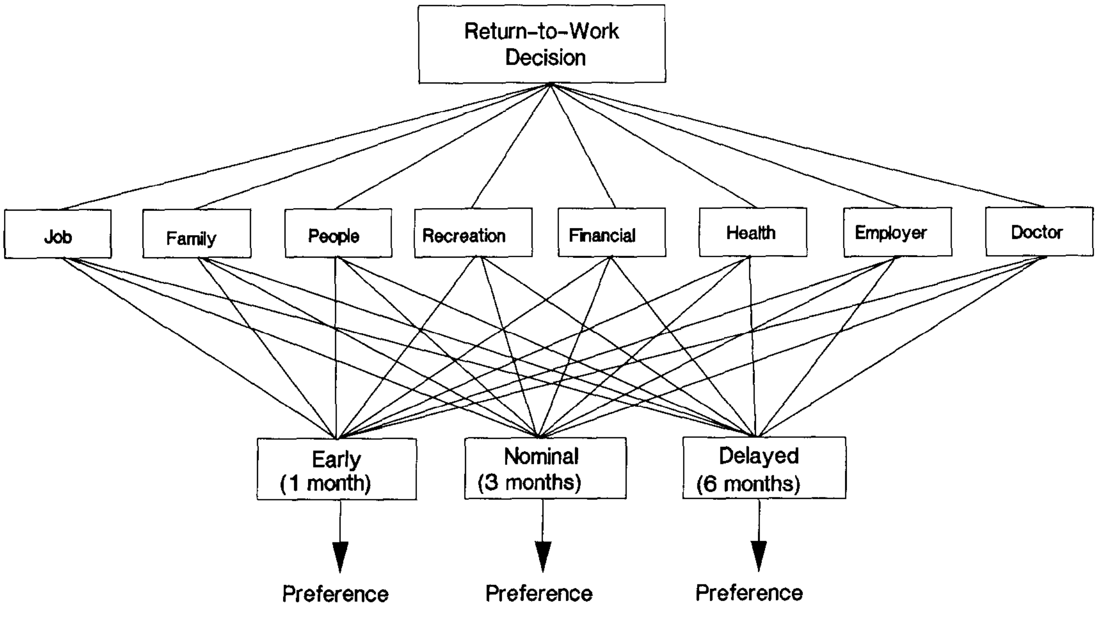

FIG. 4. Hierarchy of Aspects Influencing Return-to-Work Preferences

Figure 5 shows the average scores for the eight considerations. Most important are health concerns and the doctor recommendation, together more important than all others combined. We were surprised that employer concerns have little perceived importance.

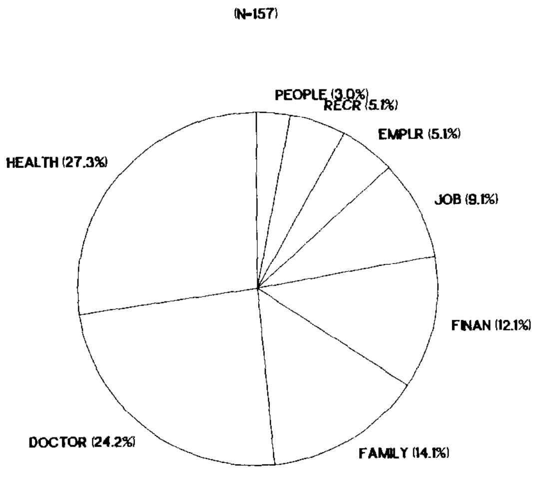

FIG. 5. Influences on the Return-to-Work Decision

Multiplying preferences for each time period with respect to each aspect by the weight on each aspect, then summing, gives the overall preference for early, nominal, and delayed return to work. Actual return-to-work times were categorized as early (less than 60 days), nominal (60-119 days), or delayed (120 days or more). The results in Table 1 show that the preferences measured soon after discharge are highly predictive of actual choices that were made.

TABLE 1. Predictive Ability of Preference Measures ($N = 143$, $p < 0.0003$)

		Actual Return-to-Work		
		Early	Nominal	Delayed
Preferred Return-to-Work	Early	46	15	6
	Nominal	20	29	10
	Delayed	4	11	2

Scores obtained a month later highlight the importance of the treadmill test. Those who were treadmill tested placed nearly twice the weight on early return to work compared to Usual Care patients.

Choice Model

The preceding results suggest that to maximize the effectiveness of the intervention, effort should be targeted towards changing what the doctor recommends and on improving the patient's health perceptions. These were, in fact, two key aims of the intervention. Direct feedback to doctors following the treadmill test was aimed at overcoming their reluctance to recommend early return to work. The treadmill test and A/V program promoted patients' confidence for resuming work and their perceived healthfulness. The payoff: full-time return to work occurred at a median of three weeks earlier (51 days Intervention group vs. 72 days Usual Care, $p < 0.002$).

A quantitative choice model was developed to parcel out the importance of return-to-work influences. A Power Model estimates the fraction of patients choosing each return-to-work interval given their preferences (Usual Care group only). The parameter k (Eqn. 1) was estimated by minimizing the squared error between the predicted choices and actual return-to-work times. The results in Table 2 show that the predicted fractions (line 2) correspond very closely with the actual fractions that were observed (line 1).

TABLE 2. Choice Model Results (Usual Care Group)

	Fraction Choosing Each Interval		
	Early	Nominal	Delayed
(1) Actual	.35	.50	.15
(2) Predicted by model	.39	.48	.13
Sensitivity Cases:			
(3) To doctor's concerns	.43(+4%)	.44(-4%)	.13
(4) To health concerns	.44(+5%)	.44(-4%)	.12(-1%)
(5) To employer's concerns	.40(+1%)	.47(-1%)	.13
(6) To both doctor and health	.48(+9%)	.41(-7%)	.11(-2%)

Sensitivity analysis indicates the effectiveness of hypothetical programs. For example, an intervention aimed at the doctors could increase their acceptance of earlier return-to-work, and thereby alter patients' choices. Patients had rated the three return-to-work times in terms of their doctors' concerns; this enters the calculated score for each alternative. If a hypothetical intervention increased by 50% the ratio of the weight on early to the weight on nominal or delayed return in terms of their doctors' concerns, then the predicted fraction choosing early return increases by 4% to 43%, as shown in Table 2 (line 3).

Similarly, patients had rated the desirability of return to work times in terms of their health concerns. If a hypothetical intervention increased by 50% the ratio of the weight on early to the weight on nominal or delayed return in terms of health concerns, then the fraction choosing early return increases by 5% to 44% (line 4). A similar calculation on the effect of the employers' concerns shows that there is little gain by intervening on the employer (line 5).

Finally, the combined effect of intervening on both the doctor and the patient as above yields 48% choosing early return, a gain of 9% (line 6). By comparison, the intervention surpassed this, since the fraction that actually returned early was 59%.

These results, which suggest that the intervention was well-targeted by focusing on both the patient and his doctor, have helped guide further refinement of the intervention.

V. DISCUSSION

Quantitative measures of consumer preferences are important for developing attractive and responsive products and services. This paper describes an application of the Analytic Hierarchy Process to elicit quantitative preference data and demonstrates the use of these measures in a choice model that can be used for market analysis.

We ascribe our high response rates and consistencies largely to the AHP methodology. By decomposing complex issues and employing pairwise comparisons, the respondent's task is greatly simplified. The redundant information improves confidence in the results and provides a consistency measure that can screen out poor respondents.

The results give insights into the relative importance of components of the new program. Preferences elicited in-hospital were highly predictive of patients' behaviors up to several months later. Analysis using a choice model confirms that the best use of health care resources is to convince doctors and patients of the safety and benefits of early return.

It is important to recognize the limitations of this approach. Dependencies between aspects may compromise the accuracy of the choice model; careful structuring is required to overcome this possibility. Although the scores can be used to generate choice probabilities, they have no readily interpretable scale (such as dollars). This may limit the ability to assess new alternatives not originally rated. Some of these limitations are addressed by recent refinements to AHP and by other methods such as conjoint analysis. Comparisons of various methods in similar applications would be extremely useful.

The approach described here is particularly useful when the choices involve diverse, intangible, and complex concerns. Such choices may be difficult to structure using other approaches, which often require that the attributes of the decision be precisely defined, and can be evaluated against a common scale.

This approach can be used outside of healthcare to design and evaluate products and services. As a refinement, the preferences can be measured interactively (e.g., by computer), allowing each respondent to specify relevant aspects and correct some answers.

But this use of the AHP to get a "snapshot" of preferences is only a start. The techniques can also be used to provide personalized attention and ongoing feedback to customers, based on their preferences. By collecting such information at regular intervals, a program can be made highly flexible and responsive.

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