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Stated Preference & Choice Models – A Versatile Alternative to Traditional Recreation Research

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Abstract: In outdoor recreation research and visitor management applications, stated preference and choice methods have not enjoyed the same amount of popularity when compared to other directions of applied research. This is somewhat surprising considering the fact that decisions that managers of protected areas and outdoor recreation in general face are typically multi-attribute in nature and require an understanding of the trade-offs that decision-makers of clients are willing to make. This paper provides an overview to stated choice research by explaining the essential considerations during the design and analysis of this approach. The various stages will be explained on hand of a simple example. Then the versatility of the approach will be demonstrated by discussing research design options in more detail.

INTRODUCTION

Stated preference and choice methods have received less attention in recreation research and visitor management of protected areas, compared to other research approaches. Yet, I will argue that under certain conditions, and for certain research questions, stated preference / choice approaches are more appropriate than visitor monitoring, or traditional social psychology methods.

Over the past few years, the analysis of observed behavior (visitor monitoring) has witnessed significant progress with the introduction of innovative monitoring equipment and GIS, both of which are accompanied by more sophisticated analytical techniques. Many contributions to this conference document these developments. However, by definition, such observational data are confined to past behavior, and if more details are desired about underlying explanations of the behavior, or evaluations about the effects of pending management decisions are desired, then observational data are of limited value.

Therefore, a wide range of behavioral research techniques, many of which are survey based, have been introduced and adapted to recreation research over the past 30 years. Behavioral research provides insights into the various behavioral antecedents, explaining why visitors behave in certain ways, and these insights might also be used for predicting future behavior. Studies focus on attitudes, motivation, satisfaction, perception, or simply preferences. Much of the traditional visitor management literature is built on these foundations of social psychology.

Research on the phenomenon of choice does not slot into the one or the other category conveniently. Choice research may be undertaken with observation type data, because any form actual human behavior actually manifests some choice. Such analysis is referred to as revealed preference or choice analysis. On the other hand, researchers may also inquire about future choices or behavioral intentions, which the literature refers to as stated preferences or choice research.

This paper will focus on the latter, stated preference and choice research. Specifically, I will present variations of the discrete choice experiment, a multivariate method that permits one to evaluate scenarios of recreation experiences, management alternatives or outcomes by describing these in scenarios composed of several attributes. Such evaluations may include currently non-existent alternatives, and provide insights into the trade-off behavior of respondents. [ultimately supporting decision making] In this paper I will provide a brief theoretical background to the method, explain the basic statistical concepts, present a simple study from recreational fishing, and document the versatility of the method by discussing variations of its application.

MODELLING PREFERENCE AND CHOICE BEHAVIOUR

Many management problems in visitor and protected areas management are of a multi-attribute nature and involve tradeoffs between several desirable policy or management goals. Among the various methods that have emerged in multi-attribute preference research, it is useful to distinguish between (a) revealed preference /choice approaches, in which the importance of salient variables influencing a decision is inferred by statistical analysis from actual behaviour, and (b) stated preference approaches, in which survey respondents evaluate hypothetical questions (Timmermans 1984). Discrete choice models, which rely on revealed preference data, have been applied successfully to transportation research (Ben-Akiva and Lerman 1985; Train, 1986), spatial analysis (Wrigley 1985; Kanaroglou and Ferguson 1996 and 1998) and also to recreation (Stynes and Peterson 1984).

Among the stated preference/choice approaches, it is important to distinguish between compositional and decompositional methods (Timmermans 1984). In compositional approaches, such as the theory of reasoned action (Ajzen and Fishbein 1980), respondents evaluate each aspect of a complex management issue separately, and thereafter the researcher calculates ('composes') an overall utility value for an alternative by combining the components of an alternative according to some predefined decision rule. Despite some interesting attempts towards wider application in various fields of environmental management (see, for example, Peterson et al. 1988), the operationalization of these compositional models has proven difficult.

In contrast, decompositional multi-attribute preference models have been applied to complex management issues with considerable success (for summaries see Timmermans 1984; Timmermans and Golledge 1990). These models have proven to be versatile, since they account for the multi-attribute nature of the management issues, permit the exploration of non-existing alternatives, and avoid the problem of multicolinearity. In these models, alternatives are defined as combinations of a set of attributes, and each set is evaluated as a whole. The alternative profiles are constructed by following statistical design principles, such as fractional factorial designs (for example, Raktoe et al. 1981). If respondents rate or rank each full profile separately, the technique is usually referred to as conjoint analysis (Green and Srinavasan, 1978). In a discrete choice experiment (DCE), two or more such hypothetical profiles are combined to choice sets, and respondents choose the most preferred alternative (profile) from each set they are asked to evaluate (Louviere and Woodworth 1983; Louviere et al. 2000). The advantage associated with a choice based response task is that the statistical analysis can be conducted with the same multinomial logit regression model (see below) that is typically applied in discrete choice models. In other words, DCEs combine the analytical elegance of the random utility model (McFadden 1974) with the experimental rigour of conjoint analysis (Green and Srinavasan, 1978). The advantages of stated choice over traditional conjoint analysis are that behaviorally, the analysis of choice - even though it is only hypothetical choice – is closer to actual behavior than a rating or ranking task, and that the statistical analysis has a rigorous error theory included (see below).

DCEs have been applied to spatial consumer choice behaviour (Timmermans et al. 1992), and to tourism and recreation issues (Louviere and Timmermans 1990; Haider and Ewing 1990). Lately, they have gained increasing popularity in resource economics (Swallow et al. 1994); more specifically, several recent studies have compared the performance of revealed and stated preference methods for resource valuation (Boxall et al. 1996; Adamowicz et al. 1997 and 1998). This interesting topic with significant relevance to outdoor recreation remains outside the scope of this paper.

THEORY - THE DCE

There are several stages to desinging a proper DCE. First, the attributes and attribute levels that are crucial to a recreation experience and/or a decision-making context need to be identified. Second, an experimental design needs to be selected. Third, statistical analysis needs to be undertaken. Finally, the results may be presented in a computerized decision support system. An example from a simple study in recreational fishing (ice fishers around Sudbury, Canada) will be used to demonstrate the various research stages of data.

Defining attributes and attribute levels

A realistic choice task requires the identification of crucial attributes and attribute levels that typically influence a respondent's decision when purchasing a good or service, or when selecting a recreational trip. Usually one considers attributes that contribute to the quality of the experience as well as the regulatory framework. Attributes and their specifications can be identified from the literature; management issues will be conveyed by managers; any variables pertaining to the experience may be elicited from potential respondents through informal interviews or in focus groups sessions. Attributes and their specifications for the ice fishing study are summarized in Table 1.

Selecting a fractional factorial design

Second, profiles need to be created, and thereafter two or more profiles need to be combined to choice sets. If one were to use all possible profiles (combinations of attribute levels) in a study, one would refer to it as a full factorial design, and ANOVA could be used as statistical analytical procedure. Given the large number of attributes and levels that make up a DCE, a full factorial approach is out of question. An alternative is to show respondents only a small set of all possible combinations. For that purpose, one can select appropriate fractional factorial design plans, which follow precise statistical design principles (for example, Raktoe et al. 1981). In most cases such fractional factorial designs ensure that attributes remain orthogonal (independent) of each other; The cost of employing a fractional factorial design is that many or all interactions may not be estimable (they are aliased with main effects). The obvious advantage is that respondents consider the attributes in the context of each other.

ATTRIBUTE	LEVELS
Travel	
Travel time to lake	• Half as much as today's • Same as today's • Twice as much as today's
Regulations	
Size limit	• None • 40-50cm slot
Creel limit	• 6 fish per day • 4 fish per day
Gear restrictions	• 2 lines • 1 line
Bait restrictions	• live bait allowed • artificial lures only
Length of season	• current (Jan 1 – April 30) • closes February 28
Expectations	
Number of fish	• many • few
Size of fish	• mostly small fish • mostly large fish

Table 1:List of Attributes and Levels for the ice fishing study.

If respondents rate or rank each profile separately, the technique is usually referred to as conjoint analysis (Green and Srinavasan, 1978). In a DCE, two or more such hypothetical profiles are combined to choice sets by following one further simple factorial design plan. Respondents choose the most preferred alternative (profile) from each set they are asked to evaluate (Louviere and Woodworth 1983; Louviere 2000). For a simple example of a choice set, see Table 2.

In the ice fishing study we used a total of eight attributes, seven of which were presented on two levels, and one as a three-level variable. We selected a 16^2 resolution III fractional factorial design plan (Raktoe et al. 1981), which permitted the estimation of all main effects. The three-level variable (travel time) was accommodated into the design by showing only two of the three levels in each of the two profiles of a choice set. Interviews were conducted at the fishing sites, and therefore the 16 choice sets that were required by the design were divided into four sets of four choice cards each, so that each respondent faced four choices. Respondents choose either of the two hypothetical lakes (Lake A or Lake B), or could also select to not fish. Presenting such a common base alternative is important, because it provides a shared platform for analysis.

	LAKE A	**LAKE B**
Travel time	Half of today's	Same as today
Size limit	40-50 cm slot	None
Creel limit	4 fish /day	6 fish / day
Gear	2 lines	1 line
Bait	Artifical lures only	Live bait only
Season	Current	Closes feb. 28
Number	Few	Many
Size	Mostly small	Mostly small
YOUR ' CHOICE	❐ **Lake A** ❐ **Would not fish**	❐ **Lake B**

Table 2: Example of a choice set.

Statistical analysis

The analysis of DCEs is based on the assumptions of the general discrete choice model (McFadden 1974 – also referred to as the random utility model), which in its original form is used for analysis of revealed preferences and is based on the following assumptions. Individual behaviour is considered as deterministic, but because of the inability of the research process to account for all influencing attributes and the need to aggregate individual choices across individuals, the modelling of behaviour is undertaken stochastically (Train 1986; Ben-Akiva and Lerman 1985). Therefore, it is assumed that the overall utility (U_i) contained in any one alternative is represented by a utility function that contains a deterministic component (V_i) and a stochastic component (e_i). Selection of one alternative over another implies that the utility (U_i) of that alternative is greater than the utility of any other alternative (U_j). The overall utility of alternative i is represented as (McFadden 1974; Train 1986):

$$U_i = V_i + \varepsilon_i$$
(Equation 1)

An individual will choose alternative i if $U_i > U_j$ for all $j \neq i$. However, since the utilities include a stochastic component, one can only describe the probability of choosing alternative i as:

$$\text{Prob } \{\text{i chosen}\} = \text{prob } \{V_i + \varepsilon_i > V_j + \varepsilon_j \,;\, \forall j \in C\}$$
(Equation 2)

where C is the set of all possible alternatives. If one assumes that, for the entire sample, the stochastic elements of the utilities follow a Gumbel distribution, the standard multinomial logit (MNL) model can be specified (McFadden 1974; Ben-Akiva and Lerman 1985):

$$\text{Prob } \{\text{i chosen}\} = e^{Vi} / \quad e^{Vj}$$
(Equation 3)

where the aggregate probability of choosing alternative i equals the exponent of all the measurable elements of alternative i over the sum of the exponent of all measurable elements of all j alternatives. This standard MNL model supports the estimation of parameters that allow one to express the choice probability of a given alternative as a function of the attributes comprising that alternative and those attributes of all other alternatives in the choice set.

The analysis produces regression estimates for each attribute level, which are referred to as partworth utilities, and typically are presented in a table jointly with standard error and t-value associated with each estimate (Table 3). All attributes were dummy coded (0,1). The estimate represents the part-worth utility for the attribute level compared to its 0-level, i.e. the level not shown. All the estimates have the expected signs, and all estimates are significant at the 5% level except size limit, and creel limit is significant at the 10% level only. In the design, the variables were arranged so that the interaction between the variables gear and bait was also estimable, and it was significant in the sense that if both attributes were changed to a more restrictive level at the same time then the support for these policies would decline even further. The results show that enacting gear and bait restrictions would be the least popular regulatory changes, while other regulations are more acceptable. With such knowledge resource managers can make more informed decisions between acceptability of regulations and their likely effects on the resource.

Attribute	**Estimate**	**Standard Error**	**t-value**
Intercept	2.033	0.045	45.446
Travel (same)	0.208	0.030	6.885
Travel (half)	0.147	0.019	7.797
Size limit (slot)	0.012	0.016	0.726
Creel limit (4 fish)	-0.030	0.016	-1.874
Gear (1 line)	-0.178	0.016	-11.345
Bait (artificial)	-0.298	0.017	-17.545
Season (short)	-0.087	0.016	-5.436
Exp_numb (many)	0.088	0.017	5.286
Exp_size (m. large)	0.159	0.017	9.537
Interaction Gear*Bait	0.096	0.019	4.994

Table 3: Results of the ice fishing study

A DECISION SUPPORT SYSTEM

In addition to documenting the part-worth utilities for each of the variable levels, the decompositional nature of the DCE also permits the instantaneous evaluation of any profile that can possibly be generated as a combination of the experimental variables. In other words one can model the joint effects of several changes simultaneously. This overall evaluation is based on the calculation of the probability of choice for one alternative over any other alternative(s), as suggested by the last equation above. The layout of such a decision support system (DSS) follows the original layout of the choice sets closely (Figure 1). It is interactive in the sense that any possible profile can be evaluated by simply changing any attribute levels in the interface window.

In the example of Figure 1, Lake A represents pretty well the current situation, except that the travel time is halved. Lake B contains several regulatory changes (a lower creel limit, only one line, artificial lures only, and a shorter season), while the expectations remain the same. As to be expected, Alternative B is considered much less attractive. Its market share reduces to 22%, while Alternative A's increases to 72%. The rate of non-anglers increases by almost 2%. One can now continue with the evaluative game and assume that such a drastic change in regulations would eventually improve the quality of the fishery. By adjusting the size and number of fish one can expect to catch to the more favorable levels, the share of Lake B would recover to a certain extent to 31.8%. Obviously one can play through several demographic or experience related criteria.

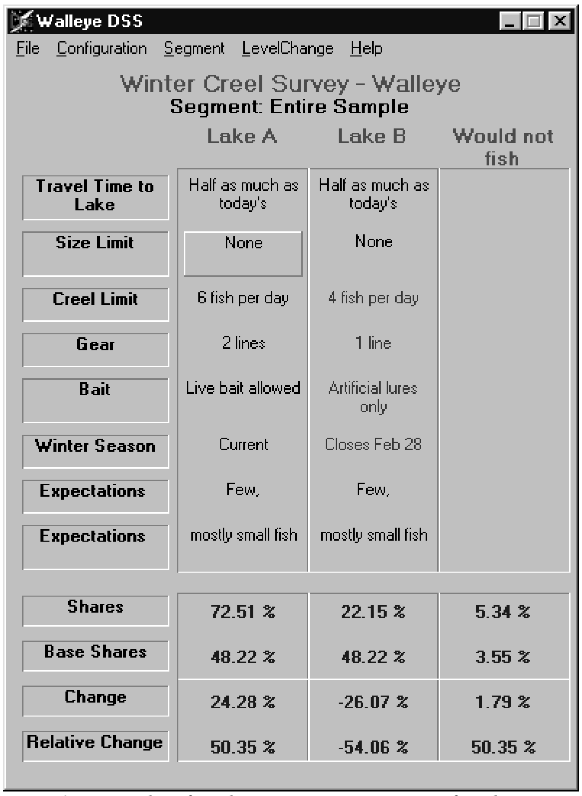

Figure 1: Example of a decision support system for the ice fishing study.

THE VERSATILITY OF DCES DURING APPLICATIONS

A DCE does not need to be constrained to a simple choice between two hypothetical scenarios. In the contrary, any one of its features can be adapted to suit the purpose of investigation. Several options will be explored below. The limited space available in these proceedings does not permit me to show examples for all these issues. These examples will be presented during the conference.

Number and types of scenarios in a choice set

Rather than asking respondents to choose among two alternatives, one may ask them to choose among several alternatives. Including more than two scenarios into a choice set may not be very useful in a generic model (i.e. the profiles are simply labeled A vs. B as in the example above). However, in many applications the realism of a choice set may increase by labeling the scenarios, which leads to an alternative specific design. Theoretically, any variable can take on the role of defining the alternatives. Usually one has a good reason for selecting an alternative specific variable, such as trip destinations (Haider and Ewing 1990), brand names such as sports equipment, or fish species (Aas et al. 2000; Fedler et al. 1999). One needs to estimate an intercept (constant) for each alternative, which amounts to an estimate for that variable.

Response tasks and use of base alternatives

In some situations it might be appropriate to consider an alternative to the simple binomial or multinomial choice task. Especially in recreation studies it frequently appears appropriate to model the repeated allocation of choice between different scenarios over the course of a season or for the duration of a trip. In such a case, one can ask respondents to allocate a total of, say, ten trips among the scenarios in one choice set. A respondent may then allocate five out of ten recreational day trips to a protected area among hiking, mountain biking, and kayaking. Depending on which other variables are associated with the study, the choice among these options might vary considerably from choice set to choice set. The advantages of such an allocation task are that one actually collects more data with the same amount of effort. Furthermore, depending on the circumstances, an allocation task might also be behaviorally more meaningful.

Depending on the respondent's decision making or choice context, it might be of interest to disaggregate the base alternative further. For example, if respondents do not find any of the scenarios presented in a choice acceptable, one might want to know if they would consider a different activity in the same location, or would rather search for an activity substitute in the vicinity, or would consider a substitute in a very different region, or would decide to abandon both activity and location. Obviously, the method can be used for designing sophisticated research on substitution behavior.

Interactions and Cross-effects

Modelling the interactions between variables is possible, if a design is set up accordingly from the beginning (see example above). Many designs have sufficient room for targeting a couple of two-way interactions. If one can anticipate the most salient interactions a priory, a design can be laid out in such a manner that the desired interaction will be estimated. Dellaert et al. (1995) present a rather elaborate study of interactions in an application to urban tourism.

In alternative specific models it might be of interest to determine potential effects from one alternative on the other. This phenomenon is referred to as the cross-effect, which also can be estimated. However, in praxis it is often difficult to interpret such cross-effects when they emerge as significant.

Alternative presentation of stimuli

In most cases the attributes and choice sets are simply presented as written statements. In recreation research, visual landscape components might constitute important determinants of choice. Such concerns might range from the attractivity of outstanding landscape features, and issues of crowding, to human effects such as logging. It is conceivable that one any one attribute can be presented visually. In one study on the effects of forest harvesting on tourism we presented the quality of the forested landscape in northern Ontario in digitally calibrated images (Orland et al 1995). The digital calibration of images refers to a much more rigorous design process, in which one or several variables describing the landscape become an integral component of the fractional factorial design, and then a digital imaging technique is used to create a photo-realistic landscape image that represents these attributes. Figure 2 shows one example of the calibration process for the study in northern Ontario. The two columns on the left list the eight variables that were created in the image. In this study we used a total of 64 different images, which where then embedded into each scenario. Other attributes described the type and quality of the fly-in fishing location, and the fishing quality.

Nested and partial designs

The basic assumption in most DCEs is that respondents process all information simultaneously. In certain recreation applications such an assumption may be incorrect, when recreationists might consider experience components separately. For example, a destination and a mode of transportation, both of which are multiattribute phenomena in their own right, may be considered sequentially or separately. In such a situation a hierarchical or nested model structure might be appropriate, in which respondents evaluate one

Scene 1

Attribute:	**Levels:**
Buffer Width -	100m
Residuals -	single conifers
Road -	no road
Forest Type -	conifer
Size -	large
Shape -	regular
# Blocks -	multiple
Colours -	fresh brown

Figure 2: An example of a digitally calibrated image

component before the other. Sometimes the number of attributes that a researcher desires to include in a study might be too large for presentation in one scenario. In that case, again a hierarchical design, or a partial design, in which only a subset of all variables appear in each choice set are elegant ways for building a larger model while still keeping the response task manageable. For a thorough discussion of many of these issues, see Dellaert et al. (1997) and Oppewal et al (1994).

CONCLUSIONS

The above presentation documents the versatility and adaptability of stated choice modeling to different behavioral context as well as to theoretical questions and applied issues. The main advantages associated with stated choice methods can be summarized as the following:

- respondents evaluate a recreation experience or the outcome of a management action as a whole, while the statistical analysis derive utility measures for each attribute;
- respondents think inevitably in terms of trade-offs, and whatever issue might be at the forefront of management concerns is somewhat disguised in the larger context;
- respondents may be better at expressing relative preferences than absolute ones;
- the statistical design ensures attributes are uncorrelated, obviating the problem of multicolinearity often encountered in revealed preference studies;
- the method allows the researcher to control the alternatives and choice sets presented to the respondent;
- truly different alternatives, some of which may not exist presently, can be evaluated.

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