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Research Paper

Providing information to respondents in complex choice studies: A survey on recreational trail preferences in an urban nature park

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ABSTRACT

This paper examined the recreational trail preferences of visitors in the Medvednica Nature Park, a protected forest area on the outskirts of the City of Zagreb, the capital of Croatia. A discrete choice experiment (DCE) was conducted to get the insight into relative importance of different resource, social and managerial conditions in the park. Accounting for multiple site conditions requires a relatively large number of choice attributes, which may impose too high cognitive burden on respondents. On the other hand, ignoring relevant attributes may lead to the omitted variable bias. A split sample approach was used to find the balance between the possibility of omitted variable bias and cognitive burden; one version of the questionnaire used DCE with the lower number of attributes, of which some were multidimensional, while the other version used DCE with the greater number of more specific attributes. By using partial profile design in the latter experiment, the number of attributes in the choice task was identical in both experiments. Perceived difficulty of the choice task, self-reported choice certainty and choice consistency were similar across the two experiments. Heterogeneity in preferences and scale was detected in both experiments. Indications of non-compensatory behavior, and greater error variance among less experienced trail users were found in the partial profile experiment with more specific trail attributes, but not in the experiment with multidimensional attributes. Based on the research results, important managerial implications were derived. Non-visual sensory experiences of nature, namely fresh air and soundscape, were generally more important to trail users than visual experiences. Crowding was detected as an important characteristic of trail experience; however, trail users were willing to tolerate relatively high levels of crowding.

1. Introduction

Increased crowding, noise, air and visual pollution are some of the adverse social and environmental impacts often detected in urban environments (Kil, Stein, & Holland, 2014; Parumog, Mizokami, & Kakimoto, 2006). Green areas such as urban forests often serve as spaces to counter the stress of urban life and provide relief from high population densities (Bakhtiari, Jacobsen, & Jensen, 2014; Karjalainen, Sarjala, & Raitio, 2010). Such areas are popular places for outdoor recreation activities; however, recreational benefits which they provide might be threatened by excessive levels of visitor activity (Arnberger & Mann, 2008; Mieno, Shoji, Aikoh, Arnberger, & Eder, 2016). Outdoor recreation activities contribute to biophysical and aesthetic changes in environment, often reflected in degradation of land cover, soil erosion, disturbance of wildlife and littering (Kil et al., 2014; Manning, 2011). High use levels and undesirable user behavior can also lead to crowding and user conflicts (Arnberger & Mann, 2008; Manning, 2010). Understanding visitors' preferences for resource conditions (e.g. trail condition, surrounding landscape), social conditions (e.g. type and level of use, visitor behavior) and managerial conditions (e.g. vegetation and litter management) of natural environment is valuable in designing effective landscape management strategies (Reichhart & Arnberger, 2010).

Discrete choice experiments (DCEs) have become increasingly popular in outdoor recreation studies to investigate the preferences of visitors and tradeoffs in recreational conditions they are willing to make (e.g. Arnberger & Eder, 2011; Bullock & Lawson, 2008; Hanley, Wright, & Koop, 2002; Kainzinger, Arnberger, & Burns, 2016; Lawson & Manning, 2002; Manning, 2011; Newman, Manning, Dennis, & McKonly, 2005; Reichhart & Arnberger, 2010). Their popularity owes to the possibility of simultaneously evaluating different site conditions and underlying trade-offs, which was not possible with normative and univariate approaches used in the earlier studies. However, simultaneous evaluation of different conditions (called

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attributes in DCE methodology) imposes greater cognitive burden on respondents, and there is a limit on the number of attributes respondents can process at the same time (Zhang, Johnson, Mohamed, & Hauber, 2015). When asked to process too much information when making choices among competing alternatives in a DCE task, respondents often alter their decision rules (e.g. ignore some of the information presented to them) to simplify the choice task (Colombo & Glenk, 2014; DeShazo & Fermo, 2002; Erdem & Thompson,2014). This violates DCE assumption of compensatory behavior or unlimited substitutability between the attributes, and may contribute to an increased error variance and affect the validity of utility estimates (Dellaert, Donkers, & van Soest, 2012). Therefore, information gain from providing a more complete description to respondents may be outweighed by higher cognitive burden from the larger number of choice attributes that describe a setting, which usually forces researchers to omit the attributes that they think are not essential for most of the population (DeShazo & Fermo, 2002; Louviere, Pihlens, & Carson, 2010). This could however lead to the omitted variable bias as respondents may be influenced by attributes that are not included in a DCE, causing bias in the utility estimates, particularly if omitted and included attributes are correlated (Witt, Scott, & Osborne, 2009). Giving respondents more complete information rather than offering only a subset of relevant attributes or their aggregated definition could improve the consistency and confidence respondents have in choices due to a more meaningful interpretation of alternatives (Hensher, 2006a).

The survey design should find the optimal balance between the interests in various attributes (i.e. omitted variable problem) on the one hand and complexity of the choice task on the other (DeShazo & Fermo, 2002; Witt et al., 2009). This paper discusses survey design features that may help in finding this balance – type of information presented to respondents (multidimensional vs. unidimensional attributes), and type of experimental design used to deliver information to respondents (full profile vs. partial profile design). A split sample approach was used with two different choice experiments that evaluated recreational trail preferences of forest visitors in the Medvednica Nature Park on the outskirts of the City of Zagreb, the capital of Croatia, but differed in the provision of information about the recreational setting. One experiment used full profile design and included multidimensional attributes to keep the number of choice attributes manageable for respondents, while considering all relevant aspects of visitors' experience. The other experiment included a greater number of more specific, unidimensional, attributes to describe the recreational setting. A partial profile design was used in this experiment to prevent a large increase in choice task complexity. In a partial profile design only a subset of attributes appear in each choice set (Kessels, Jones, & Goos, 2012), thus the number of attributes per choice task was kept constant across experiments. A core set of attributes used in other outdoor recreation studies was expanded by including the influence of non-visual sensory experiences, namely air and noise pollution, which were considered a concerning aspects of visitor activity by the park management. Previous studies have been mostly focused on visual experiences of visitors; however, sensory experiences, such as noise, could have a strong influence on the perception of natural landscapes and visitors' experience (Buchel & Frantzeskaki, 2015; Hallo & Manning, 2009). We compared self-reported choice certainty and perceived choice difficulty across the two experiments and investigated how different presentation of information about recreational setting affected decision behavior of respondents, utility estimates and response error variance. Understanding how respondents attended to information presented in the choice tasks and identifying limitations and advantages of alternative attribute presentation methods allows improving the design of the future choice studies (Colombo & Glenk, 2014). As environmental valuation generally involves trade-offs between complex goods and services that cannot be easily described with a restricted number of attributes, how to optimally describe a choice context to respondents is an important consideration.

The following hypotheses were examined: a) non-visual sensory experiences of nature, namely fresh air and soundscape, could be more important to peri-urban forest visitors than visual experiences, b) different information provision strategies influence propensity to non-compensatory choice behavior, and c) different information provision strategies affect the utility estimates and error variance (or choice consistency).

2. Methodology

Within DCEs, respondents are presented with multiple choice sets consisting of at least two alternatives, and asked to select their preferred alternative in each set. Alternatives differ in the values of attributes, such as resource, social and managerial trail conditions (see e.g. Arnberger & Eder, 2011; Bullock & Lawson, 2008; Hanley et al., 2002; Lawson & Manning, 2002; Newman et al., 2005; Reichhart & Arnberger, 2010). Experimental designs are used to generate the choice sets (Hoyos, 2010). Typical experimental design is based on full profiles where the levels of all attributes vary in each choice set. Partial profile designs systematically vary only a subset of attributes, i.e. the levels of the selected number of attributes remain constant in each set (Kessels et al., 2012). Primary reason for using partial profile designs is reducing the complexity of the choice tasks by limiting the number of trade-offs, but they can be also useful in preventing non-compensatory behavior, especially dominant or lexicographic preferences (Kessels et al., 2012). Such preferences arise when respondents have a tendency to focus on a single attribute or on a sub-set of attributes, while ignoring all other differences between the alternatives. Holding the levels of a subset of attributes constant in each choice set encourages respondents to trade-off between all attributes even if their decision strategy is not fully compensatory.

Econometric analysis of DCE data is based on random utility theory. As utility is a latent and unobservable construct, only indicators of utility are observed in form of choices made by respondents, i.e. $U_{ij} = V_{ij} + \varepsilon_{ij}$ where j denotes the choice made by individual i among J possible choices, V_{ij} is the systematic component and ε_{ij} the random component of utility. The systematic component is usually a function of choice attributes (X_{ij}) and characteristics of respondents (Z_i). Choosing one alternative over others implies that its utility is higher (Lancsar & Louviere, 2008). Respondents' choices are used to estimate the preference weights for each attribute. The standard model for analysing choice data is the multinomial logit (MNL) model. The probability that individual i chooses alternative j from the set of J alternatives is specified as (Lancsar & Louviere, 2008):

$$P_{ij} = \frac{e^{\mu V_{ij}}}{\sum_{k=1}^{J} e^{\mu V_{ik}}} = \frac{e^{\mu (X_{ij}^{'}\beta + Z_i^{'}\gamma)}}{\sum_{k=1}^{J} e^{\mu (X_{ik}^{'}\beta + Z_i^{'}\gamma)}} \quad (1)$$

Parameter μ represents a scale parameter that is inversely proportional to the variance of the error term σ_ε (Pedersen, Kjaer, Kragstrup, & Gyrd-Hansen, 2011). As μ cannot be identified in a single data set, it is usually normalized to unity (Hoyos, 2010). This model assumes that error variance is constant across respondents, which could be relaxed by using a (parameterized) heteroscedastic MNL model and allowing the scale parameter to be a function of covariates, such as respondent characteristics and design properties (Bech, Kjaer, & Lauridsen, 2011; Hensher, Louviere, & Swait, 1999).