A NORMATIVE METHODOLOGY
FOR MODELING CONSUMER RESPONSE
TO INNOVATION

by

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Abstract

After emphasizing the role of consumers in the success and failure of products and services, a methodology is proposed to improve the effectiveness of the creative design and strategic implementation of innovative new products and services. This methodology integrates knowledge in the fields of psychometrics, utility theory and stochastic choice modeling. The methodology consists of a consumer response and a managerial design process. The design process is one of idea generation, evaluation, and refinement while the consumer response is based on consumer measurement, models of the individual choice process, and aggregation of predictions of individual choices. The consumer model interacts with the design process by providing a forecast of consumer acceptance for evaluation and by providing diagnostics on consumer perceptions, preference, choice and segmentation for refinement.

The individual response model processes the consumer measures by "reducing" them to an underlying set of perceptual dimensions. "Abstraction" defines homogeneous groups based on preference. "Compaction" describes how the measures of perception combine to produce a scalar goodness measure for each consumer and for each choice alternative. These goodness measures are linked to probability of choice for the new products and services and for competing products and services. In each step theoretical, empirical, and statistical issues are identified. Various existing techniques and new techniques are introduced and described for each phase.

The techniques are demonstrated based on the survey data collected at MIT to support the design of a health maintenance organization (HMO). After discussing the issues of testing the model, the managerial design implications are shown by application to the MIT HMO case.

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Introduction

A common problem that is faced by almost all organizations is how to develop and introduce successful new products or services. This problem receives high strategic importance since such innovation is linked to increased effectiveness and productivity. In the private firm successful new products result in sales and profit growth. For example, approximately 50% of the growth in sales over a five year period in many industries were accounted for by new products (Booz, Allen, and Hamilton [5]). In services like transportation, additional ridership, efficiency, and revenue can be obtained by new services such as computer controlled mini buses. Innovation in the design of service packages in the fields of insurance and finance can improve the competitive positions of companies and insure a stable base for corporate growth. In the field of health, the health maintenance organization (HMO) provides an example of an innovative new service. A successful HMO could have lower costs and higher quality of care along with high enrollment and re-enrollment. Although the measures of effectiveness vary across public and private industries, new products and services are critical to vital functioning and achievement of goals.

While new products and services are crucial to organizational growth and effectiveness, they also represent a high risk to the organization. Many new products fail. Approximately 33% of the new products introduced by firms in the market fail and over 70% of the resources devoted to developing new products are allocated to products that are not a success in the market (Booz, Allen, and Hamilton[5]). In public organizations many

failures have been recorded in public programs such as low cost housing, mass transit services, and preventive health services. Many of these failures reflect a lack of acceptance by consumers. The products did not sell enough or the public services were not utilized by the clientele.

The critical role of the consumer in the management of innovation is being more clearly recognized. Private firms who sell directly to the mass market have long recognized that understanding consumer needs is the key to successful innovation. New evidence indicates that even in high technology fields over 80% of successful technical innovation is the result of ideas generated by marketing or consideration of consumer needs (Utterback [55]). Since it is clear that most successful innovation in private firms is due to understanding consumer needs and responses, it is probably reasonable to posit that this same effort directed at consumers could increase the rate of success of innovations in public organizations as well.

Private firms allocate substantial effort and resources to developing new products through R&D and marketing departments. Figure one depicts a process for development of innovative products and services (Hatch and Urban [18]). The first step is design. In this step consumer studies are integrated with technology and creative efforts to generate new ideas. These ideas are then evaluated and refined based on consumer reactions, production issues, and financial considerations. After an idea has been established as a viable and significant innovation, it is tested in a pilot program or test market. If the test is successful, the product can be introduced.

Figure 1: Process For Development of New Products and Services

This paper will address itself to the problems of the design stage of new product development. Emphasis will be on integrating consumer response into the design activities of idea generation, evaluation, and refinement. This integration will be done through a behavioral process model of individual response to innovation. After summarizing the relevant existing work in the fields of psychometrics, utility theory, and stochastic choice theory, criteria for the modeling methodology will be presented. Then the macro model structure will be defined. Next the measurement, estimation, and micro structural issues will be discussed. Throughout this exposition specific examples will be provided based on the problem of designing a new prepaid, comprehensive health service plan (HMO). After discussing the testing of the model and its implementation in the organizational design process, the paper will close with a description of future research needs.

Existing Work

Psychometrics

Psychometricians concentrate on the issues of how consumers perceive new products and services. Using measurements of perceived similarity among stimuli and measurements of attributes for new and existing stimuli, perceptual maps can be developed by multi-dimensional scaling procedures (Kruskal [30], Young and Torgerson [57]). These perceptual maps identify the important dimensions which consumers use to distinguish between stimuli and indicate the position of each stimuli relative to these dimensions. In marketing, the stimuli are products and the map defines market structure. Opportunities for new products are identified by examining the gaps in the market structure (Stefflre [47], Green and Carmone [14]).

Preference judgements can be integrated with the perceptual data to indicate high opportunity areas. PREFMAP is a popular method for accomplishing this task (Carroll and Chang [8], Carroll [7]). PREFMAP derives an "ideal" position and relative importances of the dimensions from stated preferences of the consumers regarding the existing stimuli. Another approach is through conjoint analysis (Tversky [51]), which produces relative importances by requiring consumers to rank order preferences for factorially generated combinations of product attributes rather than with respect to the existing stimuli (Green and Wind [16]).

While PREFMAP and conjoint analysis use statistical procedures to impute the importances, other psychologists use models which require

consumers to directly state the importances, as well as their perceptions, of the attributes. These "expectancy value" models are linear additive combinations of the importances times the perceptions (Fishbein [10], Rosenberg [42]). The dependent prediction is then correlated with some measure of preference to assess the adequacy of the formulation.

Utility Theory

While the psychometricians apply a methodology based on multi-dimensional scaling and statistical preference analysis, utility theorists approach a similar problem from a substantially different point of view. Prescriptive utility theory is oriented towards helping managers make policy decisions under uncertainty and derives its strength from a rigorous set of axioms (von Neumann and Morgenstern [56]) and theorems which specify unique functional forms, e.g., additive, multiplicative, and quasi-additives (Raiffa and Schlaifer [41], and Keeney [21, 23, 24, 25], Ting [48], and Fishburn [11]). The coefficients of these functions reflect the relative importances of the relevant performance measures, their interdependencies, and the risk averseness of the decision maker. The theorems also indicate techniques to directly assess and test the preference parameters by asking managers to state when they are "indifferent" between two alternative stimuli. The dependent value of the utility function is a single cardinal measure of goodness of an alternative. Since the theory is used to guide the decision rather than describe it, the decision maker chooses the alternative with the highest expected utility value.

Most empirical applications have been based on directly assessing the utility function of one or a small number of decision makers based on a set of quantifiable attributes of alternatives [Keeney [22]]. This is in contrast to the psychometrician's approach which is based on interviewing many consumers based on perceived attributes that must be individually scaled.

Stochastic Choice Theory

Recognizing that there will always be uncertainty in any prediction of choice behavior, economists, transportation demand theorists, and mathematical psychologists concentrate on axioms to determine selection probabilities from observable "scale" values (Luce [32], McFadden [34]). Economists and demand theorists parameterize scale functions and statistically estimate the parameters from observations on actual choice among existing alternatives. Popular models for this are the multinomial logit and other "random utility" models (McFadden [33]).

Mathematical sociologists model the stochastic choice process directly through diffusion, learning, Bernoulli and semi-Markov models (Massy, Montgomery, and Morrison [36]). These models describe the dynamics of choice probabilities over time but do not link attributes of products or consumer preferences to choice.

Discussion

Although a good deal of work is being done, it is clear that the work is very diverse. Each discipline reflects different measurement approaches, analytic techniques, and foci. Psychometricians are concerned with perceived attributes and statistical recovery of importances from stated consumer perceptions and preferences. Utility theorists are concerned with theoretical soundness through axiomatic consistency and with direct assessment of relative importances, attribute interdependence, and the risk characteristics for the purpose of aiding decision making. Choice theorists axiomatically model linkages to probability of choice, but do not consider linkages between consumer perception and managerial prediction of attributes or axiomatic specification of their functional utility forms.

The approaches also differ in how they treat the issues of aggregation. Psychometricians develop average representations of perception and preference, but explicitly check that they are homogeneous with respect to perception and preference (Carroll and Chang [8, 9], Tucker and Messick [50]). Utility theorists work completely idiosyncratically and have not directed much effort at the problems of mass assessment of utility functions. Demand choice theorists directly model individual response and then aggregate, but their statistical techniques force judgemental specification of segments before parameter estimation.

While the approaches are incomplete and diverse, they are complementary with each being primarily directed at a different phase in the

consumer choice process. One can visualize a process of perception, preference, utility, and choice that would integrate the approaches to form a complete consumer response model. Some initial work has been done to integrate these disciplines, but only at an aggregate level (Urban [53], Pessemier [37]).

If a comprehensive integration could be accomplished, the issues of linking this technology to the organizational design process could be more effectively addressed. The purpose of this paper is to affect such an integration. Existing work in these three fields will be drawn upon and extended to define a normative methodology for individual response to innovation. This integration will require new measurement methods, new linkages of psychometrics to utility functions, improved procedures for homogeneity definition, advances in utility theory, more powerful probability of choice models, innovation in testing procedures, and effective methods of linking the technology to management decision processes. After describing criteria for the methodology of modeling consumer response, these new procedures will be positioned in the methodological framework.

Criteria For The Methodology

A normative methodology must be more than a predictor of who will choose what. It must interact well with the design process, reveal why consumers respond the way they do, indicate how to improve this response, and guide creativity in the design of new alternatives. Specifically the methodology should meet the following criteria.

Complete and integrating: The methodology should model the complete choice process and thus be applicable to the wide variety of choice decisions. To do this it must integrate existing approaches into a cohesive but modular process which offers a variety of techniques of varying complexity and data requirements. As such the methodology must respond and adapt to the diverse needs of decision makers and data availability.

Theoretically sound: The methodology should reflect the acceptance phenomena at a level consistent with what is known about behavior, taking into account the degree of modeling simplification required. All models require assumptions, but the methodology should make its assumptions explicit and force submodels to make their assumptions explicit. In doing so, the methodology should isolate weaknesses in existing techniques, and indicate where improvements need to be made. In addition, it should prevent models from being used in applications which violate their assumptions. Finally, the conclusions reached by the methodology must result from the use of consistent mathematical logic.

Useful Predictive Powers: It must be technically and economically feasible to obtain the required measurements for the model. The methodology

must be able to predict response to changes which are controllable in the design. For example, if the price of a new health maintenance organization (HMO) can be varied, then the model should include this variable. Finally, the methodology should be extendable to design changes or to new alternatives which are outside of existing consumer experience. For example, the model should be able to predict the consumer response to a new HMO, even if none currently exist in the community.

Facilitate Successful Innovation: The design of new products or services requires creativity. The methodology should elicit and focus creativity by identifying characteristics relevant to the choice process and by explicitly measuring relative importance of these characteristics. No matter how technically accurate the methodology is, it will only be used if it is acceptable to the organization which must design the innovation. This means that although some steps can be "black boxes", the underlying choice process must be understandable to non-technical as well as technical members of the design team. The outputs of each step must be clear and understandable. The methodology should help the design team to visualize the choice process while being sufficiently robust to prevent absurd answers from discrediting the model. Finally the methodology should be normative. It should be oriented toward the design and refinement of alternatives rather than simply describing the choice process. The ultimate objective of the methodology is successful innovation in products and services.

Macro Description of the Methodology

In this section the criteria specified above will be reflected in a model, measurement, and estimation methodology to aid in the design of new products and services. First the macro structure will be defined. The later sections consider the detailed submodels and micro issues.

The overall methodology is represented by a managerial design process and a parallel consumer response process. See Figure 2. The analytics, and the focus of this paper, are in the consumer response process. First, measures of perception and preference with respect to the relevant choice alternatives are observed for a sample of consumers. These measures are used to estimate the parameters of a model of the individual choice process. Finally, an estimate of group response is obtained by aggregating individual acceptance measures (probabilities). The measures of group response are then input to the evaluation model in the managerial design process which includes consideration of investment, operating costs, risk, and externalities as well as consumer acceptance.

It is rare that a new product or service will be implemented based upon a single cycle through the methodology. Instead a screening process will result which identifies the most promising alternatives for further consideration. These alternatives are refined based on detailed diagnostic information generated by the individual choice models (see arrow marked B in Figure 2). The refined design can be analytically tested in the individual choice models and the simulated results can be used iteratively to lead towards a "best" design (see Arrows A and B in Figure 2). This "best" design identified by the iterative process is then tested by either

Figure 2: Macro Description of the Methodology

taking new consumer measures and cycling through the entire methodology (arrows C and D) or by advancing the design to pilot test (see Figure 1).

The individual choice process consists of the analytic phases of (1) reduction, (2) compaction, (3) abstraction, and (4) probability of choice. See Figure 3. In the reduction phase the perception portion of the measurement set (Ω) is reduced to a smaller set of underlying performance dimensions. This reduced set is represented by X and is made up of each consumer's (i) perception of each performance dimension (m) for each choice alternative (j). In the compaction phase, the vector of individual performance scale values for each alternative for each dimension ($\underline{x}_{ij} = (x_{ij1}, x_{ij2}, \dots, x_{ijm}, \dots, x_{ijM})$) and a vector of individual preference parameters ($\underline{\lambda}_i$) are variables in a real-valued function ($c(\underline{x}_{ij}, \underline{\lambda}_i)$) which compacts them into a scalar measure of goodness (c_{ij}). A separate goodness value is determined for each individual (i) in the sample and for each of his choice alternatives, (a_j).

Based on the preference parameters ($\underline{\lambda}_i$) of the compaction functions homogeneous groups of consumers are abstracted for designation as segments (s) of the target population. Within each segment (s) distributions of the performance dimensions (X_s), the preference parameters (Λ_s) and the functional form of the compaction function ($c_s(\underline{x}_{ij}, \underline{\lambda}_i)$) are determined. Empirically it is observed that consumers do not always choose the alternative with the highest scalar measure of goodness. In this methodology, the scalar values are considered as independent variables in a probability of choice models which links an individual's vector of goodness measures ($c_{i1}, c_{i2}, \dots, c_{ij}, \dots, c_{iJ}$) to his choice probabilities (p_{ij}). Each

Figure 3: Consumer Response Components

individual choice probability (p_{ij}) for each alternative (a_j) is derived by a function ($p_s(a_j | c_{i1}, c_{i2}, \dots, c_{iJ})$). The subscript s indicates that the functions, but not the probabilities, are the same for all individuals in segment s .

The final step aggregates the individual choice probabilities to obtain group response measured by the mean ($\overline{ms}_j$) and variance ($\overline{ms}_j^2$) of share of choice, or in some cases the mean ($\overline{N}_j$) and variance ($\overline{N}_j^2$) of the total number of people choosing each alternative. If it is managerially useful, aggregation can be done separately within segments.

The consumer response process is modular, because this structure allows more effective integration of the disciplines of psychometrics, utility theory, and stochastic choice theory which are each closely associated with one module. Furthermore, by explicitly modeling the various stages of consumer response useful diagnostics can be identified for the refinement model. These diagnostics help the managers understand the market structure, segmentation, relative importances and interdependence of product attributes, and the risk characteristics of the choice process. The model itself processes individual information, but aggregate results from reduction, abstraction, and compaction are important in eliciting creativity for the design of innovative alternatives. For example, in reduction, average perceptual maps of product positioning and in compaction, average values of the importance weights and risk coefficients guide the manager in effective refinement of new products or services.

The following sections describe each phase of the consumer response model and give examples of the measurement and estimation procedures based on health service innovation.

Micro Aspects of the Methodology

Measurement

A good model is dependent upon high quality input. A model is accurate only if the measurements it requires are valid and reliable. It is useful only if the measurements are feasible. This section discusses the measurement issues of the methodology and provides examples from its application to the design of a new health maintenance organization.

First, consumer perceptions, preferences, and choice behavior must be observed with respect to the product or service alternatives which are relevant. For example, there may be a large number of products available, but each consumer is only aware of a few of these. In a study of seven consumer products, consumers had an average of only three brands which were relevant to their purchase decisions (Urban [53]). In services, the number of alternatives is often so small that one must force awareness by the use of concept statements in order to have sufficient perceptual inputs. For example, in a study of HMO design at MIT the evoked set was expanded to four options by specifying three new options in concept form. The options included an MIT HMO, the Harvard Community Health Plan, and a hypothetical Massachusetts Health Foundation. See figure 4 for a description of the MIT HMO option. One thousand surveys were mailed to a random sample of the MIT community and 447 faculty, students, and staff completed the questionnaire.

Next a set of important product attributes are identified and consumers evaluate each relevant choice alternative with respect to each attribute. These attributes and their descriptions are generated from in-depth inter-

DESCRIPTION OF THE M.I.T. HEALTH PLAN

M.I.T. announces a new health care plan for YOU AND YOUR FAMILY. By joining the M.I.T. HEALTH PLAN you can get comprehensive health care at a low, fixed monthly charge. Virtually all your medical needs will be met. You will not have to face unexpected doctor or hospital bills and you will not have to worry about finding a good doctor for you or your family.

The cost of joining the M.I.T. HEALTH PLAN is only a little more than regular Blue Cross/Blue Shield health insurance, but you get more services and comprehensive care. There are no charges for doctor visits, nursing and laboratory services, or hospital services. Women in the plan pay nothing extra for prenatal, delivery, or maternity care. The services are comprehensive and include mental health care and emergency services.

The costs are kept low by the utilization of preventive care to keep you well. The plan succeeds by keeping you and your family well and out of the hospital. In addition, the use of trained paramedics and technology helps reduce costs while maintaining the quality of care.

You choose your own personal doctor (specialist in internal medicine for yourself and a pediatrician for your children) from our staff of physicians. Your doctor supervises your total health care at the health center and in the hospital. He will be sure you get the highest quality of care. When you are a member of the M.I.T. HEALTH PLAN you can be sure of getting health care around the clock from the staff of physicians, nurses, social workers and allied health personnel.

The M.I.T. HEALTH PLAN delivers its services from the Homberg Memorial Building on the M.I.T. campus. Parking is available during patient visits. Hospital services are provided by the Mount Auburn and Cambridge City Hospitals. Maternity and gynecological care are provided through the resources of the Boston Hospital for Women. For emergencies outside the Boston area, local hospitals can be used.

You can become a member of the plan by paying \$1.50 per month more than your Blue Cross/Blue Shield coverage if you are single and \$4.00 more per month if you are married. If you are a single student and do not have hospital insurance, the cost is \$8.25/month more than the student health fee you are currently paying; if you are a married student, the cost is \$20.00/month more than the student health fee. These fees cover all of your medical costs except: the first \$50 and 20% of the balance of prescription charges and the excess of \$10 per visit for psychotherapy (over \$5 per visit for group therapy). The plan does not include eye glasses, hearing aids, cosmetic surgery, custodial confinement, or dental care done outside a hospital. If you join the plan, you must remain a member for one year.

The M.I.T. HEALTH PLAN is designed to make comprehensive, high quality health care available to you and your family at a low cost.

Figure 4: Concept Description

views with individual or groups of consumers or by Kelly's triad procedure, in which consumers describe how the two most similar of three stimuli are alike and how the two most dissimilar are different (Kelly [26]). Consumers then rate the attributes on bipolar or agree/disagree scales. In the HMO study, perceptions were measured on a 1 to 5 agree/disagree scale for each of 16 statements that consumers had earlier defined as relevant to their health care (see Figure 5).

After perceptions have been determined, rank order or constant sum preference measures are obtained. Where possible constant sum paired comparisons are preferred, since they yield interval scales (Torgenson [49]). The initial MIT HMO survey was done by mail and hence the easier to answer rank order preference measures were collected. A later small sample personal interview survey collected constant sum preferences.

Consumers are then given choice alternatives. In transportation this may be the available modes of travel or in consumer products it may be based on a simulated retail store environment. In services, most options may be new options and hence the consumer should be presented with a scenario that attempts to simulate the choice situation. Consumer choices based on concept statements often yield trial probabilities. Repeat, or steady state, probabilities may be different because consumers' perceptions may change after trying a real alternative. In the HMO study, consumers were given choices (0,1) between existing care and the HMO. If they chose MIT, a 5-point intent scale was administered. Then other alternatives were added to the choice set and new intent measures taken.

While the procedures for measurement of perception and preference are relatively well developed, this is not true in utility theory. There

	strongly agree	agree	neither agree nor disagree	disagree	strongly disagree
1. I would be able to get medical service and advice easily any time of the day and night.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
2. I would have to wait a long time to get service.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
3. I could trust that I am getting really good medical care.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
4. The health services would be inconveniently located and would be difficult to get to.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
5. I would be paying too much for my required medical services.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
6. I would get a friendly, warm, and personal approach to my medical problems.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
7. The plan would help me prevent medical problems before they occurred.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
8. I could easily find a good doctor.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
9. The service would use modern, up-to-date treatment methods.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
10. No one has access to my medical record except medical personnel.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
11. There would not be a high continuing interest in my health care.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
12. The services would use the best possible hospitals.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
13. Too much work would be done by nurses and assistants rather than doctors.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
14. It would be an organized and complete medical service for me and my family.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
15. There would be much redtape and bureaucratic hassle.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>
16. Highly competent doctors and specialists would be available to serve me.	<u>a</u>	<u>b</u>	<u>c</u>	<u>d</u>	<u>e</u>

Figure 5: Measuring Perceptions

are no reports of measurement of consumer utility functions. This is in part because past uses of utility assessment were oriented as prescriptive decision applications with one or few decision makers (Keeney [22]). When consumers are considered, two assessment issues must be addressed:

- (1) How can perceptual phenomena be integrated in the measurement? and
- (2) Is it possible to have consumers understand the required lottery and trade-off questions and give meaningful answers?

When utility models are to be supported, data is required to measure risk averseness, importances, and interactions relative to various "performance measures." Prescriptive utility theory requires these to be quantifiable, instrumental variables such as cost or waiting time rather than perceptual measures like quality or personalness of health care. The former are easier for the manager to relate to, but the latter better reflect the consumer choice process. In this methodology it is proposed that the psychological dimensions obtained by reducing the perceptions of choice alternatives be used as performance measures.

In the HMO study, the 16 attributes were factor analyzed to obtain four perceptual measures (see reduction section of this paper for a more detailed description of the procedures). The dimensions were named quality, personalness, convenience, and value, and 80 additional consumers rated the health alternatives directly on 7-point scales for these four dimensions. Utility functions were then assessed relative to the performance measures defined by the perceptions of the 7-point scales. After utility assessment the overall 7-point scale values can be correlated to the factor scores and therefore to the original perceptual ratings. By defining performance measures through perceptual scaling methods, utility theory can be meaningfully linked to psychometrics.

The use of a reduced number of perceptual dimensions as performance measures also makes consumer utility measurement more feasible. Since the number of dimensions is small (usually four or less), measures of risk aversion and importance only need be collected on this smaller set of performance measures.

Risk averseness is measured by having the consumer consider a lottery on the performance measures. Although it was anticipated that this would be a difficult task for consumers, it was found in a study of 80 students, that they related well to a carefully designed questionnaire if simple lottery questions were included to educate them to the task required and the meaning of a probability. The procedure is schematically represented in figure 6. The respondent sets the area of a probability wheel so he would be indifferent between the certain health plan outcomes and uncertain health plans as represented by lottery outcomes. Most respondents were comfortable with this task and all completed the interview. Those who experienced the most difficulty were those who knew probability theory and tried to give expected value answers rather than their true feeling. Utility assessment requires two lotteries for each performance measure or a total of eight lottery judgements in the HMO case. One lottery, where one performance varies while all others are held fixed, is enough to determine the risk characteristics of that performance measure if constant risk aversion and utility independence are assumed (Raiffa [39], Keeney [21]). The second lottery is needed to verify utility independence.

Relative importance weights are determined by asking consumers to trade-off one performance measure, say convenience, with another, say value, while holding all others fixed. See Figure 7. Another trade-off question then varies the fixed values to verify preferential independence, which together with utility

Instruction to Consumer:

Imagine you can only choose between two health plans, plan 1 and plan 2. In both plans personalness, convenience, and value are good (rated 5). You are familiar with plan 1 and know that quality 2 is satisfactory plus (rated 4). You are not sure of the quality of plan 2. If you choose plan 2, then the wheel is spun and the quality you will experience for the entire year depends on the outcome of the wheel. If it comes up yellow, the quality is very good (rated 6) and if it comes up blue the quality is just adequate (rated 2). Graphically this is stated:

Instruction to Consumer:

At what setting of the odds (size of the yellow area) would you be indifferent between plan 1 and plan 2? (Respondent is given wheel and adjusts it until size of yellow area is appropriate. He is challenged by being given the choice with his setting. If he prefers one plan or the other, the interviewer iterates the question until a true indifference setting is determined.)

Figure 6: Schematic of Risk Aversion Question

independence specifies uniquely the form of the utility function (Keeney [21]). Thus two trade-off questions are required for all but one of the performance measures or a total of six questions in the HMO case. Finally a complex lottery involving simultaneous changes in all the performance measures is used to measure interactions.

The results from the HMO study indicate perceptual dimensions can function adequately as performance measures and it is feasible at least in the case of students to measure consumer risk aversion and importances. Future research will assess the practicality of measuring utility parameters in a general population sample.

Figure 7: Schematic of Trade-off Question

Instruction to Consumers:

Now consider the two plans below and choose the level of the value factor in such a way that you are indifferent between the two plans. (Consumer is challenged and the question iterated until a true indifference is determined).

Plan A

Quality = 5 (good)
 Personalness = 5 (good)
 Convenience = 6 (very good)
 Value = 2 (very poor)

Plan B

Quality = 5 (good)
 Personalness = 5 (good)
 Convenience = 2 (very poor)
 Value =

Extremely Poor
 Very Poor
 Poor
 Satisfactory
 Good
 Very good
 Excellent

After completing perception, preference, and utility measurement, demographics and other consumer descriptors are collected in order to adequately project from a sample population. For example, in the HMO study patterns of health care utilization and satisfaction were measured in addition to demographics such as age, sex, family size, and health status. These data complete the measurement necessary to support the individual modeling of response.

Reduction

In the reduction phase of the consumer response model, the perceptual data collected in the measurement phase are reduced to a smaller underlying set of psychological dimensions.

Several multidimensional scaling approaches are available. In the HMO study, common factor analysis was used to reduce the ratings on the sixteen scales for the four plans across 300 individuals to four underlying dimensions. These four factors explained 97 percent of the common variance.¹ Figure 8 presents the factor loadings (correlations) of the raw scales to the new underlying dimensions. By examining the high loadings on each dimension they were labeled judgmentally: (1) quality, (2) personalness, (3) value, and (4) convenience. Quality correlated to trust, preventive care, availability of good doctors, and hospitals. Personalness reflected a friendly atmosphere with privacy and no bureaucratic hassle. Value was not just price, but rather paying the right amount for the services. Convenience reflected location, waiting time, and hours of operation. Based on this factor analysis, factor scores were obtained which describe the location of each plan on each dimension for each individual.

An alternate approach would be to use discriminant analysis or information theory (Boyle [6]) for reduction of the ratings of non-metric techniques if similarity judgements rather than ratings had been collected. In many studies the evoked set is too small ($n < 8$) or too varied across individuals to allow use of non-metric techniques. Factor analysis of a data matrix in which each row reflects an individual rating of a stimuli, allows effective reduction even if the evoked set is small or varies across people.

ATTRIBUTE SCALE*		QUALITY	PERSONAL	VALUE	CONVENIENCE
1	DAY + NIGHT CARE	0.37244	0.07363	-0.31379	0.65939
2	WAITING TIME	-0.22082	0.26204	0.15514	-0.64370
3	TRUST-GOOD CARE	0.72125	-0.21823	-0.09556	0.24702
4	LOCATION	0.01144	0.24706	-0.12544	-0.72964
5	PRICE/VALUE	0.03066	0.12810	0.72384	-0.09961
6	FRIENDLY/PERSONAL	0.40986	-0.51317	-0.12235	0.18762
7	PREVENTIVE CARE	0.55403	-0.14187	-0.44353	-0.03653
8	EASILY FIND GOOD MD	0.64412	-0.15036	-0.21491	0.27113
9	MODERN TREATMENT	0.72288	-0.13441	-0.15906	0.08618
10	ACCESS TO RECORDS	0.45412	-0.49053	0.18749	-0.05992
11	CONTINUITY OF CARE	0.20491	0.47900	0.47727	0.04725
12	ASSOCIATED HOSPITALS	0.68006	-0.08256	0.10854	0.00555
13	USE OF PARAMEDICALS	-0.05303	0.67033	0.12333	0.16722
14	ORGANIZED/COMPLETE	0.47725	0.01627	-0.52893	0.14816
15	HASSLE/REDTAPE	-0.13081	0.69824	0.11180	-0.27903
16	COMPETENT MD'S	0.73953	-0.19335	-0.13971	0.18691

* see Figure 5 for field rating scale descriptions

Figure 8: Factor Loadings

Abstraction

This methodology proposes that the criterion for abstraction be homogeneity of preference.² This is managerially useful because segments defined by homogeneity of preference reflect groups which value the attributes differently. These groups represent opportunities for alternative product or service design. Innovation may be more successful by meeting each segment need separately than by designing an average product or service which does not exactly meet the needs of anyone. A second reason for abstraction by preference is that if importances are statistically estimated, homogeneity is required for theoretical soundness in defining groups for statistical analysis.

One method of preference abstraction can be accomplished with AID (Automatic Interaction Detection, Sonquist, Baker and Morgan [46]) based on relations between perception and demographics. In the HMO study AID was used with rank order preference of the MIT plan as the dependent variable and individual descriptors and demographics as the explanatory variables (Greer and Suuberg [17]). The most significant segmentation variables were measures of an individual's current pattern of care (e.g., currently MIT health department versus use of private doctor). However, the evidence was not very strong. The AID analysis explained 24% of the variation while simulations based on random data explained 16%.

Another abstraction method would be to cluster individual preference parameters obtained from individual utility assessment. This is an attractive method since it is based on direct individual parameters rather

than a statistical search for common structure.

After segments are abstracted they are tested for adequacy, accuracy, and interpretation by comparison to random data and by judgment. It is proposed that a useful segmentation strategy has (1) significantly different importance coefficients between groups, (2) better preference fits in each segment than in the total group, and (3) is strategically relevant. These criteria can be used to select the best segmentation strategy from statistical identification, clustering of utility parameters, and prior beliefs.³

Compaction

After the numerous attitudinal measures have been reduced to a more parsimonious set of performance measures and homogeneous groups have been abstracted, the next task is to model the linkage to choice. In this methodology, the performance measures are compacted into one scalar measure of goodness for each alternative for each individual and then these goodness measures are linked to the probability of choice (see Figure 3 to review micro structure of model). Compaction generates an understanding of how the performance measures combine and guide the decisions that must be made in generating a best design for the new product or service. For example in an HMO should one increase the quality of the health service and charge a premium price or should the price be minimized subject to an adequate level of quality? Compaction addresses these issues by explicitly identifying the importance of each performance measure and their interaction in

defining preference. When utility theory is used the risk characteristics of the choice process are also identified.

Specifically, in compaction a function, $c_s(\underline{x}_{ij}, \underline{\lambda}_i)$, is determined which maps the vector of performance measures, $\underline{x}_{ij}$, and a vector of individual specific choice parameters, $\underline{\lambda}_i$, into a scalar measure of goodness (a real number). The performance measures are the result of the reduction step in the methodology and the choice parameters result from the measured preferences, tradeoffs, and lotteries. For a given alternative, e.g., health plan a_j , this scalar measure of goodness, c_{ij} , has the property that with all other alternatives held fixed, any set of performance measures yielding the same value, c_{ij} , must also yield the same probability of choice for alternative a_j . In other words, compaction compresses the performance measures for an alternative into a one-dimensional measure, and knowing the value of this measure for each and every alternative is then sufficient to predict choice.

The parameters of the compaction function can be estimated in several ways. The most elementary is to ask consumers to scale the importance of each measure and form a linear compaction function. In new product applications these functions have not generally correlated well to preference⁴, and better fits have been obtained with PREFMAP (Carroll and Chang [7], Green and Carmone [14], Green and Rao [15]). PREFMAP is based on a regression of individual preference for the consumers' evoked set of dimensions. Conjoint measurement utilizes monotonic regression of rank order preference for stimuli defined by factorial combinations of the performance measures to derive a compaction function. Logit analysis assumes an additive representation and statistically estimates the importances from

observations of actual choice.

In the HMO study two variations on these approaches were used. In the first the respondents were grouped into three segments - faculty, students and staff. In each group the individual rank order preference measures were regressed against the four perceptual measures.⁵ This was done across individuals and stimuli and there were over 800 total observations in the regressions. Table 1 gives the results. All regressions were significant at the 1% level and all regression coefficients were significant at the 5% level. The R^2 fit statistic is not the most appropriate measure of fit since the dependent variable is rank ordered. Table 1 also reports a more appropriate measure - the fraction of times the predicted rank order preference was equal to the actual rank order preference. The Chi squared

Table 1: Compactions By Regressions For MIT HMO

	Coefficients (t Statistics)					rank order fit	first prefer- ence fit
	R^2	Quality	Personal- ness	Value	Con- venience		
Overall	.27	6.17(9.16)	3.86(6.4)	5.69(12.2)	3.34(6.00)	.447	.49
Faculty	.38	6.04(5.61)	5.93(5.67)	5.95(9.60)	3.34(3.50)	.48	.48
Students	.31	6.59(6.10)	1.69(1.87)	7.82(8.26)	4.38(4.38)	.54	.63
Staff	.18	4.98(3.60)	5.15(4.32)	3.54(3.98)	2.08(2.06)	.42	.45

statistic for the matrix of actual versus predicted rank order was significant at the 5% level in all regressions. In addition, the fraction

of times first preference was indicated is also reported. These statistical results are quite encouraging and reflect adequate accuracy for compaction. Table 2 indicates that all respondents value quality highly. The importance of quality is highest for faculty, but value is highest for students, and personalness is highest for staff. Based on the rank order fits, the results in each segment are better than the aggregate results except in the staff group where the fits are approximately equal. This indicates the abstraction of the segments was justifiable based on homogeneity of preference.

While the statistical approach to compaction is encouraging, there are disadvantages to this approach. It does not explicitly consider risk and interdependency of performance measures and does not have any axiomatic theory which identifies functional forms. On the other hand, utility theory draws on axioms to derive unique functional forms and to directly assess risk aversion, importances, and interactions.⁶ However, until now, utility theory has been used exclusively for prescriptive decision making. Compaction adds the requirement that the theory allow stochastic choice, i.e., that the probability of choosing a utility maximizing alternative is not necessarily certain. To use utility theoretic results for descriptive choice a theoretical construct of stochastic preference was defined⁷ and it was found necessary to augment the von Neumann-Morgenstern [56] axioms with a psychological choice axiom which can be shown to be similar to simple scalability^{8,9} (Luce [32], Krantz [29], Tversky [52]). These additions enabled the establishment of an isomorphism between utility and compaction theory and thus the ability to apply many utility theoretic

results including identification of functional forms and direct assessment to descriptive compaction theory. (The full proofs are contained in Hauser [19].)

As a preliminary test of this technique, compaction functions over the four performance measures describing health care delivery were assessed by a personal interview for a random sample of 80 members of the MIT student population. The compaction function was approximated with a relatively simple functional form, which was separable, multiplicative, and constantly risk averse in each dimension. Mathematically, the function, with individual specific parameters, is stated here for four performance measures:

$$c_{ij} = \sum_m k_{im} u_{im}(x_{ijm}) + \sum_m \sum_{\ell > m} K_1 k_{im} k_{i\ell} u_{im}(x_{ijm}) u_{i\ell}(x_{ij\ell}) \\ + \dots + K_1^3 k_{i1} k_{i2} k_{i3} k_{i4} u_{i1}(x_{ij1}) \dots u_{i4}(x_{ij4})$$

$$\text{with } u_{im}(x_{ijm}) = [1 - \exp(-r_{im} x_{ijm})] / [1 - \exp(-r_{im} x_m^*)]$$

Where

c_{ij} = individual i 's scalar measure of goodness for alternative a_j , i.e., the value of the compaction function, $c_j(x_{ij}, \lambda_i)$ evaluated for individual i and alternative a_j .

$u_{im}(x_{ijm})$ = uni-attributed conditional "utility" scaling function. The form shown here is for constant risk aversion,¹⁰ and is scaled from $u_{im}(0) = 0$ to $u_{im}(x_m^*) = 1$.

x_{ijm} = the level of the m^{th} performance measure as perceived by individual i for alternative a_j

x_m^* = the maximum value of the m^{th} performance measure

r_{im} = individual i 's risk aversion coefficient relative to the m^{th} performance measure

k_{im} = individual i 's importance coefficient for the m^{th} performance measure

K_i = individual i 's interaction coefficient relative to the four performance measures

Before assessment, the multiplicative form was selected based on prior theory and in-depth interviews aided by an interactive utility assessment computer program developed by Sicherman [44]. In full scale assessment, independence questions were used to check the validity of the assumptions necessary for the multiplicative form. It was found that these assumptions were correct for 66% of the respondents. Based on the results of administering the utility questionnaire (see "measurement" section of this methodology) the parameters $\lambda_i = \{k_{i1}, k_{i2}, k_{i3}, k_{i4}, r_{i1}, r_{i2}, r_{i3}, r_{i4}, K_i\}$ were calculated and are shown in Table 2.

Table 2: Compaction by Utility Theoretic Procedures For MIT Students

	Importances (k_{im})			Risk Aversion Coefficients (r_{im})				Interaction Coeff. (K_I)	
	quality	personal- ness	value	convenience	quality	personal- ness	value		convenience
Median	.800	.525	.706	.682	.693	.332	.424	.310	-.992
Inter-quartile interval	.650 - .900	.360 - .726	.492 - .800	.525 - .800	.424 - 1.10	.000 - .693	.203 - .549	.000 - .693	-.998 - -.939
Inter-quartile range	.250	.367	.308	.275	.675	.693	.347	.693	.059

An unexpected empirical result is that the risk aversion coefficients and importances are highly correlated indicating that the student group is more concerned with risk for the more important performance measures. As a first comparison against the statistical technique, the individual specific perceptions, $\underline{x}_{ij}$, and preference parameters, $\underline{\lambda}_i$, were used to calculate scalar measures of goodness, c_{ij} , for each alternative for each individual. When compared against rank order preference these resulted in a rank order fit of .474 and a first preference fit of .495. These are in the same range as the fits of statistical procedure. Because of the differences between the statistical and direct compaction techniques especially in their relation to the rest of the methodology and because of the non-linear relationship between the factor scores and the directly measured performances, and because of the risk averse scaling function, stronger, and more explicit comparison tests need to be devised before importances can be compared. This is the subject of future research work.

The outcome of compaction is a functional form and parameter estimates. Together they produce scalar measures of goodness for each consumer and for each choice alternative.

Probability of Choice

Now attention is focussed on estimating how many consumers will choose their new product or service and how many of the potential consumers will select each of the various competing alternatives. In the probability of choice phase of the methodology individual choice probabilities are computed based on the scalar measures of goodness determined in the compaction phase

of the analysis. This is necessary because empirically people do not always choose the alternative with the largest goodness measure.

The outputs can be one time Bernoulli probabilities, $(p_s(a_j|c_{i1}, c_{i2}, \dots, c_{ij}, \dots, c_{iJ}))$, which estimate each individual's selection probabilities within a segment (s) for each alternative (a_j) conditioned on the scalar goodness measures for each alternative ($c_{i1}, c_{i2}, \dots, c_{ij}, \dots, c_{iJ}$). In cases where repetitive choice decisions are made by a consumer, separate trial and repeat choice parameters would be estimated based on the goodness measure before use and after use of the new product or services. In some applications the probabilities could be Poisson rates. If γ is the choice rate for an alternative, then the probability that the individual will choose an alternative in small time period Δt is $\gamma \Delta t$.

A simple approach is to use the binary logit (Ashton [2]) to determine the probability of choosing the alternative with the highest goodness measure, i.e.:

$$p(a_1|c_{i1}, c_{i2}, \dots, c_{iJ}) = e^{a+bc_{i1}} / (1 + e^{a+bc_{i1}})$$

where a and b are statistically determined by linear regression

$$\left(\ln \left[\frac{p_{i1}}{1-p_{i1}} \right] \right) = a + bc_{i1}. \text{ The remaining probabilities are determined}$$

similarly. For empirical examples see Silk and Urban [45].

Another stochastic approach is the multinomial logit model in which compaction and probability of choice are performed simultaneously. A compaction function, linear in its parameters, is postulated and the following probability model is derived from distributional and behavioral

hypotheses¹¹ (McFadden [34]):

$$p(a_j | c_{11}, c_{12}, \dots, c_{1J}) = e^{c_{1j}} / \sum_{l=1}^J e^{c_{1l}}$$

The functional form and the compaction parameters are assumed the same for all individuals in a segment and maximum likelihood techniques are used to estimate the parameters. This model has been used extensively in transportation demand prediction¹², see for example, Ben-Akiva [4].

In formulating the goodness measure, utility theory was postulated as a compaction procedure. One approach is to invoke the utility axiom directly, which gives deterministic predictions based on each consumer choosing the maximum utility alternative. Several reasons why such a deterministic approach may not be appropriate are measurement errors, specification errors, and non-stationarity in consumer response.

Another alternative is processing directly assessed utility values by directly substituting them into the multinomial logit formulation, however, this does not leave any parameters free for estimation and therefore does not effectively use the observed choice data. In order to fully integrate compaction and choice data a new model is required. A Bayesian model is proposed for this task.

This Bayesian formulation is based on the assumption that any two individuals with the same set of scalar measures of goodness will have the same choice probabilities and on the symmetry assumption that switching two scale values switches the choice probabilities. If compaction is successful then the first assumption is true by definition.

The model, stated here for two alternatives, is calibrated as follows. Let e_1 be the event that an individual chooses that alternative which maximizes his scalar measure of goodness. Let c_1 be that maximum value. Define e_2 , c_2 similarly. We can easily observe the posterior distributions $p(c_1, c_2|e_1)$ and $p(c_1, c_2|e_2)$ and also the percentages n_1 and n_2 choosing e_1 and e_2 . Bayes theorem gives the desired probability of choice conditioned on the goodness measures.¹³ This model can be shown to be consistent (Hauser [19]):

$$p(e_1|c_1, c_2) = \frac{n_1 p(c_1, c_2|e_1)}{n_1 p(c_1, c_2|e_1) + n_2 p(c_1, c_2|e_2)}$$

This Bayesian model was calibrated and tested on data collected prior to national introduction of a new aerosol deodorant. The scalar measures of goodness were constant sum paired comparison scale values and the choice was actual initial trial in a simulated purchase environment (Silk and Urban [45]). The prior percentages were $n_1 = .83$, $n_2 = .15$, $n_3 = .02$, and $n_j = 0$, $j > 3$, and the posterior distributions

were fitted with multivariate beta distributions. Based on this model predictions were made of choice probabilities.

Whether done by binary logit, multinomial logit, direct parameterization, or the Bayesian formulation, the outcome of the probability of choice model component is a predicted probability for each individual consumer for each choice alternative.

Aggregation

The final step in the consumer response process model is aggregation. It combines the individual choice probabilities to produce numerical estimates of the total share of choices and number of people choosing each alternative. If relevant population segments were identified in abstraction, aggregation explicitly uses them to extrapolate from the sample population to the target population. In addition to expected choices, the variances on the group choice is also useful in considering the risk associated with the new venture.

In most applications, individual choice probabilities are roughly independent and thus the Central Limit Theorem can be used to calculate the joint probability distribution of the market shares. The grand means are determined by averaging the individual results obtained by direct substitution of the individual goodness measures in the probability of choice models (p_{ij}). The variance is based on the sum of the individual variances $(p_{ij}(1-p_{ij}))^{14}$. In some cases it is convenient to represent a distribution across the goodness measures and then integrate

to find the mean and variance.⁵ For example, given that the vector of performance measures, $\underline{x}_j$, for each alternative, a_j , and the preference parameters, $\underline{\lambda}$, are distributed across the population segment with joint probability distribution $p_s(\underline{x}_1, \underline{x}_2, \dots, \underline{x}_j, \dots, \underline{x}_J, \underline{\lambda})$ the predicted market share for that segment is shown here for alternative 1 of two alternatives:

$$\overline{ms}_j = \int p_s[a_j | c(\underline{x}_1, \underline{\lambda}), c(\underline{x}_2, \underline{\lambda})] p_s(\underline{x}_1, \underline{x}_2, \underline{\lambda}) d\underline{x}_1 d\underline{x}_2 d\underline{\lambda}$$

The variance is:

$$ms_1 = \int N^{-1} p[a_j | c(\underline{x}_1, \underline{\lambda}), c(\underline{x}_2, \underline{\lambda})] \{1 - p[a_j | c(\underline{x}_1, \underline{\lambda}), c(\underline{x}_2, \underline{\lambda})]\} p(\underline{x}_1, \underline{x}_2, \underline{\lambda}) d\underline{x}_1 d\underline{x}_2 d\underline{\lambda}$$

The final step in aggregation reflects the fact that all the measurement and estimation is based on consumers who evoked the alternative by past experience or who were made aware of the alternative in the interview. The adjustment is to multiply the aggregate share of choices for an alternative times the estimated level of evoking and awareness that the new product or service is expected to achieve based on the predicted level of marketing effort or the evoking rates for competing alternatives.

The aggregate group response is the primary output from the consumer model into the managerial evaluation process. The next section will describe the relationship between the analytic consumer response model and the managerial design process.

Interaction with Design Process

The first interaction of the consumer model with the managerial process is in evaluation (see Figure 3 to review the micro structure of the methodology). The prediction of consumer acceptance and its variance are critical evaluation inputs, but other factors such as investment, cost, risk, or political considerations must be integrated in a model that results in a decision to terminate (NO), or to continue development (ON), or to introduce to the market (GO). Several approaches can be taken to such a model. Decision theory, (Raiffa [39], Keeney [22]), risk analysis, (Hertz [20]), and other analytic models (Urban [54]) have been successfully used for this task.

If the evaluation results are acceptable and an ON decision is made, the design is subjected to a refinement effort. A criterion for the methodology was that it facilitate successful innovation by eliciting and focusing creativity. One reason for breaking the methodology into a series of identifiable steps is that each step provides insight and diagnostics for refinement: (1) reduction identifies the performance measures relevant to the choice process and calculates their average values for each alternative, (2) abstraction identifies strategically relevant segments homogeneous with respect to preference, (3) compaction explicitly identifies the relative importances of the performance measures, how strongly they interact, and how important risk characteristics are in the choice process, and (4) probability of choice gives numerical implications of the scalar measures of goodness.

Each phase in the consumer response model provides information, but in order for that information to provide useful insight and stimulate creativity for design revision, it must be presented in a comfortable form which managers can mentally internalize and process. For example, in reduction, a perceptual map of each alternative in "average" perceptual space might be presented (see the case section of this paper, for the HMO perceptual space). In compaction, importance weights and risk coefficients (see Table 2) or indifference curves might be presented. Figure 9 presents an indifference curve between HMO quality and convenience at various value levels and a given level of personalness. This curve is based on the median utility parameters reported in Table 2.¹⁶ It graphically provides a view of how much quality and convenience are necessary to support a given price/value level.

Just as managerial outputs can result from many steps in the consumer process model, changes in design decisions can be input at many steps. Specific refinements such as changing the hospital affiliations of a health maintenance organization can be tested by changing the inputs to the reduction step by changing the average rating of hospital quality (i.e., scale 12 in Figure 5). This is reflected in the reduced space perception and then through compaction and probability of choice. The simulated outcome provides an estimate of the change in consumer acceptance for the design change. More general changes can be simulated to guide the intuition of the manager. For example, an increase in the perceptions of quality of care could be judgementally inputted as a change in the mean or variance of the individual factor scores of the quality dimension. These changes are then input to the

Figure 9: Indifference Curves

compaction step. If an entirely new concept is formulated, this probably would require presenting a sample population with a new set of choice alternatives in addition to a simulation of the design changes in the consumer model.

In the early stages of development attention is focused on reduction, abstraction, and compaction since at this point the combination of product attributes and psychological positioning must be specified. This is the stage at which the MIT/HMO study was done. As the design becomes more clearly specified new measures are taken and attention is focused more on probability of choice and aggregation. This more refined forecast of acceptance is critical to the GO/ON/NO decision. The model evolves as it recycles through the measurement, estimation, and aggregation phases. In each phase the information that can be feasibly obtained from consumers is maximized and used to adaptively update the parameters, structure, and predictions. The decision to take new measures is a function of the confidence in the existing results, the information value of new measures, and the costs of collecting new information.

In summary, the methodology facilitates testing and screening of alternatives by the evaluation step which uses the outputs of aggregation. But perhaps even more important, it encourages successful innovation through flexible interactions between the refinement procedures and the reduction, abstraction, and compaction submodels of the individual choice process.

Testing

The proposed methodology incorporates many diverse submodels in its various stages. In many cases a user of this methodology will need to choose among competing submodels and will need some test of the accuracy of the prediction process. Since the individual choice process plays a key role in the methodology, aggregate indicators such as a comparison of predicted to actual share of choices will not adequately test the basic accuracy of the models. What is needed is a test which explicitly considers the predicted individual choice probabilities and individual choice outcomes.

The traditional least squares test breaks down for individual choice because the predicted values are probabilities, ($0 \leq p_{ij} \leq 1$), while the outcomes are events (an individual either chooses alternative a_j or not). In fact, it can be shown that the expected value of a least squares test can be optimized by assigning probability 1.0 ($p_{ij} = 1.0$), to the event believed most likely and probability 0.0 ($p_{ij} = 0.0$) to all other events even if the "true" values are between 0.0 and 1.0 ($0.0 < p_{ij} < 1.0$) (Hauser [19]). Another test, maximum score, simply adds up the number of correct classifications. Although robust this test does not discriminate very well since it assigns the same reward whether the predicted p_{ij} was .9999 or .5001. The Chi Squared test based on a frequency table of actual versus predicted rank order choices is theoretically sound, but it is not very sensitive to the comparison of individual probability and individual outcomes.

It is worthwhile considering the design of a different test for this methodology. The following introduces a new use and interpretation of Raiffa's honest reward theory [40] by identifying information theoretic

benchmarks for the statistical tests. This is a powerful test if probabilities are predicted and only yes/no (1/0) outcomes are observed.

First, consider some criteria that the test should satisfy. The test should be honest, relevant, invariant and have strong discriminability. A test is honest if the expected reward is optimized by the correct probability assignments; it is relevant if the reward depends only upon the probabilities assigned to events which actually occur; it is invariant if the test depends only upon probabilities and outcomes but not upon the characteristics of the alternatives; and it has strong discriminability if the test favors more detailed prediction, e.g., predicting the exact temperature rather than just the range. These concepts, developed and formulated by Raiffa [40], imply a unique test.

The idea of the test is to assign a reward, $r(p_1, \text{outcome})$, to every individual based on the predicted probabilities for that individual, p_1 , and the choice he makes. The total reward, R , is the sum of the individual rewards and the best test is the one with the highest reward. Raiffa shows that under the four criteria stated above the unique individual reward is:

$$r(p_1, a_j \text{ is chosen}) = A \log p(a_j | c_1) + B$$

where A , B are arbitrary constants and $A > 0$.

It can further be shown that with the proper choice of A and B , $r(p_1, \text{outcome})$ is the mutual information provided about the outcome, a_j , by the vector of scalar measures of goodness, c_1 (Hauser [19]). This concept of information is used extensively in communication and in pattern recognition (Gallagher [12]). Furthermore, the expected total reward, $E[R]$, is equal

to the number of individuals, N , times the expected mutual information.

The test described above meets the criteria of being honest, relevant, invariant and discriminatory. This is potentially a stronger test since the information theoretic test provides benchmarks which metrically allow an assessment of the validity of the model.

In order to implement this test, the first step is to compute the entropy, $H(A)$, of the system which represents the total uncertainty in the system:

$$H(A) = - \sum_j m_j \log m_j$$

where m_j is the empirical share of choices. Then compute the average expected reward $E[R]/N$. Since this is the average mutual information it can be shown that this represents the reduction in uncertainty due to the model (Gallagher [12]). (I.e., the uncertainty after the model, $H(A|C)$ is just $H(A) - E[R]/N$.)

The closeness of the actual reward to the expected reward measures the accuracy of the model. The relative size of the average expected reward to the entropy of system measures the usefulness of the model. (See Figure 10.)

As well as testing the theoretical aspects of the methodology, the effect of the model on the managerial design process should be undertaken by application to an actual innovation problem. These tests are less formal than the statistical tests proposed for the analytic consumer response model. The following section describes the initial managerial testing of the methodology in the design of an HMO.

Figure 10: Schematic of the Information Test

Case Application

The proposed methodology for modeling consumer response to innovation has undergone an application to the problem of converting the MIT health department into an HMO. Some of the empirical findings have been cited earlier. This section will concentrate on the managerial use of the model in evaluation and refinement of the HMO design.

The model estimation was based on consumer interviews of 447 faculty, students, and staff. Of these 367 were prospective members of the HMO and 80 were members of a pilot HMO begun a year earlier.

First perceptual maps were derived by a factor analysis of the ratings of existing and new health plan descriptions. Figure 11 gives the overall average factor scores (see Figure 4 for a concept statement, Figure 5 for the rating scales, and Figure 8 for factor loadings).

First, it should be noted that the average perceptions of the existing care system are better than those of the MIT HMO concept based on the measures from the prospective members on all dimensions except convenience. The lower quality rating was based almost entirely on a low score for MIT on hospital quality. This was because the MIT plan hospitals were smaller and not well known as compared to the prestigious Boston hospitals. The Harvard Community Plan (HCHP) was higher on quality based on its hospital ratings (Beth Isreal, Peter Bent Brigham, and Childrens Hospital). On other dimensions HCHP, on average, was perceived less favorably by the MIT population.

When comparing existing care perceptions with the perceptions of

Figure 11: Overall Average Factor Scores

those in the MIT pilot plan, a substantially different picture emerges. The MIT pilot plan exceeds the average existing care perceptions on all dimensions. The stated intent to re-enroll of over 90% supported the notion that the plan was very effective as seen by those in the pilot plan. It is clear that perceptions based on actual pilot plan performance of the HMO are much better than perceptions of the plan based on the concept statement. Although this could be post purchase rationalization, it is more likely that this is a case of a good product where few people perceive it as such until using it.

The perceptual maps indicated two major managerial findings. First, quality of the plan was low and probably would be improved by better hospital affiliation and second, if the HMO was to be successful it would have to develop an aggressive campaign to communicate actual plan performance to perspective members.

Analysis of preferences indicated that overall the rank order of importance of the four relevant attributes was quality, value, personalness, and convenience. However, in segments there were differences. Students attached most importance to value and relatively more to convenience while the faculty and staff weighted quality and personalness most highly (see compaction section of this paper for empirical results). These findings indicated that the communication strategy could be much more effective if it was differentially addressed to each segment. The results also suggest a more comprehensive and higher cost option (e.g. include dental care and no deductables) could be considered as a way to better meet consumer needs of faculty and staff.

The choice model and empirical observations were used to forecast new enrollment and re-enrollment for the next year. Figure 12 gives the forecast based on the estimated probability of enrollment given that the respondent was aware at the level presented by the survey and based upon an estimate of how many potential users would be aware at this level. Since the choice probabilities are different in each group, the new enrollment is based on each component segment. Re-enrollment is based on the estimated probability of re-enrollment (92.5%) and estimates of migration out of the MIT community. The total enrollment forecast of 3600 families is just financially sufficient to maintain the HMO. Considering the inherent risk involved in any new service venture, the decision to expand the existing pilot HMO could not be supported based on the initial design.

However, the existing pilot was not the best design. The use of aggressive communication to close the gap of perceptions and performance and the change of hospital associations were identified as methods of improvement. The model was used to simulate¹⁷ the effects of these design changes by assuming the communication campaign and the association with prestigious hospitals could move the perceptions one half of the distance from concept to actual pilot performance on quality, personalness, and value (see Figure 11) and 85% awareness would be created rather than 70%. The consumer response model forecast an enrollment of 5400 families based on estimates of importance weights and a linear compaction function produced by the regression of factor scores against preference (see Figure 12). Other simulations were done based on assumptions of competition from the Harvard Community Health Plan which indicated the enrollment could

CASE I - EXISTING DESIGNNew Enrollment:

<u>Groups</u>	<u>Number not now in pilot HMO</u>		<u>Enrollment if aware</u>		<u>Estimated awareness</u>		<u>Estimated Enrollment Number</u>
Students	8000	x	33%	x	70%	=	1848
Faculty	3800	x	15%	x	70%	=	399
Staff	<u>3400</u>	x	<u>22%</u>	x	<u>70%</u>	=	<u>523</u>
Total	17,200		23%		70%		2,770

Re-enrollment:

<u>Existing HMO Subscribers</u>		<u>Repeat Rate</u>		<u>Estimated to Remain at MIT</u>		
1067	x	92.5%	x	86.3%	=	852

Total Enrollment = 3622

CASE II - IMPROVED DESIGNNew Enrollment:

<u>Groups</u>	<u>Number not now in pilot program</u>		<u>Enrollment if aware</u>		<u>Estimated awareness</u>		<u>Estimated Enrollment Number</u>
Students	8000	x	42%	x	85%	=	2856
Faculty	3800	x	25%	x	85%	=	808
Staff	<u>3400</u>	x	<u>30%</u>	x	<u>85%</u>	=	<u>867</u>
Total	17,200		31%		85%		4,531

Re-enrollment:

<u>Existing HMO Subscribers</u>		<u>Repeat Rate</u>		<u>Estimated to Remain at MIT</u>		
1067	x	95%	x	86.3%	=	874

Total Enrollment = 5,405

Figure 12: Forecast of MIT Enrollment

drop to 2400 with HCHP offered at MIT and no improved design. The most likely forecast was based on HCHP being offered with an improved MIT plan and was for 4950 family enrollments. This was sufficient to make a positive recommendation based on the response of consumers to the revised communication and design strategy. MIT is now expanding its HMO to meet the indicated need and will market its HMO to faculty, staff, and students as facilities become available.

Based upon this initial application it appears that the consumer response model is relevant to the management of innovation and can be useful in improving designs of new products or services, forecasting the acceptance of innovations, and reducing the risk of failure.

Summary

This paper proposes and presents evidence for a normative methodology to elicit and guide creativity in the design of innovative products and services. The strength of the methodology is that it effectively integrates state of the art analysis techniques from the fields of psychometrics, utility theory, and stochastic choice theory in a model based analysis process oriented toward the needs and desires of managers and staff responsible for innovation. Its primary use is to enhance early creative identification and design of high potential products and services by providing important diagnostics which describe consumers' perceptions of the alternatives and consumers' preferences relative to measures of these perceptions. It also identifies managerially relevant segments based on homogeneity of preference and gives numerical indications of consumer response within each segment. Diagnostics are produced for design insight, but the methodology also simulates and evaluates quantitative and qualitative design changes in the characteristics of the alternatives or in the implementation strategy. Thus managers can readily test and improve the intuition they develop based on previous experience and on the previous outputs of the methodology.

In addition to structuring the process and providing new theory where necessary, this paper also relates empirical experience with two parallel paths through the analytic models of the methodology. Figure 13 summarizes these paths through the MIT HMO case.

Figure 13: Alternative Empirical Analyses of HMO Data

Both paths begin by combining management priors and formal and informal focus group techniques to identify the relevant choice alternatives and a complete set of attributes to describe these alternatives. Path 1 then uses common factor analysis to reduce the attributes to a parsimonious set of performance measures (quality, personalness, value, and convenience) to describe perception and to map the alternatives in perceptual space. Abstraction is attempted with AID, clustered analysis and managerial priors. Within the identified segments (students, staff, and faculty) compaction is statistically performed by preference regression on the factor scores. Probability of choice uses binary logit analysis based on conducting new measurement in a simulated choice environment. New alternatives are tested by using the empirical models of consumers.

Path 2 also begins reduction by common factor analysis but remeasures individual perceptions of the reduced performance measures. Compaction uses utility theoretic assessment procedures to identify importance, interactions, and risk characteristics and to compact the performance measures into a scalar goodness measure for each alternative for each individual. Segments would be abstracted by using cluster analysis on the preference parameters. The empirical Bayesian model and the central limit theorem produce numerical estimates of the mean and variance of choice shares. Finally, new alternatives are tested by using the individual compaction functions as a simulated consumer pool.

Path 2 has the relative advantages of axiomatic identification of functional forms, individual specific preference parameters, and

abstraction based on the individual parameters. Its main disadvantages are that it is measurement intensive and does not have a structure to explicitly deal with measurement errors.¹⁸ Path 1 has the relative advantage of easier measurement and a robust method of compaction in a segment, but does not provide individual compaction parameters and is limited to abstraction by indirect methods.

These paths represent a first test of the techniques and concepts presented in this paper. These techniques and the modular, managerial design oriented methodology will be tested in future work. Attention will be directed at confirming the validity of (1) the new measurement instruments developed to allow mass direct assessment of consumers' utility functions, (2) the use of psychometrics to get a complete and parsimonious set of performance measures for utility assessment, (3) the criteria and methods of abstraction of segments based on preference, (4) the stochastic interpretation and choice axiomization which allows an isomorphism between utility theoretic results and compaction, (5) the empirical Bayesian probability model, and (6) the information theoretic testing techniques for assessing the accuracy of predicted individual probabilities.

In addition, alternative techniques will be compared at each step in the methodology, for example, comparison of compaction by utility theory to that done by conjoint analysis and multinomial logit theory. At the probability of choice phase, the information test will be used to compare the Bayesian, logit, and multi-nominal logit probability models. Perhaps the most crucial and difficult research advance needed is an explicit modeling of error sources in the measurement of complex utility functions.

The methodology is being tested and elaborated on in several real decision environments. It is currently being used to study the consumer response to possible repositioning of the master of science program at MIT's Sloan School of Management, to the design of financial service packages, and the positioning of new frequently purchased consumer products (antacids, personal care products, and pain relievers). Other high potential uses are being explored in the design of banking services, the improvement and understanding of consumer reaction to new transportation modes such as Dial-a-Ride,¹⁹ and the marketing of preventive health services. Experience in these applications indicates that the methodology is useful in helping managers to create new products and services, to understand consumer response to innovation, and to reduce the risks of failure.

Footnotes

1. Commonalities were defined by iteration with the BIOMED statistical routines. 40% of the total variance was common. Principal components analysis yielded a similar interpretation of factors and factored 55% of the total variance into the four factors.
2. A common approach is abstraction by homogeneity of perception. In the HMO study the Howard-Harris clustering program was used to cluster analyze the individual factor scores. It explained 48% of the variance in perceptions with four clusters as opposed to 44% of the variance of random data with four clusters (Greer and Suuberg [17]).
3. Of course if the population is completely homogeneous no segmentation strategy may exist.
4. Fits in the range .1 to .2 are reported in Sheth and Talarzyk [43]. However, Bass and Talarzyk report correct prediction of first preference by linear attitude model in the range of .63 - .75 for frequently purchased consumer brands.
5. Green [13] has shown that least squares regressions closely approximate monotonic regression for integer rank order preference variables.
6. Unique up to a positive linear transformation. Of course verifiable assumptions, e.g., utility independence, preferential independence, and constant risk aversion, are necessary for some forms. See Keeney, [21, 23, 24, 25] and Raiffa [38].
7. Basically a_1 preferred to a_2 implies a_1 has a greater choice probability. The rigorous development is contained in Hauser [19].
8. Basically simple scalability implies that there is a scale value for each alternative and that the probability of choosing a_j from a choice set A depends only on the scale values for the alternatives in A. Further the probability of choosing a_j is monotonically increasing in the scale value for a_j and decreasing in the other scale values.

9. Let $p(a_j \text{ from } A)$ be the probability of choosing a_j from a choice set A . Then the axiom states that if $p(a_j \text{ from } A) = p(a_\ell \text{ from } A)$ and if $p(a_k \text{ from } A) = p(a_m \text{ from } A)$ then $p(a_j \text{ from } A - a_k) = p(a_\ell \text{ from } A - a_m)$. This axiom restricts the class of choices allowable and forces explicit modeling of hierarchical choices. The rigorous development is contained in Hauser [19].
10. If the individual is risk neutral, $u_{im}(x_{ijm}) = x_{ijm}/x_m^*$. Note that the constantly risk averse form of $u_{im}(x_{ijm})$ approaches this as $r_{im} \rightarrow 0$.
11. Basically utility maximizing consumers are assumed and the utility is composed of an observed term, c_{ij} , plus an additive error term which is distributed as a Weibull variate. The error terms for different alternatives are independent and identically distributed. See McFadden [33] and Manski [35] for extension.
12. McFadden [33] lists many programs capable of such estimation.
13. If only $c_i = c_{i1} - c_{i2}$ matters, and if $p(c_i|e_1)$ and $p(c_i|e_2)$ are normal with common variance, then a binary logit model results. Quarmby [38]. The extension to more than two choices is non-trivial.
14.
$$ms_j = (1/N^2) \sum_{i=1}^N p_{ij}(1-p_{ij})$$
15. In transportation demand prediction, this integral needs to be evaluated for every zonal interchange. This problem and techniques to simplify or approximate these calculations are discussed in Koppleman [27] and Koppleman, Ben-Akiva, and Roberts [28].
16. The interaction coefficient, K_1 , was chosen to be consistent with the median importances reported in Table 2.

17. The result was obtained by using the consumer sample as representative of the population. This is equivalent to implicitly performing the integration for $\overline{ms}_j$ by Monte Carlo simulation. (See the integral equation in "aggregation".)
18. Utility assessment is done with no degrees of freedom and assumes no measurement error.
19. A dynamically routed (often by computer) mini-bus system which provides door-to-door service on demand. Much like a taxi except that the bus deviates from direct service to serve other pickups and deliveries. Systems are implemented in Rochester, N.Y., Ann Arbor, Mi., and other cities in the U.S. and Canada.

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