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RESEARCH ARTICLE

A review of research into discrete choice experiments in tourism: Launching the Annals of Tourism Research Curated Collection on Discrete Choice Experiments in Tourism

Astrid Kemperman

Eindhoven University of Technology, PO Box 513, 5600MB Eindhoven, the Netherlands

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ABSTRACT

This article presents a systematic review of all 49 papers published in the top five tourism journals between 2010 and 2020 on discrete choice experiments in tourism research. Discrete choice experiments are used for measuring and predicting individuals' preferences and choices of alternatives and provide quantitative measures of the relative importance of attributes of tourism destinations, products, or services and might include tourists' willingness to pay for various services. Results of the review are presented, and research gaps and challenges are identified and discussed. Future research and methodological approaches to help progress discrete choice experiments in the field of tourism research are proposed. This article launches the Annals of Tourism Research Curated Collection on Discrete Choice Experiments in Tourism.

Introduction

All tourists make decisions including, whether to travel or not, destination choice, travel mode choice, trip duration choice, travel party choice, accommodation choice, and what activities to undertake while they are at a destination. It is important to understand the choices tourists make, both from a scientific, managerial, and policy point of view. Discrete choice modeling using choice experiments has been widely used in a variety of fields of research including transportation, marketing, retailing, health, and environmental economics, as it provides an excellent technique to explain and predict preference and choice behavior (Hensher, Rose, & Greene, 2015; Louviere, Hensher, & Swait 2000). In the tourism context, discrete choice experiments can be used to determine for example, how attractive tourists consider competing destinations with respect to each decision attribute (e.g., Masiero & Qiu, 2018; Morley, 1994); how tourist evaluations of different tourism product attributes relate to their socio-demo or psychographic characteristics (e.g., Chen, Masiero, & Hsu, 2019; Sedmak & Mihalic, 2008); whether different market segments can be identified based on tourists' opinions about competing tourist accommodation (e.g., Arana & Leon, 2008; Randle, Kemperman, & Dolnicar, 2019); and what the effect is of a position change by a competitive tourist attraction on market share (e.g., Alexandros & Jaffry, 2005; Hong, Kim, & Kim, 2003).

Discrete choice experiments are based on the random utility theory proposed by Thurstone (1927), which postulates that a person will choose the alternative that maximizes his or her utility, and is extended by McFadden (e.g., McFadden, 1974; McFadden, 1986; McFadden, 2000). McFadden (1974) was the founder of discrete choice models to explain choice situations

E-mail address: a.d.a.m.kemperman@tue.nl.

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involving a limited set of exhaustive and mutually exclusive choice alternatives, and his ideas were further developed in parallel by economists and cognitive psychologists. Various aspects of the modeling approach, data collection, estimation algorithms, and forecasting methods, are over the years further developed and advanced by several researchers (e.g., Ben-Akiva & Lerman, 1985; Bhat, 2001; Greene, 2012; Hensher et al., 2015; Louviere, Hensher, & Swait, 2000; Train, 1986; Train, 2003). For a complete excellent handbook for the study of choice behavior see Hensher et al. (2015).

Discrete choice models can be applied to various types of data. Generally speaking, there are two types of data: revealed choice data and stated choice data. However, also a combination of these two types has been advocated (e.g., Hensher, 1994). Revealed choice data is based on observations of behavior in real market situations, whereas stated choice data is based on individuals' preferences and choices expressed under controlled experiments (Louviere & Woodworth, 1983). Both types of data have their advantages and disadvantages. In a stated, or also called discrete choice experiment, people are asked to respond to new products or services, thus the potential market for new products can be measured and predicted. Also, when revealed data are missing discrete choice experiments are the only option. Furthermore, if choice alternatives in observational data have limited to no variance, data collected with a discrete choice experiment might be a good alternative as it allows the researcher to control attribute variation and covariation.

In this paper, the main focus will be on discrete choice experiments, also called stated choice modeling, or conjoint choice modeling, in tourism research. The study by Louviere and Hensher (1983) was the first one to apply discrete choice experiments in a tourism context. This is followed, over time, by many articles and also some interesting review papers on the topic. Louviere and Timmermans (1990) reviewed stated preference and choice models applied to recreation research; Crouch and Louviere (2000) reviewed 43 choice modeling studies in tourism, hospitality, and leisure; and more recently, Hergesell, Dwyer, and Edwards (2019) specifically addressed tourist decision making and choice behavior with also a side step to discrete choice experiments. Also, Viglia and Dolnicar (2020), in a review on the use of experiments in tourism research, discussed a variety of application areas in tourism research where discrete choice experiments have been used. They conclude that compared to field experiments and quasi-experiments, discrete choice experiments have, in general, a lower external validity but, if designed well, a higher internal validity. This paper does not aim to duplicate these previous studies but will build upon them.

The objective of this paper is to provide and discuss an overview of recent discrete choice experiment studies in the field of tourism research, and to give recommendations and directions for future research. This article launches the Annals of Tourism Research Curated Collection on Discrete Choice Experiments in Tourism. The paper starts by explaining the basics of discrete choice experiments, followed by a systematic literature review of 49 articles published in the top 5 tourism journals in the period 2010–2020 applying the approach. The results are presented and discussed, research gaps and challenges are identified and future research and methodological approaches to help progress the field are proposed.

Discrete choice experiments

The conceptual model of individual choice behavior that underlies discrete choice experiments is derived from various sources, such as Information Integration Theory (Anderson, 1970, 1974), probabilistic choice theory (Luce, 1959), and random utility theory (Thurstone, 1927). A general conceptualization of this model (cf. Louviere, 1988; Timmermans, 1982), in which we use tourist destination choice as an example, illustrates that destination choice behavior is the outcome of an individual decision-making process. In this process, a tourist goes through various phases in selecting a destination from a set of considered alternative destinations. Taking into account the tourist's characteristics, context, and preferences for different destinations, there will be one destination that optimizes the visitor's experience.

The destinations are perceived by the tourist as bundles of features, usually called attributes. The attributes can take on different values, for example, the type of destination, accommodation options available, crowdedness, friendliness of local population, price level, etcetera. Some of the attributes are quantitative such as price, others are more qualitative such as perceived quality. All destinations and their attributes define physical reality. It is assumed that the decision problem, what destination to choose, together with the tourist's value system, motivation, information level, etcetera, defines a set of decision criteria, conditioning the tourist's perception of the physical environment. This phase involves subjective filtering based upon imperfect information and results in a cognitive environment. The tourist is usually only familiar with a subset of all destinations and a small, not necessarily perfectly known, number of attributes defining the destinations. Shocker, Ben-Akiva, Boccara, and Nedungadi (1991) discuss developments in the measurement and modeling of consideration set effects on decision-making and argue that more research is needed to enable a more precise understanding of the constraints which affect consideration set formation and change, and the choice decisions that follow.

Several models of tourist destination choice processes have been proposed (e.g., Crompton, 1992; Crompton & Ankomah, 1993; Karl, Reintinger, & Schmude, 2015; Um & Crompton, 1990; Woodside & Lysonski, 1989). The central topic of their work are choice sets, and in most proposed models the decision process is conceptualized as a multistage process of narrowing down from a relatively large choice set of destination alternatives to the destination that is finally selected. The set of perceived destinations defines an evoked set of destinations from which the tourist has to make a choice. The tourists are assumed to discriminate between the limited number of destinations available in their cognitive environment based on a limited set of attributes. The perceived value of each attribute by a tourist is evaluated in terms of its attractiveness and then combined by the tourist into an overall evaluation of the destination alternative. This integration process is subjective and implies a weighted evaluation of the attributes (marginal utilities). The preference utility value of a destination is a function of the marginal utilities of its attributes. The preference structure consists of an ordering of the destinations based on their utility in satisfying the particular needs underlying the tourist decision problem. A decision rule is applied by the tourist to determine which destination is chosen from the evoked set, and it is usually assumed that the destination with the highest utility is selected. However, also modeling approaches are developed that assume other decision-making rules, such as a tourist selecting the alternative that minimizes the anticipated regret (Chorus, 2010; Chorus, Arentze, & Timmermans, 2008; Masiero, Yang, & Qiu, 2019), or a lexicographic strategy, meaning that the tourist determines the most important attribute and chooses the best alternative accordingly (Green & Srinivasan, 1990; Jung, Sydnor, Lee, & Almanza, 2015).

Setting up a discrete choice experiment involves a number of steps (e.g., Hensher et al., 2015; Louviere & Timmermans, 1990): elicitation of influential attributes; specification of relevant attribute levels; selection of experimental design; constructing the choice task; data collection procedure, and model estimation. Each of these steps is briefly discussed in turn.

Selecting attributes and assigning their levels

First, based on the research question asked the influential attributes relevant in the choice process of the tourists need to be identified. Of course, it might be a challenge to include all relevant attributes, but the most important ones relevant to the majority of respondents must be included (Kløjgaard, Bech, & Søgaard, 2012). Otherwise, respondents can make assumptions about missing attributes, which can affect the validity of the experiment.

A literature review is usually conducted to identify the relevant factors in the choice process. But also, several qualitative methods such as focus groups, expert interviews, factor listings, and repertory grid, can be used to elicit relevant choice dimensions (Louviere & Timmermans, 1990). Of course, one also needs to consider whether the included attributes are of planning and/or managerial interest. Then, the number of attributes that will be included in the experiment needs to be defined. Including many attributes may make the task more complex for the respondents and complicate the experimental design. On the other hand, including too few attributes may produce unreliable results because the task for the respondents may become unrealistic. It may become more difficult for the respondent to imagine what the alternatives represent, and different respondents may make different assumptions about the attributes that cannot be observed by the researcher. This may increase response bias. Hensher (2006) concludes that overall, the respondent seems to trade-off effort spent on each attribute against the number of attributes considered, but also that the processing strategy is dependent on the nature of the attribute information, and not strictly on the quantity.

In addition to the number of attributes, the appropriate levels of each attribute need to be defined. The range of the levels should be within the range of current experience and the believability of each individual and competitive trade-offs should be ensured. Lancsar and Louviere (2008) state that the level range is particularly important for the price attribute if it is to be used to calculate implicit prices of other attributes using marginal rates of substitution. Generally, to be able to construct balanced designs it is better to use the same number of attribute levels or for example combinations of two and four-level attributes. If one wants to estimate quadratic effects, at least three levels are required.

Experimental design

The next, important step involves the selection of an experimental design to generate hypothetical alternatives based on the attributes and their levels. The design should maximize the identification possibilities of the utility function and choice model and the precision of the estimation of the parameters. Traditionally, and specifically still mainstream for practitioners, orthogonal designs are used. A full-factorial design consists of all possible combinations of attribute levels and allows independent estimation of all main effects and all two-way and higher-order interactions. However, a full factorial design leads, in most cases, to too many hypothetical alternatives, and it is not possible to have study participants evaluate all possible options and combinations. Hence, researchers often use fractional factorial designs that allow the estimation of at least all main effects while giving up the possibility of estimating some interactions and which leads to a significantly lower number of hypothetical alternatives. However, to avoid confoundment of interaction effects a design that allows estimation of all first-order interaction effects is preferred.

Increasingly so-called efficient designs (e.g., D-efficient designs, D-optimal designs, Bayesian efficient designs) have been proposed (Rose & Bliemer, 2009). A design is more efficient if it can generate alternatives and choice tasks that maximize the collected information in the data, yielding more reliable parameter estimates with an equal or lower number of observations than the traditional orthogonal designs (van Cranenburgh, Rose, & Chorus, 2017). However, for the construction of these designs, prior parameter estimates are needed as input. Then, the degree of efficiency of the final design depends on the accuracy of these priors. Rose and Bliemer (2014) provide an overview of the state-of-the-art of efficient discrete choice experimental designs. However, they also conclude, based on a literature review, that little consensus exists yet as to what specific experimental design theory, or aspects thereof, are appropriate for discrete choice experiment studies.

Choice task and data collection

After constructing the hypothetical alternatives, one needs to decide on the manner of assigning the profiles to choice sets. A general approach is to randomly select the choice alternatives to place them in the sets. However, this approach will not work when alternative specific attributes are used, meaning that some attributes and/or levels differ across alternatives (e.g., Huybers, 2005; Lancsar & Louviere, 2008). Then, a design is necessary that also guarantees orthogonality between the alternatives in a choice set. Fig. 1 shows an example of a choice set that is presented to respondents in an online survey and includes

	Hotel		Airbnb		Neither
	Hotel room type	Apartment room (with private small kitchenette and private bathroom)	**Airbnb room type**	Entirely private apartment	
	Price difference	15% more expensive than Airbnb	**Household amenities**	No extra amenities	
	Online review score (1 - 10)	6	**Number of reviews**	10 online reviews of which majority positive	
	Breakfast	Free breakfast	**Check-in convenience**	Check in after 15:00. Check out before 12:00	
	Hotel type	Boutique style hotel	**Promotional material**	Abundant and clear pictures of the entire accommodation	
	Location	Near the central train station	**Location**	Near tourist attractions	
Please choose an accommodation for:					
A city trip with **1** other adult	O		O		O
A city trip with **5** other adults	O		O		O

Fig. 1. Example of a choice set (Trepels, 2018).

two alternative specific accommodation options with different attributes: a hotel and an Airbnb alternative. The respondents were requested to choose the accommodation option they would prefer for a city trip with one other adult and for a trip with a travel party of five adults (Trepels, 2018). Asking respondents to choose between pairs (or among triplets) of alternatives in one set and including a non-choice option leads to a quite natural task for the respondents.

The number of choice sets presented to each individual will depend on the size of the design and the strategy employed in designing the choice sets. More choice sets per respondent mean more observations, are better for reliability, and reduce data collection costs. On the other hand, presenting them with too many sets might increase the respondent burden and cause fatigue, boredom, or patronized responses, leading to unreliable results. Burgess and Street (2006) specifically tested the best choice set sizes to use to maximize the statistical efficiency of a choice experiment and concluded that it is a trade-off between gains in statistical efficiency with potential losses in respondent efficiency. A procedure called blocking can be used to split the choice sets in the experimental design into a limited number of sets for each respondent to promote response efficiency (e.g., Johnson et al., 2013). Desirable statistical properties of the experimental design (e.g., orthogonality among attribute levels), however, may not hold for individual blocks.

The choice sets including the choice alternatives need to be presented to the respondents so they can make their decisions about the alternatives they prefer in a given context. Accurate verbal descriptions can be used to present the hypothetical profiles, but also visualization techniques such as photographs or pictures can be used to present the alternatives or part of the alternatives (e.g., Karlsson, Kemperman, & Dolnicar, 2017). It might be easier for people to understand images, but if the pictures convey too much information that is not controlled for, the responses cannot be confidently associated with the attributes that are being assessed (Cherchi & Hensher, 2015). Thus, it is important to eliminate all the elements that can distract from the main focus to avoid confounding the attributes of interest with features we do not want to measure. Nowadays, with new multi-media possibilities also video and virtual reality techniques provide options to present choice situations to the respondents (e.g., Van Dongen & Timmermans, 2019).

Model estimation

Once the choice sets are presented to the respondents and their answers are collected, the model estimation can take place (see Hensher et al., 2015; Louviere et al., 2000). Random utility theory (Thurstone, 1927) forms the base and assumes that the utility for an alternative consists of a systematic or deterministic component and a random error component. The systematic component in turn depends on how individuals combine their part-worth utilities. The error component reflects inconsistencies exhibited by individuals and factors that cannot be measured or are omitted by the researcher. By making different assumptions about the distribution of the error component, a variety of probabilistic discrete choice models can be formulated. For example, Thurstone (1927) assumed a normal distribution of the random error component, which yields a probit model, while McFadden (1974) assumed a Gumbel distribution (Gumbel, 1958), which results in the multinomial logit (MNL) model. The MNL model is the most widely applied choice model to date, mainly because the probability function that can be derived from the Gumbel distribution has a closed-form solution and can be estimated relatively easily. The most important limitation of the MNL model is the Independence from Irrelevant Alternatives (IIA) property. The IIA-property is implied by the assumption of independently and identically distributed error terms and independency of the ratio of choice probabilities between two alternatives. This IIA property implies that the systematic component of the utility function is a function of only the attributes of the alternative and is independent of the existence and the attributes of all other alternatives in the choice set. This assumption may not always be desirable, especially when it is expected that the choice probabilities of alternatives may be affected by the presence and or characteristics of other alternatives in the choice set. Moreover, the MNL model does not take variation in preferences between individuals into account.

Over the years, more flexible modeling approaches have been developed (see Hensher et al., 2015; Train, 2003). The nested logit model can account for similarities between choice alternatives, by considering scale heterogeneity with a hierarchical tree-like structure linking alternatives that share common scale or error variances in one nest. Mixed logit models can be used to measure heterogeneity in attribute parameters, thus taste differences between individuals, similar alternatives in non-binary choice sets, and can include panel effects. Latent Class Models are typically used to find clusters of individuals with similar preferences.

Willingness to pay measures can be derived from the model estimates when a cost or price attribute is included in the experiment. These willingness to pay measures are, in general, obtained as the ratio between the marginal utility of the attribute and the marginal utility of the price/cost (Masiero, Heo, & Pan, 2015). A more advanced approach is to estimate the distribution of willingness to pay directly, through a re-parameterization of the model (Hensher et al., 2015; Scarpa, Thiene, & Train, 2006).

Literature selection systematic review

This paper aims to provide and discuss an overview of articles on discrete choice experiments recently published in the field of tourism research, and subsequently to give recommendations and directions for future research. To find articles on discrete choice experiments in tourism a systematic review is performed in Clarivate Analytics' Web of Science, a platform referencing to international journal articles from all fields of science (including Science Citation Index (SCI): 1945 – present; Social Sciences Citation Index (SSCI): 1956 – present; Arts & Humanities Citation Index (AHCI): 1975 – present; and Emerging Sources Citation Index (ESCI): 2015 – present), also including the major Tourism journals.

Because many articles on discrete choice experiments have been published in respected tourism journals, a selection is made of the top five tourism journals based on their current impact factor (April 2020): Tourism Management (6.01), Annals of Tourism Research (5.49), Journal of Travel Research (5.34), International journal of hospitality management (4.47), and Journal of Sustainable Tourism (3.40), to capture the state-of-the-art. Web of Science includes 5621 articles and review papers from these journals published in the period from 2010 to April 2020. As mentioned, a number of reviews articles on discrete choice experiments in tourism research have already been published (Crouch & Louviere, 2000; Hergesell et al., 2019; Louviere & Timmermans, 1990), and the aim of this paper is to complement these reviews; the focus of this systematic review is on recent developments. Therefore, articles published from 2010 onwards are selected based on the following key search words mentioned in the title, keywords or abstract: 'model & experiment', 'model & stated', 'model & conjoint', 'choice & model', 'tourist & choice', 'choice & experiment', and 'preference & experiment'. Note that very broad search words are used to ensure that all relevant articles are included. Subsequently, all these articles are screened to check whether they indeed use discrete choice experiments, and all duplicates are removed, leading to a final selection of 49 studies.

Results and discussion

The 49 articles resulting from the systematic review and their specific information are summarized in Table 1. For each article, the author(s) and year of publication, research topic, type of choice addressed, the design approach to create the hypothetical profiles (and choice sets), the modeling approach used for estimation, and specific unique contributions of the study are included the table. Most articles are published in Tourism Management (19), followed by the Journal of Travel Research (14). Not surprisingly, these journals do have a long tradition in publishing studies applying more quantitative research approaches.

Research topic and tourist choice

The research topics and tourist choices addressed in the selected articles cover a wide range from various types of destination choices: from general holiday destinations to very specific ones, such as ski, coastal, and eco-tourism destinations. Accommodation choice is also often a topic of research with eight studies focusing on hotel choice behavior specifically, and a few others addressing Airbnb and general holiday accommodation choices. Furthermore, a variety of tourist experiences and activity choices are investigated: dining experience, restaurant visit, cultural heritage site preference, vacation experience, bird watching course, cruise experience package, and wildlife conservation area and program preferences. Also, nine studies investigate tourist travel mode choices, with some specifically focusing on sustainable transport mode choices. For example, Hergesell and Dickinger (2013) investigate holiday transport mode choices among students, and Deenihan and Caulfield (2015) develop a value-based system for cycling infrastructure planning in tourist locations based on a discrete choice experiment. Length of stay or duration choices are not the main topics of choice behavior investigated, while we know it is an important choice made by tourists (e.g., Decrop & Snelders, 2004). However, length of stay or trip duration is sometimes included as an attribute in describing the hypothetical profiles or indicated in the choice task context description (e.g., Randle et al., 2019). Moreover, for describing and predicting length of stay typically different research techniques are applied, using for example revealed data or count data models (e.g., Boto-García, Baños-Pino, & Álvarez, 2019).

As the tourism industry worldwide is facing a variety of challenges related to, for example, climate change, overcrowding, disasters, and sustainability, it is of interest to see that several studies do address these topics in their discrete choice experiment

Table 1
Summary of 49 discrete choice experiment studies.

Authors	Research topic	Type of choice	Experimental design	Model[a]	Unique[b]
Adhikari, Basu, and Raj (2013)	Pricing of experience products under consumer heterogeneity	Choice of dining experience offering	Efficient design	Hierarchical Bayes method (followed by cluster analysis on part-worth scores)	WTP
Arana, Leon, Carballo, and Gil (2016)	Designing tourist information offices: the role of the human factor	Choice of service design	Bayesian efficient design	MNL, ML, LCM, GenMNL, Scaled MNL	Comparison of models
Arenoe, van der Rest, and Kattuman (2015)	Game theoretic pricing models in hotel revenue management	Choice of hotel	Choice based conjoint design	MNL	Propose integration with game theory
Bach and Burton (2017)	Proximity and animal welfare in the context of tourist interactions with habituated dolphins	2 experiments: Choice of proximity and likelihood of dolphin interaction & Choice of feeding logistics, welfare concerns and alternative activities	Fractional factorial designs	Conditional fixed effects logistic regression model	WTP
Chaminuka, Groeneveld, Selomane, and van Ierland (2012)	Tourist preferences for ecotourism in rural communities	Choice of ecotourism alternatives	Fractional factorial design	Conditional probit model	WTP
Chen et al. (2019)	Chinese outbound tourist preferences for all-Inclusive group package tours	Choice of group package tours	Efficient design	LCM	Model includes socio-demographics & consumption values
Choi, Ritchie, Papandrea, and Bennett (2010)	Economic valuation of cultural heritage sites	Choice of services at a cultural heritage site	D-optimal design	ML	WTP
Choi and Ritchie (2014)	Willingness to pay for flying carbon neutral in Australia	Choice for voluntary carbon offset	D-efficient design	RPL	WTP
Concu and Atzeni (2012)	Conflicting preferences among tourists and residents	Choice of tourist development	Fractional factorial design	RPL	
Crouch, Del Chiappa, and Perdue (2019)	International convention tourism: host city competition	Best-worst scaling task & choice of convention site	fractional factorial design	Conditional logistic regression analysis	
Deenihan and Caulfield (2015)	Tourists' value of different levels of cycling infrastructure	Choice of cycling infrastructure	Fractional factorial design	NL	Images included in hypothetical alternatives
Figini and Vici (2012)	Off-season tourists and the cultural offer of a mass-tourism destination	Choice of holiday package	Fractional factorial design	CLM	WTP
Fleischer, Tchetchik, and Toledo (2012)	The Impact of fear of flying on travelers' flight choice	Choice of flight itinerary	Fractional factorial design	ML	Fear of flying included in the model as a latent variable
Grigolon, Kemperman, and Timmermans (2012)	The influence of low-fare airlines on vacation choices of students	Choice of transport mode in the content of vacation choices	Fractional factorial design	MNL	Stated portfolio choice experiment
Hergesell and Dickinger (2013)	Environmentally friendly holiday transport mode choices among students	Choice of holiday transport mode	Fractional factorial designs	MNL & NL	The degree of environmental friendliness in attitudes and behavior is included
Jung et al. (2015)	How consumers choose where to go for dinner	Choice of restaurant	Fractional factorial design	Repeated measures logistic regression model	Consumers' willingness to trade-off gains and losses from attributes & lexicographic decision-making strategies
Karlsson et al. (2017)	May I sleep in your bed? Getting permission to book	Choice (acceptance or rejection) of an Airbnb booking request	Fractional factorial design	LCM	Hypothetical profiles include both a picture and written text
Keshavarzian and Wu (2020)	The effect of sequentially receiving airline and destination information on the choice of tourism destinations	Choice of destination	D-Efficient design	MNL	
Kim and Park (2017)	The moderating role of context in the choice for a hotel	Choice of hotel	Bayesian D-optimal	MNL & RPL	Incorporating choice context into a discrete

Table 1 *(continued)*

Authors	Research topic	Type of choice	Experimental design	Model[a]	Unique[b]
			design		choice model
Kim and Perdue (2013)	The effects of cognitive, affective, and sensory attributes on hotel choice	Choice of hotel	Bayesian D-optimal design	RPL	Includes cognitive, affective, and sensory attributes
Kim, Kim, Lee, Kim, and Hyde (2019)	The Influence of decision task on decoy and compromise effects in a travel decision	Choice of travel destination	Full factorial design	Binary logistic regression analysis	Test whether decoy and compromise effects influence travel destination decisions
Koo, Collins, Williamson, and Caponecchia (2019)	Effect of safety risk information and alternative forms of presenting on traveler decision rules in international flight choice	Choice of flight	Bayesian efficient design	Latent elimination model	WTP & Modeling elimination behavior
Koo, Wu, and Dwyer (2010)	Transport and regional dispersal of tourists	Choice of travel mode	Fractional factorial design	MNL	Trip context effects included
Kubo, Mieno, and Kuriyama (2019)	Wildlife viewing, the impact of money-back guarantees	Choice of tour participation	D-efficient design	RPL	Impact of refund mechanisms on choice & WTP
Lacher, Oh, Jodice, and Norman (2013)	The role of heritage and cultural elements in coastal tourism destination preferences	Choice of trip	D-efficient design	RPL	
Landauer, Haider, and Probstl-Haider (2014)	The Influence of culture on climate change adaptation strategies	Choice of ski destination	Fractional factorial design	MNL	Both images and text attributes used for the profiles
Landauer, Probstl, and Haider (2012)	Managing cross-country skiing destinations under the conditions of climate change	Choice of ski destination	Fractional factorial design	LCM	Perception and acceptance of adaptation strategies & images included in profiles
Lee, Lee, Kim, and Mjelde (2010)	Preferences and willingness to pay for bird-watching tour and interpretive services	Choice of bird watching course	Fractional factorial design	MNL	WTP
Liu (2017)	Testing on-site sampling correction	Choice of wildlife conservation area visit	Fractional factorial design	Truncated Poisson regression model	Model estimation with on-site sampling correction & WTP
Lyu (2017)	Accessible travel products for people with disabilities	Choice of accessible travel product	Fractional factorial design	RPL	WTP
Mahadevan and Chang (2017)	Valuing shipscape influence to maximize a cruise experience	Choice of cruise experience package	D-efficient design	RPL	WTP & segmentation based on life stage and attitudes
Masiero et al. (2015)	Determining guests' willingness to pay for hotel room attributes	Choice of hotel room	Efficient design	ML	WTP
Masiero and Nicolau (2012)	Tourism market segmentation based on price sensitivity	Choice of tourist cards	Fractional factorial design	ML (followed by cluster analysis on the individual parameters)	Includes price sensitivities
Masiero, Pan, and Heo (2016)	Asymmetric preference in hotel room choice and implications on revenue management	Choice of hotel room	Efficient design	ML (followed by cluster analysis on individual parameters)	Includes reference-dependent behavior
Masiero and Qiu (2018)	Modeling reference experience in destination choice	Choice of destination	Efficient design	ML	Includes the concept of reference-dependent behavior
Masiero et al. (2019)	Hotel location preference of customers, comparing random utility and random regret decision rules	Choice of hotel location	Efficient design	MNL & ML	Comparing random utility and random regret decision rules & WTP
Mathies, Gudergan, and Wang (2013)	The effects of customer-centric marketing and revenue management on travelers' choices	Choice of airline & hotel	Combination of full factorial designs	LCM with reference-dependent fairness effects	Specific travel context included & WTP
Mejia and Brandt (2017)	Utilizing environmental information and pricing strategies to reduce	Choice of trip	Fractional factorial design	RPL	Includes the impact of additional trip information & WTP

(continued on next page)

Table 1 *(continued)*

Authors	Research topic	Type of choice	Experimental design	Model[a]	Unique[b]
	externalities of tourism				
Olmsted, Honey-Roses, Satterfield, and Chan (2020)	Leveraging support for conservation from ecotourists, the role of relational values	Choice of conservation program	Fractional factorial design	ML	WTP
Oppewal, Huybers, and Crouch (2015)	Tourist destination and experience choice, decision sequence effects	Choice of holiday destination & experience	Combinations of design strategies	MNL	2 experiments to measure decision sequence effects
Randle et al. (2019)	The role of cause-related corporate social responsibility (CSR) in accommodation choice	Choice of holiday accommodation	Fractional factorial design	LCM	
Roman and Martin (2016)	Hotel attributes, asymmetries in guest payments and gains	Choice of hotel	Fractional factorial design	Panel ML (estimated in preference and WTP/WTA space)	Reference dependent utility function & WTP & WTA
Sarman, Scagnolari, and Maggi (2016)	Acceptance of life-threatening hazards among young tourists	Choice of holiday	D-efficient design	Hybrid choice model	
Scuttari, Orsi, and Bassani (2019)	Assessing the tourism-traffic paradox in mountain destinations	Choice of transport option	Fractional factorial design	NL	Simulations based on management strategies
Seekamp, Jurjonas, and Bitsura--Meszaros (2019)	Influences on coastal tourism demand and substitution behaviors from climate change impacts and hazard recovery responses	Choice of trip	Full factorial design	CA	The impact of potential coastal hazards on trip choice
Tyrrell, Paris, and Biaett (2013)	A quantified triple bottom line for tourism	Choice of business (contribution to community)	Fractional factorial design	CA	
van Cranenburgh, Chorus, and van Wee (2014)	A stated preference of revealed preference approach for vacation behavior under high travel cost conditions	Portfolio choice of vacation destination, length of stay, accommodation & transport	Pivoted experimental design	Error component portfolio choice model using generalized SP-off-RP estimation procedures	A stated preference of revealed preference choice experiment
Walters, Wallin, and Hartley (2019)	The threat of terrorism and tourist choice behavior	Choice of travel package	Fractional factorial design	RPL	
Westerberg, Jacobsen, and Lifran (2013)	The case for offshore wind farms, artificial reefs and sustainable tourism	Choice of offshore wind farms	D-efficient design	LCM	Both text and images used in profiles, WTP & WTA

[a] CLM = conditional logit model; GenMNL = generalized multinomial logit model; MNL = multinomial logit model; ML = mixed logit model; NL = nested logit model; LCM = Latent Class Model; RPL = random parameter logit model; CA = conjoint analysis.
[b] WTP = willingness to pay; WTA = willingness to accept.

studies. Walters et al. (2019) investigate tourist travel choices as the threat of terrorism increases. Seekamp et al. (2019) model the influence of climate change impacts and hazard recovery responses to coastal tourism demand. Also, Sarman et al. (2016) focus on life-threatening hazards, but then the acceptance among young tourists. Some studies focus on the support of tourists for conservation strategies (Mejia & Brandt, 2017; Olmsted et al., 2020). These studies show that discrete choice experiments seem a good approach to model preferences and provide information for still to be implemented environmental tourism-related planning and policy drivers and strategies.

In the studies reviewed still limited attention is paid to the impact of technology related changes the tourism industry is facing and to the impact of intelligent systems in tourism (Gretzel, 2011; Tussyadiah, 2020). An exception is a study by Arana et al. (2016) who evaluate the preferences of visitors for tourist information services, specifically whether they prefer personal interaction or through automated processes based on new technology. They conclude that personal interaction continues to be an important element, but new technology may increase the quality of the provision of services and visitor satisfaction. Further research on the preferences for and acceptance of new technological innovations in tourism such as service robots (Murphy, Gretzel, & Pesonen, 2019), using discrete choice experiments, is an interesting direction for future research. Especially as the method supports measuring preferences for still to be developed products and services that are yet not available in the market.

Single versus combined choices

No matter the choice topic under investigation, we see that most studies reviewed focus on single choices, and only a few authors investigate multiple decisions made by tourists or more complex tourist decision making processes (Grigolon et al., 2012; Oppewal et al., 2015; van Cranenburgh et al., 2014). As discussed by Grigolon et al. (2012) portfolio choices (i.e. the choice of multiple facets making up a choice alternative) do present a challenge in discrete choice experiments. Standard experimental designs typically involve single-faceted profiles. Combined choices or portfolios increase the number of possible combinations of attribute levels exponentially and therefore the construction of a feasible, realistic, and not too demanding experimental design offers a challenge. Or, for example in the case of a vacation planning process, multiple choices are developed over time, and they do influence each other. The choice for a specific nature of activities or the choice for a specific transport mode may limit the choice for a possible destination. Consequently, the estimation of the parameters of a portfolio choice model offers a challenge. Moreover, it often means a challenging and complex choice task for the respondents involved.

Hergesell et al. (2019) discuss several strategies to manage these problems. One approach is to limit the number of attributes across sub-decisions. Another strategy is to focus on the sub-decision of interest and keep the decision components, which are not of primary interest, fixed in the experimental task (e.g., Dellaert, Ettema, & Lindh, 1998). The study by Grigolon et al. (2012) develops a portfolio model of vacation choices concerning the combined choice of destination type, transport mode, duration, accommodation, and travel party for vacations. The attributes of the transport modes are systematically varied in the experiment, while respondents are faced with three options for the other choice facets.

Oppewal et al. (2015) examine the combination of travel motives and destination choices. It is tested whether early exposure to geographical destination or experience type information in a decision task influences consumers' final choices when choosing a holiday. The study compares two choice tasks that have the same instructions and attributes but differ with respect to which attribute is exposed first and is used to label the choice options: the destination name or the experience type. The results show that sequential effects can be very important in shaping tourist decision-making.

Another approach is developed by van Cranenburgh et al. (2014), a portfolio choice model based on a stated preference of revealed preference (SP-off-RP) choice experiment. They assume that a vacation decision is a combination of destination, length of stay, accommodation type, mode of travel, and associated travel cost and travel time choices. The key idea behind the portfolio choice model is that the utility of a vacation portfolio is a function of the structural components (the principle attributes) plus additional portions of utility that come from specific combinations of these structural components (interaction effects). Their experiment first asks respondents to compose six alternatives that they consider for a given vacation period. Then, in the stated preference part, alternatives are constructed by pivoting of the revealed preference alternatives. All attributes are varied except for the destinations. Therefore, the stated choice tasks only consist of destinations that are considered by the decision-maker, making it more realistic.

An interesting modeling approach that needs to be mentioned in the context of portfolio tourist decision making is the Multiple Discrete-Continuous Extreme Value (MDCEV) model developed by Bhat (2005). In short, the model can be applied to analyze both discretionary choices and time allocation/duration decisions simultaneously. He uses the model for the analysis of a choice situation where an individual chooses the type of leisure activity to participate in and the duration of the participation. An example in the tourism context is a study by Rashidi and Koo (2016) who use a multinomial discrete-continuous model to analyze the interrelationships between tourist travel party choice, travel mode choice, and expenditure decisions.

To conclude, in line with Hergesell et al. (2019), still a limited number of studies investigate tourist choices in combination or sequence or relation to each other, although it is widely accepted in the literature that they are interrelated in some way. As a separate analysis of each choice dimension may be misleading (Dellaert, Borgers, & Timmermans, 1997), researchers must find a balance between focusing on one choice dimension at a time and making the choice task not too complex for respondents and on the other hand, presenting them with realistic scenarios. Using advanced modeling approaches, such as the MDCEV model, in combination with choice experiments might also be an interesting research avenue to investigate interrelated tourist choices.

Experimental setting

The experimental design refers to the process of generating the hypothetical profiles consisting of specific combinations of the attributes and their levels that the respondents evaluate in a choice task. The choice of experimental design is an important step in setting up a discrete choice experiment as it needs to be in line with the research objectives and the modeling approach selected and it needs to lead to accurate collected information and reliable parameter estimates (Bliemer & Rose, 2011; Johnson et al., 2013).

Over half of the studies presented in Table 1 use a common orthogonal fractional factorial design to create the hypothetical profiles of interest and a few studies apply a full factorial design. Efficient design strategies (e.g., Bayesian efficient design, D-optimal design) are used as well in one-third of the studies to generate the profiles (and choice sets). This is similar to other fields of research, where the use of efficient designs is growing within the literature, although remaining in the minority (Bliemer & Rose, 2011). In studies using an efficient design, a two-step approach is required with first a pilot study or pre-test data (or a previous study) to be able to find parameter estimates for the attributes that can subsequently be used as informative priors for the construction of the efficient/optimal design used for the creation of the profiles (and choice sets) for the main study.

The question is whether the use of an efficient design provides, in the end, better results. Bliemer and Rose (2011) prove that D-efficient designs result in lower standard errors in estimation, and require smaller sample sizes, compared to the more traditional orthogonal designs. However, the prediction quality depends on the accuracy of the parameter priors that are needed to generate efficient designs, showing the relevance of the pilot studies. To conclude, it would be of interest to see more efficient design strategies used and/or evaluated in tourism research, specifically in studies dealing with small sample sizes.

The attribute profiles are, in most studies investigated in this review, presented in a verbal way to the respondents. Only five studies explicitly mention the use of visual information for the presentation of the profiles in the choice sets. For example, Landauer, Haider, and Probstl-Haider (2014) use both images and text attributes in describing ski destinations. The benefits of visual information are that it provides greater realism in tasks and improves the reliability and validity of the discrete choice responses because it helps the respondents in constructing and maintaining vivid representations of alternatives in their memory (Arentze, Borgers, Timmermans, & DelMistro, 2003; Patterson, Darbania, Rezaeia, Zacharias, & Yazdizadeha, 2017). A drawback is that unintended information might affect respondent choices; constructing visual profiles without adding extra information except for the attributes is a difficult task.

Arentze et al. (2003) test, in another field of research, different presentation formats within a discrete choice experiment, and conclude that the presentation method has no significant impacts while task complexity does have significant effects on data quality. Patterson et al. (2017) found that a virtual reality platform appears to have better-focused respondent attention, but visual attributes do not gain importance relative to text-only attributes. They conclude that using the advantages of a virtual reality environment with well-integrated verbal information might lead to the best results as it can help respondents to concentrate and prevents the visual elements from taking on greater importance. In addition, Jansen, Boumeester, Coolen, Goetgeluk, and Molin (2009) conclude that when including visual elements in a discrete choice task, it is of utmost importance to make sure that all potentially disturbing details are cleared away. Moreover, Cherchi and Hensher (2015) suggest that given the rapid technological developments such as eye-tracking, virtual reality, and simulators, an important direction is given to improve the use of images in discrete choice experiments.

Vass, Rigby, Tate, Stewart, and Payne (2018) suggest, based on an exploratory study in a medical context, that eye-tracking could be used as a method to identify how respondents complete a discrete choice experiment and reveal information on their choice strategies. They conclude that eye-tracking is a promising method to understand more about how respondents view the choice task and identify different decision-making strategies when different formats are used to present the survey. An example of eye-tracking in tourism research is the study by Li, Chen, Wang, and Liu (2020) who test children's attention toward cartoon executed photos in an experimental setting using eye-tracking.

To conclude, specifically, in a tourism context where tourists often lack knowledge or a realistic image about a specific destination/service it might be of interest to present them with more visual, virtual reality, or interactive choice scenarios and measure their reactions in different ways. Then, it is also important to test the effect of various presentation formats.

Modeling approaches

In terms of the modeling approach, we see in Table 1 that about a quarter of the studies apply the basic Multinomial Logit (MNL) model (note that while a MNL model is strictly not the same as a conditional logit model, the two approaches are often used interchangeably in the literature). Seven studies apply some kind of segmentation modeling approach (e.g., Latent Class Model), and half of the studies use a mixed logit (ML)/random parameters logit (RPL) model. Thus, a large part of the studies results in the estimation of individual or group preferences instead of the estimation of the mean preference of the entire group of respondents (in case of MNL model estimation). Identification of individuals or groups with different preferences has a clear advantage for successfully marketing tourist destinations or services or for implementing tourism-related strategies and policies. Also, of interest to notice is that about one-third of the studies calculate some kind of willingness to pay (WTP) measure; an important indicator for the tourism industry. However, they in general measure willingness to pay by calculating the ratio between the marginal utility of the attribute and the marginal utility of the price/cost instead of applying the more appealing alternative method of obtaining an estimate of willingness to pay by reparametrizing the model to estimate the parameters in the willingness to pay space (Hensher et al., 2015).

Most of the modeling approaches described in the reviewed studies are based on random utility maximization (McFadden, 1974; Thurstone, 1927) as this has traditionally formed the basis for discrete choice experiments. The idea behind it is that people generally choose their most preferred alternative and where they do not, this is explained by random factors. The underlying decision-making process is unknown, and the utility maximization paradigm is likely to be only an approximation to the real decision process used. Realizing that decisions we make, including tourist choices, vary in terms of complexity, their importance, and consequences, the amount of effort that is spent on processing and valuing the information required for decision making and the uncertainty that is involved, it seems realistic to acknowledge that decisions are context-dependent (e.g., McCabe, Li, & Chen, 2016; Pan, Rasouli, & Timmermans, 2019). Hess, Daly, and Batley (2018) address in detail the question of what departures from the traditional paradigm may be necessary or wise to accommodate richer behavioral patterns. They provide an overview of alternative behavioral approaches and discuss their consistency with random utility maximization and their practicability for calculating willingness to pay. Also, in the tourism papers reviewed we see some recent studies testing some of these alternative approaches.

First, Masiero and Qiu (2018) propose the integration of tourists' past reference experiences into a model for long-haul destination choice. By analyzing the preference of tourists regarding various attributes of a tourist destination, this study consolidates the concept of reference-dependent behavior in the context of tourist destination choice and introduces the concept of reference-level bias. Mathies et al. (2013) examine how the simultaneous use of customer-centric marketing and revenue management affects travelers' perceptions of fairness and ultimately their purchasing choices. They propose and empirically test a choice model that incorporates reference-dependent fairness adjustments for both price and nonprice attributes but within a random utility framework. Roman and Martin (2016) report about the existence of asymmetries in the preference formation of potential guests regarding their perception of hotel attributes and confirm that similar asymmetries exist in their willingness to pay measures based on the valuation of losses or gains. They conclude that the specification of a reference-dependent utility function allows for the application of prospect theory to an analysis of choices made by consumers when they evaluate attributes that define hotel service quality. Prospect theory (Kahneman & Tversky, 1979) assumes that losses and gains are valued differently, and it demonstrates that people think in terms of expected utility relative to a reference point rather than absolute outcomes.

The study by Jung et al. (2015) investigates compensatory and non-compensatory decision-making strategies of consumers in restaurant choice settings under competing options of quality and price. Specifically, they test for lexicographic decision making, meaning that if two products are equal on the most important attribute, the consumer moves to the next most important, and, if still equal, to the next most important one. They conclude that approximately a quarter of the respondents show lexicographic decision making and suggest that profiling these consumers may be an important but difficult task. Koo et al. (2019) develop a latent elimination choice model to examine how travelers respond to different levels of safety risk in making decisions about flight choices. They find a pattern of eliminatory and compensatory decision-mix where travelers have varying thresholds of risk acceptance. Below this threshold, the options are eliminated, whereas above the threshold the safety attribute can be traded off with other flight attributes. They conclude that the latent elimination choice model can be used for retrieving elimination behavior in an information-rich online decision context that characterizes many tourism choices, including understanding how travelers respond to destination safety risk information.

Masiero et al. (2019) investigate customer preference toward various hotel location attributes comparing the well-established utility-based decision rule with a regret-based decision rule. They conclude that the two decision rules investigated in the study provide similar estimation results with regard to the significance of the estimated coefficients of different factors, although the random regret minimization model performs significantly better than the random utility maximization model. Random regret minimization (Chorus, 2010) seems the most accepted alternative for random utility maximization. Chorus, van Cranenburgh, and Dekker (2014) review 43 studies and compare their performance using random utility maximization and random regret minimization and conclude that in terms of model fit either one or the other model is statistically preferred over the other. However, they find that differences are nearly always small. Also, Hess et al. (2018) conclude that many, though not all, of the behavioral approaches discussed in the literature, can be approximated sufficiently closely by a random utility framework, allowing researchers to retain the many advantages that the random utility approach possesses. But of course, much more research is needed, also within the tourism context, to test more of these alternative approaches.

Another type of model that has been developed as an extension of discrete choice models in an attempt to represent a behaviorally more realistic choice process is the so-called hybrid choice model (Abou-Zeid & Ben-Akiva, 2014; Kim, Rasouli, & Timmermans, 2014). A hybrid choice model incorporates a latent variable model into a discrete choice model to improve the explanatory power of the choice model by considering the effects of decision-makers' latent attitudes (Kim et al., 2014). Only one of the studies in Table 1 estimates a hybrid choice model: Sarman et al. (2016) apply a discrete choice experiment and adopt an integrated choice and latent variable model to analyze the impact of potentially life-threatening events at a destination on the decision to undertake a leisure trip. The results show how different hazards, their potential magnitude, and respondents' risk perception influence decisions. As in tourism research, it is often argued that motivations, attitudes, needs, perceptions, beliefs, and values are important factors influencing the choice process (McCabe et al., 2016), this hybrid choice model provides an interesting approach to include and test the influence of these factors in tourist decision making in a variety of contexts.

A stream of research that also deserves attention, but unfortunately none of the reviewed papers has explicitly included this in their research, is the integration of social context, meaning the process of having one's behavior be affected by others, into discrete choice experiments. In the field of transportation, there is an emerging stream focusing on social influence as an additional explanatory source in understanding people's activity-travel decisions. For example, Manessa, Cirilloa, and Dugundji (2015) discuss the incorporation of social influence in travel behavior using discrete choice models. Another study by Pan et al. (2019), also published in the field of transportation research but with a tourism context, provides an interesting example as well. They introduce a model that captures the effect of social influence on tourists' choice behavior in the context of city trips. They use a sequential stated adaptation experiment, and by transforming the choice set of the second-choice stage, social influence is made a function of tourist's socio-demographic and personality traits, social network type as well as the relationship between the tourist and a member of his/her social network. Specifically, in tourism research, where sharing experiences with others, word of mouth information, social media such as online reviews and social influencers, are more and more important, including the influence of someone's social network, colleagues, peers, and family members in predicting outcomes of decision making is a promising avenue of future research.

Finally, a factor that is argued to influence tourist decision making and should be of interest to include in discrete choice experiments are individual needs. Dekker, Hess, Arentze, and Chorus (2014) highlight that leisure trips and related decisions regarding trip destinations are determined by more than personal characteristics and preferences, and they specifically focus on individual needs and related satisfaction as driving factors behind choices for leisure activities. The idea is that individuals' preferences may depend on needs, and needs are conceptualized as an inherently dynamic factor developing over time (Arentze, 2015). The preference for a tourist destination/product or service generally is assumed to be stable over time, while needs, such as the need for new experiences, relaxation, being in the open air, or social contact, are dynamic by nature and give rise to saturation effects and variety-seeking behavior (Arentze & Timmermans, 2009). Arentze, Kemperman, and Aksenov (2018) predict city trip activities and take into account a multi-attribute utility function of points of interest as well as dynamic needs of the tourist on a trip. A discrete choice experiment is designed where the current need is manipulated as a context variable and activity choice alternatives are varied. A latent-class analysis shows that significant differences exist between tourists in terms of how they make the trade-offs between the factors and respond to needs.

Conclusion

Discrete choice experiments have, over the years, proven to be a very fruitful technique to describe and predict a variety of tourist choices, including, destination choice, travel mode choice, accommodation choice, and activity choices. Discrete choice experiments aim at understanding and predicting individuals' preference and choice behavior and provide quantitative measures of the relative importance of the characteristics and drivers of tourism destinations, products, or services. Important is that it supports forecasts of future demand for new products, destinations, services, and might include tourists' willingness to pay for various products or services. Moreover, the impact of different (future) marketing, managerial, and planning initiatives and strategies on individual or group preferences and choices can be simulated to optimize tourist experiences.

In the past, a number of reviews of discrete choice experiment studies in leisure and tourism research have been published (Crouch & Louviere, 2000; Hergesell et al., 2019; Louviere & Timmermans, 1990). This study builds upon them by a systematic review of all 49 journal articles on discrete choice experiments in tourism, published in the top five tourism journals in the period 2010 - April 2020. The findings of the review show that discrete choice experiments are applied to explain and predict a variety of tourist choices, covering a wide range of application areas. As we see that the tourism industry worldwide is facing several developments and challenges, including overcrowding, sustainability, and climate change, applying this technique to measure tourists' preferences and choices for new solutions and strategies to handle these problems seems like a promising approach. Also, as we see that technological advances and developments are changing the way we travel and promise a more interactive and exciting tourist experience, discrete choice experiments might provide insight into the preferences and acceptance of tourists for these new technologies (before they are implemented), and how much tourists are willing to pay for these improvements.

Another aspect of these rapid technological developments is that it also supports and improves the use of virtual reality, simulators and eye-tracking in discrete choice experiments. Specifically, because tourists often are not familiar with a specific destination/service presenting them with more visual, virtual reality or interactive choice scenarios might be of interest to better measure their preferences and choice behavior.

Although discrete choice experiments have been applied successfully in many different contexts, the most important critique is that it does explain the output of individual choices and preferences but does not address the underlying decision-making process. While it seems realistic to assume that tourist decision-making processes might vary and are context-dependent. Therefore, it is of interest to see that in recent years, also in the field of tourism research, several studies tackled some of these issues. For example, tourists' decisions relative to past experiences are investigated, more complex decision strategies and processes are addressed, including needs, motivations, and influences of a social network. The hybrid choice model, which incorporates latent attitude variables, also provides an interesting approach to improve the explanatory power of a choice model in a variety of contexts. To conclude, there is a challenge for more research and evidence to progress the use of discrete choice experiments in tourism research and improve our knowledge of tourist preference and choice behavior.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Astrid Kemperman is an Associate Professor of Urban Planning & Quality of Life at Eindhoven University of Technology. Her area of expertise focuses on smart urban environments to promote healthy living and well-being. She investigates how technological devices, systems and spatial environments can be integrated most effectively to support tourists' and residents' activity patterns. Research topics also include the development of smart tourist and leisure activity systems.