Tourist Choice Processing: Evaluating Decision Rules and Methods of their Measurement

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ABSTRACT

A detailed understanding of decision rules is essential in order to better explain consumption behaviour, yet the variety of decision rules used have been somewhat neglected in tourism research. This study adopts an innovative method, greedoid analysis, to estimate a non-compensatory type of decision rule known as lexicographic by aspect [LBA]. It is quite different from the weighted additive [WADD] model commonly assumed in tourism studies. By utilizing an experimental research design, this study enables the evaluation of the two types of decision rules regarding their predictive and explanatory power. Additionally, we introduce a novel evaluation indicator ('cost'), which allows further investigation of the heterogeneity in the use of decision rules. The results suggest that although the out-of-sample accuracy is lower, the LBA model has a better explanatory performance on respondents' preference order. Moreover, the different perspective provided by the LBA model is useful for obtaining managerial implications.

Keywords: *Tourist decision making, destination choice measurement, non-compensatory methods, greedoid analysis, China outbound market.*

INTRODUCTION

As one of the cornerstones of tourism research, a great number of studies can be found investigating and theorizing tourism decision making, providing valuable insights about consumer processes. Recent reviews however, reveal two fundamental problems regarding the body of knowledge established so far. Firstly, most of the theory developed in this area has been based on a variance perspective, which focuses only on the decisions made, at the expense of understanding the processes by which decisions are reached, and this has constrained theory building in relation to tourism consumer behaviour (Smallman and Moore 2010). Secondly, among the studies exploring how tourists choose destinations (e.g. Papatheodorou 2001; Seddighi and Theocharous 2002), a single type of decision rule, the weighted additive model [WADD], is always implied. The result is that other types of possible decision rules have been largely overlooked (McCabe, Li, and Chen 2016).

The WADD model has its roots in the theory of ecological rationality, which assumes that decision makers are able and willing to make comprehensive trade-off evaluations, which allow the disadvantage of certain attributes to be compensated by the advantage of other attributes. The alternative with the highest summed-up utility will always be chosen (Araña and León 2009). However, the general applicability of the WADD model is questionable. For instance, due to cognitive limitations, consumers have been shown to use simplified rules, based on non-compensatory preferences (i.e. complex trade-off evaluation does not occur) in order to make judgements and decisions quickly and efficiently (Yee, Dahan, Hauser and

Orlin 2007). Alternative models do exist, for example, the lexicographic model is a very prominent type of multi-attribute decision rule, whose existence has been widely acknowledged in behavioural and consumer research (e.g. Svenson 1979; Yee et al. 2007; Dieckmann, Dippold and Dietrich 2009).

In contrast to the comprehensive weighing process of attributes assumed by the WADD model, the lexicographic model proposes that decision makers evaluate alternatives based on the most important attribute. If there are ties between choices on this attribute, the decision maker moves to the second important attribute and so on. Although the final choice may not be the alternative with the highest utility, the evaluation process requires much less time and effort than that presupposed by the WADD model. When the attributes are binary variables or categorical variables (which is the case of our research), the lexicographic rule is known as the Lexicographic by aspect [LBA] model. Apparently, the type of decision rule applied can make a substantial difference to what is chosen (Sen 1997) and different decision rules provide different perspectives to explain preference ordering, and this can also be applied to tourist decisions. Therefore, it is appropriate to explore possibilities of different decision rules to enrich the body of knowledge in tourism decision making.

Beyond the field of tourism, choice theory is a well-established aspect of buyer decision research. Yet empirical studies on decision rules remain sparse across disciplines and contexts, largely because the concept has been deemed rather opaque. The abstract nature of the problem requires advanced methods of analysis that are able to approximate the relevant mental processes, and these have only recently been developed. Additionally, the use of decision rules is likely to vary according to different people and different contexts (Crompton 1992; Crompton and Ankomah 1993). In order to investigate the heterogeneity in the use of different decision rules, a range of estimation methods together with evaluation indicators will need to be developed and deployed (McCabe, Li, and Chen 2016).

However, excepting a single article (Decrop and Kozak 2009) which briefly discussed the possible kinds of decision rules, hardly any empirical research can be found to infer different decision rules used in tourism destination choice, let alone to evaluate their performance and suitability. Above all, this study aims to contribute to the body of (tourism) decision making research in the following ways: to apply an alternate perspective to the conventional WADD model to understand the process of destination choice; to introduce an innovative method (geedoid method) to approximate the high probability that the LBA decision rule is adopted by tourists; and to explore a new indicator for evaluating the different models (WADD vs. LBA).

THEORETICAL BACKGROUND

How does a tourist choose a destination?

Among so many alternative destinations, how does a tourist decide on one in particular? The mental processes underlying decision making are known as decision rules, and in relation to destination choice can be complex, and as such have been the subject of research for decades (e.g. Woodside and Lysonski 1989; Um and Crompton 1990; Mansfield 1992; Seddighi and Theocharous 2002; Nicolau and Mas 2005, 2008; Grigolon, Kemperman and Timmermans 2013). Tourists selecting a destination will necessarily resort to a certain rule (perhaps unconsciously), to make comparisons consistent, to work out their preference order among the alternatives and eventually to make a final choice. Although theoretically, tourists may evaluate destinations in a holistic sense (Decrop and Kozak 2009), often they do not derive utility by possessing or using travel destinations as a whole, but by consuming destination related attributes such as transport, accommodation or attractions (Morley 1992; Tussyadiah, Kono and Morisugi 2006). Although decision making is also influenced by contextual factors (e.g. travel companion), the attributes serve as evaluation instruments to attain different outcomes in the choice (Dellaert, Arentze and Horeni 2014). To keep the research focused, this study refers to decision rules as the ways that destination-related attributes are considered and evaluated to reach a final choice among alternatives.

Multi-attribute evaluation rules are usually classified as either being compensatory or non-compensatory (Harte and Koele 2001). If values on different attributes can be traded off against one another (i.e. perceived negative value of one attribute can be compensated by positive values of other attributes), the rule is said to be compensatory. Otherwise, the rules are non-compensatory (Abelson and Levi 1985). The WADD model is a typical compensatory decision rule which assumes decision makers would weigh each attribute he/she considers and assign a part-worth utility value to each attribute aspect based on their judgement and then select a destination with the highest utility (Wright 1975).

For example, let us assume price level and temperatures are the two attributes considered by a tourist. There are two destinations: destination A with temperature at 20 degree (7) and price level at 13000 (3) and destination B (temperature at 30 degree (2), price level at 9000 (4). The part-worth utilities assigned by this tourist for the attribute aspects are 7, 3, 2 and 4. Thus, destination A with a utility score of 10 (7+3) is preferred over destination B with a utility score of 6 (2+4). As the numbers of destinations and attributes increase, compensatory rules, especially the WADD model, demand complex cognitive processing on the part of the decision-maker (Crompton and Ankomah 1993). The issue of information overload is becoming ever more pertinent in the current digital and globalised era (McCabe, Li and Chen 2016). Thus comprehensive information search and complex problem-solving may be substituted by decision rules which require less intensive information processing (Hyde 2008).

Additionally, due to the intangibility of tourism products, destination choice may sometimes be based less on objective criteria and more on desired experience or impressions about places (Smallman and Moore 2010). These attributes are associated with emotions rather than cognitive processing, implying that the absence of a certain attribute may generate sufficient negative emotion for tourists to avoid using a compensatory strategy (Araña and León 2009). For instance, the idea of trading off an attribute such as the safety of a destination against other attributes can provoke significant negative emotions (Drolet and Luce 2004). These characteristics make the arena of destination choice a promising context to investigate the use of simpler non-compensatory rules. The literature distinguishes between three classic types of non-compensatory decision rules: conjunctive, disjunctive and lexicographic (Abelson and Levi 1985; Bettman, Johnson and Payne 1991).

The conjunctive rule is also called the satisficing strategy (Rossi and Allenby 2003). It assumes that decision-makers define minimum cut-off points for several important attributes. If an alternative falls below any of the cut-off points, it is rejected. In a tourism context, a destination would be selected only if minimum cut-off points on all important attributes are exceeded. The disjunctive rule also requires a set of cut-off points on the attributes. In contrast to the conjunctive rule, an alternative may be accepted when it has at least one value greater than the corresponding cut-off. The disjunctive rule is often used to screen a wide range of alternatives to generate a smaller, more manageable consideration set in which each alternative surpasses a threshold on at least one criterion. These two types of rules do not require any ranking or weighting of attributes by the decision-maker.

However, in many decision making contexts, the evaluation attributes considered by decision makers are not equally important. When attributes are rank ordered in importance, they are said to be in lexicographic order (Laroche and Kim 2003). The lexicographic model proposes that individuals compare attributes amongst alternatives in a stepwise fashion (Crompton and Ankomah 1993). When the attributes presented are binary or categorical variables such as the mode of transport (the aspect can be 'bus', 'plane', 'car', etc.) used to reach the destination, the process is known as the lexicographic by aspect (LBA). According to the LBA model, a decision-maker starts with the most important attribute, and only the alternatives possessing the desired attribute aspect are selected for further consideration. When there are ties, the comparison process is continued based on the second most important attribute aspect. This is repeated until all alternative destinations have been sorted, and the top-ranked destination is the final choice. The hierarchical order of these aspects that decision makers use to make the selection is termed the *'aspect order'*. In a recent theoretical paper on tourism decision making, it was argued that when faced with the complex travel decision problems, this kind of structured hierarchical approach of mental representation is usually adopted by tourists (Dellaert et al. 2014).

According to Sen (2003), different decision rules reflect different selection preferences, which often lead to different choices. The WADD rule is usually adopted to identify the most attractive combinations of attribute aspects, which emphasizes the compensatory relationships among different attributes, whilst the LBA model focuses on the hierarchical order of the attribute aspects in terms of their importance, which reflects potential non-negotiable preference patterns of decision makers. Therefore, the investigation of the decision rules applied is fundamental for us to get a better insight into tourists' preferences.

In addition, it is evident that decision rules differ in terms of how much effort they require (Bettman et al. 1991). Tourists using a lexicographic decision rule make less effort in sorting information than those using a WADD rule. In certain contexts (e.g. time poverty, emotionally involved), tourists may tend to adopt simplifying decision rules (Araña, León and Hanemann 2008). In this research, the data were obtained from Chinese long-haul (outside Asia) outbound tourists since most are first-time tourists (Li, Meng, Uysal and Mihalik 2013). They have limited knowledge of long-haul alternative destinations to make a comprehensive compensatory evaluation, which implies a promising context in which the non-compensatory decision rule may be adopted. Besides, unlike the short-haul market, this group of long-haul tourists has not been studied comprehensively in previous research. The issues considered by this market may be different from their short-haul counterparts such as their concerns regarding visa application processes (Lai, Li, and Harrill 2013). Thus the findings of this study contribute to our understanding of an important emerging market in addition to choice processing.

How to estimate tourists' destination choice?

In decision making studies, various methods can be found for multi-attribute choice investigation. One type of method consists of qualitative techniques only focusing on tracing the train of thought leading to a final decision, such as the information display board, verbal protocol analysis (Harte and Koele 2001) and causal network elicitation technique (Dellaert et al. 2014). By observing (e.g. information display board) or asking the subject to think aloud (e.g. verbal protocol analysis) while performing the evaluation task (Araña and León 2009), researchers are able to speculate the type of decision rules applied or to construct the mental representation of respondents. These qualitative methods are quite valuable for exploring the possible decision rules applied and making a general inference. However these techniques suffer from the disadvantages of being time consuming, containing inconsistencies of judgement (Harte and Koele 2001) and social desirability bias (Dellaert et al. 2014). Thus further quantitative estimation is required for more objective and accurate inference of the existence or model fit of certain decision rule(s).

The other type of methods include the AHP analysis (Analytic Hierarchy Process) (e.g. Hsu, Tsai, and Wu 2009), conjoint analysis (e.g. Ciná 2012) and discrete choice experiments (DCEs) based on quantitative data utilizing various logit regressions (e.g. Papatheodorou 2001; Seddighi and Theocharous 2002; Grigolon, et al. 2013) . These methods serve to provide insights on the actual Decision making decision making process by incorporating some simulations of reality. AHP analysis explains the decision making as a hierarchical comparison process in which the decision criteria (attributes) can be divided into several layers of sub-criteria. Conjoint analysis assumes that decision making is a selection process of attributes' combinations and can be used to determine what combination of attributes has most influence on respondent choice (Dieckmann et al. 2009). DCEs are rooted in random utility theory, which can be very similar to choice-based conjoint analysis, but are usually based on various logit regressions and emphasize the influence of contextual factors on the probability of an alternative being chosen (Louviere, Flynn and Carson 2010). Despite the fact that the methods are different in form, they all investigate the part-worth utility of attributes or attribute aspects, which implies that estimations are based on a compensatory (weighed additive) decision making process. Furthermore, these methods focusing on a single type of decision rule do not allow for further investigation on consumer heterogeneity. The existence of other types of decision rules is largely neglected in empirical tourism studies. One reason for oversight may be due to the lack of advanced estimation methods and evaluation tools.

Recently however, a new tool, called the greedoid method, has been developed to deduce non-compensatory (lexicographic) decision processes from preference data in consumer research (Yee et al. 2007, Kohli and Jedidi 2007). Although the greedoid method is not able to estimate part-worth utilities of the attributes, it is specifically designed for lexicographic decision models in which the computer deduces the aspect order through a matching procedure rather than identifying utility values of attribute aspects through regressions. It provides a possible tool to quantify lexicographic decision rules empirically (Kohli and Jedidi

2007). Therefore, this study adapted the greedoid analysis method to infer lexicographic decision rules that might be used in tourism destination choice by Chinese long-haul outbound tourists. In order to answer the key question of how powerful the LBA model can be for explaining or predicting tourists' preference, the WAAD model estimated by conjoint analysis with ordinary least squares (OLS) regression[i] was used as a conservative benchmark for comparison.

METHODOLOGY AND STUDY DESIGN

Greedoid analysis

Greedoid analysis is based on a so-called 'greedy algorithm'. The greedy algorithm aims to solve a combinatorial optimisation problem step by step (Edmonds 1971; Korte and Lovász 1984). It can be used to mimic non-compensatory decision rules, particularly lexicographic preferences. Generally speaking, greedoid analysis serves two functions. Firstly, in analysing respondents' preference data regarding a range of alternatives (different combinations of attribute aspects), greedoid analysis deduces the 'aspect order' (i.e. the ranking) that was used to make a selection. Secondly, since not everyone follows a perfect LBA rule, the greedoid analysis provides a 'cost' indicator for each respondent that reveals the extent to which the LBA rule was applied (Yee et al 2007). In this research, we adopted the greedoid algorithm introduced by Yee et al (2007), which had previously been applied on ranking data. Here, a simple example of tourism destination decision making is presented to illustrate how greedoid analysis works.

Assume there are 3 important attributes (each one of them has 2 aspects) considered by tourists in their destination choice: price (13,000 and 18,000), distance (long-haul and short-haul) and types of destination (natural landscape and culture). There are 8 combinations of the different attribute aspects. In the empirical set-up, each respondent is presented with a corresponding set of 8 'stimuli cards' and asked to rank them in order of preference.

A typical preference ranking of the 8 possible combinations presented by stimuli cards may be 1>2>3>4>5>6>7>8:

INSERT TABLE 1 HERE

By observing the preference ranking, it is possible to tell that this respondent uses a perfect LBA decision rule, since all long-haul destinations are put forward before any other destinations and then wherethere are ties, the destinations with lower price level are ranked above the destinations with higher ones; and then if there are still ties, the ones with natural landscape are ranked before cultural destinations. Thus, the 'aspect order' deduced for this respondent is long-haul > price 13, 000 > natural landscape.

However, sometimes respondents do not follow a perfect LBA rule and no such aspect order can be deduced to replicate a respondent's preference ranking exactly. In these cases, the greedoid programming would find the best-fit aspect order to replicate the closest preference ranking at the minimum 'cost'. The 'cost' is the number of violated ranking pairs produced by comparing the preference ranking of the respondent and the preference ranking produced by the deduced aspect order. A higher number of violated ranking pairs, means the less likelihood that the LBA strategy can be inferred.

Take the example above, if the preference ranking of the respondent is 1>2>3>4>5>8>7>6, the best-fit aspect order deduced would be long-haul > price 13, 000 > natural landscape and the replicated preference order based on the best-fit aspect order is 1>2>3>4>5>6>7>8. The number of violated ranking pairs by comparing the two ranking orders would be 3 (Errors: 8>7, 8>6, 7>6). So the output of the greedoid analysis for this respondent would be "Aspect order: long-haul > price 13, 000 > natural landscape; Cost: 3".

The original algorithm used in Yee et al (2007) calculates the number of violated ranking pairs irrespective of whether the error happens at the beginning or at the end of the ranking sequence. However, based on observation during the data collection for this study, for the selection of tourist destinations, it was noted that people tended to restrict their attention to a subset of the destinations presented; that is, some of the destinations they simply did not consider to be places they would visit, and they consequently spent less time evaluating them. This suggests that the ranking order at the beginning may be more reflective of respondent's real preferences than the ranking order at the end.

If the errors at the beginning are counted as equal to those at the end, there is a risk that the detection of the optimal aspect order may be driven by the responses (rankings) that are actually least reflective of a respondent's preferences. This concern raises a critical question about how to calculate the 'cost' in greedoid analysis. We opted to use a weighting scheme to calculate the 'costs'. Since there was no reference in the literature specifying criteria or strategies for weighting, we chose to apply a linearly decreasing scheme[ii]

Thus for a ranking of N options, the weights for calculating the violated pairs from the first to the second last position (rank) are from (N-1) to 1. Following the previous example, there are two errors which happened at the third last position (8>7, 8>6 with weight 2) and one at the second last position (7>6 with weight 1). So the 'cost' (i.e. weighted number of errors) is 5 (2*2+1*1). The modified algorithm (See Table 2) would find an aspect order which costs the minimum weighted number of violated ranking pairs.

INSERT TABLE 2 HERE

One point of clarification: the greedoid analysis can deal with full-rank (i.e. respondents have to rank all the stimuli cards provided), partial-rank (i.e. respondents can randomly select a few cards among the stimuli cards provided and rank them) and consider-then-rank tasks (i.e. respondents can select the cards they would consider first and then only rank these cards). For conjoint analysis, the respondents need to fully rank all the stimuli provided. If a respondent only ranked some of the stimuli, since he/she assumes the remaining stimuli are the same, his/her preference data cannot be analysed, which is a waste of useful information. Since greedoid analysis does not need the stimuli to be fully ranked, it requires a smaller respondent workload than traditional conjoint analysis, which could lead to higher response rates.

Questionnaire design

A stated preference experimental survey was designed for estimation of the LBA model and the WAAD model. Commonly considered evaluation attributes by Chinese long-haul outbound tourists were identified from previous studies through desk research (e.g. Yu and Weiler 2001; Kim, Guo, and Agrusa 2005; Arlt 2006; Sparks and Pan 2009) and these were compared and confirmed through six in-depth interviews with staff[iii] in major tour operators. These interviewees were selected due to their knowledge of the Chinese outbound tourism market. They were familiar with various long-haul destination packages, which ensured that the attribute aspects (i.e. level of price) used in the experimental design adequately represented actual destination products.

Through this process, 5 attributes with 11 aspects were confirmed for the experimental survey design. The 5 attributes (in italics) and their aspects were:

(1) *Package price per person*: around Ren Min Bi [RMB] 9,000, around RMB 13,000-17,000, above RMB 18,000.

(2) *Risk involved in obtaining a visa:* less risk/more risk of being refused

(3) *Whether the destination country is well known by the Chinese public*: famous country/non-famous country

(4) *Suitability for branded shopping opportunities*: good for brand shopping/not suitable for brand shopping

(5) *Time schedule:* tightly organised journey with tours of more scenic spots/relaxing journey with more free time

The 48 ($3*2^4$) possible combinations based on the 5 attributes' aspects were reduced to an 8-profile nearly orthogonal design. This plan generated by SPSS ensures the highest level of coverage of different combinations of aspects with the minimum number of stimuli necessary for the estimation of conjoint analysis. Besides the 8 profiles, another 2 hold-out profiles randomly generated by SPSS were included in the design (See Table 3). The hold out profiles were not used for the estimation of different decision rule models but to test how well the models derived from the analysis predict new data. The use of hold-out profiles enables comparison on predictive accuracy between compensatory and non-compensatory choice models.

The questionnaire consisted of two parts. The first part was a tailor-made experimental design in which respondents were asked to sort and rank the 10 stimuli profiles, where 1 was the most attractive destination tour and 10 the least. No attempt was made to present respondents with actual destinations, and the cards were labelled simply 'Destination itinerary 1' through to 'Destination itinerary 10'. The 10 stimuli cards are presented in Figure 1. The second part of the survey was composed of three demographic questions including gender, age and occupation to distinguish different groups of tourists.

INSERT TABLE 3 HERE

INSERT FIGURE 1 HERE

Data collection

A survey was conducted by using a convenience sampling approach from March to June 2012. In total, 201 participants completed the survey. Of those, 78 were recruited at a tour operator[iv] while they were enquiring about information about outbound trips or when they were identified as imminently due to take an outbound trip. Due to a low response rate (25%), it took an average 8 hours each working day to recruit 8 respondents who met the requirements and were willing to assist with the survey.

In order to control the bias that may generated due to the selection of a particular tour operator, the other 123 respondents were recruited through a snowball sampling method. The initial respondents of the snowball sampling were generated from leads provided by the interview informants, who then recommended relatives or friends. The criterion for the selection of respondents was that they planned to take a long-haul outbound trip within six months. Since the experimental task is relatively complex, the survey was conducted face to face and the sorting process of each respondent was observed in order to obtain more reliable and complete data. The sorting task took on average 15-20 minutes for each to complete.

Although the convenience sampling method may not produce representative results for the whole population, there were two reasons for its use in this research; the exploratory nature of the study and, the difficulties encountered in locating actual or potential long-haul outbound tourists. Although convenience sampling may be weak regarding statistical inferences relating to the population outside the sample, it has proved very useful for identifying issues, exploring promising hypotheses and collecting other sorts of non-inferential data (Fricker & Schonlau, 2002). As the main purpose of the study was to explore the use of non-compensatory choice models rather than the generation of generalizable statistical conclusions, this approach was deemed appropriate.

Data analysis

The data analysis included two steps: preference estimation based on LBA choice model and model fit evaluation between the LBA decision rule and the WADD decision rule. Because greedoid analysis is a preference estimation method based on a non-compensatory decision rule, it reveals the hierarchical aspects order for each respondent. Unlike the indicator of overall utility, which is central to conjoint analysis, it is not possible to average aspect orders to obtain a description of preferences in the whole sample. Instead, based on aspect orders of each individual, we constructed a hierarchical clustering tree for the whole sample. The procedure was used to summarise the proportions of the respondent sample selecting a given aspect as their primary choice criterion. Subsequently, it summarised the proportions selecting a given aspect as their second choice criterion within the group of respondents who chose the same primary choice criterion. The procedure continued until all the aspect orders were summarized.

In terms of model fit evaluation, two indicators were used to evaluate the two choice models: the accuracy of prediction on the hold-out data and the number of costs. Since cards 9 and 10 were hold out profiles, the rankings of the two cards were used as the hold-out data. The hold-out accuracy has been widely used to compare the out-of-sample predictive power of choice models in marketing and consumer studies (Kohli and Jedidi 2007; Yee et al. 2007; Dieckmann et al. 2009). However, for the respondents whose destination preference could be predicted accurately by both models, this basis of comparison is intrinsically unable to provide a verdict about which of the two models would be more appropriate. This is the reason why the study explored the cost as the basis for comparing the two choice models, which is the power to replicate the observed preference order.

The cost was calculated in greedoid analysis as an indicator to assess the extent to which the LBA rule was applied during the sorting process. In order to make a comparison, the cost in the case of the weighted additive choice strategy was calculated manually, in two steps. Firstly, by summing-up the part-worth utilities of attribute aspects provided by conjoint analysis, we obtained the utility score of each destination card for each respondent. Then we deduced a ranking order for each respondent based on the assumption of the WADD rule (i.e. Destinations with higher utility scores are preferred).

Secondly, the cost (i.e. weighted number of violated ranking pairs) was calculated for each respondent by comparing the deduced ranking order with the actual observed ranking order. If the respondent followed a perfect weighted additive strategy, the deduced ranking order should be exactly the same as the ranking order provided by the respondent and the number of costs would be zero. Otherwise, the higher the number of costs, the less possibility that a WAAD rule was applied by the respondent.

One point to note is that among the 201 useable questionnaires, 184 respondents provided a full ranking of the 10 stimuli destination cards, while the remaining 17 respondents were able to provide only a partial ranking of the destination cards. Thus all 201 respondents were processed by greedoid analysis to reveal the preferences based on the LBA model. For the model fit comparison, since the conjoint analysis cannot make estimations based on a partial ranking, only the 184 full ranking orders were used for that part of the analysis.

FINDINGS

Preference estimation based on a non-compensatory (LBA) decision rule

Among the 11 attribute aspects, the most popular first aspect used by the respondents was price at RMB9, 000, which was used by 25% (51) of participants (See Table 4). In other words, for one quarter of respondents, low price (RMB9, 000) was the most important criterion (aspect) on which to evaluate alternative destinations. For these respondents, all destinations not meeting this criterion were put aside, no matter how attractive they were in terms of other attributes. For 14% of the respondents (28), a relaxing journey with more free time was the most important criterion, and for yet another 13% (27) an easy visa application (low risk of rejection) was the single most important attribute. Famous country and price at 13,000-17,000 were endorsed by 12% (24) of respondents as their primary criterion. The proportions of the respondents who used the other six aspects as their first evaluation criterion were relatively small (no more than 10% for each aspect).

INSERT TABLE 4 HERE

The hierarchical clustering tree was constructed to identify the clusters which used the same/similar aspect order to make their selections. Due to space limitations, Figure 2 presents only a partial tree with important nodes. These nodes represented the most commonly used attribute aspect(s) at each stage. For example, for the clustering of the first aspect used, only five attribute aspects mentioned above were included since these five aspects were the most commonly used, each accounting for more than 10% of respondents. For the group of respondents (51) who used price as their first criterion, they used 10 aspects as their second important criterion. Only those aspect(s) chosen by more than five respondents as their second criterion were included. This was price 13,000-17,000 which was used by 36 out of 51 respondents. Among the 36 respondents, only the aspect(s) used by more than five respondents as the third criterion were presented.

Model fit evaluations

For the 184 respondents with complete rankings, the WAAD model predicted about 80% (147) rank orders of the hold-out data correctly, whereas the LBA model predicted a slightly lower proportion correctly (76%, 140 respondents).

The results of the cost indicator for each choice model are presented in Table 5. The average cost of the whole sample is 17.39 for the LBA model and 21.4 for the WAAD model. The standard error of mean and standard deviation for the LBA model are smaller than for the weighted compensatory model. A smaller standard error indicates that the sample mean of the costs more accurately reflects the mean of the costs for the actual population (all Chinese long-haul outbound tourists). A smaller standard deviation indicates that individual costs vary less from the mean.

INSERT TABLE 5 HERE

The maximum value of the cost within the whole sample was 84 for the LBA model and 134 for the weighted compensatory model. Since the theoretical maximum cost is 285, the averaged percentage cost for each model is 6% (17.39/285) LBA and 8% conjoint analysis (21.4/285) respectively (from data in Table 3). In other words, the LBA model could replicate 94% of observed preference orders of the whole sample; the weighted compensatory model could replicate 92%. Based on these statistics, it can be inferred that the LBA model performs slightly better in replicating the observed ranking order than the WADD model.

To further examine the suitability of each model at an individual level, for each respondent the decision rule model that produced the fewest errors (least cost) was assigned to him/her. The frequency statistics of the respondents assigned to the two choice models are presented in Table 6. These tests revealed that 67 respondents (36%) were predicted better by the WADD choice model and 117 respondents (64%) were predicted better by the LBA choice model. Based on this indicator, the LBA model performs better in explaining the preferences of the sample than the weighted compensatory model.

INSERT TABLE 6 HERE

A further point to note was that among the 184 respondents, there were 20 respondents (10%) whose observed rankings could be perfectly reproduced (No cost) by the LBA model. Although the number of respondents within this group is too small to produce any significant findings, it is still worth looking at the preference characteristics of this group, since it may provide promising hypotheses for further studies investigating non-compensatory decision making. A frequency analysis was run on the first important aspect used by these 20 respondents. Instead of lowest price, the first aspect most frequently used by these perfect LBA decision-makers was a relaxing journey with more free time (7). But there remained a significant number of people (6) who used lowest price as their first choice criterion.

DISCUSSION

Issues regarding the non-compensatory decision rule

Although the WADD model has been widely employed in many studies of tourism decision making (e.g. Morley 1994; Papatheodorou 2001; Seddighi and Theocharous 2002; Ciná 2012), it is evident that under certain circumstances – notably where the decision maker has limited time, energy and information – simpler, non-compensatory decision rules are favoured (Yee, et al. 2007; Hauser, et al. 2009). However, the use of the non-compensatory strategy model has not previously been quantified within tourism decision making contexts and this exploratory study offers potential for future researchers. The findings of the study suggests that the LBA model can be used to explain a large proportion of respondents' preferences and it offers additional insights to conventional, compensatory model approaches.

For instance, the time schedule is one of the most important attributes used by Hong Kong residents in choosing a package tour (Wong and Lau 2001) and in the study of Chinese outbound tourists conducted by Zhu (2005), the time schedule was also an important attribute. However, the non-compensatory estimation offers the potential for additional insight into how this attribute is preferred. The present study found that a relaxing journey with more free time was the second most popular aspect used by tourists as their first-choice criterion (and was the most popular among those respondents who followed a perfect LBA strategy). This information can be critical for tour operators to make product improvements to this market.

Moreover, the investigation of the non-compensatory decision rule reveals the non-negotiable nature of preference on certain attributes under certain circumstances, which provides a different perspective for understanding the mechanisms behind tourist decision making behaviour. This non-negotiable aspect of preferences holds intuitive appeal for some special tourism destination choices such as solar or lunar eclipse tourism (i.e. the destination choice is solely based on one attribute). It could also help us to understand why some destinations come to be rejected, since destinations not containing 'must-have' aspects, will be automatically dropped from consideration.

The non-compensatory (LBA) decision rule estimated in this research is based on the lexicographic preference first introduced by Georgescu-Roegen (1954) within economics and the greedoid analysis used to infer the LBA model was introduced by Kohli and Jedidi (2007) and Yee et al. (2007) independently in marketing research. The application of the non-compensatory theory and the estimation method from these other disciplines entailed more than a simple process of quantifying theories of consumer decision making, but involved a process of careful knowledge adaption and reflection, based on the particular characteristics of tourism products. Tourism is a useful context to explore how knowledge can be translated across fields and disciplines. The current study advocates the further adaptation of knowledge from economics, psychology and marketing to tourist behaviour.

Due to the intangibility of tourism products, some of the choice criteria used by tourists tend to be more abstract and associated with more emotional engagement than those used to select everyday products, such as the colour of a cell phone or the amount of computer memory. Therefore a more careful identification of these choice criteria (attributes) and their values (aspects) was required. The attributes and the aspects of the attributes presented to respondents should be ones that reflect the real performance of the available destinations. This revealed the importance of the qualitative interview stage to ensure the attributes and aspects were genuinely relevant to actual destination packages, and the need for multi-method, multi-component studies.

Evaluation of model fit

The evaluation process assumed by compensatory and non-compensatory decision rules are totally different. To provide advice on which type of decision rule is more appropriate for certain group of people, we need to derive measurements for assigning individual participants to certain decision rules. This research provides two possible estimation methods to evaluate the predictive ability of different choice strategy models. One is the test on hold-out data, while the other is the power to replicate the real preference order (the 'cost'). The former has been widely used in previous studies but the latter is an innovation in tourism research. Although the weighted additive (WAAD) model outperforms the LBA model in terms of the out-of-sample accuracy, it does not perform better on preference explanation of each individual respondent.

The inclusion of the 'cost' indicator is necessary and important because it can help us to identify those individuals who can be explained more accurately by a certain choice model. Even for the tourist who does not use a certain decision rule consistently, this indicator is able to suggest to what extent a certain rule is applied. As a matter of fact, this is a promising measurement to estimate the suitability of different models or decision rules at the individual level. It serves the same function as the qualitative methods of process tracing mentioned earlier, but overcomes some important disadvantages (e.g. judgement inconsistency and social desirably bias) identified in the qualitative approaches.

The methods used to calculate the cost was another issue addressed in this study. Although Yee et al. (2007) and Kohli and Jedidi (2007) used different programs to generate their aspect orders, the principles they used to identify the 'best' aspect order were identical, which involved finding the aspect order that generates the minimum number of violated pairs (costs). This principle does not consider the fact that the importance of particular pair violations may vary with their position in the observed ranking order. A linearly decreasing weighting was used in this research Whether or not the linearly decreasing weighting is the most appropriate weighting scheme to reflect the actual preference, it does offer a useful starting point for further investigation. An alternative weighting scheme might be developed to give larger weights for all the alternatives within the consideration set and smaller weights for all the other alternatives.

Managerial implications

The investigation of which choice model is more appropriate for a specific tourism market is of great importance for practitioners (e.g. tour operators and destination organizations) to develop more effective advertising and destination products. For example, for the Chinese long-haul tourists who can be understood better by a lexicographic decision rule, the advertisement should focus on the most important attribute(s) and emphasize their performance (expected attribute aspects). While for the group which can be predicted better by a WADD model, it may be more effective to emphasize the wider range of attributes in combination and their components.

Moreover, the hierarchical clustering based on the aggregation of individual aspect orders can provide valuable guidance for market segmentation and product design. For example, the aspect order ‘RMB9, 000 > RMB 13,000-17,000 > Less risk (Visa)’ suggests a preference for cheap price and less risk while the aspect order ‘Relaxing journey with more free time > Good for brand shopping’ suggests two distinguishable markets. Therefore the hierarchical preference clustering could yield a range of new product/market opportunities for destinations.

CONCLUDING REMARKS

Tourism is a complex and broad ranging phenomenon, which may lead to a diverse set of choice contexts, including more comprehensive compensatory decision rules and simpler non-compensatory decisions, each leading to different choice outcomes. Thus the assertion that all tourism decisions arise through the application of one specific decision-making process (the WADD rule) could create a limitation for tourism research. For the first time, this study adopted a ‘greedy’ algorithm to investigate the applicability of alternative decision making processes for destination choice, which quantified the use of non-compensatory decision rules. At a fundamental level, the study casts doubt on the economic rationality that is implicitly assumed in conventional models of tourist consumer behaviour and opens up opportunities for future studies and theorising of the situational and individual differences in preferential choice processes in tourism contexts.

Although the efficacy that the LBA model estimated by the greedoid method could be used as a replacement of the robust WADD model is doubtful, and this was not the underlying purpose of this research, the use of a non-compensatory decision structure offers great *additional* potential for understanding tourists’ destination choices based on a hierarchical order of attribute aspects. Moreover, together with the measurement of cost, the greedoid method enables a statistical judgement about under what circumstances and for whom the lexicographic model is superior to compensatory decision processing. Exploring the application of cost as an indicator of model fit is another contribution of this research, which provides a promising quantitative measurement to supplement qualitative process tracing methods.

As an exploratory study, this research has a number of limitations regarding methodology as well as research focuses. Based on these limitations, recommendations are made for future studies. Firstly, the destinations investigated in this study were not real destinations but stimuli which contain different combinations of destination attributes' aspects. A further link with actual destinations could be undertaken in future studies. Yet the qualitative data was useful to help generate realistic attributes for this specific market. For example, ease of obtaining a visa is relatively fixed for each destination country; Australia or New Zealand are relatively easy as opposed to the USA, for example, which contains a greater risk of visa rejection for Chinese tourists. Besides, the discrete choice experiment method used to elicit preferences can be adopted in future studies to link tourists' preferences with their real choice behaviour.

Secondly, particular decision rules chosen by the individual are context-based (Swait et al. 2002). This research only investigated a specific target market (Chinese long haul outbound) in which the LBA strategy may be suited. Other tourism related decision making scenarios (e.g. choice of other markets with different cultures, choice of short-haul destinations, choice of travel mode, hotel or tour operators, in-destination choices) may be considered and investigated in the future. The number of tourism choice contexts in which non-compensatory approaches could be applied is potentially very wide.

Finally, the main purpose of this research was to emphasize the different preference functions revealed by different decision rules and to explore how to distinguish the use of different types of decision rules. Thus instead of hybrid model decision rules, single type rules were investigated and compared. However, it has been proposed in previous consumer studies that combining lexicographic and compensatory processes in a two-stage model might be a more realistic approximation of decision making (Gilbride and Allenby 2004; Reisen, Hoffrage and Mast 2008). Further studies into the tools to infer and estimate these more complicated hybrid Decision making decision making models could be very interesting for future studies of tourism decision making. This paper offers one approach in which these might be developed.

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[i] By including hold-out profiles in the design of the data collection, conjoint analysis allows an out-of-sample predictive evaluation, which cannot be achieved by the AHP analysis. Since the purpose of this research is not to investigate the probability of certain choice being made or to improve the predictive power of the WADD model, the simpler but still robust OLS regression was adopted for the estimation rather than the more complicated logit regressions (e.g. hierarchical Bays) used in some DCE studies.

[ii] With the help of Michael Yee, which the authors acknowledge, this study modified the greedoid program by adding a weighting scheme to the software.

[iii] Tour guides on international trips and marketing managers for international destinations.

[iv] Among the top four tour operators in terms of the number of tourists receives in Beijing, this is the only one tour operator (the name can be provided on request) which gave permission to access their customers.

Tourist Choice Processing: Evaluating Decision Rules and Methods of their Measurement

Figure1 The stimuli cards used for the sorting task

Destination itinerary 1
Price: RMB 9,000 per person
Visa: more risk of being refused
Brand Shopping: not suitable
Time schedule: relaxing
Famous: non-famous country

Destination itinerary 2
Price: RMB 9,000 per person
Visa: more risk of being refused
Brand Shopping: good
Time schedule: tightly organized
Famous: non-famous country

Destination itinerary 3
Price: RMB 18,000 per person
Visa: less risk of being refused
Brand Shopping: not suitable
Time schedule: tightly organized
Famous: non-famous country

Destination itinerary 4
Price: RMB 9,000 per person
Visa: less risk of being refused
Brand Shopping: not suitable
Time schedule: relaxing
Famous: famous country

Destination itinerary 5
Price: RMB 18,000 per person
Visa: more risk of being refused
Brand Shopping: good
Time schedule: relaxing
Famous: famous country

Destination itinerary 6
Price: RMB 9,000 per person
Visa: less risk of being refused
Brand Shopping: good
Time schedule: tightly organized
Famous: famous country

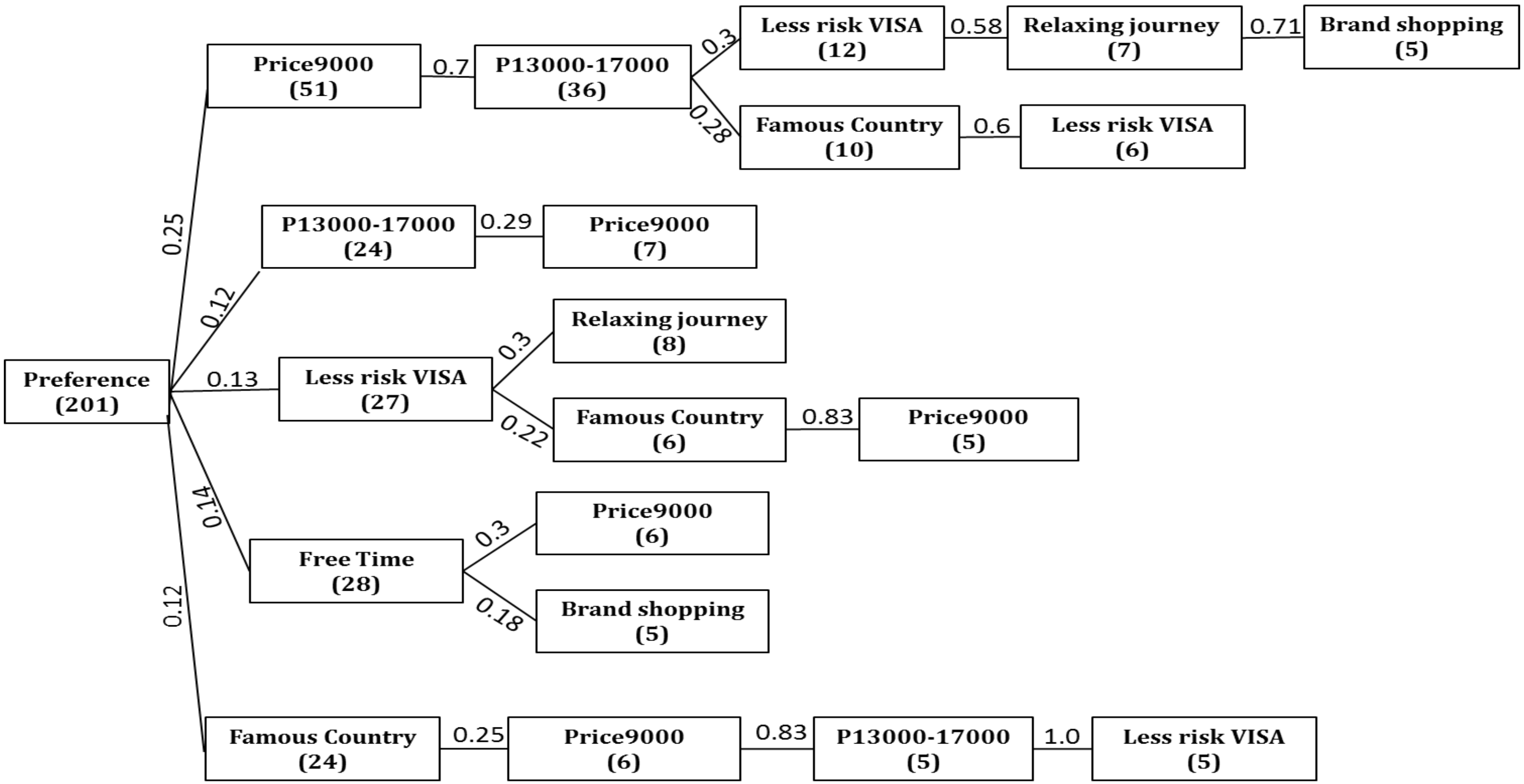
Destination itinerary 7
Price: RMB 13,000 per person
Visa: more risk of being refused
Brand Shopping: not suitable
Time schedule: tightly organized
Famous: famous country

Destination itinerary 8
Price: RMB 13,000 per person
Visa: less risk of being refused
Brand Shopping: good
Time schedule: relaxing
Famous: non-famous country

Destination itinerary 9
Price: RMB 18,000 per person
Visa: more risk of being refused
Brand Shopping: not suitable
Time schedule: tightly organized
Famous: famous country

Destination itinerary 10
Price: RMB 9,000 per person
Visa: less risk of being refused
Brand Shopping: not suitable
Time schedule: tightly organized
Famous: non-famous country

Figure 2 Hierarchical Clustering Tree



Tourist Choice Processing: Evaluating Decision Rules and Methods of their Measurement

Table1 An example of preference ranking

1. Price 13,000, long-haul, natural landscape
2. Price 13,000, long-haul, culture
3. Price 18,000, long-haul, natural landscape
4. Price 18,000, long-haul, culture
5. Price 13,000, short-haul, natural landscape
6. Price 18,000, short-haul, natural landscape
7. Price 13,000, short-haul, culture
8. Price 18,000, short-haul, culture

Table2 Algorithm for finding aspect order L that provides the best fit to profile order X

begin

$J(\varnothing)=0$

for $k=1$ to $|E|$

for all (unordered) subsets, $S \subseteq E$ of size k

for all $i \in S$

$c(S\backslash\{i\},\ i)$= weighted number of errors caused

by aspect i following set $S\backslash i$

next i

$J(S) = \min_{i\in S}[J(S\backslash\{i\}+c(S\backslash\{i\}, i)]$

$L(S)$ is the ordering of aspects in S yielding

$J(S)$ [retained]

next S

next k

end

*Let E be a set of attribute aspects. When Algorithm terminates, J (E) is the number of 'cost'. L (E) are the best-fitting lexicographic aspect orders, which might or might not be unique (a visial example of how the algorithm works can be found in Appendix).

Table3 Aspects combinations of the 10 stimuli (destination cards)

Price	**Visa**	**Brand Shopping**	**Time Schedule**	**Famousness**	**Stimuli Number***
RMB9,000	More risk	Not suitable	Relaxing	Non-famous country	1
RMB9,000	More risk	Good	Tight	Non-famous country	2
RMB9,000	Less risk	Not suitable	Relaxing	Famous country	4
RMB9,000	Less risk	Good	Tight	Famous country	6
RMB13,000	More risk	Not suitable	Tight	Famous country	7
RMB13,000	Less risk	Good	Relaxing	Non-famous country	8
RMB 18,000	Less risk	Not suitable	Tight	Non-famous country	3
RMB 18,000	More risk	Good	Relaxing	Famous country	5
RMB 18,000	More risk	Not suitable	Tightly	Famous country	9 (hold-out)
RMB9,000	Less risk	Not suitable	Tightly	Non-famous country	10(hold-out)

*** The 10 profiles designed are randomly numbered by SPSS and the stimuli number is the card number of the destination itinerary used for the sorting task (See Figure 1).**

Table 4 Frequencies of first aspect used by tourists

Attribute aspects	Frequency	Percent
RMB9,000	51	25.4
RMB13,000-17000	24	11.9
RMB18,000	9	4.5
Less risk (Visa)	27	13.4
More risk (Visa)	2	1.0
Good (brand shopping)	9	4.5
Not suitable (brand shopping)	11	5.5
Tight journey	14	7.0
Relaxing journey	28	13.9
Famous country	24	11.9
Non-famous country	2	1.1
Total	201	100.0

Table 5 Statistical comparison of costs between two decision rule models

		Lexicographic by aspect	Weighted compensatory
N	Valid	184	184
	Missing	0	0
Mean of costs		17.39*	21.40*
Std. Error of Mean		1.17	1.59
Std. Deviation		15.82	21.52
Maximum		84	134

*A T-test was performed and it reveals the mean of costs of LBA is significantly lower than WADD (p=0.023, p<0.05)

Table 6 Frequencies of the respondents suits different decision rules

Choice model	Frequency	Percent
Weighted compensatory	67	36.4
Lexicographic by aspect	117	63.6
Total	184	100.0