Multiattribute Utility Models

Multiattribute utility models can be traced back to the pioneering work of Kelvin Lancaster (1966). Their development arises from questions that are not satisfactorily addressed by traditional economic theory. For example: (i) Why do some consumers consume Pepsi and others Coke? (ii) Why are Coke and Pepsi closer substitutes than Coke and Canada Dry Ginger Ale? (iii) Why do we see the current set of soft drink offerings rather than some other? (iv) Why does the demand curve for Pepsi look as it does? A related set of questions interest
marketing managers. (i) What should be the characteristics of a new brand? (ii) How can our brand be changed to increase profit? (iii) Can we group consumers with similar tastes, and, if so, which groupings should our marketing efforts target? (iv) What should our advertisements to these segments focus on? Multiattribute utility modelling offers insights into each of these questions.

This entry presents an overview of multiattribute utility models. It begins by looking at multiattribute models in general. Next, alternative multiattribute utility concepts are discussed. Estimation issues are then addressed. Lastly, some issues ripe for further research are raised.

**Multiattribute models of consumer behaviour**

There are three broad types of multiattribute models. Unlike traditional economic theory, each hypothesizes that the consumer does not judge a brand in and of itself. Rather, the consumer's preference for or choice of a particular brand depends on the levels of the relevant physical and psychological factors (attributes) inherent in the brand as well as its price. The three types differ in how they deal implicitly with the fact that it is costly for consumers to collect and process information about brands. Information may be actively searched for (for example, by reading labels or consumer magazines or talking with friends) or retrieved from memory. Regardless of how much or what information is collected, mental, time and monetary costs are incurred. Rarely is it worthwhile to collect complete information on all the relevant brands since the cost of doing so exceeds the benefit. Consequently, consumers assess the purchase situation and chooses the brand evaluation process they feel will lead to the best choice given the cost of using the process and its related information collection costs. The different types of multiattribute models correspond to different evaluation processes. A limitation of the three model types is that none explicitly incorporates the tradeoff between the additional cost of more information search and its expected benefit.

The simplest type of model borrows heavily from the psychology and behavioural economics literatures. Reasonable heuristics or 'rules of thumb' dictate choice. Many of these rules can be seen as variants of Simon's (1959) idea of satisficing, where the consumer chooses the first brand they encounter that is 'satisfactory'. Some 'rules', such as buy the first car you find that provides more than 30 miles per gallon and costs less than $10,000, involve multiattribute brand evaluations. Many do not. One such heuristic is to purchase the brand of laundry detergent your mother used. Another is to buy the line of clothing most fashionable to your social set. Very little information is collected and its processing is reduced to a minimum. Hence, these 'rules' are associated with low-involvement purchase situations. The rationale is that for routine choices or choices among brands that all generate little benefit or difference in benefits,
there is little incentive to invest much in collecting and processing information, so following a simple rule is most cost-beneficial. See Earl (1995) for a more detailed discussion.

Noncompensatory preference and choice models constitute the second set of multiattribute models. These models also arise from the psychology literature and explicitly involve multiattribute brand evaluation. They earn the noncompensatory title because tradeoffs among the attributes are not allowed — the effect of an unfavourable level of one attribute on the preference for a brand cannot be compensated for by a highly favourable level of another attribute. Two common examples of this type are the conjunctive and the priority-based models. They both depict the consumer as setting cutoff levels for each attribute. The conjunctive model assumes the consumer has a checklist of requirements and dismisses from consideration any brand having any attribute level below its cutoff. A consumer acting according to a set of priorities first rejects brands that fail to meet the top priority target, tests the remainder against the second priority and so on, and keeps working down the priority list until only one brand is left. Thus, noncompensatory models utilize a simple evaluation process that typically requires a limited amount of brand information. An economic rationale for these models is offered by Shugan (1980) who argues that the cost of collecting and processing brand information makes it optimal, in an expected benefit versus cost sense, to ignore some available information, in this case through the use of a noncompensatory model. Representation of these models functionally (that is, as a multiattribute utility function) is possible if extremely nonlinear functions are allowed. Earl (1995) again provides a thorough overview of these models.

Multiattribute utility models — the focus of this entry — form the third broad of multiattribute model. These models are compensatory — tradeoffs among the attributes are modelled — and require the greatest amount of information collection and processing (referred to as brand decision costs, hereafter). The utility of brand \( i \) to consumer \( m \) is depicted as a function of the levels of the attributes it provides. That is, \( U_{im} = f(z_{1im}, z_{2im}, \ldots, z_{Jim}) \) where there are \( J \) attributes relevant to the consumer (price being one of these) and \( z_{ijm} \) is the level of attribute \( j \) perceived to be derived from product \( i \). A similarity to Becker’s (1965) household production function idea, mapping goods into consumption activities, is clear. Brand decision costs are incorporated implicitly through the consideration set. Before forming their preferences in any particular product class (set of competitive brands), the consumer collects information about the brands’ attribute levels. Because this search is costly, the consumer must trade off between the amount and quality of information to collect about each brand and the number of brands to collect information on. Compensatory models assume that the consumer leans more towards the former (while noncompensatory models tilt more towards the latter). Consequently, the
consumer develops a consideration set of brands for possible purchase that is unlikely to include all the brands in the product class. For each brand in this consideration set, data concerning each relevant attribute is collected. Imperfect and incomplete collection of information typically results in inaccurate perceptions of the attribute levels inherent in the brands. Information processing amounts to a utility assessment of each brand and the choice of the one that maximizes perceived utility.

**Multiattribute utility**

Insights into the questions raised in the introduction depend intimately on understanding the tradeoffs individual consumers make among the attributes when assessing brand utilities and the heterogeneity in these tastes across individuals. Two streams of research have developed to model these tradeoffs theoretically and to assess them empirically. Economists developed mathematical models to better understand the consumer’s decision process (Lancaster, 1966) and firms’ brand choices (Rosen 1974). These models utilize objective attributes, such as horsepower and miles per gallon, and empirical work uses aggregate level sales data and logit analysis to assess the utility function of a ‘representative’ consumer. Marketers’ use of multiattribute models is much more prevalent and has its origin in the use of regression analysis to understand empirically which attributes are most strongly related to a particular individual’s preferences over a set of brands. The attributes evaluated are often subjective in nature (for example, comfort and style). Besides a better understanding of consumer behaviour, many papers in this stream are interested in predicting choice behaviour under simulated ‘what if’ scenarios. Gradually the two streams have merged. For example, utility-based modelling is now common in marketing and the industrial organization literature shows a strong interest in generating managerially relevant multiattribute insights based on less-aggregated data.

Two functional forms for multiattribute utility generally are used. The linear model assumes constant marginal utility for each unit of an attribute. That is, the utility that consumer $m$ has for brand $i$ is:

$$U_{im} = \sum_{j=1}^{J} w_{jm} z_{jm}. \quad (1)$$

The $w_{jm}$ term reflects the relative importance of attribute $j$ to consumer $m$’s preference formation and is referred to as an attribute weight. The relative magnitudes of the attribute weights reveal the tradeoffs the consumer makes among the attributes when assessing brand utilities.

The part worths model does not impose any a priori structure other than
additivity. Marginal attribute utilities need not be constant and more of each attribute need not be preferred to less. However, estimation concerns restrict the researcher to a limited number of levels (generally two to four) for each attribute. The resulting utility formulation is:

$$U_{im} = \sum_{j=1}^{J} \sum_{k=1}^{K_j} u_{ijkm} D_{ijkm}$$  \hspace{1cm} (2)$$

where each attribute has $K_j$ levels. The $D_{ijkm}$ variables constitute the attribute level information and are represented as dummy variables equal to one if brand $i$ has a perceived level $k$ of attribute $j$, and zero otherwise. The $u_{ijkm}$ terms represent the utility (attribute weight) consumer $m$ associates with level $k$ of attribute $j$.

The use of multiattribute utility models is typically associated with high involvement choice settings (for example, middle- to high-priced or infrequently purchased products). However, since they also depict behaviour well for inexpensive and frequently purchased products (Johnson and Meyer, 1984), and are easy to estimate, they are commonly used in place of noncompensatory models.

Given that consumers have inaccurate and incomplete information about the brands’ attribute levels or prices, expected utility rather than utility modelling is actually more appropriate (Horsky and Nelson, 1992). Functionally, after some simplifying assumptions mostly concerning risk attitude, expected utility boils down to adding an additional overall uncertainty ‘attribute’ to the multiattribute utility function. The uncertainty arises from the consumers’ knowledge that their attribute level and price perceptions may be inaccurate. The overall uncertainty attribute (risk premium) is generally statistically significant and models including it provide better prediction than models assuming consumer certainty (Hauser and Urban, 1979). Despite these findings, consumer uncertainty and, hence, expected utility, is rarely modelled.

**Estimation**

Multiattribute studies typically involve individual consumer level estimation of equations (1) or (2) based on survey data. Regardless of the eventual managerial or academic objective behind the study, estimation of each individual’s attribute weights (the $w_{jm}$’s in equation (1) or the $u_{ijkm}$’s in equation (2)) is desired. Average weights pertaining to a ‘representative’ consumer do not reflect the distribution (heterogeneity) of consumer tastes very well. Thus, individual-level analysis allows more accurate prediction of both individual and aggregate behaviour, better representation of individual behaviour, and an opportunity to
group the population into 'benefit segments' which are needed for cost-effective targeting of the firm's marketing efforts. Typically, fewer than eight attributes are modelled.

Before attribute weight estimation can take place, the attributes relevant to consumers must be identified. Often a list of brands likely to be considered must also be identified. Personal interviews, focus groups and past experience are typically used to identify preliminary lists. Further personal interviews are used to condense these lists. Two statistical techniques, nonmetric multidimensional scaling and factor analysis, are often used to help identify the final attributes. These techniques usually result in a limited number of subjective (psychological) attributes and explain behaviour fairly well (Wilkie and Pessemier, 1973).

Once the attribute list has been decided upon, a large representative sample of consumers is surveyed. Two types of preference responses are utilized to estimate each sample consumer's personal attribute weights (the $w_{jm}$'s or $u_{jm}$'s). The respondents may simply be asked to reveal the relative preference they have for each attribute or attribute level by, say, dividing 100 points up between the attributes. Edwards (1977) provides a nice overview of this direct elicitation or self-explicated weights technique. Because of predictive validity concerns, more often respondents are asked instead to provide their stated preferences over a set of real or hypothetical brands (Wilkie and Pessemier, 1973). The relationship between these preferences, which serve as a proxy for utility, and the brands' attribute levels is used to estimate the individual's attribute weights. When hypothetical brands are used this procedure is referred to as conjoint analysis.

When collecting stated brand preferences the consumers are asked to rate how much they like (prefer, intend to buy, or are willing to pay for) a brand on a scale of, say, 0 to 100 with a value of 0 meaning strongly dislike and 100 meaning strongly like. Alternatively, the respondent may simply provide a ranking of the brands or perform comparisons among various brand pairs. Regression analysis is the most popular estimation technique with one of the stated preference measures as the dependent variable and the attribute as the independent variables. The parameter estimates are the attribute weights (the $w_{jm}$'s or $u_{jm}$'s). Other estimation techniques include MONANOVA, logit and linear programming. See Green and Srinivasan (1990) for further details.

Attribute-level data are often not collected from the consumer. Individual-specific perceived attribute levels (the $z_{jm}$'s) are collected in many studies utilizing stated preferences for real brands to estimate the consumer's utility function. However, conjoint analysis is more prevalent since it does not require the respondent to answer the many questions needed to acquire attribute perception data. The descriptions of the hypothetical brands contain their attribute levels (thus, $z_{jm} = z_j$ for all consumers $m$), so only preference data is collected. In either case, the attributes may be objective, such as miles per gallon,
price and engine size, or subjective, such as comfort, image and style (typically measured on a 1–7 scale).

Recently, a desire to reduce the number and complexity of the questions asked the consumer has led researchers to use both self-explicated weights data and stated brand preferences to estimate individual-level attribute weights. These hybrid techniques use self-explicated weights as priors and then ask brand preference questions (often simply ‘How much do you prefer Brand A to Brand B?’) which are used to update these weights (Green, 1984). A popular commercial example is adaptive conjoint analysis by Sawtooth Software. Similarities to Bayesian updating in statistics and belief change in philosophy are clear.

**Future research areas**
Four promising areas for additional research in multiattribute utility are the relationship between subjective and objective attributes, context effects, revealed versus stated preferences and choice, and the modelling of hierarchical multiattribute evaluations.

There is a trend to define utility as a function of a long list of objective attributes rather than a limited number of subjective attributes. The rationale behind this is as follows. Brand design engineers must choose particular levels of objective attributes when designing a brand. The mapping of objective to subjective attributes is many to one and, furthermore, not exactly defined. So, to avoid these mapping problems, why not just define utility with respect to the objective attributes? Two pitfalls arise, however. First, consumers do not directly evaluate the objective attribute levels of the brands. Hence, the utility function is misspecified. This may hurt predictive ability but more importantly may generate misleading attribute weight estimates. Second, a statistical problem arises since the number of independent variables (attributes) in the regression equation increases dramatically while the number of observations (brands) cannot since the number of real brands is limited, as is the number of hypothetical brands which the respondent can credibly assess. This degrees of freedom problem requires that utility function estimation be done at the segment or aggregate level and we have already mentioned the problems associated with such estimation. It may be more fruitful to make a better assessment of the subjective–objective attribute mapping, often referred to as quality function deployment or the house of quality (Horsky and Nelson, 1992).

Multiattribute utility modellers have largely ignored the idea that the consumers’ preferences, and, hence, their utility functions, may be context dependent. A vast literature in psychology and marketing provides anecdotal evidence that stated preferences are dependent on among other things, the
situation and type of question asked. This has led to numerous theories that explain these ‘deviations from rationality’, the most generic and well known of which are prospect theory (Kahneman and Tversky, 1979) and transaction utility or reference price modelling (Thaler, 1985). This issue poses an alarming problem both to utility theorists and managers. To theorists these deviations from rationality question the assumptions behind expected utility theory. To managers, the quality of all multiattribute study results is questionable because of concerns about whether the context in which the data were collected matches the contexts under which managers will implement their marketing decisions.

A particular context effect gaining interest with multiattribute modellers is the relationship between stated preferences, stated choices and actual choices (revealed preferences). Marketers have found that, for example, price sensitivity is often underestimated when consumer utility functions are estimated using stated preferences for a set of real or hypothetical brands. Consequently, there has been a movement towards estimation based on stated choices (Carroll and Green 1995). This involves consumers looking at different sets of hypothetical brands and choosing their favourite in each set. Logit analysis is then used to generate maximum likelihood estimates of the attribute weights. Unfortunately, once again there is usually a degrees of freedom problem, which causes estimation to be done at the segment or aggregate level. In addition, stated choices among hypothetical, or even real, brands may not reflect actual behaviour. For example, Horsky and Nelson (1992) show that consumers’ stated first choices do not match perfectly with their actual choices.

Hierarchical choice models have become fairly standard in the analysis of grocery store scanner data. That is, consumers are first modelled as choosing between, say, powdered and liquid laundry detergents and then choosing among the various brands within the product type chosen. However, this type of modelling has not found its way into the multiattribute utility literature in more than a qualitative manner. For example, because of brand decision costs the consumer may first decide what price range to consider and then use a compensatory model to assess the brands in that price range. Alternatively, the consumer may first disregard all cars providing less than 20 miles per gallon fuel economy, then use a compensatory model to compare among broad types of cars such as compact, utility, sport and luxury, and finally perform a final compensatory analysis (with different attribute weights) of the brands within the chosen product type.

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Bibliography


