Understanding the destination choice: A Study of the Chinese long-haul outbound tourists

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Abstract

Among tourism decision making studies, choice heuristics are barely explored. Choice heuristics are a set of rules decision makers use to process information about their choice criteria. The types of rules applied in the process can make a substantial difference to eventual outcomes, which for tourists includes not only the final choice of the tour package but also the choice process (Sen, 1997). Therefore, in order to better understand tourists' decision making behaviour, choice heuristics deserve greater attention. However, whilst compensatory choice heuristics are commonly applied in consumer focused tourism research, and conjoint analysis is often used for modelling compensatory heuristics, mirroring the predominant approach in consumer research, less attention has been afforded to non-compensatory heuristics. Recently, a greedoid method was introduced by Kohli and Jedidi (2007) and Yee et al. (2007) independently to that contributed to methodology for estimating non-compensatory heuristics. The aim of this study was to provide a greater understanding of consumer decision-making processes, based on the exploration of different choice heuristics used by the Chinese long-haul outbound tourists. This thesis makes theoretical contribution by providing insights on (1) how the concept of choice heuristics can be used to better understand the process of decision making and (2) how choice heuristics are used for the selection of complicated intangible services, tourism destinations in this case. The study also sheds light on the possible measurements for evaluating the fit of different choice heuristic models. In addition, the information found regarding the destination preference of Chinese long-haul outbound tourist is of great use for marketers and suppliers to improve their destination products as well as their advertisement campaigns.

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Table of content

List of Tables

List of Figures

Chapter 1 Introduction

1.1 Context of the Research: The Global Tourism Market

Tourism is a dynamic and growing industry which has become a major force in the world economy. The World Travel and Tourism Council (WTTC) estimated that, in 2012, the travel and tourism industry directly and indirectly contributed around US$6.6 trillion in GDP, 260 million jobs, US$760 billion in investment and US$1.2 trillion in exports. This contribution represented 9.3% of global GDP, 1 in 11 jobs, 5% of investment and 5% of exports (WTTC, 2013).

Although domestic tourism is still significant, international tourism has increased markedly since 1950 (Knowles, 2001), particularly in recent years. The number of international arrivals rose from only 25 million in 1950 to surpass 1 billion in 2012 and is expected to reach almost 1.6 billion by the year 2020 (UNWTO, 2013). Overseas visitors need accommodation, food, local transport, entertainment, shopping, etc. Therefore travel creates employment and business opportunities for development. A report presented by the United Nations World Tourism Organization (UNWTO) (2008a) indicated that over 75 countries received more than US$1 billion of annual income from international tourism in 2006 (e.g. United Sates $85 billion; United Kingdom $34 billion; Australia $18 billion). Consequently, many countries have regarded international tourism as an important pillar of their economy and an increasing number of developing countries are paying more attention to the tourism sector.

Development of international tourism by region

International tourism is evident throughout the world. Europe and America were the main tourist-receiving regions in last century. According to UNWTO statistics (2008a) these two regions shared around 95% of the global tourism market in 1950; although their market share had fallen to 67% by 2012 (UNWTO, 2013a), the tourism market in the two regions had seen an annual growth rate of 6.5% and 5.8% respectively. The dominant position of Europe and America has been challenged because other regions are growing at a faster pace, which represents a new trend in inbound tourism (i.e. non-residents arriving at a country). By 2012, although Europe still accounted for 51% of world tourist arrivals, Asia and the Pacific (23%) had replaced the Americas (16%) to become the second largest regional destination in terms of tourist arrivals. The Middle East and Africa showed a sharp increase as well, but from a low base, and their combined share of the market was comparatively modest in 2012, at 10% (UNWTO, 2013a).

The situation in terms of outbound tourism (i.e. residents travelling to another country what may be regarded as the 'source market'), the worldwide situation is similar to inbound tourism. The two most mature tourism regions – Europe and the Americas again – generated 72% of international departures in 2006. But they have produced only near or below average growth rates since 2000: Europe at 2.9% a year and the Americas at less than 1.4% a year. In contrast, Asia and the Pacific consolidated its third-rank position in terms of outbound tourism, with a world share of 20% by 2006, and maintained an annual growth rate of 6.5% between 2000 and 2010. Outbound tourism from Africa (+7.4%) and the Middle East (+10%) has grown rapidly since 2000. However, the two regions each generated only 3% of international departures.

Over the last decade of the twentieth century, the Asia-Pacific region was the fastest-growing tourism region in the world due to the extraordinary economic growth of many Asian countries. After the turn of the millennium, the region maintained its positive growth and surpassed the Americas, becoming the second biggest international tourism region in terms of both destination (inbound) and source market (outbound). Within this region, China undoubtedly represents the lead country, having performed outstandingly in relation to both inbound and outbound tourism.

China as a new emerging outbound tourism market

China, along with India, is now recognised as a major emerging outbound tourism worldwide market (WTTC, 2006) and considering that only 4% of China's urban population has travelled overseas, the Chinese outbound travel market has huge growth potential (Li et al., 2009). By 2012, China has become the world number one tourism source market. (UNWTO 2013b). Despite worldwide attention to this new emerging market, knowledge of the decision-making behaviour of Chinese outbound tourists, especially their destination preferences, is very limited. In this research, China's outbound tourism market will be used as the case study, for two reasons.

Firstly, as the biggest tourism source market with huge potential to grow in the future, China has attracted the interest of destination marketers worldwide. Therefore, an investigation of how Chinese tourists select overseas destinations will provide valuable information which marketers can use to build a positive image of their destinations, to improve the tourism products and to design more effective advertising campaigns for the Chinese market.

Secondly, unlike travellers from mature outbound markets (countries in North America and Europe), the recent emergence of China's outbound tourism market implies that most Chinese outbound tourists, especially long-haul travellers, are first-time visitors. They have no previous experience as to how to base a 'consideration set', nor have many of those from whom they might get recommendations. Therefore, it is even more crucial to find out what issues are seen to be of chief concern by those potential tourists and what kind of destination products would attract them.

Moreover, it is necessary to investigate the Chinese outbound tourism market because the findings can then be compared with those from other emerging long-haul markets in the Asia-Pacific region (e.g. India).

This research therefore aims to provide comprehensive knowledge about Chinese long-haul outbound tourists for the first time. The study focuses on an investigation of tourists' preferences regarding destinations, thus decision-making theories and concepts are tested and explored. The theoretical background to the research is briefly introduced below; thereafter, the research objective and research questions are presented. Finally, the structure of the thesis is outlined.

1.2 Theoretical Focus of the Research

In a broad sense, tourism decision-making is a process that can happen at any stage of a leisure travel trip. That is, as well as the choice of destination, further decisions must be made regarding the components of a holiday, such as transport mode, accommodation and on-site activities (Woodside & Dubelaar, 2002). This research focuses solely on the choice of destinations.

Among so many alternative destinations, how does a tourist decide on one in particular? The mental processes underlying decision-making in relation to choice of destination can be complex, and have been the subject of research for decades (e.g. Decrop, 2010; Jang & Cai, 2002; Morley, 1994; Recker & Schuler, 1981; Rewtrakunphaiboon & Oppewal, 2008; Seddighi & Theocharous, 2002; Um & Crompton, 1990; Woodside & Lysonski, 1989). All kinds of social, cultural, economic and psychological factors are likely to be involved in the decision-making process.

In general terms, the evaluation of a potential destination is likely to be based on a bundle of relevant attributes, such as the cost of the trip, local climatic conditions, personal recommendations and so on (Lancaster, 1966). A large number of tourism studies have sought to identify the important attributes and then to ascertain the preferred level or value of each attribute for different tourist groups. Such information can help us to understand and even predict tourists' choices. Take a tourist, John, as a simple example. Let us suppose we know the attributes that John will use to select a destination: temperature and transport mode. John prefers higher temperatures and travelling by car. There are two potential destinations, A and B. A has an average temperature of 20°C at that time of year and can be reached by car; B has a temperature of 18°C and can be reached by airplane alone. In such a case, it would be straightforward for John to select destination A. And by knowing the attributes that are important to John, we would be able to predict his choice.

However, it would be harder for John to choose between destination A and B if he preferred higher temperatures and to travel by air. In such a case, John would need to employ certain criteria to make comparisons when each alternative contains something he does not prefer. For instance, John could somehow weight each attribute (temperature and transport mode) in deciding which destination has the better overall performance. Or he could rank the attributes by their importance and select the destination which has the better performance with regard to the most important attribute. The method that decision-makers use is called a choice heuristic. We cannot predict John's preference until we first establish the choice heuristic he would use, since different heuristics may lead to different outcomes.

In terms of actual destination choice, when tourists face a number of alternatives with all kinds of combinations of attributes, they will necessarily resort to some sort of choice heuristics (perhaps unconscious) to enable them to process a great deal of information, to make the comparisons consistent, to work out their preference order among the alternatives and eventually to make a final choice (Czerlinski et al., 1999; Hauser et al., 2009). Thus, in order to understand tourists' decision-making process and to increase the accuracy of predictions of their preferences, it is necessary for researchers to explore the choice heuristics used by tourists, in addition to the attributes tourists use as choice criteria.

Within tourism decision making research, while studies have investigated the attributes on which decision-making has been based (e.g. Basala & Klenosky, 2001; Beerli & Martin, 2004; Go & Zhang, 1997; Haahti, 1986; Um & Crompton, 1990), they have stopped short of investigating choice heuristics. The few studies that have explored tourists' evaluation processes more deeply have generally applied a single (albeit popular) type of choice heuristic known as the weighted additive heuristic (e.g. Papatheodorou, 2001; Seddighi & Theocharous, 2002; Woodside & Lysonski, 1989) whilst other types of heuristic have been overlooked. To the best knowledge of the author, excepting a single article by Decrop and Kozak (2009), which briefly discussed the possible kinds of choice heuristics used for destination choice, there are no empirical studies that have attempted to estimate and evaluate different choice heuristic models used in tourism destination choice, which means that there is a crucial gap in the knowledge concerning the whole picture of decision making processes in tourism.

On a broader level, although some studies in general consumer decision making research have investigated different types of choice heuristics, they either focus on testing which choice heuristic is used more often to form the consideration-set (e.g. Brisoux & Laroche, 1981 Crompton & Ankomah, 1993; Parkinson & Reilly, 2002), or explore how to estimate the predictabiliy of each choice heuristic model (Dieckmann et al., 2009; Kohili & Jedidi, 2007; Yee et al., 2007). However, in these studies, the investigation of the choice heuristiccomponent was limited to a summary and modelling of different mental mechanisms that are used by decision makers in to compare which model was more predictable. They did not go on to use the information generated from the different heuristic models to describe, explain and to better understand the preferences and implications of choice outcomes of the target group.

In addition, simply asking a set of consumers 'What choice heuristic do you use?' is unlikely to produce meaningful responses. Questions of how to collect and analyse the data are therefore major challenges for scholars, especially in regard to the inference of non-compensatory choice heuristics. Although Kohli and Jedidi (2007) and Yee et al. (2007) introduced greeodid analysis to infer non-compensatory choice heuristic in marketing research, all the studies that have adopted this method estimated decision making for tangible products such as laptops (Kohli & Jedidi, 2007), mobile (cell) phones (Yee et al., 2007) and skiing jackets (Decrop, 2010). In addition, the results of these studies are not consistent with each other. Therefore, further empirical studies of greedoid analysis are needed to provide more detailed exploration of this method. Moreover, in previous studies (Dieckmann et al., 2009; Kohili & Jedidi, 2007; Yee et al., 2007), the "predictability of the hold-out data" was often used as the indicator to compare the fitness of different choice heuristic models. Whether this indicator is good enough to make a comprehensive comparison among different choice heuristic models and whether there is any alternative measurement which can be used as supplementary to test the predictability are the important questions that require further exploration. Therefore further research is required to provide answers to these issues.

1.3 Research Objective and Research Questions

The research objective of this study is to provide a greater understanding of consumer decision-making processes, based on the exploration of different choice heuristics used by the Chinese long-haul outbound tourists. In order to achieve the objective, the following research questions were investigated.

1. What are the important attributes (choice criteria) considered by Chinese outbound tourists when they select long-haul destinations?
2. How is each such attribute preferred by these tourists based on different choice heuristics?
3. What methods can be used to analyse the different types of choice heuristic used?
4. How can the fitness and predictability of different choice heuristic models be estimated?

Answers to these questions should afford a deep insight into the nature of Chinese outbound tourists, including the attributes of (choice criteria for) a destination they consider important and, more importantly, an insight into how those attributes are dynamically processed in the selection of a destination. The research should contribute valuable information regarding the destination preferences of this emerging but little studied market. In fact, the present research sought to quantify the important concepts (choice criteria and choice heuristics), as well as to test various theories of decision-making in the tourism context. These theories included utility maximisation theory; lexicographic preference theory and choice-set theory.

As mentioned above, there has not been an empirical study reported in the tourism literature evaluating the use of different choice heuristics. This is an exploratory study adopting methods used in other disciplinary fields to evaluate the use of choice heuristics in the selection of tourism destinations. Two such methods in particular were evaluated: conjoint analysis and greedoid analysis. Each method was modified to suit the character of tourism decision-making, and their adaptability in this regard was compared. Moreover, the measurement instruments that can be used to evaluate the predictability and fitness of each choice heuristic model were also explored.

Some points of clarification are warranted at the outset. Firstly, the destination choice referred to in this research is actually a destination-based package tour. Since the majority of the Chinese outbound tourists prefer to take a package tour, especially long-haul tourists (Sparks & Pan, 2009), this research focuses on package tourists rather than individual tourists. This means that attributes of the package as a whole, in addition to attributes solely of the destination, may be implicated in the decision-making processes. Secondly, the respondents of the survey were approached through a convenience sampling including the clients of a Beijing tour operator and some acquaintances (through a snowball sampling technique). And thirdly, the research posited a series of attributes of 10 hypothetical destinations that respondents were asked to choose between, not real destinations.

1.4 Thesis Structure

This chapter has provided an overview of the context of the study, the theoretical background to the research and the research objective and questions.

Chapter 2 is a broad review of studies on tourism decision-making. In the first section, the studies on the main issues relevant to tourism decision-making – such as travel motivation, information search, destination image and previous travel experience – are summarised to get a general idea of the knowledge structure intrinsic to tourism decision-making. The second section focuses on studies that have sought to model destination choice. These studies are more relevant to this research. Based on the review, three challenges for tourism decision-making research are presented.

Chapter 3 provides the theoretical background for understanding this research. The two key concepts (choice criteria and choice heuristics) that are investigated in this study are elaborated. The choice criteria used in previous tourism decision-making of studies are presented for later comparison. Different choice heuristic models are illustrated. No empirical study has investigated the choice heuristics used in selecting a destination in the tourism context, and so, instead, the findings of empirical studies on the selection of tangible products such as cell phones and skiing jackets are reviewed. In addition, information on China's tourism market, the profile of Chinese tourists and their preferences revealed by previous studies are provided so that the results of the present research can be seen in context.

Chapter 4 describes the methods utilised in this research. The first section reviews the research methods available for investigating tourists' choice of destination. The following section provides a rationale for having two phases for the research: interviews of staff working at international tour operators in China; and a survey of the clients (and their acquaintances) of a tour operator – a group we may described as Chinese long-haul outbound tourists. The interview was conducted to identify the choice criteria, while the survey was used to evaluate different choice heuristics. The procedures of the empirical study, including the data collection and the data analysis, are then described in detail. The section on data collection presents the interview questions, the design of the survey and the participants. The data analysis section is divided into two parts: the analysis of the interview and the analysis of the survey. Due to the lack of tourism research on the evaluation of choice heuristics, the analysis of the survey results was a challenge as well as the major contribution of this research. The application of conjoint analysis for estimating the compensatory choice heuristic model and the exploration of the greedoid analysis for estimating the non-compensatory choice heuristic model are reported in detail.

Chapter 5 presents the interview results. The interviews were conducted to provide the qualitative information on the Chinese long-haul outbound market and to identify the choice criteria used by Chinese long-haul outbound tourists. Hofstede's cultural dimensions theory was integrated into the analysis in order to reveal the cultural traits in Chinese tourists' decision-making behaviours. The results and findings of the interviews were crucial for understanding the destination choice of Chinese long-haul outbound tourists. More importantly, the interview phase ensured the relevance and accuracy of the choice criteria used within the survey phase. Five such attributes (choice criteria) with 11aspects were identified and chosen for further investigation.

Chapter 6 elaborates the results and findings of the survey. The choice heuristics used by Chinese long-haul outbound tourists have not been previously investigated. An overview of the respondents' profile is first presented in the chapter. After that, the results of both conjoint analysis and greedoid analysis are presented to reveal how the five choice criteria are incorporated within these two choice heuristic models. The role of each attribute at the stage of 'consideration set' formation is presented. In order to compare the fitness and predictability of these two choice heuristic models, two measurement instruments were explored and adopted in this research. The use of the instruments for model evaluation and the findings are described in the third part of the chapter. The chapter ends with a section summarising and discussing the key findings.

Chapter 7 discusses the implications of the key findings in relation to the knowledge production in tourism decision-making as well as broader decision-making theories. It also provides the general conclusion of the thesis. It begins with a summary of the main findings. There follows a discussion of the implications of the research. Finally the limitations of the study and suggested future directions for research are outlined.

Chapter 2 Literature review

2.1 Overview of the chapter

The previous chapter introduced the theoretical background to the study. This chapter reviews the literature on the tourism decision-making, especially studies that have focused on explaining and modelling destination choice. The chapter starts with a section on decision-making studies – initially in general terms, across a range of disciplines, but then narrowing this down to tourism and to the selection of a holiday destination. This is followed by a section on different approaches to modelling destination choice; these include economic, psychological and sociological approaches, as well as the approaches used in other research fields such as operation management studies, marketing and consumer research. The third section addresses three challenges that exist in relation to knowledge production regarding tourism decision-making. They are: knowledge integration, knowledge adaptation and knowledge update. How this study contributes to these challenges is presented in the following section. The chapter ends with a summary.

2.2 Studies of Decision-Making

Human beings are all fundamentally decision-makers (Saaty, 2008). Decision-making is the mental or cognitive process of reaching a decision (American Psychological Association, 2010). This topic has been studied by scholars from a variety of social science disciplines, including psychology, sociology, political science and economics.

In psychology, decision-making is viewed as a process of human thought and as a reaction to the external world, such that the focus of the psychological perspective is on decision-making as a perceptual, emotional and cognitive process (Doyle & Thomason, 1999; Oliveira, 2007; Svenson, 1979). Research in sociology and political science generally shares this perspective with psychology, and so acknowledges that, for example, emotional elements will influence decision-making. Sociologists, however, tend to investigate relationships between social factors and decision-making (Bodenhausen & Lichtenstein, 1987; Ferrell & Gresham, 1985; Loewenstein et al., 1989). Their focus is more on the allocation of rewards and resources among the whole community or the behaviour of formal organisations. By contrast, political scientists ask additional questions regarding how power relations and political institutions affect cognitions, perceptions and emotions; their research extends to political systems and behaviours such as elections and policy-making, and the subjects of such research are mainly voters and politicians (Bartels, 1996; George, 1969; Herstein, 1981; Lau & Redlawsk, 2001; Tsebelis, 1995).

Compared with other social science, economists assume that decision-makers are rational so that they can always choose the alternative with maximum utility. Utility theory was first introduced by Jeremy Bentham in 1748 (in Read, 2007). Although absolute rationality has been questioned by scholars – normally people do not make decisions that are absolutely logical or necessarily even reasonable (Kahneman & Tversky, 1979; Mosley, 1976; Pfeffer et al., 1976) – it is a fundamental theory in economics which provides a basic framework or starting point for researchers. Simon (1972) has proposed an alternative basis for the mathematical modelling of decision-making, which is known as bounded rationality. Bounded rationality suggests that, in decision-making, the rationality of individuals is limited by: the information they have; the cognitive limitations of their minds; and the finite amount of time they have to make a decision (Simon, 2000). Under such circumstances, choice heuristics are helpful, or even necessary, for decision-making.

Thus, different disciplines have used different perspectives to study decision-making. Tourism decision-making, and specifically destination choice is indeed an issue that needs to be explained by multidisciplinary perspectives, since tourism itself is a field that involves many disciplines (Au & Law, 2000). The details of how tourism decision-making has been studied using a variety of approaches are presented below.

On the one hand, tourism destination choice as a special kind of consumer decision-making behaviour provides a good context for scholars of different disciplinary backgrounds to test general decision-making theories and concepts. On the other hand, more and more researchers (e.g. Saraniemi & Kylanen; Sirakaya & Woodside, 2005; Smith, 1994; Um & Crompton, 1990; Woodside & Lysonski, 1989) realise that the unique characteristics of the tourism industry and tourism products make decision-making in this field different from that regarding the purchase of manufactured products. The investigation of tourism decision-making may therefore provide new insights regarding traditional decision-making theories. Moreover, by understanding how tourists evaluate alternatives, destination marketers can select the relevant information to deliver to potential tourists, thus enhancing the efficiency of their advertising. And greater understanding of tourist preferences will increase the accuracy of predictions of which destinations tourists might choose.

Due to the theoretical and practical importance of tourism decision-making, extensive studies have been carried out by scholars trying to explain it. It is important to have a critical review of the research of tourism decision-making so that a clear picture of what has been done and what needs to be done can be drawn.

2.2.1 Tourism decision making stages

The aforementioned tourism decision-making process can happen at any stage of the trip or holiday, and can entail a range of choices and decisions (Woodside & Dubelaar, 2002). According to the classic five-stage model of buying-decision process introduced by John Dewey in 1910 (Mansfeld, 1992), the whole decision process includes: (1) problem recognition, (2) information search, (3) evaluation of the various alternatives, (4) final choice and purchase, and (5) post-purchase evaluation. This five-stage model reveals the idea that consumer decision-making begins long before the actual purchase and continues after the purchase is made (Comegys et al., 2006). In the context of tourism decision-making, Van Raaij and Francken (1984) proposed a five-stage vacation selection model by slightly modifying the Dewey's information-processing theory. Their five-stage model comprised: (1) generic decision (whether to travel), (2) information acquisition, (3) destination evaluation and joint decision-making, (4) vacation activities, and (5) post-purchase feedback (satisfaction and complaints).

In reality, the sequence of processes does not have to follow the order of numbering. For example, purchases may be driven by emotions, so that information acquisition comes only after (rather than before) the actual purchase. Also, the stages are not necessarily independent. For instance, it is well known that the information sought after a purchase is different from the information sought beforehand. Nonetheless, this framework does provide a macro-level description of the tourism decision-making process and it has been adopted in various studies (e.g. Bargeman & van der Poel, 2006; Cai et al., 2004; Crompton, 1992; Fodness, 1992; Jeng & Fesenmaier, 2002).

The predictive ability of this kind of grand model is weak, however. Van Raaij and Francken's model does not provide a detailed explanation of how individuals evaluate alternatives to arrive at a decision, and does not incorporate important factors such as the motivation for travelling, destination image, information search or the influence of previous experience. Most importantly, it does not attempt to model the decision-making in the selection of a destination.

2.2.2 Important issues of tourism decision making

Understanding the tourists' motivations in destination choice is the key issue in many tourism decision- making studies (Crompton, 1979; Ross & Iso-Ahola, 1991; Fodness, 1994; Gnoth, 1997; Mannell & Iso-Ahola, 1987; Yoon & Uysal, 2005). Motivation has been defined as the drive that directs human behaviour

(Kassin, 1998; Murray, 1964) towards the fulfilment of physiological and psychological needs (Berkman et al., 1997). According to (Mansfeld, 1992), it is travel motivation that determines travel decisions before actual travel. Thus, by investigating tourists' motivations, we will be able to answer the fundamental question of why people travel, which in turn will contribute to our understanding of tourism decision-making, as well as of the psychological reasons behind the destination evaluation and selection stage. In addition, exploring different motivations of different tourists groups will also be helpful in segmenting the tourism market (Weaver et al., 1994).

The majority of the motivation studies for tourism decision-making have focused on identifying and classifying motivation factors (Chang, 2006; Crompton & McKay, 1997; Eagles, 1992; Iso-Ahola, 1980, 1982, 1983; Kerstetter et al., 2004; Lee, 2000; Mehmetoglu, 2007). For example, Iso-Ahola (1980, 1982, 1983) proposed that people are motivated to pursue leisure travel for two major reasons – seeking and escaping. Kerstetter et al. (2004) identified adventure, education and a holistic approach as the three driving factors for eco-tourism, while Mehmetoglu (2007) reported that the motivations for nature tourism include nature, physical, novelty/learning, social contact and so on.

In order to classify a variety of tourists' motivations, McIntosch and Gupta (1977) proposed four constructs of motivation: physical, cultural, interpersonal status and prestige. Later, Fodness (1994) provided five categories of travel motivation: ego enhancement, knowledge, punishment minimisation, self-esteem and reward maximisation. The most commonly used classification of motivations was introduced by Dann (1977). This simply divides tourism motivations into two types, namely 'push' and 'pull' factors (Goossens, 2000; Jang & Wu, 2006; Yoon & Uysal, 2005; Yuan & McDonald, 1990).

Push factors are internal and refer to the social and psychological reasons for travelling, such as escape, prestige, novelty seeking, etc., while pull factors are external to the individual, and include, for example, the attributes of a destination, like natural beauty, the exotic local culture and so on. The push motivations help to explain why tourists decide to take a holiday trip (the generic decision) and the pull motivations help to explain why tourists find a specific destination attractive based on the destination attributes (destination evaluation). The choice criteria that tourists use to make the decision are derived from these motivation factors.

Besides motivation, destination image is another pertinent issue that helps explain destination choice. Many studies have shown that positive impressions of a destination increase the likelihood that this destination is chosen (Alhemoud & Armstrong, 1996; Echtner & Ritchie, 1993). Scholars define destination image as tourists' overall impressions, beliefs or perceptions on the attributes of a specific destination (Fakeye & Crompton, 1991) or as their mental picture of the destination (Alhemoud & Armstrong, 1996; Echtner & Ritchie, 1993; Gallarza et al., 2002). Therefore destination image is measured either through a multi-attribute approach (Beerli & Martín, 2004; Court & Lupton, 1997; Echtner & Ritchie, 1993; Tsai & Chen, 2004) or through a holistic approach, with a single general impression of the destination (Baloglu & McCleary, 1999). Simon (2000) points out that images (or impressions) of a destination can be generated from more functional attributes, such as scenery, attractions and price, or more psychological attributes, such as friendliness, safety and atmosphere.

Destination image has been split into cognitive image and affective image (Pike & Ryan, 2004; White, 2004). Cognitive image is based on knowledge of functional attributes, while affective image represents the emotion and feelings generated by the destination. The latter are generally paired over a spectrum, such as arousing–sleepy, pleasant–unpleasant, exciting–gloomy and relaxing–distressing (Pike & Ryan, 2004). Studies of destination image have involved the investigation of a specific destination (Joppe et al., 2001; Pike & Ryan, 2004; Parker et al., 2003; Vogt & Andereck, 2003) or have compared multiple destinations (Pike &

Ryan, 2004; Scott et al., 1978). To some extent destination image will determine tourists' choice of destination but image also determines their satisfaction *after* the trip, as well as the intention to recommend the destination or to return (March & Woodside, 2005). Two important factors influencing destination image have been identified by previous research: prospectively, the results of any information search the tourist does before visiting the destination (Baloglu & McCleary, 1999; Woodside & Lysonski, 1989) and retrospectively, past experience of the destination (Beerli & Martín, 2004; Mazursky, 1989). These are evidently two important issues factors in tourism decision-making more generally.

In order to make a decision, tourists need to retrieve information on a destination. Therefore, information search as an important stage of tourism decision-making has been widely studied (Chen & Gursoy, 2000; Fodness & Murray, 1997; Gursoy, 2003; Gursoy & McCleary, 2004; Money & Crotts, 2003). Although information search could serve multiple functions, from the destination choice to travel planning regarding accommodation, transport or on-site activities, the present review focuses on the information search used for destination evaluation and decision. For a greater understanding of search behaviour, previous research has investigated the 'strength' of information search, the sources and channels of information search and the factors influencing search behaviour.

The strength of the information search refers to the extent of individual efforts made during the search, principally in terms of the amount of time spent and number of sources used (Comegys et al., 2006). Tourists can acquire information through a range of sources and channels. According to (Engel et al., 1995), these sources can be classified based on whether they are commercial or not and whether they are in the form of personal communication or not. In general, sources include word-of-mouth, advertisements in print and electronic media, travel agents and direct contact from a retailer (Assael, 1987; Beatty & Smith, 1987; Smith, 1994; Hawkins et al., 1998).

Knowing the efforts and sources used by tourists during the information search is extremely useful for destination marketers in developing an efficient advertising strategy. However, information search behaviour will vary from person to person and will depend on a series of factors. Investigating these factors is helpful for explaining different types of search behaviour and for segmenting tourism decision-making groups. Thus, there is an extensive literature on these factors (Beatty & Smith, 1987; Bettman, 1979; Bloch et al., 1986; Money & Crotts, 2003; Moore & Lehmann, 1980; Punj & Staelin, 1983; Ross, 1979). They include: characteristics of the vacation; characteristics of the decision-makers; motivational factors (Fodness & Murray, 1997); uncertainty (Hyde et al., 2008); and familiarity (Read, 2007). The factors that are of particular relevance to this research are: (1) psychological (e.g. risk aversion and other personality traits); (2) economic (wealth); (3) life cycle (and its consequences for motivation). These factors are discussed in the results of the interviews.

The majority of the studies mentioned above concentrate on what might be termed an external information search. The 'search' can, though, be 'internal' when previous experience and knowledge are available. Previous experience has in fact proved to be an important factor that influences the extensiveness of the external information search (Cai et al., 2004). This is one of the reasons that after-purchase feedback is regarded as an important stage in tourism decision-making. Although it does not influence the choice made for current travelling, it will form part of the (internal) information store for a future destination choice. The role of travel experience in tourism decision-making is an issue worthy of note.

Two critical effects of previous experience have been identified in previous studies: the effect on travel intention (e.g. Juaneda, 1996; Perdue, 1985; Sonmez & Graefe, 1998; Bigne et al., 2001; Prentice, 2006) and the effect of word-of-mouth communication on choice of destination (Bigne, et al., 2001; Gitelson & Crompton, 1984). For example, empirical studies have shown that a positive travel experience to specific regions both increases the intention to travel there again and decreases the intention to avoid areas, particularly risky areas (Belhassen & Caton, 2009); furthermore, for those tourists who seek variety and prefer new destinations, satisfaction with a travel experience will increase their intention to recommend the destination to their friends (March & Woodside, 2005).

To sum up, tourists' motivation, destination image, information search and previous experience are the critical issues broadly involved in tourism decision-making. However, while these may be the relevant factors influencing this process they cannot provide a detailed and systematic explanation of the specific decision-making process itself. In fact, only if we have the answers to the question of how the evaluation process is carried out by tourists can we fully explain tourism decision-making and predict destination choice more accurately. So, modelling the individual decision-making process and explaining the evaluation process at a micro-level is a key part of this study.

2.3 Different approaches to modelling decision-making in choice of destination

Different disciplines have investigated the decision-making process from different perspectives; in tourism, decision-making is a topic that requires a multidisciplinary approach. The main approaches used to study tourism decision-making include: the maximum utility theory from the economic perspective; the planned behaviour theory from the psychological and sociological perspective; the choice-set model from consumer and marketing research; and hierarchical analysis from operations management. These are considered in turn.

2.3.1 Utility theory: the economic approach

The investigation of decision-making from an economic perspective uses a normative approach that assumes that decision-makers are economic agents, which means they always behave rationally and make decisions based on the evaluation of the benefits and cost of each alternative product. The economic approach to decision-making seeks a universal formula into which are entered a series of values to produce a result. Here, the tourist, as a rational economic agent, provides the values of the independent variables (the relevant attributes of each destination) so that the value of the dependent variable (i.e. preference for any particular destination) can be calculated. In economics, the benefit gained by consumers from the product is termed utility and the cost is termed a constraint. It is assumed that people, as rational economic agents, always follow a utility-maximisation principle, which means the product chosen should be the one providing the highest utility to the individual, subject to the constraints. In fact, of course, in many situations people are not rational, the utility-maximisation theory will not apply. Nonetheless, the majority of tourism decision-making studies have used it as a basic principle to explain choice of destination. In this case, in order to understand tourists' choices, we need to identify the alternative destinations' utilities so that predictions can be made based on the utility scores.

In traditional demand theory, products are objects that generate utility, which means they are always compared as a whole unit. If we could estimate the utility of each alternative destination based on tourists' preferences, we would be able to know, among a selection of destinations, which has greatest chance of being chosen. However, this holistic measurement (calculating an overall utility score for each destination) provides no extra information on why one destination is preferred to another, or how improvements can be made for competitive advantage.

In light of these problems, Lancaster (1966) provides a 'characteristic' theory to understand and estimate the utility. Instead of assuming utility is derived directly from the product itself, Lancaster argues that the utility is generated from the characteristics or attributes of the product. This theory fits the tourism context well, since tourists do not derive utility by possessing or using travel destinations as a whole, but by consuming the components (e.g. transport, accommodation and attractions) of the destinations (Tussyadiah et al., 2006). Due to its explanatory value, Lancaster's characteristic theory was first used by Rugg (1973) in a tourism context to identify the determinants of destination choice. It was subsequently adopted and developed by others (e.g. Apostolakis & Jaffry, 2005; Morley, 1994; Papatheodorou, 2001; Seddighi & Theocharous, 2002). More recently, (Tussyadiah et al., 2006) extended Lancaster's theory to explain destination choice.

According to the demand model proposed by Rugg (1973), destination choice is based on maximising utility over a range of destination attributes, subject to income and time constraints. In economic terms, the overall utility of a destination is a function of the individual's income, the time available for touring, the cost, the tour characteristics, and the prices of other destinations (Morley, 1991). By using least-squares regression, positive relationships have been found between identified destination attributes (e.g. amount of sunshine, level of rainfall and number of museums) and destination demand (as indicated by tourist traffic flow and duration of stay at each destination), while negative relationships have been found between constraints (e.g. time, distance) and destination demand. Those significant relationships uphold the hypothesis that the modified Lancaster characteristic model can be used as a valid representation of tourists' destination choice.

Rugg's demand model provides a basic and useful framework to estimate the utility/influence of each attribute considered by tourists during the selection. But this is a standard consumption model, in which the choice of destination is measured by continuous variables (i.e. traffic flow at each destination or average time spent at each destination). Although, to some extent, these indicators reflect tourists' preferences, they are general rather than specific to the individual. Thus later studies (e.g. Apostolakis & Jaffry, 2005; Jeng & Fesenmaier, 2002; Morley, 1994; Seddighi & Theocharous, 2002) adopted a 'discrete choice' economic model to investigate whether tourists select certain destinations (Seddighi &

Theocharous, 2002) or how tourists select destinations from several alternatives (Morley, 1994). Unlike Rugg's study, which analyses the aggregated or averaged derived data (e.g. using gross domestic product as the nearest proxy to the incomes of potential tourists), the discrete choice model has been used to analyse survey data (individuals' responses within a study). These analyse shave been conducted mainly in two ways. In the study of (Seddighi & Theocharous, 2002), the importance of each destination attribute was rated directly on a three-point Likert scale and choice of destination was determined by a dichotomous question, 'Will you revisit Cyprus?' The probability of a revisit to Cyprus, given the characteristics of tourists and the Cyprus tourism product, were then calculated by a conditional logit model. Instead of asking actual tourists to rate the importance of each attribute and to choose a real destination (or to reflect on that choice), Morley (1994) argues that simulated choice experiments give the researcher more experimental control of contexts, variables and values.

In a simulated choice experience, destinations are presented as stimuli which consist of a set of combinations of attributes with varying levels/aspects. The respondents are asked to express their preferences on each stimulus (Apostolakis & Jaffry, 2005). Based on tourists' preference order of the destination stimuli, it is possible to calculate how much utility/influence each attribute level has on a decision. In marketing and consumer research (considered below), this kind of simulated experiment has been further developed as conjoint analysis by (Green & Srinivasan, 1978), which in turn has been widely adopted in tourism decision-making studies (e.g. Basala & Klenosky, 2001; Suh & Gartner, 2004; Tsaur & Wu, 2005; ZYL, 2012).

2.3.2 Planned behaviour theory: the psychological approach

Rather than investigating how rational people should make a choice and work out a universal formula for everyone, the psychological perspective focuses on the individual's mental and emotional functions in the process of decision-making. Instead of explaining how people *should* make a choice, it tries to reveal how people *actually* make a choice, based on a range of psychological factors, such as motivations, perceptions, beliefs and attitudes. The classic psychological theory used to explain tourists' decision-making is planned behaviour theory, which is a theory of reasoned action extended by adding control elements into the explanation (Ajzen, 1991; Fishbein & Ajzen, 1975).

This theory states that if people believe that certain behaviour will lead to a beneficial outcome, they tend to carry out this kind of behaviour and that there is a strong positive relationship between intention and actual behaviour. The judgement of the value of an outcome is shaped by three belief dimensions: behaviour belief (attitude towards the behaviour), normative belief (subjective norms), and control belief (perceived behavioural control). In the context of tourism decision-making, scholars adopting a psychological perspective propose that whether tourists actually travel to a certain destination can be predicted by whether they have the intention to travel there.

Many tourism studies have sought to identify the factors influencing travel intentions. For example, Qu and Ping (1999) examined Hong Kong residents' intention to go on cruises in relation to motivation factors. Shima et al (2005) found that, for mature travellers, past travel experience influences future travel intention. Lancaster (1966) found that positive experiences lead to stronger travel intentions.

The planned behaviour theory provides a useful framework to summarise the type of factors that determine tourists' intentions. These factors include tourists' attitude towards travelling to a destination, their subjective norms and their perceived control on travelling to the destination. Attitude here is the predisposition or feeling towards a destination (e.g. favourable, pleasant, fun, etc.) (Moutinho, 1987). Since Lancaster's characteristic theory is widely accepted in tourism studies, tourists' attitudes towards one destination is usually measured as the sum of the attitudes towards the destinations' perceived attributes (Crompton, 1992; Um & Crompton, 1990; Yoo & Chon, 2008). And the attitude towards each attribute can be calculated as the likelihood of experiencing this attribute at a certain destination multiplied, for example, by the benefit value of this attribute granted by tourists.

Subjective norm reflects the tourist's perception of his/her reference group's belief as to whether he/she should travel to this destination. The subjective norm is determined both by the individual's beliefs about 'what others would think about it' and how much this individual would like to comply with the considerations of the reference group (Ajzen & Fishbein, 1980).

Perceived behavioural control relates to the perceived ease or difficulty of travelling to a certain destination. The validity of the application of planned behaviour theory in tourism decision-making has been tested in several studies (Gnoth, 1997; Yoon & Uysal, 2005). In the study by (Lam & Hsu, 2006), past behaviour (frequency of previous travel) was added into the framework to increase the predictability of travel intentions.

2.3.3 Behaviour theory: the sociological approach

If we could say the economic perspective on tourism decision-making focuses on the normative choice process, and the psychological perspective focuses on descriptive mental processes of the chooser, then the sociological perspective focuses on the interplay between social structure and the individual decision-maker. It assumed that tourists' motivations to travel and their preference are embedded within the context of the social structure and are influenced by these factors such as social identities, reference groups and culture. The investigation of the tourism decision-making process from a sociological perspective has mainly covered three dimensions: the typology of tourism decision-makers, based on social-psychological variables; joint decision-making and the influence of reference groups; and cultural differences in tourism decision-making.

Regarding typology, tourists can be classified and characterised by social-psychological variables, for instance according to social context (Gilbert, 1991). At the individual level, the sociological approach tries to understand tourists' decision-making by segmenting different types of decision-makers, based on social-psychological characteristics such as values and lifestyles (Madrigal & Kahle, 1994; Thrane, 1997), attitudes, interests and opinions (Davis et al., 1988), motives (Cha et al., 1995), or personality types (Plog, 1974). A classic and widely cited (Pearce, 1982; Redfoot, 1984; Wickens, 2002) example of such a study is that by (Cohen, 1972), whose typology of international tourists classed them in the roles of drifter, explorer, individual mass and organised mass. The general idea of the classification is based on to what extent the tourists desire to experience novelty through places, people and cultures that are different from their familiar social environment.

Cohen's theory was developed by Mo (1993) into a 20-item scale. The study of (Jiang et al., 2000) tested the validity of the 20-item scale based on novelty-seeking regarding destination, service and social contact with local people; they found that although the typology scale could reveal tourists' preferences to a degree, the predictability would increase if it was supplemented by other measures. Other scholars also argue that a tourist typology based only on social-demographic and social-psychological variables is insufficient explain tourists' choice (Oppedijkvan Veen, 1983; Woodside & Carr, 1988) and there is a need to develop more integrated tourist typologies, by incorporating factors such as information search, decision-making styles and so on (Decrop & Snelders, 2005).

Another dimension of the sociological focus on tourism decision-making is the influence of other people at a social level. Rather than attending only to the simple relationship between the decision-maker and decision, the sociological perspective always try to understand the individual within a social context, which involves the recognition that decisions are not be made in a vacuum, without any influence from other people and the environment. For instance, joint decision-making with spouse (Fodness, 1994) and the influence of children (Mannell & Iso-Ahola, 1987), family (Chen, 2000; Fodness, 1992) and friends (Bonsall, 2004) on destination choice have been studied. The subjective norm (one dimension of planned behaviour theory – see above) is another example of the sociological approach to tourism decision-making being used to explain the effects of social pressure on tourist' attitudes and preferences in selecting holiday destinations (Hee, 2000). So to some extent, the theory of planned behaviour can be seen as a combination of the psychological and sociological approaches.

On a broader level, cultural differences in tourism decision-making have been of interest from a sociological perspective. Culture reflects the character of a society and it determines the type, kind and extent of actions, reactions and interactions (Hartley & Hawkes, 1997). Previous studies have shown that culture does influence tourist behaviour (Pizam & Sussmann, 1995), destination image (Goh & Law, 2002) and tourists' information search (Chu & Choi, 2000). Cultural difference also affects the decision-making process (Dunn Ross & Iso-Ahola, 1991; Qu & Lam, 1997). For example, a study by (Dunn Ross & Iso-Ahola, 1991) revealed that a decision to visit Lisbon was shaped by the likelihood of visitors accepting social differentiation, their sense of individualism and their long-term orientation.

2.3.4 The choice-set model: the marketing and consumer behaviour perspective

Compared with the traditional academic disciplines, marketing and consumer research is more business and practice oriented. Tourists are regarded as consumers and the objective is to collect tourists' preference information, to help devise marketing strategies. As a result, instead of trying to provide a comprehensive explanation of this complex mental process by considering all kinds of attributes and factors, marketing research tends to seek to simplify the process and to provide more readily applicable results (Sirakaya & Woodside, 2005). The chief approach here is the choice-set model.

The work of Woodside and Sherrel (2001) was the first attempt to conceptualise choice sets for leisure travel. This model describes a funnel-like process in which a tourist first develops an initial set of destinations, widely known as the awareness set, then eliminates some of those destinations to form a smaller late-consideration or evoked set (Bradlow & Rao, 2000; Manrai & Andrews, 1998) and finally selects a destination from the late-consideration set. The awareness set is defined as comprising the destinations that a traveller noticed as available alternatives through passive receipt of information. The consideration set is the group destinations that a traveller is considering as probable destinations within some period of time (Bettman et al., 1998). The awareness set, consideration set and final choice are the key elements widely acknowledged by most researchers (Crompton & Ankomah, 1993).

Based on this simple two-stage choice-set model, other choice sets, such as inert set, inept set and action set, were developed in later research (Crompton, 1992; Decrop, 2010) so that the position of each destination within the tourist's mind can be revealed more accurately. Although the more elaborate choice-set model provides theoretical insights into tourists' decision-making processes, the original purpose of the choice-set approach was to simplify the decision-making process into several outcome stages where alternative destinations can be positioned within a certain choice-set so that destination marketer could be able to make effective advertisements and improvements according to the information.

2.3.5 Hierarchical analysis: the operations management approach

Operations research is a discipline that deals with the application of advanced analytical methods to help make better decisions. Saaty (1977; 1980) introduced the Analytic Hierarchy Process (AHP) for operation studies to analyse multi-criteria (attributes) decision-making. It is a methodology that provides a systematic problem-solving framework. Specifically, it enables us to estimate the priority of elements within the hierarchical structure by conducting a series of paired comparisons. As mentioned in the economic approach of tourism decision-making, since the utility of a destination is based on the utilities generated from a destination's attributes, and how to estimate the relative importance of each destination attribute is a key question for predicting tourists' choice.

Saaty suggests that the AHP has an advantage in estimating the relative importance of attributes that are difficult to compare, as their scales are loosely defined, which is suitable for tourism decision-making. Thus, tourism scholars have incorporated this method into tourism decision-making studies (Chen, 2006; Hsu et al., 2009) to predict tourist preferences. Unlike asking respondents to assign preference values to each criterion or attribute directly, AHP decomposes decision-making into a hierarchy from broader criterion/attribute to more specific criterion/attribute. Respondents need only to compare the importance of attributes at the same level and compare only two attributes each time. AHP provides a systematic way to calculate the relative importance of each attribute based on this paired comparison and to ensure the judgements of the respondent are consistent with each other through the whole process. AHP allows a consistency ration measurement which is used to check whether the comparisons of respondents are rational in terms of transitivity.

Hsu et al. (2009) used AHP to investigate tourist destination choice. A four-level AHP model with 22 sub-criteria at the fourth level was used. Unlike tourism decision-making studies using regression methods, it was able to provide the relative weights of a large number of attributes (22) at one time. Furthermore, by clustering attributes into different levels, the tourist respondents needed only to evaluate attributes of a similar nature, which made the comparison easier. For instance, the 22 attributes estimated by Hsu et al. (2009) were initially divided into internal factors and external factors, and the internal factors were then placed into four categories and the external factors into two categories. On each occasion, the tourists needed only to compare two attributes at the same level and within the same superior criterion.

Summary

The economic approach provides an explanation of rational tourism decision-making and a normative framework (i.e. utility maximisation) that can be used to predict tourists' preferences and choices. Tourists are objective judgers and the choice is purely determined through weighing the utility of destination attributes and constraints. The psychological approach treats tourism decision-making as a complex mental process and a descriptive framework (i.e. planned behaviour theory) is adopted to present how motivation, affect, attitude and intention lead to a choice. Tourists are cognitive and emotional individuals and the choice is made based on the individual's subjective perceptions. The sociological approach tries to understand tourism decision-making as a social behaviour and the focus is on segmenting. Tourists are social beings whose behaviour and choices are influenced and determined by their social structure (e.g. values and beliefs) and social environment (e.g. social pressure and reference groups).

Since the sociological approach focuses on the influence of social factors on decision-making instead of the modelling of the process, this approach is always combined with the psychological framework, providing supplementary elements. Scholars from a marketing and consumer research background investigate tourism decision-making as a normal consumption of products and the framework (i.e. choice-set model) aims more to provide information for destination marketing. Tourists are consumers and establishing the preference position of each destination is as important as predicting the final choice. Although operations research does not provide a general decision-making theory, it offers some systematic analysis methods (e.g. AHP) which enable researchers to decompose a complex problem into simpler steps and make data collection easier.

Although different disciplines provide different perspectives on tourism decision-making, the pieces of knowledge established within each disciplinary approach have not been integrated well and there are still some pieces missing from the existing body of knowledge.

2.4 Challenges revealed in the literature review

In studies of tourist decision-making, most theories and concepts have been borrowed from other disciplines and adapted. How to manage this process of borrowing and adaptation is a key question that needs to be answered to assure the quality and validity of the knowledge produced on tourism decision making. There are three issues generated from the literature review: knowledge integration, knowledge adaptation and knowledge update.

Firstly, due to the multidisciplinary nature of knowledge production on tourism decision-making, the resultant body of knowledge has been constructed using all kinds of theories and concepts borrowed from different disciplines. And since different disciplines adopt different perspectives and study different issues connected to decision-making, the strands of evidence produced tend to be independent of each other. Such isolated pieces of knowledge are not enough to give a comprehensive picture of tourist decision-making. For example, normative decision-making from an economic perspective cannot explain irrational choices, and this happens frequently in the selection of a holiday destination. The basic choice-set framework from marketing research tells us nothing about the determining factors that influence tourists' decision-making.

In addition, different definitions and descriptions of the same concepts from different disciplinary perspectives may lead to confusion. For instance, tourists' preferences for destinations are based on the sum of attribute utilities in the economic approach, but from a psychological point of view preferences are based on tourists' attitudes towards each attribute. In recent years, with the introduction of a more thoroughgoing interdisciplinary approach in tourism (Tribe, 1997) scholars have start to appreciate the importance of knowledge integration for tourism studies, which requires elements to be assembled, concepts to be unified and theories connected and circulated (Belhassen & Caton, 2009; Darbellay & Stock, 2012).

In some tourism decision-making studies, efforts at knowledge integration can be seen. For example, in the updated choice-set model proposed by Fry and Prentice (2006), psychological elements such as destination image, familiarity and affect are integrated in the model as filtering criteria to explain this choice set's narrowing process, so that more tourist preference information can be obtained. The study found that familiarity plays an important role between consideration sets and action sets, which means that if people are familiar with a destination (either through researching information or by having travelled there before), that destination will have a high chance of being put into the action sets that tourists intend to visit. The study was able to rank position each destination and also gave an insight into the reasons and factors behind each stage of choice.

The work of Decrop and Snelders (2005) provides an example of elements being assembled in order to understanding tourist decision-making; it combined social-psychological factors and decision-making style factors (e.g. transport mode, trip length, etc.) to increase the accuracy of tourist typology so that the tourists' decisions could be predicted more accurately (based on their typology). These studies provide examples of theories and frameworks having more explanatory power by combining different disciplinary elements together. More such studies are required, especially ones that would unify concepts and connect theories.

The second concerned knowledge adaptation. In studies of tourist decision-making, it is necessary to refer the validated knowledge and theories from other disciplines and adapt them as necessary. But at the same time, the process of knowledge production is not a simple knowledge borrowing and application process, since it requires careful screening and refining by tourism scholars and this process should always concern the special character of tourism products. In general, the particularity of the tourism destination as a product arises for two reasons: the complexity of destination components and the destination's service-intensive nature.

The destination is not a simple product that serves a single function but is a mixed and dynamic product that involves all kinds of tangible and intangible factors. Therefore, the destination choice should not be viewed as a simple normal product selection but a complicated information-processing and analysis process. In past years, most tourism decision-making studies focused on applying theories and models borrowed from other disciplines in a tourism context and testing the validity of these theories and models, but they ignored the complexity of tourism products. This problem has been increasingly raised by tourism scholars (Morley, 1991; Papatheodorou, 2001).

More recently, a few works have been produced on theory adaption. For example, the original destination decision-making model proposed by Raaij and Francken (1984) is based on traditional information-processing theory borrowed from consumer research. That model incorporated the generic decision, information acquisition, joint decision-making, vacation activities, and subsequent satisfaction and complaints. But given that the 'consumption' of a destination has many components, Bargeman and Poel (2006) extended the original vacation decision-making model with a separate stage, which is a further information search, done in order to prepare for the vacation once the destination itself has been chosen.

In addition, identifying unique destination factors such as political instability (Seddighi & Theocharous, 2002), stimuli (Yoo & Chon, 2008) and past travel experience (Lam & Hsu, 2006) influences tourism decision-making and are another way of distinguishing the tourism product from 'normal' products. Paying attention to the unique characters of tourism not only ensures that knowledge adaptation is more appropriate but also generates opportunities to supplement and improve the general decision-making theories, through new elements or insights found in tourism decision-making studies.

Finally there is the issue of knowledge update. Many classic theories from other disciplines have been used in the tourism decision-making context. However, with further knowledge development within the original disciplines, the theories and concepts incorporated into tourism studies also need to be updated. For example, the utility maximisation theory from economics has been the dominant theory used in tourism decision-making studies to estimate the importance of particular attributes and to predict tourists' choice until now. But more and more scholars from economics have questioned the possibility of completely rational choice. Many more theories have been established to explain and describe bounded rational or irrational decision-making, such as prospect theory and regret theory. These theories have not been widely used in the tourism decision-making context to produce complementary knowledge.

It is the same with regard to the theories borrowed from psychology; in most tourism decision-making studies tourist choice strategy is assumed to have been a weighted additive choice which assigns importance to each relevant attribute and the tourist chooses the destination with the best value score. Abad value for one attribute can be compensated by a good value for another attribute. However, in many cases decision-makers do not allow such a trade-off between attributes. For example, the tourist may choose only a destination with a temperature of around 20°C. No matter how attractive the other attributes are, he will not select a destination that does not meet this requirement. This kind of choice strategy is named a non-compensatory choice heuristic in psychology; alternatives include conjunctive, disjunctive and lexicographic heuristics (Abelson & Levi, 1985; Bettman et al., 1991). Although different choice heuristics may lead to totally different choices, the existence of different types of choice heuristic has not been widely accommodated in tourism decision-making studies.

As for the tourism decision-making of Chinese outbound tourists, despite the fact there has been a growing interest in Chinese outbound tourists (Guo et al., 2007; Yu & Weiler, 2001; Zhang & Heung, 2002), only a few researchers had investigated the destination decision-making of Chinese outbound tourists (Kim et al., 2005; Sparks & Pan, 2009). Although these researchers have provided useful information, they have focused on preferences for a certain destination and simply identified the important attributes (Kim et al., 2005; Sparks & Pan, 2009). Further information regarding how each attribute affects the decision-making is still unknown.

In conclusion, given the knowledge gaps revealed from general tourism decision-making studies and the empirical research of Chinese outbound tourists, this study aims to add some of the pieces hitherto missing from the body of knowledge on tourist decision-making and also to provide useful insights on general decision-making theories in the following three respects:

(1) This research clarifies and explains two concepts (choice criteria and choice heuristic) that are essential for describing and understanding the destination evaluation stage of decision-making. Previously, these two theoretical constructs have been used in isolation, because they originate from different approaches. The present study therefore represents an instance of knowledge integration between different approaches, as highlighted above. Furthermore, by integrating the utility maximisation theory, non-compensatory preference theory and the basic framework of choice-set theory, this research tries to provide a more comprehensive insight into tourists' decision-making processes.

(2) Because Chinese long-haul outbound tourists were studied, a supplemental aspect of the present research is that the characteristics of (mostly) first-time travellers with limited information and limited previous experience are considered.

It reveals how these unique characteristics may influence choice of destination.

(3) Besides applying conjoint analysis on an interesting sample (Chinese long-haul outbound tourists), an innovative analysis method termed greedoid analysis, recently introduced in consumer behaviour research, is explored in this study, where it is used to evaluate tourists' preferences in relation to choice of destination. These two methods of preference analysis and the decision-making models behind them are then evaluated and compared.

2.5 Conclusion

This chapter provides a critical review of the tourism decision-making literature, at both the macro and the micro levels. From the macro level, the stages from 'problem recognition' (here, the need to select a holiday destination) to the post-purchase evaluation involved in tourism decision-making are investigated, as well as the important issues relating to this process –motivation, destination image, information search and travel experience. At the micro level, the study of tourism decision-making focuses on the single stage of evaluating and selecting from a set of alternative destinations. How the alternatives are evaluated and selected is the core question that needs to be answered from a micro level investigation.

Different disciplinary approaches have been used to describe and explain the process of tourism decision-making made at a micro level. Based on the literature review, the pieces of knowledge derived from these different disciplinary approaches have not been well integrated and sometimes the knowledge and theories borrowed from other disciplines have been applied in a tourism context without due reflection and modification. Besides, the theories and methods adopted from other disciplines in tourism studies have not been updated to account for recent advances in those other disciplines. These challenges are considered and tackled in this research. As mentioned above, two key concepts (choice criteria and choice heuristics) and the theories behind them are investigated in this research by using data on Chinese long-haul outbound tourists.

The next chapter provides the theoretical background for the investigation of the two concepts and the Chinese outbound market.

Chapter 3 Theoretical background for the research

3.1 Introduction and overview of the chapter

To understand the processes of destination evaluation and selection, there are two key concepts: choice criteria and choice heuristic. Choice criteria, also described as 'evaluation criteria' or 'determinants of decision' in other studies, are the attributes of a destination (e.g. cost of the trip, destination culture or beauty of the resort) considered important by tourists, and based on which they will make a selection. The comparison of the *values* assigned to each attribute by the tourist for the alternative destinations contributes to the choice. Choice heuristic, also termed the 'evaluation rule', 'decision strategy' or 'choice calculus', is the way a tourist combines different criteria to evaluate alternative destinations. For example, tourists may average the values of important attributes and select the destination with the highest average; or they may apply thresholds or cut-off points for important attributes and select among only those destinations that exceed all cut-off values.

The final decision of which destination to choose is a function of choice criteria and choice heuristic combined. Tourists need to set their choice criteria first and then use a certain way to use and combine them (choice heuristic) so that they can select a destination (Crompton & Ankomah, 1993; Decrop & Kozak, 2009). For example, assume tourist C only cares about two attributes, namely the seasonal average temperature at the destination and the price of the trip, so he sets these two attributes as his choice criteria. And the choice heuristic he uses is to set a cut-off point on each criterion (the temperature should be above 10°Cand the price of trip should be below £200). There are two destinations, A and B. The temperatures of these two destinations are, respectively, 20°Cand 8°Cand the trip prices are £180 and £100. According to tourist C's choice heuristic, only weather and price are important and only a destination that exceeds both cut-off values will be selected, leading to the choice of destination A.

According to previous research (Brisoux & Laroche, 1981; Crompton & Ankomah, 1993; Gensch, 1987), the evaluation process can be divided into two stages. At the first stage, a large number of all possible destinations are discarded to form a small set, termed the 'consideration set'. At the second stage, the several alternatives in the consideration set are evaluated again so that the final destination is selected (Um & Crompton, 1990). The goal of the first stage of evaluation is to reduce the list of all alternatives to a manageable number of acceptable options, while the second stage of evaluation is to select the most satisfying alternative from the acceptable ones. Because of the difference in the purpose of each of these stages, the choice criteria and rules used by tourists in these two stages may be different and consequently it is necessary to investigate them both.

The next section presents empirical findings concerning choice criteria from by previous studies of tourist decision-making. These findings were referenced for the identification of the choice criteria of Chinese long-haul outbound tourists in their selection of destination tours offered by the tour operators. To the best knowledge of the researcher, there has been no empirical research into choice heuristics in relation to the selection of a tourist destination; instead, therefore, the different choice heuristics are summarised and illustrated. The third section of the chapter presents information about the Chinese outbound market; it also summarises knowledge of their choice criteria and choice heuristics from previous studies as the starting point for this research into Chinese long-haul outbound tourists.

3.2 Choice Criteria

Tourism destinations are different from manufactured products because they are mixtures of social, cultural and physical environments as well the 'tourist' components such as attractions, transport and lodging facilities and other travel-related services (Liu, 2000). Therefore, the utilities (in the economic sense) perceived by tourists are derived from different parts of this package. In contrast to traditional consumer theory, where economic agents derive utility directly from goods, Gorman and Lancaster argue that utility in tourism is related to the joint consumption of a (tourism) product's bundle of intrinsic properties, or characteristics, or, here, attributes (Papatheodorou, 2001). Seddighi and Theocharous (2002) adopted the product characteristics approach in their tourism decision-making model. It breaks down the tourism product into a set of characteristics such as cost of living at the destination, price of the tourist package and facilities, etc. Their model indicates that tourists make decisions based on their perceptions or feelings derived from those characteristics. The evaluation of potential travel destinations is a multi-attribute assessment of the destination (Sparks & Pan, 2009). The characteristics or attributes used by tourists to facilitate their selections are termed choice criteria.

A vast body of literature has sought to identify which attributes are important for tourists in destination selection (e.g. Um & Crompton, 1990; Ajzen & Driver, 1992; Crompton & Ankomah, 1993; Chi & Qu, 2008; Seddighi & Theocharous, 2002). The many variables identified have been categorised as: internal variables (internal to the tourist, that is, for example attitudes, values, lifestyle, images, motivation, beliefs and intentions); external variables (e.g. constraints, pull factors of a destination, marketing mix, influences of family and reference groups); the nature of the intended trip (e.g. distance and duration); and trip experiences (e.g. mood and feelings during the trip, post-purchase evaluations) (Sirakaya & Woodside, 2005). However, the choice criteria used by tourists, especially first-time tourists, are mainly drawn from the set of external variables and nature of the intended trip, since the internal variables are more like the motivations or the reasons behind the selection of the choice criteria and trip experiences cannot be obtained prior to travelling.

These findings on choice criteria are supported by an alternative formulation, in which, similarly, two kinds of attributes are often considered by tourists as important in selecting a destination: (1) situational constraints, including cost, travel time to the destination, potential health problems and physical accessibility (e.g. Ajzen & Driver, 1992; Crompton & Ankomah, 1993; Um & Crompton, 1990); and (2) destination attributes, such as landscape, cultural, food etc., (Chi & Qu, 2008; Seddighi & Theocharous, 2002; UNWTO, 2008).

Regarding constraints, Crompton and Ankomah (1993) indicated that the greater the distance is to a destination, the smaller will be the number of opportunities that are likely to be available for people to be exposed to information about that destination. As a result, distance is a key attribute. In terms of destination attributes, research has demonstrated that a beautiful landscape, shopping opportunities, cultural exchange, infrastructure (e.g. accommodation, dining), safety issues and activities are often deemed important (UNWTO, 2008; Yee, et al., 2007). Another key characteristic of a tourism destination is the political stability in the destination (Seddighi & Theocharous, 2002).

Although previous studies provide useful information on what attributes might be important in destination selection, the *function* of these choice criteria or how they are used to judge destinations has not been well studied. This question needs to be answered by understanding the choice heuristics of tourists.

3.3 Choice heuristics

A choice heuristic is the sequence of mental operations used to transform an initial state of knowledge into a final goal state of knowledge, the point at which a particular decision has been made (Decrop & Kozak, 2009). In other words, it is the way decision-makers process information about their choice criteria so that they are able to select one of the alternatives.

The processing can be of two general types: processing by alternative and processing by attribute. In the former case, multiple attributes of a single alternative are considered in conjunction before information about a second alternative is processed. In contrast, in the latter case, the values of several alternatives on a single attribute are processed before information about a second attribute is processed (Bettman et al., 1991; Decrop & Kozak, 2009). Which form of processing will be used by decision-makers depends on the specific choice heuristic they adopt.

In consumer decision-making, choice heuristics have drawn much attention from scholars (Bettman et al., 1991; Laroche & Kim, 2003; Peter & Tarpey, 1975; Wright, 1975). In general, different choice heuristics are used in different situations. For example, simple choice heuristics such as the 'satisficing' heuristic (a neologism coined to combine notions of 'satisfy' and 'suffice' in the decision-making) will be used more often when consumers face riskless or repetitive choices (Hoyer, 1984),while more complex heuristics, such as an additive utility strategy, will be used in more risky situations (Peter & Tarpey, 1975). The following classification and description of the most common heuristics will provide more details about what they are and under what circumstances they are used.

One of the most important distinctions among choice heuristics is based on the decision-maker's preference function, which is a key concept in economics. Two common preference functions have been proposed in economic studies: the neo-classical (compensatory) preference function and the non-compensatory preference function.

3.3.1Compensatory choice heuristics

Compensatory choice heuristics require commensurability, which essentially means that values on different attributes can be traded off against one another. Sophisticated choice processes therefore require a translation of two disparate attributes or dimensions onto a common scale of utility (Abelson & Levi, 1985).

In other words, consumers will evaluate alternatives across a number of different attributes and then determine the most preferred by summing across those attributes. Compensatory choice heuristics include weighted compensatory heuristics and unweighted compensatory heuristics. Both are based on utility theory. The weighted compensatory heuristic seeks to account for the importance attached to each attribute and only then is the utility values of all attributes summed, after weighting, before the alternative with maximum utility is selected. The unweighted compensatory heuristic is similar except that all the attributes contribute to the utility equally, which simplifies the processing.

Both weighted and unweighted compensatory heuristics are alternative-based rather than attribute-based processes (Bettman et al., 1991), which means consumers consider information on attributes within one alternative first and then move on to the next alternative. However, as the number of alternative destinations and attributes increases, compensatory heuristics, especially the weighted compensatory heuristic, assume complex cognitive processes on the part of the decision-maker (Crompton & Ankomah, 1993). While people sometimes do make decisions in ways consistent with such a normative procedure, more often people appear to make decisions using simpler processes. In addition, for first-time tourists travelling to long-haul destinations, information on each attribute of each alternative is likely to be limited. This implies that sometimes these tourists may use other heuristics– ones which require less information. Most non-compensatory choice heuristics are simpler than compensatory ones and some of them do not require extensive information on attributes.

3.3.2 Non-compensatory choice heuristics

Non-compensatory heuristics do not allow a trade-off between attributes and are therefore also suitable when commensurability is absent. Non-compensatory evaluation rules suggest that decision-makers evaluate alternatives on two or three key attributes and eliminate the ones that are perceived to be inadequate on any of them. The literature distinguishes three types of non-compensatory decision heuristics: conjunctive, disjunctive and lexicographic (Abelson & Levi, 1985; Bettman et al., 1991).

The conjunctive heuristic is also called the satisficing heuristic, which is one of the oldest heuristics identified in the literature (Rossi & Allenby, 2003). It assumes that the decision-maker defines minimum cut-off points for important attributes. If an alternative falls below any of the cut-off points, it is rejected. When more than one alternative exceeds the cut-offs on all dimensions, the decision-maker may then proceed either by making the cut-offs more stringent or by using a different choice rule that will yield a single alternative. In a tourism context, it means a destination is selected only if minimum cut-off points on all important attributes are exceeded.

The disjunctive heuristic also requires a set of cut-off points on the attributes. In contrast to the conjunctive heuristic, an alternative is accepted when it has at least one value greater than the corresponding cut-off. The disjunctive heuristic leads to a consideration set of alternatives, each of which surpasses a threshold on at least one criterion. Whereas the conjunctive heuristic emphasises the negative end of attribute scales, the disjunctive rule focuses attention on the positive pole. These two heuristics, however, do not require any ranking or weighting of attribute dimensions by the decision-maker. When dimensions are rank ordered in importance, they are said to be in lexicographic order (Laroche & Kim, 2003).

The lexicographic heuristic uses all attributes in stepwise fashion. It assumes that alternatives are first compared with respect to the most important attribute. If one alternative has a higher value on this attribute than the others, that alternative is chosen, regardless of the values the alternatives have on the other attributes. If the alternatives are equally attractive on the most important attribute, the decision will be based on the attribute next in order of importance. For tourists with lexicographic preference, destinations are evaluated on the most important attribute first. If there is a tie, then they are evaluated on the second most important attribute, and so on (Crompton & Ankomah, 1993). Thus, lexicographic heuristic is an attribute-based process.

It is evident that choice heuristics differ in how much effort they require (Bettman et al., 1991). For example, for tourists using a lexicographic choice heuristic, the effort they have to make in searching for information is less than what they need for a weighted compensatory heuristic. According to Sen (2003), the process of choosing, and in particular the act of choosing, can make a substantial difference to what is chosen. Therefore, investigating the choice heuristics used by decision-makers is necessary for us to get a clear insight into decision-making behaviour.

3.3.3 Previous studies on choice heuristics

Although it has been noted that an individual's use of decision heuristics is likely to vary from one situation to the next (Crompton & Ankomah, 1993), it is still possible to test which choice heuristics are most frequently implemented by a certain group of consumers in a specific situation. Parkinson and Reilly (2002) used a composition approach to test which heuristics can be used to predict the consideration set (a few alternatives seriously considered) of consumers purchasing toothpaste and deodorant. They compared the actual consideration set with the one predicted by the specific decision heuristics using data on perceptions, importance of attributes and cut-off points. They found that weighted compensatory and lexicographic heuristics gave the best predictions of the consideration set. A study carried out by Brisoux and Laroche (1981) found that for men who regularly drank beer, a conjunctive heuristic was the best fitting one, followed by a linear compensatory heuristic. This finding was confirmed by Laroche and Kim (2003).

In terms of the use of the choice heuristics through the whole decision-making process, Yee et al. (2007) investigated the use of choice heuristics for the selection of a mobile phone and they found that the lexicographic heuristic model gave at least equal predictions as the weighted compensatory choice heuristic model. In contrast, Kohili and Jedidi (2007) and Dieckmann et al. (2009) found that the compensatory choice heuristic gave a better fit for their samples. The study by Kohili and Jedidi (2007) concerned the choice of computers while the study of the Dieckmann et al. (2009) concerned skiing jackets. One reason for the inconsistent results between studies is that the use of choice heuristics depends to a great extent on the nature of the decision and the context.

As we can see, all these studies involved tangible products. A focus on choice heuristics is rare in studies of service-based products, and especially tourism research. Although it has been suggested by several authors that travellers do use choice heuristics in their decisions (Bonsall, 2004; Woodside & King, 2001), operational rule-based models have rarely been studied. Notable exceptions include(but are not limited to) two studies by Law and Au (Au & Law, 2000; Law & Au, 2000) and one study by Middelkoop (2003), in which decision heuristics have been studied regarding tourists' shopping and transportation. Studies on destination choice heuristics are even fewer. To the best knowledge of the author, only Decrop and Kozak (2009) have briefly discussed the possible kinds of choice heuristics used for destination evaluation.

Although the choice heuristics used by tourists may vary both between people and by the same person on different occasions or in different contexts, it is still worth abstracting any common principles and distinctive features. In any case, it seems there are some similarities regarding the decision-making behaviour of a certain group of people who have the same purpose for travelling (Chen, 2000) and the same culture background (Pizam & Sussmann, 1995). And exploring the choice heuristics that might be used by a certain group and evaluating the predictive ability of each choice heuristic model would increase the predictability of tourists' decision-making behaviour. In this study, the targeted group is Chinese long-haul outbound tourists. The following section provides the essential information regarding Chinese long-haul outbound tourists, beginning with some general information on the development of China's outbound tourism, the profile of Chinese outbound tourists, especially the long-haul ones, and their preferences and destination choices found by previous studies. This cultural and demographic background information will be helpful for understanding the choice criteria and choice heuristics studied here.

3. 4 Chinese Outbound Tourists and Their Destination Choice

Before we go any further with the analysis of Chinese outbound tourists' destination choice, it is useful to have some background knowledge. This section therefore presents information on several relevant issues: (1) the development of China's outbound tourism; (2) China's outbound tourism market and the outbound destinations; (3) the profile of Chinese outbound tourists; (4) the influence of culture on Chinese tourism behaviour; and (5) research findings on the destination choice of Chinese outbound tourists.

The development of China's outbound tourism

Over the past decade China has been the fastest-growing tourism source market in the world. Since 2000, the volume of international trips by Chinese tourists has grown from 10 million to 83 million in 2012. Expenditure by Chinese tourists abroad has also increased almost eightfold since 2000. Boosted by an appreciating Chinese currency, Chinese travellers spent a record US$ 102 billion in international tourism in 2012, a 40% increase from 2011 when it amounted to US$ 73 billion. With this sustained growth, China became the new number one tourism market in terms of spending globally in 2012. In 2005 China ranked seventh in international tourism expenditure, and has since successively overtaken Italy, Japan, France and the United Kingdom. With the 2012 surge, China leaped to first place, surpassing both previous top countries Germany and second largest United States. (UNWTO 2013b)

Generally speaking, the development of China's international tourism is the outcome of economic reform and the relatively recent openness of the country to the outside world, along with the changes in the Chinese political and economic systems (Zhang et al., 2000). China is a late-comer in world international tourism; indeed, for a long time it was regarded as the last frontier for the tourism industry. Until the late 1970s, travel and tourism was officially regarded a part of foreign affairs and was never favoured by the government. Since 1978, however, as a result of the economic reforms and the open-door policy introduced by Deng Xiao-Ping, both domestic and international tourism have been recognised by government as instruments for economic development and modernisation (Lim & Wang, 2008). With the policy of openness to foreign visitors and the construction of tourism facilities (accommodation, restaurants, etc.), travellers from abroad flooded in, which made inbound tourism an important means of earning foreign exchange.

After 1990, economic development and an overall improvement in living standards, as well as political liberation in China, have contributed further to the growth in demand for international travel. The development of China's international tourism started to shift from a seller's (inbound) market to a buyer's (outbound) market (Arlt, 2006; Li et al., 2009; Zhang et al., 2000). According to a report on tourism market trends, the outstanding feature of the Asia and Pacific region (UNWTO 2008b) over the last two decades has been the emergence of China as an important generating market after outbound travel was liberalised.

In China, travelling across the border for leisure was an activity officially ignored until the middle of the 1990s. Before 1995, the general policy of the Chinese government on tourism was to encourage the development of inbound and domestic tourism rather than outbound tourism (Wei and Wei 2005 in Arlt 2006).

For example, the introduction of ADS system [1] was initially meant to restrict the number of Chinese people travelling abroad so that the government could control the development of outbound tourism (Arlt, 2006). The previous government policy, which restrained the development of the outbound travel, made no allowance for the increasing demand for outbound tourism.

Since the introduction of economic reform and decentralised economic decision-making in 1978, China has experienced rapid economic growth, with an average annual growth rate of real gross domestic product (GDP) of 9.42% and an average growth in per capita gross national income (GNI) of 7.15%. In 2000, the GNI per capita of Chinese citizens was US$840, which was more than four times that in 1978 (Lim & Wang, 2008). The tremendous increase in personal disposable income became a strong impetus for increased demand for outbound tourism.

In addition, increased leisure time is another stimulus. For example, in 2002, the Chinese government introduced the 'Golden Week Holiday' policy. The three national holidays (namely, the International Labour Day in May, China's National Day in October and the Spring Festival between January and February) increased from 4 days to 7 days, which enable Chinese people to undertake more domestic or outbound travel.

The gradually increased demand pushed the government step by step to relax the policy on outbound tourism (Arlt, 2006). For instance, the application for a private passport has gradually been made easier, with the processing period being reduced from six months to one month or within ten days for urgent situations, which is more convenient for overseas travel. Moreover, by late 2011, around 140

[1]The ADS system is based on bilateral tourism agreements whereby a government allows self-paying Chinese tourists to travel for pleasure to its territory within guided package groups and with a special visa. Only ADS countries can openly be promoted as tourism destinations in Chinese media.

countries had signed the ADS agreement with China so that Chinese tourists could travel to these destinations for leisure purposes; among these destinations, 112 countries have implemented the agreement while the others are working towards this (Chao & Jing, 2011).

To sum up, economic development, additional free time and relaxation of government policy have facilitated the explosive growth of the Chinese outbound travel market.

China's outbound tourism market and destinations

According to Euromonitor International (2012), the number of trips made by Chinese outbound tourists increased at an average rate of 11% since 2000. The growth in the numbers of outbound trips accelerated in the past a few years, peaking at 22% in 2011 (70.25 million overseas trips). According to the Chairman of China's National Tourism Administration (ChinaTravelNews, 2012), by 2015, the number of Chinese traveling abroad on holiday is expected to top 83.75 million.

As for Chinese tourists' outbound travel destinations, Asia occupies a dominant position, especially Hong Kong and Macao (Arlt, 2006). Asian destinations attracted 81.5% of Chinese outbound tourists, with Hong Kong and Macao alone sharing about 68.4% of the total traveller volume (Song, 2012). However, long-haul destinations like Europe, Australia and New Zealand have seen fast growth, especially in the past few years, owing to their recently obtained ADS status and aggressive marketing (Burnett et al. 2008 in Li et al. 2009). For instance, by 2008, China had become New Zealand's fourth (Tourism New Zealand, 2010) largest source market. In addition, China is the second largest market for Australia's total inbound economic value (Tourism Research Australia, 2010).

Besides Asia, Europe is the largest destination region for Chinese tourists with over 3 million trips in 2011. Although the share held by Europe slightly decreased over time, in absolute terms the growth in volume to this region is impressive, with arrivals roughly tripling in just over a decade, from 1.1 million in 2000 to 3.1 million in 2011 (CTA, 2012). Furthermore, due to the attractive destination image of Europe, the convenience brought by the Schengen visa – which allows visa holders to travel to most member states of the European Union on a single visa – and lower exchange rate after the economic crisis, more and more Chinese tourists flock to Europe, with a dramatic increase in spending power (CCTV, 2012). The study of Li et al. (2009) estimated that the current Chinese outbound travel market comprises approximately 22 million city residents, among whom 11.5 million have travelled or plan to travel to destinations outside Asia. As mentioned in the Introduction, China has been recognised as one of two (along with India) major emerging outbound tourism markets in the world (WTTC, 2006) and considering that only 4% of China's urban population has travelled overseas, the Chinese outbound travel market still has huge growth potential (Li et al., 2009).

Profile of Chinese outbound tourists

Given that outbound tourism, especially long-haul travel, is still a luxury for most Chinese people, it is not difficult to deduce that persons in high occupational positions, with high educational levels, small household size and high income account for the majority of long-haul outbound trips. Li et al. (2009), with a sample of 15,728, reported that nearly half of their respondents (48.2%) had some college education or beyond, which is much higher than the 9.9% across the population overall. Most respondents were employed full-time (60.5%), were 25–59 years old (72.9%). According to the estimation of UNWTO and ETC (2012), a large share of Chines outbound travelers (47%) is from the income range of CNY 5,001-10,000 per month (around 500 to 1,000 pounds); 11% earn more than CNY10, 000.

The information available about the gender of Chinese outbound travellers varies but, by analysing the national figures of different receiving countries, Arlt (2006) found that destinations that receive a large number of business travellers – for meetings, conferences and exhibitions –show a bias towards male visitors, whereas destinations that receive travellers more for the purposes of leisure, tourism and visiting friends and relatives show a more even gender balance (Arlt, 2006). In general, for outbound leisure tourism beyond Hong Kong and Macao and beyond neighbouring countries, the most important provinces are Beijing (Municipality), Shanghai (Municipality) and Guangdong, followed by Zhejiang, Fujian and Tianjin (Arlt, 2006; Li et al., 2009).

The influence of culture on Chinese outbound tourists' destination choice

Chinese cultural values are largely influenced by the philosophy of Confucius. The key ideas of Confucian philosophy include hierarchical social relationships, family orientation, 'face' and persistence. Using Hofstede's cultural dimension framework, a few researchers have tried to reveal the cultural influences on the tourism behaviour of Chinese outbound tourists (Arlt, 2006; Mok & Defranco, 2000). Four hypotheses have been tested.

(1) Respect for authority (high power distance). Chinese tourists are more likely to engage in branded shopping activities during their trips, as this involves symbols of fortune and status. And they are more likely to be influenced by opinion leaders than are Westerners. Chinese tourists expect to see the most important and famous sights and to served and honoured.

(2) Interdependence (low individualism). Chinese consumers are more responsive to relationship marketing techniques. They tend to go where everybody goes and to do the typical things. Memorable group photos in front of well-known sights strengthen and document the collective experience.

(3) 'Face'. Chinese consumers are likely to be more brand conscious than Westerners.

(4) Low level of uncertainty avoidance. Chinese outbound tourists prefer flexibility in planning and executing travel arrangements. When they encounter unknown situations or persons, they do not perceive them as a threat but as a reason for curiosity and amusement. Li and Cai (2011) found that Chinese outbound tourists tend to hold a positive attitude if a destination appears novel, which might be a reflection of low level uncertainty avoidance.

Research findings regarding the Chinese outbound tourists' destination choice

Some studies have investigated the important attributes considered by Chinese outbound tourists. Ryan and Mo (2002) researched the decision-making processes of Chinese tourists visiting New Zealand and found that the main motivation was to see new places. Kim and Guo (2005) found mainland Chinese respondents considered 'safety' and 'beautiful scenery' to be the most important attributes, whereas 'level of economic development' and 'good place for shopping' were regarded as the least important. The importance of 'safety' perceived by Chinese outbound tourists was also reported by Sparks and Pan (2009). In addition, Sparks and Pan (2009) proposed a theory in which the intention to visit a certain destination is determined by subjective norm influence, attitude to visiting destinations and constraints and perceived control. This research investigated potential Chinese outbound tourists' values in terms of destination attributes, as well as attitudes to international travel. Five destination attributes were rated as most important by this potential group of tourists and included 'the natural beauty and icons of a destination', 'quality infrastructure', 'autonomy', 'inspirational motives' and 'social self-enhancement'.

Besides the studies focusing on tourists from mainland Chinese, some studies have investigated tourists from Hong Kong and Tai Wan. Lee et al. (2010) indicate that 'safety', 'excellent quality of accommodation' and 'reasonable travel cost' were the three most important attributes determining the attractiveness of a honeymoon destination for young couples from Tai Wan. Moreover, trip expenditure, length of stay during the trip, size of the travel party, monthly household income, discovering new places and/or things, and getting away from daily routine, obligation, stress and troubles have been reported to have a significant influence on Hong Kong residents' destination choice (Guillet et al., 2011). As for the choice of travel itinerary, Tsaur and Wu (2005) conducted a survey of consumers who enquired about visiting Japan at travel agencies in Taipei (Taiwan). This study found that most of the consumers were affected by the price of the travel products when they were selecting the package tour. The duration of tour and type of flight were important factors to respondents under 40 years old. The older the tourists were, the more attention they paid to the contents of the tours.

Although these studies based on Chinese tourists from Hong Kong and Taiwan provides a good reference, the preferences of mainland Chinese may be different from those of their kin from Hong Kong and Taiwan. As for the studies focusing on mainland Chinese tourists, most of the studies reviewed here used samples of Chinese tourists who were visiting a certain destination; that is, during the data collection, the decision regarding destination had already been made. Therefore, we cannot take the attributes identified from previous studies for granted. A double-check is necessary to clarify the relevance of those attributes and to reveal any important attributes not identified by previous studies. And, more importantly, the choice heuristics that might be used by Chinese long-haul outbound tourists have not been empirically investigated at all. So the exact choice criteria and how they are used to facilitate the decision-making process of Chinese long-haul outbound tourists are still unknown.

3.5 Conclusion

This chapter clarifies the two key concepts (choice criteria and choice heuristic) that are investigated in this research to understand tourism decision-making processes. It reviews the attributes that could be used as the choice criteria for destination choice as well as the classification of these attributes. When compared with choice criteria, it is much more difficult to investigate and estimate choice heuristics. The second section of this chapter elaborates the popular types of choice heuristics together and reviews the studies which compare the predictive power of different choice heuristic models. Most of these studies have tested models on normal tangible products rather than on service-intensive, products such as tourist destinations. And the inconsistency regarding the models' predictive power in previous studies suggests the fitness of choice heuristic models can vary due to the nature of the products and the circumstances of the decision.

The last section of the chapter provides background information on Chinese outbound tourism and tourists. The review of previous studies identifies the specific knowledge gaps regarding the destination choice of Chinese long-haul outbound tourists. In this light, the aims of the present research are: (1) to double-check the choice criteria identified in similar studies; (2) to explore tourists' preferences in relation to destinations, based on different choice heuristic models; and (3) to compare the fitness of different choice heuristic models.

Chapter 4 Methodology

4.1 Overview of the chapter

Having outlined the theoretical context and research questions to be answered in previous chapters, this chapter discusses the methods adopted in this research, as well as the theories behind these methods. Based on a positivist orientation, this research used a mix of methods, both qualitative and quantitative, interview and survey. The results from the interviews were tested and quantified by the survey.

This chapter has five sections. It begins by critically reviewing the methodological background, that is, the methods available for the investigation. Section 4.2 explains the research design in terms of the choice of the data collection methods and the adoption of the two methods of statistical analysis. Sections 4.3 and 4.4 elaborate the data collection and data analysis. A brief summary is presented in section 4.6.

4.2 Methodological background for the research

Since tourists' decision-making is a complicated mental process, it has been a challenge for tourism scholars to find out how to investigate it and to apply research methods satisfactorily. All kinds of quantitative and qualitative research methods have been used to investigate tourists' decision-making. As a matter of fact, different perspectives require different instruments. In order to understand which method is the most appropriate for different circumstances or research questions, it is important to have a clear understanding of wide range of available methods, the purposes these methods serve and the goals that can be achieved through each. This section critically reviews the methods that are available and useful for the investigation of tourists' decision-making. More importantly, it provides a context in which the methodology of this study can be better understood.

Although the process of tourist destination choice can be very complex, there is one area of agreement among scholars, and that is that the criteria are set by tourists according to their own preferences. Tourist destinations are different from manufactured products because they consist of a range of intangible and tangible attributes, including social, cultural and environmental features. The 'utility' of a destination perceived by tourists is derived from this amalgamation of characteristics. Generally, tourists' evaluations of destinations are based on a combination of how highly they evaluate them on each of the relevant attributes and the relative importance they attach to each of those attributes.

Therefore, investigating tourists' evaluation criteria is key to understanding their preferences and their choice behaviour. There are three important questions that need to be answered regarding tourists' decision-making:

(1) What attributes are used as evaluation criteria by tourists?

(2) How important are each of these attributes in their decision-making?

(3) How are the evaluations of the various attributes combined by tourists to evaluate alternatives? That is, what choice heuristic is employed?

We will address these key questions below as a framework for the discussion and evaluation of the available research methods.

4.2.1 Which attributes are selected as evaluation criteria by tourists?

The simplest way to find out which attributes or factors are important for tourists is to ask them straight forwardly, in the form of either questionnaires or interviews. In previous questionnaire-based studies, researchers have tended to generate a list of possible attributes of a destination that are deemed to be important to tourists, such as price, safety and weather, and then ask respondents to indicate the importance of each by way of a Likert-type scale or a rating or ranking task (e.g Go & Zhang, 1997; Haahti, 1986; Um & Crompton, 1990). For example, Um and Crompton (1990) used a 3-point scale questionnaire item to classify 20 different attributes into perceived inhibitors, neither perceived inhibitors nor perceived facilitators, and perceived facilitators. They then used a 5-point scale to assess the relative strength of each attribute as a facilitator or inhibitor. Using this method, based on the positive or negative role of each attribute, the attitudes of tourists to each destination can be estimated.

If too many relevant attributes are found to be important in the decision-making, a factor analysis is sometimes conducted to reduce the number of attributes to a smaller number of dimensions or factors (Stewart, 1981). The attributes themselves need to be in the form of ordinal data, and thus the reliability of each dimension is indicated by Cronbach's alpha, which is a coefficient of internal consistency. A study conducted by Beerli & Martin (2004) is a useful and highly cited example of the use of factor analysis to classify the attributes that form a positive destination image, as well to identify the motivations behind destination selection.

In qualitative interviews, open-ended questions such as 'What attributes do you consider when you choose a tourism destination?' are often asked, and the qualitative data provided can be analysed using content analysis, in which frequently used phrases and words can be coded and generalised as common attributes that are considered important (Klenosky, 2002).

These two methods ask only for tourists' opinions on each attribute, without comparisons between the attributes, which makes the response task easy to understand and to complete. Therefore, the response rate should be higher than with more complicated methods requiring the respondent to perform complex tasks. Normally, for a new market or an unfamiliar market for which consumer preferences are still unknown, qualitative interviews or simple questionnaires are very useful to explore the relevant attributes and how they are used as criteria in decision-making. However, since respondents do not need to compare different attributes directly and as qualitative interview methods cannot provide generalizable descriptions, the relative importance of each attribute cannot be obtained and it is impossible to estimate directly how much the decision would be affected if valuations of the selected attributes changed. In order to know more about this, it is necessary to quantify each attribute's importance and the most common approaches used in tourism studies are a range of regression methods, including simple regression, multinomial logistic regression and conditional logistic regression. The following section outlines these approaches.

4.2.2 The relative importance of attributes in tourists' decision-making

Regression analysis can provide estimates of the relative importance of each attribute and how the total preference of destinations changes when any one of the relevant attributes varies. The value of total preference can be indicated by the number of tourist arrivals in the destination or by the assigned values of how much tourists prefer a destination. Additionally, the relevant attributes can be derived from researchers' hypotheses or from previous exploratory studies.

Different types of regression have different functions. If the interest is only in testing the specific influence of a single attribute (e.g. price or climate) on the choice, a simple regression can be used. The most common simple regression used in studies of tourist destination choice is linear regression, which assumes that a change of the independent variable (the attribute) results in a change of the dependent variable (the preference) and that the pattern of change is in the form of straight line (Churchill & Iacobucci, 2009).

For example, if the independent variable is transport price and the dependent variable is the number of annual arrivals at a particular destination, a simple linear regression may be able to find that transport price is inversely proportional to the annual arrivals and every unit increase in the transport price will generate a 0.6 unit decrease in the number of annual arrivals. Sometimes the influence of the attribute on the preference is not linear but curvilinear (Osborne & Waters, 2002), which is often the case with the (seasonal average) temperature of the destination. The preference may start to increase at lower temperatures, reach a peak at a slightly higher temperature and thereafter decrease again. In such situations where linear regression is not suitable, polynomial regression (e.g. quadric regression and cubic regression) can be used to explore a relationship in any form of non-linear. (In the temperature example, a quadratic regression would be the correct method for finding the temperature that generates maximum preference.)

However, due to the complexity the 'product', it is rare that a destination is selected on the basis of only a single attribute. Therefore, simple regression is normally used to analyse the influence of a certain attribute on decision-making. In order to gain a more comprehensive insight into the decision-making process, we need look into the combined effect of a group of attributes together and hence a multiple regression approach is required. Multiple regression is an extension of simple regression that incorporates two or more independent variables in a prediction equation for a dependent variable. A study undertaken by Sonmez & Graefe (1998) is an example that adopted both simple regression and multiple regression techniques to test the effect of different demographic characteristics on risk perception (multiple regression) and the influence of risk perception on the preference of foreign tourists (simple regression). Other examples include the ordinary least-squares (OLS) regression, used, for example, to explore the impact of personality on perceived destination values (Ekinci & Hosany, 2006), and a multiple regression of tourists visiting Australia (Crouch et al., 1992). In addition, significance tests such as ANOVA and the *t*-test provide a way of measuring the quality of the findings, since they can indicate to what extent the relationship found by the regression can be a product of mere chance and sampling variance.

Normally, regressions deal only with ratio or interval data or ordinal data that can be regarded as reflecting continuous variables. But in circumstances where the dependent variable is dichotomous or categorical – for instance with choice of destination – linear OLS regressions are inadequate. The dependent variable here is the final choice of tourists, which can be formulated in terms of either whether or not a certain destination is chosen (dichotomous variable) or which destination among a few options is chosen (categorical nominal variable). In this situation, it is possible to use logistic regression, also known as a logit model, to find the probability of each outcome, given the independent variables (the predictors).

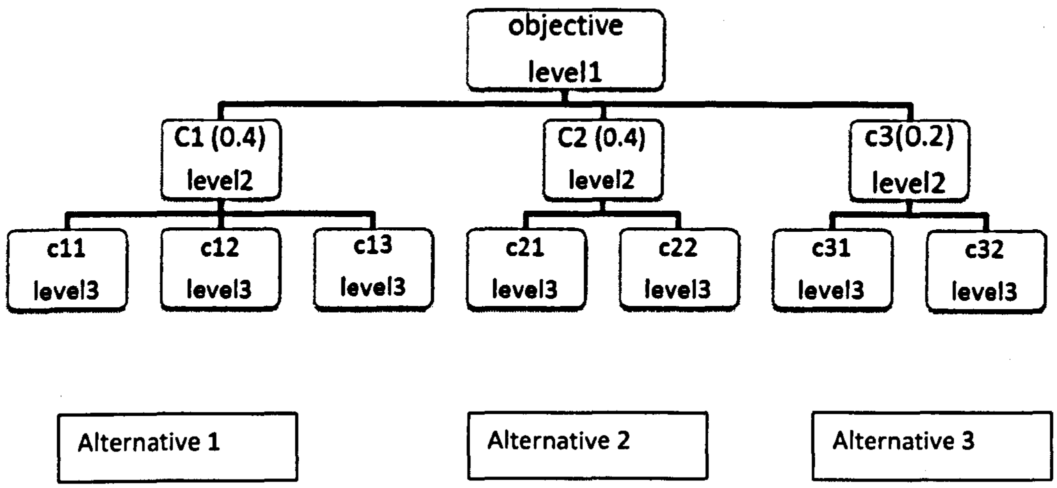
Two types of logistic regression are used frequently in studies of tourist destination choice: multinomial logit and conditional logit. Basically, multinomial logit is used to identify the influence of individual characteristics (e.g. Morley, 1994) such as demographics or attitudes of tourists in decision-making, while the conditional logit is used for testing the influence of destination characteristics on final choice (Seddighi & Theocharous, 2002).

Regression analysis simplifies the complex mental decision-making process into an input–output relationship between independent variables and dependent variables. The simplification enables the estimation of coefficients that express the relation between dependent and independent variables but it does require the analyst to make assumptions about the process of tourist decision-making that themselves cannot be easily tested within the regression approach.

In recent years, a more sophisticated method, Analytic Hierarchy Process (AHP), has been widely used in a variety of multi-criteria decision-making fields, including government, industry, healthcare and education. The AHP was initially introduced by Saaty (1997) for studies in the field of operations management. It is a method that provides a systematic problem-solving framework. Specifically, it enables the researcher to estimate the relative priority of elements within the hierarchical structure by conducting a series of paired comparisons. Compared with traditional multi-criteria decision-making analysis methods such as the regressions mentioned above, respondents generally find the AHP method requires less difficult mental processing, since the questions to be answered are very straight forward Respondents also perceive the findings about the importance of each attribute more trustworthy (Schoemaker & Waid, 1982). A brief summary of how this method works is presented below.

AHP decomposes a decision-making problem into a hierarchy. A simple hierarchical structure of decision-making from top to bottom is comprised as follows: choice objective; criteria; sub-criteria; and alternatives (see figure 1). Actually, the criteria can be further divided into many layers of sub-criteria. Decision-makers then compare the criteria pair-wise (N= 3 in figure 1 at level 2) by expressing their preference between every possible pair of criteria. For the example listed by figure 4.1 Criterion1 is two times more important than criterion 3 but equally important as criterion 2, criterion 2 is two times more important than criterion 3. These paired comparisons can be formed into a (N * N) preference matrix. Using the eigenvector solution, the preference matrix can be used to quantify the numerical priority values for each criterion. Necessarily, the priority values at each level sum to 1.

Figure 4.1 Example of the AHP



As can be seen in figure 4.1, the calculated priority values for the three criteria at level 2 are 0.4, 0.4 and 0.2.Following the same paired comparison and calculation process, the local priority values for the sub-criteria within each criterion at level 3 can be calculated. In order to compare the importance of c11 to c32, it is necessary to know the global priority values. These global priority values are local priority values multiplied by the weight of their superior criterion. This method uses subjective judgements from respondents. And in order to make sure the judgements of the respondents are consistent with each other through the whole process, the AHP allows a consistency check of respondents' pair-wise responses.

Unlike asking respondents to assign preference values to each sub-criterion directly, this method helps respondents to go through the whole decision-making process step by step, from the comparison between broad criteria to the comparison between the sub-criteria within each broad criterion. This hierarchical process of pair-wise comparison enables respondents to make their judgements more easily and more accurately. And this advantage makes the AHP a good method to deal with evaluations among a large number of attributes with different qualities that are difficult to compare directly, which is often the case in destination choice.

An introduction to and empirical research on the application of AHP can be found in some tourism studies (e.g. Calantone & di Benedetto, 1991; Crouch & Ritchie, 2005; Deng et al., 2002). Additionally, this method was used by Hsu et al. (2009) as a method to investigate tourists' preferences of destination choice. A four-level AHP model with 22 sub-criteria on the fourth level was used in this study. Compared to other tourism decision-making studies using regression methods, it was able to provide the relative weights of a large number (22) of attributes at one time. Furthermore, by clustering attributes into different levels, tourists only need to evaluate the attributes with a similar nature, which makes the comparison easier. The 22 attributes estimated by Hsu et al. (2009) were initially divided into internal factors and external factors, where the internal factors were further sub-divided into four categories and external factors were divided into two categories. At each stage, respondents need to compare only two attributes at the same level and within the same superior criterion.

Although the task of providing paired comparisons at each stage is quite simple for respondents, there would be a huge amount of work for them to do if there were a large number of attributes within one category. If, for example, there are 9 attributes within the same superior criterion, then the respondents need to complete 45 comparisons to compare all the attributes to each other. Additionally, where there are a large number of alternatives, the number of comparisons among alternatives regarding each attribute's quality score would rapidly become too large for respondents. Furthermore, in the traditional AHP method, the pair-wise comparison is made on a scale of 1–9, which converts human preferences between available alternatives as equally, moderately, strongly, very strongly or extremely preferred. In some real situations, respondents might be reluctant or unable to provide exact numerical values for their comparisons. Therefore, modification is required of the traditional AHP approach in light of these disadvantages. Hsu et al. (2009) combined a 'fuzzy theory' method with traditional AHP to reduce the workload of respondents, by allowing respondents to provide fuzzy judgements instead of assigning precise comparison values. It is thus clear that a smart combination of methods can be a good way to overcome the disadvantages of a single method and to make estimations more effective.

4.2.3 How are attributes combined (choice heuristics) by tourists to evaluate alternatives?

All the methods mentioned above help us to gain more understanding about which destination attributes are important to tourists and how much they are preferred. However, in order to predict final choice, we not only need to know what attributes or factors are involved, but also to understand the choice heuristics that are applied. The choice heuristic, or the evaluation rules, refers to the way tourists use multiple criteria to evaluate alternative destinations. As mentioned chapter 2, due to the huge influence of economics, most studies assume that tourists are rational and use a compensatory choice heuristic to maximise the utility of their choice. In marketing and tourism studies, conjoint analysis is the dominant estimation method used to understand consumers' preferences and choices based on the compensatory choice heuristic model.

Few studies in tourism have explored the possibility of using non-compensatory choice heuristics. In many contexts it seems reasonable to assume that, with limited information, time and energy, tourists tend to adopt a non-compensatory choice heuristic, as this simplifies their decision-making process. As discussed in Chapter 3, there is no empirical research so far testing the non-compensatory choice heuristic model in the field of tourists' choice of destination. But in the marketing research field, a relatively new method known as greedoid analysis has recently been introduced by two different authors independently to examine the use of non-compensatory choice heuristics. This also offers an alternative method to estimate non-compensatory preferences in tourist decision-making.

Both conjoint analysis and greedoid algorithm are further elaborated here, with a focus on three issues: (1) a description of these methods; (2) an overview of their application and implementation; and (3) a discussion of their advantages and disadvantages for a study of tourist consumer choices.

Conjoint analysis

Conjoint measurement was first introduced by Luce and Tukey in 1964 as a new type of fundamental measurement of extensive quantities. It differs from classic measures because it can compare the effects of combinations formed by quantities of items of different qualities rather than a comparison between combinations of quantities of one single specified kind (Luce & Tukey, 1964). For instance, people who want to buy a car may consider its colour and price. Say a person would prefer a black car and a lower price, but the manufacturer can provide only a black car at £20,000 or a red car at £18,000. In this case, only knowing the buyer's preferences for colour or price separately is not enough for researchers to make a prediction. Instead, there is a need to be able to estimate which combination (black car at £20,000 or red car at £18,000) is more attractive and conjoint measurement is an option here.

Green developed conjoint measurement further as an analysis method and adapted it to the field of marketing (Green & Rao, 1971; Green & Srinivasan, 1978; Green & Wind, 1973). Consumer researchers used the scaling aspects of conjoint analysis to find specific numerical scale values for separate product attributes under an assumed composition rule, mostly weighted additive (compensatory) composition. To be precise, researchers usually use the conjoint method to determine what combination of attributes has most influence on respondent choice by estimating the values or part-worth of each attribute.

In consumer decision-making research, conjoint analysis has become a very popular method, for two reasons. Firstly, it can estimate the contributions of different attributes and the levels of an attribute. For example, it can tell us how much the price contributes to a willingness of a consumer to buy a computer and which price level is the best to attract the most consumers. Secondly, conjoint analysis can be used to establish a model of consumer judgement, which allows us to predict consumer preferences about any combinations of attributes, even those not included in the original observations (Hair et al., 1998).

Conjoint analysis has also been widely applied in tourism contexts (e.g. Basala & Klenosky, 2001; Bernoulli, 1954; Dellaert et al., 1995; Dellaert et al., 1997; Suh, 2009). Most of these studies use conjoint analysis to estimate the importance of different attributes in order to examine tourists' choice of holiday packages or destinations. For example, Suh and Gartner (2004) used conjoint analysis to investigate the preferences of international urban travellers from Seoul, Korea, with the aim to identify the relationship between preferences for and expenditure on attributes and activities.

Conjoint analysis can be used to test different models based on relationships between consumer preferences and the nature of the attributes; these include the vector model, the ideal-point model and the part-worth function model. The vector model describes consumers' monotone preference on some continuous attributes. The most preferred value of an attribute is at infinity, as is the case for durability, for example. This model is relevant for attributes which consumers can be assumed always (infinitely) to prefer more (or, conversely, less).

The ideal-point model is also known as the quadratic model, which is appropriate for attributes of which 'too low' as well as 'too high' values exist, neither of which is preferred in comparison with an 'ideal' or 'just right' value, although the value of 'just right' may be different for different people. Temperature at a destination would be a case in point. In yet other instances the part-worth model is most appropriate. This is the case when alternative values are qualitatively different (i.e. measured at nominal level), as is the case with attributes such as the mode of travel, or when the form of the preference function is unknown (Orme, 2005).

Generally speaking, the part-worth function model provides the greatest flexibility in allowing different shapes for the preference function along each of the attributes (Hawkins et al., 1989). After the choice of vector, ideal-point or part-worth variants, there are always three essential steps involved in conjoint analysis, which are: data collection, questionnaire design and estimation. The common approaches used in previous conjoint studies for each stage are summarised below.

Data collection

There are two main ways to collect the data required by conjoint analysis: the two-factors-at-a-time procedure and the full-profile approach. The two-factors-at-a-time procedure asks respondents to rank the various combinations of each pair of factors, as preferred and not preferred (Johnson, 1974). This procedure is simple to apply and reduces information overload on the part of the respondent (Hawkins et al., 1989). But this decomposition method eliminates the influence of other attributes and it is not able to mimic the real selection situation as much as the full-profile approach since respondents are only comparing different combinations of two factors rather than two products.

The full-profile approach (also referred to as the concept evaluation task) utilises the complete set of factors, including product profiles consisting of all important product features suggested by previous literature or investigations, and these are presented to respondents. Although it will never be perfectly fully profiled and even the omitted attributes may generate bias, this approach gives a more realistic description of stimuli. Additionally, while the two-factors-at-a-time procedure provides only a set of rank orders, the full-profile approach can employ either a rank order or ratings. However, since respondents need to process the information of the entire set of attributes, the task may lead to information overload. If so, respondents might try to simplify this task by ignoring variations in the less important factors or they may even refuse to respond. Therefore, the full-profile procedure is generally confined to, at most, five or six factors in any specific sort (Hawkins et al., 1989; Gabbott and Hogg, 1994).

In recent years, a choice-based approach has been developed based on the traditional full-profile approach. Here, respondents are not required to rate or rank each profile directly. In an online survey, for example, respondents may select one preferred stimulus from a subset of stimuli until enough information is obtained for sorting all profiles. This new technique is more similar to what buyers actually do in the market place and it allows respondents to select a 'none' option, which may reveal non-compensatory preference information about the respondents' cut-off point. For example, a respondent might not choose any option within a set because the prices of all offered products are too high.

Nonetheless, information overload can still be a key problem for full-profile choice-based tasks since respondents still need to deal with lots of information to select one profile with all attributes described before giving a single answer for each choice set, which is even harder than rating each stimulus. As a result, partial-profile choice-based conjoint studies were adopted later by researchers, which provide only a subset of the total number of attributes in each choice question. Because the information gathered by this method is not sufficient for estimating the part-worth that each individual respondent assigned to attribute levels, data from groups of respondents are normally aggregated for analysis.

Questionnaire design

In reality, the number of existing brands of a product that a respondent familiar with is usually small, which means the combinations of attributes offered by real brands are not enough to estimating contributions of each attribute and their levels. For this reason, conjoint analysis is usually conducted with hypothetical stimulus descriptions (Choi, 2005).

The hypothetical stimulus descriptions can be constructed by defining a number of levels/aspects for each of the attributes (Green & Srinivasan, 1978). If a full factorial design is used, the number of possible stimuli is very large (e.g., with 4 attributes at three levels each the total number of possible descriptions is$4^3 = 64$). Therefore, fractional factorial design was introduced to reduce the number of combinations to a manageable size. Although it does not present comprehensive combinations of all attributes' levels/aspects, the design is developed in this way to make sure the critical trade-off information can be generated, also termed as keeping orthogonality (Gunst & Mason, 2009).

Estimation

Parameter (attributes) estimation is normally the last step in conjoint analysis. During this step, the part-worth utilities of each attribute are calculated so that the product with maximum utility can be predicted. According to a literature review by Green and Srinivasan(1978),there are three kinds of estimation method: (1) non-metric estimation methods such as MONANOVA and LIMAP, which assume that the dependent variable is ordinal; (2) metric estimation methods such OLS, which assume that the dependent variable is interval scaled and which compute part-worth utilities by minimising the squared sum of deviations between estimated and observed metric values; and (3) methods that relate paired-comparison data to a choice probability model or parametric estimation methods. Methods in this class are the logit and probit models.

In recent years conjoint analysis has become established as a tool in marketing research. In a survey among market research institutes, 65% of the institutes indicated having used conjoint analysis within the last 12 months, and growing usage was forecasted (Hartmann & Sattler, 2002). Compensatory models with conjoint analysis are popular because they not only predict decisions via compensatory preferences but also approximate the outcomes of other kinds of decision rules (Wahab et al., 1976). For instance, a weighted additive model can theoretically reproduce a non-compensatory decision process if, in the ordered set of weights, each weight is larger than the sum of all subsequent weights. Flexibility in assigning weights is one of the biggest advantages of conjoint analysis.

However, these utility-maximisation methods to analyse decision-making processes have been questioned by scholars since the 1970s (Beach & Mitchell, 1978; Gigerenzer & Todd, 1987; Payne, 1976; Rieskamp & Otto, 2006). Some simple non-compensatory heuristic models such as conjunctive, disconjunctive and lexicographic heuristics were introduced and proved to be more or at least equally accurate in predicting consumer behaviour in some situations (Czerlinski et al., 1999).

The time required to complete surveys and information overload for respondents are the chief disadvantages of conjoint tasks with a relatively large set of attributes. The question of how to increase response rates and to prevent unreliable answers caused by the complexity of the task remains a key problem to be solved. And this issue takes us to the application of 'greedy algorithms' to these decision-making problems.

Greedoid analysis

Greedoid analysis is based on a so-called 'greedy algorithm' and was developed by Kohli and Jedidi (2007) and Yee et al. (2007) to infer non-compensatory heuristics including: conjunctive heuristics; disconjunctive heuristics; lexicographic-by-features and lexicographic-by-aspects heuristic types. The concept of greedoid analysis was first proposed by Korte and Lovasz (1984) for the generalisation of the matroid concept for a class of optimisation problems which can be solved by greedy algorithms (Edmonds, 1971). Greedy algorithms aim to solve a combinatorial optimisation problem piece by piece and to always select the piece with the most benefit. They are simple and very easy to implement but can sometimes be 'short-sighted' since they simplify the decision process by always following the problem-solving heuristic of making the locally optimal choice at each stage.

The most common example to explain the approach of the greedy algorithm is 'making the change'. If only 50p, 20pand 1pcoins are available, the goal is to make up 74 pence with the minimum number of coins. In order to achieve this goal, the greedy algorithm is applied so that each time the coin of the highest value, but less than the remaining change owed, is selected until the whole process is finished. Therefore, one 50p coin, one 20p coin and four 1p coins are selected to 'make the change'. The algorithm, however, fails if the available coins are only 50p, 20p and 3p, since, after giving a 50p and a 20p coin, the algorithm cannot use 3p coins for the remained 4 pence change. The algorithm does not 'see' the possibility of giving one 50p coin and eight 3p coins to fulfil the task.

Greedy algorithms can nonetheless be used to mimic non-compensatory preferences because sometimes people do sometimes seem to follow just such an algorithm in their decision-making. That is, they tend to select the options on the basis of the attribute they regard as the most important, and then refine their selection based on the next most important attribute and so on until the final option is selected. They will not go back to review other information on other attributes, as this makes the decision process simple and quick, but decision-makers may miss some attractive options that did not meet their requirement on the most important attribute (but that were very compelling on other important attributes).

In order to estimate this kind of non-compensatory (lexicographic) choice process for consumers, the greedy algorithm was introduced and developed by Kohli and

Jedidi (2007) and Yee et al. (2007) independently. Kohli and Jedidi (2007) modified the greedy algorithm to infer the lexicographic preference oftwo variants (conjunctive preference and lexicographic preference by aspect) for purchase decisions of laptop computers. Because in reality there is no perfect match between a certain type of preference function and the observed preference rank order, the authors simply assigned the (statistically) best-fitting preference model to each individual. For the test of model goodness-of-fit, the Kendall tau value was used to indicate which preference model had the greater predictive power. During the data collection, each laptop was described by five attributes with 13 aspects in total. After the fractional factorial design, 16 profiles were generated and presented to 69 MBA students using cards. The respondents needed to rate each alternative according to their preference by a scale from 0 to 100. Two-thirds of the subjects in this study used non-compensatory heuristics.

Yee et al. (2007) tested greedoid-based methods with applications to smart phones and computers. They compared lexicographic preference by aspect (LBA) to two compensatory benchmarks: hierarchical Bayes ranked logit (HBRL) and LINMAP. The greedy algorithm was programmed in Java. A fractional factorial design generated 32 full profiles and a web-based questionnaire was conducted. The 339 respondents were students. They needed to rank the alternatives either in a full-rank manner or to select the ones they would consider and then rank these considered options (smart phones). The conjoint data set for computer choice was obtained from a previous study, which were rating data on a 10-point scale for 16 full profiles. The findings suggested that the lexicographic models predicted at least as well as the benchmarks.

Dieckmann et al. (2009) conducted a further study to compare predictive accuracies of the greedoid approach and standard conjoint analysis in an online study with a rating and a ranking task regarding the selection of skiing jackets. Their results differed from those obtained by Yee et al. (2007), as the lexicographic model derived from the greedoid algorithm achieved lower predictive accuracy for hold-out data than the compensatory model estimated by conjoint analysis. However, a considerable minority of participants was better predicted by lexicographic strategies.

Although greedoid analysis is not able to estimate part-worth values of the attributes, there are several advantages that make greedoid analysis a promising method to estimate tourist preference. Firstly, it is a method that provides a better insight into non-compensatory choice processes, by incorporating non-compensatory factors rather than just adapting weighting schemes to imitate the output of non-compensatory heuristics (Gabbott & Hogg, 1994). When there are numerous alternative destinations, tourists may tend to use a simplified non-compensatory choice heuristic. Therefore, the greedoid method can help us to explore the extent of non-compensatory choice.

Secondly, compared with traditional conjoint analysis, the greedoid method requires a smaller respondent workload, as it can deal with full-rank, consider-then-rank, and rating tasks. Moreover, the dynamic programming algorithm proposed by Yee et al. (2007) substantially reduces computation time and makes it feasible to identify the best lexicographic ordering for large samples of respondents and moderately large numbers of aspects.

Finally, the results of greedoid analysis can be further analysed to identify any 'must-have' aspects that tourists used to eliminate the destinations at the stage of consideration-set formation. Such information is of great help for destination marketing organisations to improve their offer, for travel agencies and tour operators to more effectively promote their products and for marketers to devise appropriate marketing strategies.

Depending on the research objectives, different preference estimation methods could be used in a range of situations. For the tourism market where little or nothing is known about tourist preference, the more direct methods, such as simple questionnaires and interviews, are useful to obtain the first impression of what attributes or factors particular kinds of tourists care about. After narrowing down the important attributes into a shortlist, it is possible to test the specific influences of certain attributes or the combined effects of multi-attributes by more sophisticated methods, such as regressions or conjoint analysis. If more detailed exploration of the mental processing in tourism decision-making is required, rather than thinking of it as a simple input and output procedure, the AHP method that decomposes decision-making into different stages may be applied. And in some contexts such as limited information available or limited time to make the decision, where tourists do not use utility maximisation, methods that are based on non-compensatory choice heuristic theory such as greedoid analysis method could be useful. However the methods mentioned above are not the only options to estimate tourist's preference but rather just the commonly used ones.

As a matter of fact, all of these methods have been adopted from other disciplines (e.g. economics) or research fields (e.g. marketing research and operations studies). Although these methods are very useful tools with which to investigate decision-making in general, tourist decision-making may have unique features. Therefore, questions of how to adapt these methods accordingly are a key issue for tourism scholars. A smart methods combination is one option. For example, due to the large number of destinations available, Hsu (2009) combined fuzzy theory with traditional AHP to reduce the huge workload of tourist respondents in comparing alternatives. Cina (2012) combined game theory with conjoint analysis to identify which combinations of attributes are suitable for different tourism festivals.

Moreover, with the development of tourist decision-making studies, more innovative research methods are desired to explore tourists' preferences beyond the stage of identifying preferred attributes or assign utility values to different attributes. For instance, do tourists evaluate destinations rationally? How do their preferences change at different stages? How is it possible to distinguish between different preference groups? All of these questions require more sophisticated theoretical models and estimation methods. Greedoid analysis provides a starting point to explore non-compensatory choice heuristics. However, further research needs to be done to apply or modify this method into tourism decision-making studies.

4.3 Research approach

The aim of this research was to reveal useful information about the destination preferences of Chinese long-haul outbound tourists and to provide a better understanding and explanation of their decision-making processes, based on an exploration of choice heuristics used. In terms of destination preference, this study explores two research questions. (1) What are the important attributes (choice criteria) considered by Chinese outbound tourists? (2) How is each attribute (choice criterion) used by Chinese outbound tourists to assist in their choosing a destination? Information about choice criteria can be obtained by simply asking tourists to indicate which among a range of attributes are important for them in the context of a specific decision. The choice heuristic, however, as a complicated mental process, cannot be elicited with a simple direct question. Relevant data need to be selected and subjected to advanced analysis.

As a result, this research has two stages of data collection and analysis, with both qualitative and quantitative methods involved. In the first stage, evaluation criteria (important attributes) were obtained from desk research of previous studies (e.g. Arlt, 2006; Sparks & Pan, 2009) and interviews of staff in travel agencies (e.g. tour guides on international trips and marketing managers for international destinations). At the second stage, a survey with a tailor-made experimental sorting task was conducted to collect the data for the investigation of preferences and choice heuristics.

A semi-structured interview was used to obtain general information about Chinese long-haul outbound tourists and the important attributes that they use as choice criteria. There are two reasons for conducting these interviews: firstly, compared with questionnaires, interviews are better to obtain detailed information about personal feelings, perceptions and opinions; and secondly, more detailed questions can be asked (Opdenakker, 2006).

As an emerging market, knowledge about Chinese long-haul outbound tourists and their destination preferences and choices is still limited. The qualitative insights from well informed tour operator staff who regularly deal with Chinese outbound tourists are very useful for a general understanding of this group of people, their demographic characteristics, and the issues they consider in selecting a destination

At the second stage of the research, in order to investigate how the choice criteria are used by tourists, an experimental sorting task was adopted to mimic the real choice of destination. To ensure the validity of the experiment, the attributes had to be the ones that tourists would actually consider and the values/aspects of the attributes needed to be realistic. Although a few previous studies have identified the attributes Chinese long-haul outbound tourists considered important in choosing a destination, most of these studies were conducted on samples of Chinese tourists who were visiting one specific destination, and they may not represent the entire population of Chinese long-haul outbound tourists; moreover, they had already chosen their destination. Therefore, in addition to the desk research, the interview was necessary to double check the findings of previous studies, and to inform the destination attributes and their values selected for use in the survey.

As reviewed in the previous section, conjoint analysis was invented for modelling compensatory heuristics, especially additive weighted heuristics (Gabbott & Hogg, 1994), and this method has predominated in consumer research. Greedoid analysis was developed to analyse non-compensatory heuristics, including: conjunctive heuristics; disconjunctive heuristics; lexicographic-by-features and lexicographic-by-aspects heuristics. To the best knowledge of the author, there has been no research in tourism using greedoid analysis to identify non-compensatory choice heuristics, so which of these different choice heuristics is more commonly used by tourists for destination selection and how they are used are still unknown. The focus of this research is to fill this knowledge gap.

At the second stage of the research, the data about tourist choice criteria were collected by an experimental survey. Both conjoint analysis and greedoid analysis are then used to estimate tourists' preferences based on different choice heuristic models and to explore the possible measurement instruments to evaluate the goodness-of-fit. Since most of the choice criteria identified from the interview are categorical variables, the cut-off points used in disconjunctive and conjunctive heuristics are not applicable in this research. Lexicographic-by-features is a special kind of lexicographic-by-aspect heuristic. Therefore, only the lexicographic-by-aspect heuristic model will be investigated in this study as a non-compensatory choice heuristic model, to be compared with the utility-maximisation compensatory choice heuristic model.

Additionally, as discussed in Chapter 2, a consideration set is a key element of consumer behaviour and many studies have demonstrated the existence of a consideration set (e.g. Cattin & Wittink, 1977; Crompton, 1992; Roberts & Lattin, 1991; Shocker et al., 1991). Louviere and Woodworth (1983) first incorporated the concept of consideration set into conjoint analysis. There are two advantages of this incorporation.

Firstly, by allowing a no-choice or current-choice option, it permits the modelling of consideration sets in which an item is selected only if its part-worth utility exceeds a threshold. As a consequence, the market share prediction for a new item can take into account both the probability that distinct subsets of items are considered, and the probabilities that items from each considered subset are actually chosen. In contrast, traditional conjoint simulations assume that a test product is always considered by each consumer.

Secondly, because the number of consumers choosing an item depends on the consideration set, choice-set experiments enable a new product to enter an existing market and position itself more competitively (Roberts & Lattin, 1991). Join and James (1991) have tested the predictive power of a two-stage model of consideration set and choice versus some simple reference models by using consumers' preference data in the ready-to-eat cereal market. They found the two-stage model gave better predictions than simple models. In addition, the products identified in the first stage (consideration) will be evaluated again in the second stage (choice). It is reasonable that consumers use heuristic processes in the consideration stage that focus on a relatively small number of important features and do so in a simple ('first cut') non-compensatory manner (Payne et al. 1988; Gigerenzer & Goldstein 1996) while the heuristic process in the second stage may consider more features, in a compensatory manner. Therefore, the stage of consideration set formation was investigated in this research and the role of choice criteria at different stages of the decision-making process was explored as well. The detailed data collection and data analysis process are set out in the following sections.

4.4 Data collection

As mentioned, there were two stages of data collection: the interviews and questionnaire survey. Data collection took place from 1 March to 25 May 2011 in China. The detailed procedure for each of the two stages is presented below.

4.4.1 Desk research and in-depth interviews

According to the desk research, 10 attributes considered important by Chinese tourists were identified by Kim et al. (2005), who interviewed 10 managers from

10 travel agencies in China and 50 tourists who had experience of outbound tourism. These attributes were: 'inexpensive travel cost', 'level of economic development', 'beautiful scenery', 'safety', 'good place for shopping', 'different cultural and historical resources', 'good weather', 'good leisure and recreation facilities', 'easiness to arrange travel plans', and 'well equipped tourism facilities'. Among these attributes, 'beautiful scenery', 'safety', and '"different cultural and historical resources' were also identified in studies as important attributes considered by Chinese tourists travelling to New Zealand and Australia (Arlt, 2006; Sparks & Pan, 2009; Yu & Weiler, 2001).

Based on the desk research, six semi-structured interviews were conducted in China with 6 outbound tourism sales managers working at different travel agencies, including the Tian Jin branch of China International Travel Service, the Tian Jin branch of China Youth Travel Service and Jun He International Travel Agency. Five of the six interviews were face-to-face and tape-recorded and the sixth was conducted by email. Each tape-recorded interview lasted 40–60 minutes. The main questions were intended to provide relevant information for further analysis and for finalising the questionnaire to be administered to (prospective) long-haul outbound tourists. These questions were the following:

(1) Who tend to take outbound trips for leisure purposes, especially long-haul trips? What characteristics do these people have?

(2) Normally, how long in advance do tourists begin to gather travel information before their departure? In general, how many destinations they will enquire about?

(3)When tourists choose destinations, what attributes do they consider (e.g. accommodation, safety, food, natural landscape, human landscape, shopping)? Among these attributes, which of them are more important? Is there any difference on preference between different demographic groups?

(4)Is there any classification of commonly visited long-haul destination countries? What about the performance of those important attributes provided by the popular destination countries?

(5)What is the general price range for a long-haul package tour? How does the cost differ among different destination countries?

(6)Are there any factors which may affect a tourist's endorsement of important attributes?

(7)When tourists face many alternative destinations, how do they choose between them?

In order to design the questionnaire for the subsequent survey, information regarding the important attributes used for selecting destinations is of crucial importance and is summarised below. The answers to the other questions are reported in Chapter 5. The following six attributes were commonly emphasised by informants as frequently used choice criteria by long-haul outbound tourists who want to purchase a package tour:

(1) Package price per person

Consisting of four levels: around RMB 9,000, around RMB 13,000, around RMB 17,000, and around RMB 21,000.

(2) Risk involved in obtaining a visa

Consisting of three levels: no risk of being refused, a bit of a riskof being refused, and quite a risk of being refused.

(3) Types of destination

Consisting of categories: natural landscape or human landscape.

(4)Whether the country and landscapes are famous

Consisting of three aspects: famous country with famous landscapes, famous country with less famous landscapes, and not famous country with not famous landscapes.

(5) Opportunities for shopping

Consisting of three aspects: good for famous brands (rather than outlets), good for outlets, and not good for shopping.

(6) Arrangement for journey

Consisting of two categories: tightly organised journey with more scenic spots, and relaxing journey with less scenic spots.

4.4.2 Survey

In the second stage of the research, data were collected from a Chinese sample of (potential) outbound tourists regarding their destination preferences, using a full-profile questionnaire. The full-profile approach was chosen because it can give a more realistic description of stimuli and is more flexible, in that it can employ both rank order and ratings. The questionnaire had three parts. The first part contained an introduction to the study. The second part consisted of the experimental ranking task, plus a few questions regarding previous travel experience and expected travelling arrangements for the next long-haul trip. In the stimuli ranking task respondents were asked to rank 10 stimuli destination cards where 1 is the most attractive destination tour and10the least. These 10 stimuli were generated through an orthogonal design based on 5 attributes with 11 aspects to ensure the highest level of coverage of different combinations of aspects with the minimum number of stimuli. The last part of the survey instrument consisted of three demographic questions to distinguish different groups of tourists.

Pre-test and finalisation of the interview questionnaire

According to the six important attributes and their levels, a fractional factorial design was constructed with SPSS 18.0, which generalised 16 profiles of destinations plus 2 hold-out destination profiles. In order to ensure the survey was readily completed and whether rating or ranking task was more suitable, two versions of questionnaires were made for a pre-test (see Appendix 1). Questionnaire version A required respondents to rate whether they each destination package among the 18 alternatives on a scale from 1 to 100 according to their preference. The other one (version B) required respondents first to choose those destinations they would consider for a holiday; they then were asked to rank the considered ones and also to rank the ones they would not consider. Each version of the questionnaire was pre-tested on 6 respondents varying from students aged around 22 to people over50.

All 6 respondents who were asked to rate destinations (version A) gave several alternatives the same rating, resulting in many ties when ordering the stimuli on the basis of the ratings. These ties can cause lack of information for estimation during the data analysis. Therefore, the ranking task seemed preferable to the rating task. In addition, 4 out of 6 respondents assigned to the rating task (version A) needed more than 10 minutes to complete the questionnaire and all of them indicated that they found it difficult to compare 18 similar-looking alternatives and rank them. This feedback brought a serious problem to the fore that might otherwise have appeared during the real data collection, which is the risk of a low response rate caused by information overload.

In order to simplify the task, the final version of the questionnaire only used 10 stimuli cards (a reduction from the 18 included in the pilot). Each card represented a destination tour defined by five attributes, which comprise 11 aspect levels (see Figure 4.2).

Figure 4.2 An example of the stimuli

Destination itinerary 1

Price: RMB9,000 per person

Visa: a bit risk in getting a visa

Shopping: good for brand product shopping

Time schedule: more free time

Famous: very well-known destination

The 5 attributes and their options/aspects are listed below.

(1) Package price per person

Consisting of three levels: around RMB 9,000, around RMB 13,000-17,000, above RMB 18,000.

(2) Risk involved in obtaining a visa

Consisting of: less risk/more risk of being refused

(3) Whether the destination country is famous

Consisting of: famous country/non-famous country

(4) Suitability for branded shopping opportunities

Consisting of: good for brand shopping/not suitable for brand shopping

(5) Arrangement of the journey

Consisting of: tightly organised journey with more scenic spots/relaxing journey with less scenic spots

The omitted attribute from the first version of the design was 'type of destination', since natural or human landscape is a relatively fixed attribute, so that change on this attribute would be very difficult even if a certain type of destination were found to be preferred. In addition, the other attributes are more reflective of the characteristic and culture of Chinese tourists.

In addition, the question about which of the 10 destination(s) participants would consider as possible options for their next long-haul trip was relocated to after the ranking task because the pilot demonstrated that this would avoid respondents having to deal with the information on alternatives twice.

Participants and procedure

Two hundred and one participants completed the survey. Since the aim of this research is to investigate Chinese long-haul outbound tourists, the respondents were selected on the basis that they were willing to pay for a long-haul trip and were expecting to take a trip within three years. The participants of the survey were approached in two ways. Seventy-eight were recruited at CAISSA Touristic, one of the biggest tour operators in Beijing. It was the only company to give permission to access their customers at their reception area after negotiations with the managers of the top four tour operators in Beijing: the China International Travel Service, China Youth Travel Service, UTour International Travel Service and CAISSA Touristic.

All 78 respondents were people who planned to take a long-haul trip in the very near future. Because of the relatively complex experiment task, in order to get more reliable and complete data, the survey was conducted one-on-one. The sorting process of these respondents was observed. For the respondents who were willing to spend more time talking about their preferences regarding long-haul destinations, the main points of their opinions were also recorded for further analysis. However, the cultural norms of Chinese society meant that it was difficult to gain trust as a stranger and to ask for cooperation. It took on 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 avoid the bias that might be generated due to the selection of a single tour operator, another 123 respondents were recruited using a snowball technique. These respondents were recommended or introduced by my friends and all of the respondents were expecting to take a long-haul trip within the near future. Among these 123 respondents, 40 completed the questionnaire by email.

4.5 Data analysis

Since the data were collected by both interview and questionnaire, the data analysis was divided into a qualitative and a quantitative stage of analysis as well. As for the data collected from the interviews, the six audio files were transcribed and the main points were recorded in an Excel file based on the seven interview questions. The answers of the six interviewees to the same questions were summarised and compared to each other as well as to findings from previous studies.

The data collected from the survey is for investigating different choice heuristic models used by the tourists. Since no previous study of tourist destination choice has examined the choice heuristics, this is the first study to explore the possible analysis methods. The analysis can be divided into three: the conjoint analysis, the greedoid analysis and the evaluation of the different choice heuristic models. The detailed procedure is presented below.

After the data collection, the data generated from the 201 questionnaires was entered into an SPSS file. For the general questions asked in the questionnaire –the demographic questions, the questions about previous travel experiences and the question concerning travel arrangements – a simple descriptive analysis was conducted to understand the profile of the respondents.

At first, conjoint analysis was run on the ranking data of the10 stimuli destination cards to estimate the tourists' preferences based on a compensatory (utility-maximisation) choice heuristic model. Since each stimuli card presented a combination of attributes and their respective options, the conjoint analysis was able to calculate the utility scores of each aspect for each respondent based on their preference order. Overall utility scores were calculated to indicate the influence of each attribute on the destination preference of the whole sample.

In addition, another indicator known as the importance value was calculated by conjoint analysis to reflect the relative importance of the attributes compared to each other. The same analyses were conducted on groups defined by demographic characteristics so that their preferences could be compared. To illustrate how the results of conjoint analysis can contribute to obtain systematic market segmentation, a cluster analysis was performed on individual-level output from the conjoint analysis. The respondents who shared similar patterns of utility scores for each attribute were clustered and the common characteristics of each cluster were explored.

In the next stage of analysis, the greedoid analysis was applied on the same data that were used in the conjoint analysis to evaluate the observed preference from the perspective of a non-compensatory (LBA) choice heuristic. This is an innovative analysis method invented recently for which no readymade ('off the shelf') software is yet available. Compared with the programming used by Kohli and Jedidi (2007), the programming introduced by Yee (2007) is more suitable for the investigation of categorical variables. Since most of the attributes identified in this research are categorical variables, the programming developed by Yee (2007) was adopted. The programming code (see Appendix 4) provided by Michael Yee (written in Java and run on Netbeans) was modified according to the research design and data-set with the help of Yijun Xue, and the modified code was subsequently used to conduct the greedoid analyses, the results of which are reported in Chapter 6.

Greedoid analysis: step1

Data were transferred into proper quantitative (number) form for the greedoid dynamic programming, which included: (a) transferring the design of the stimuli cards into a design matrix; (b) transferring preference data of respondents on 10 cards into a partial order array (from 1-10 to 0-9). In order to allow a valid comparison with the conjoint analysis, the incomplete ranking data (from 17 respondents who had managed to rank only a few of the 10 cards) were excluded at this stage.

Greedoid analysis: step 2

The best lexicographic ordering of attributes for each respondent was ascertained using the greedoid dynamic programme. An example provided by Yee et al.(2007)on how the greedoid dynamic programming finds the best lexicographic order is presented below for a better understanding of how this programme works:

Suppose that, from a full deck of playing cards, we select the aces and the jacks. We can represent these by two letters, where S = spades, H = hearts, D = diamonds, C = clubs, A = ace and J = jack. We then have 8 cards available: AS, AH, AD, AC, JS, JH, JD, and JC. Assume we ask a person to rank the 8 cards based on his preference and the ranking order is AS >JS> AH> AD > AC> JH > JD> JC. If this person used a lexicographic choice heuristic to rank the 8 cards, the programme deduces the order from the ranking data. The greedoid dynamic program algorithm generates the results presented in Table 4.1. For each subset of aspects/options (i.e. suit and rank), we compute the minimum number of errors (see examples in the following section), and record the set of aspects that can occur in the last position to achieve the least error. We begin with all singleton subsets of aspects, then all doubletons, etc. The algorithm first computes all rows of the table for subsets of size 1, then all rows for subsets of size 2, etc. This is necessary since computing results for a subset of size k requires using results from subsets of size $k-1$.

Table 4.1 Illustrative example of greedoid dynamic programming

Subset of aspects s	Min Errors $J(s)$	Best Last Aspect
{H}	6	H
{D}	8	D
{C}	10	C

{S}	0	S
{A}	3	A
{J}	13	J
{H, D}	11	D
{H, C}	13	C
{H, S}	2	H
{H, A}	5	H
{H, J}	14	J
{D, C}	15	C
{D, S}	4	D
{D, A}	7	D
{D, J}	16	J
{C, S}	6	C
{C, A}	9	C
{C, J}	18	J
{S, A}	0	A
{S, J}	10	J
{A, J}	3	J
{H, D, C}	15	C
{H, D, S}	3	D
{H, D, A}	7	D
{H, D, J}	16	D or J
{H, C, S}	5	C
{H, C, A}	9	C
{H, C, J}	18	C or J
{H, S, A}	0	H
{H, S, J}	8	J

{H, A, J}	5	H or J
{D, C, S}	7	C
{D, C, A}	11	C
{D, C, J}	20	C or J
{D, S, A}	2	D
{D, S, J}	10	J
{D, A, J}	7	D or J
{C, S, A}	4	C
{C, S, J}	12	J
{C, A, J}	9	C or J
{S, A, J}	0	J
{H, D, C, S}	3	C
{H, D, C, A}	9	C
{H, D, C, J}	18	C
{H, D, S, A}	0	D
{H, D, S, J}	7	J
{H, D, A, J}	7	D or J
{H, C, S, A}	2	C
{H, C, S, J}	9	J
{H, C, A, J}	9	C or J
{H, S, A, J}	0	H or J
{D, C, S, A}	4	C
{D, C, S, J}	11	J
{D, C, A, J}	11	C or J
{D, S, A, J}	2	D or J
{C, S, A, J}	4	C or J
{H, D, C, S, A}	0	C

{H, D, C, S, J}	7	C or J
{H, D, C, A, J}	9	C or J
{H, D, S, A, J}	0	D or J
{H, C, S, A, J}	2	C or J
{D, C, S, A, J}	4	C or J
{H, D, C, S, A, J}	0	C or J

Sample calculations

The following example calculations illustrate how each row in Table 4.1 was constructed.

Subset {H}:

Number of errors caused by having aspect H in first position = 6

(Errors: AH>AS, AH >JS, JH>AS, JH>JS, JH> AD, JH >AC) Each error here means one violated pair. So there are 6 violated pairs here.

Store J ({H}) = 6, with H as optimal last aspect

Similarly, J ({D}) = 8, and so on.

Subset {H, D}:

Cost of having H last: J ({D}) + new Errors (H after {D}) = 8 + 5 = 13

(New errors: AH>AS, AH >JS, JH> AS, JH> JS, JH >AC)

Cost of having D last: J ({H}) + new Errors (D after {H}) = 6 + 5 = 11

Store J ({H, D}) = 11, with D as optimal last aspect

Subset {S, A}:

Cost of having S last: J ({A}) + new Errors (S after {A}) = 3 + 0 = 3

Cost of having A last: J ({S}) + new Errors (A after {S}) = 0 + 0 = 0

Store J ({S, A}) = 0, with A as optimal last aspect

Subset {H, D, C}:

Cost of having H last: J ({D, C}) + new Errors (H after {D, C}) = 15 + 4 = 19

Cost of having D last: J ({H, C}) + new Errors (D after {H, C}) = 13 + 4 = 17

Cost of having C last: J ({H, D}) + new Errors (C after {H, D}) = 11 + 4 = 15

Store J ({H, D, C}) = 15, with C as optimal last aspect

Subset {H, D, C, S, A, J}:

Cost of having H last: J ({D, C, S, A, J}) + new Errors (H after {D, C, S, A, J}) = 4 + 0 = 4

Cost of having D last: J ({H, C, S, A, J}) + new Errors (D after {H, C, S, A, J}) = 2 + 0 = 2

Cost of having C last: J ({H, D, S, A, J}) + new Errors (C after {H, D, S, A, J}) = 0 + 0 = 0

Cost of having S last: J ({H, D, C, A, J}) + new Errors(S after {H, D, C, A, J}) = 9 + 0 = 9

Cost of having A last: J ({H, D, C, S, J}) + new Errors (A after {H, D, C, S, J}) = 7 + 0 = 7

Cost of having J last: J ({H, D, C, S, A}) + new Errors (J after {H, D, C, S, A}) = 0 + 0 = 0

Store J ({H, D, C, S, A, J}) = 0, with C and J as optimal last aspects

Because J ({H, D, C, S, A, J}) = 0, an order of aspects exists that is 100% consistent with the profile preferences provided by this respondent's rankings: AS > JS> AH >AD > AC> JH > HD > JC

Extracting the optimal solutions

To construct consistent aspect orders, we work backwards, starting from the set of all aspects {H, D, C, S, A, J} and seeing which aspects can occur in the last position. For this example, C or J can occur last, i.e., the aspect orders have the following patterns:

{H, D, S, A, J} >C

{H, D, C, S, A} >J

When aspect C is last, we then consider how to optimally order the remaining aspects that precede C, i.e., {H, D, S, A, J}. Looking up this subset in Table 4.1, we find that aspect D or J can occur in the next to last position:

{H, S, A, J} >D> C

{H, D, S, A}> J > C

Continuing in this fashion, we can construct all possible consistent aspect orders:

S >A > J> H> D > C

S >A > H >J> D > C

S >A >H> D >J >C

S> A > H> D> C> J

Finally, we eliminated redundant aspects. For example, because {A, J} make up a feature, once we know that A is in an order, we do not need J. Similarly, because {S, H, D and C} make up the feature of 'suit', once we know that A, H, and Dare in an aspect order, we do not need C. Based on these relationships, we eliminate J and C to get the unique order:

S > A >H >D

This aspect order reproduces the profile order with zero error, which means this respondent follows a perfect lexicographic choice heuristic for the whole process. However, most of the time, respondents do not follow a perfect lexicographic heuristic, which means there is no aspect order that can replicate the profile order with zero error. In such cases, the program will provide the aspect order with the minimum number of errors, while logging the number of errors for the respondent involved.

As a matter of fact, the original programming codes provided by Yee (2007) calculate the number of errors irrespective of where or whether the error happens, at the front or at the end of the ranking sequence. However, in the data collection people tended to be more careful and spend more time for the ranking of the destinations they would consider, and less time for destinations that they would not consider for their final choice. This suggests that the ranking orders in the front may be more reflective of respondents' real preferences than the ranking order at the end. If we count errors in the front as equally to those at the end, then we run the risk that the detection of the optimal aspect order may be driven by the responses (rankings) that are least reflective of a respondent's preferences. This concern raises a critical question about how to calculate the number of errors in greedoid analysis. We decided to use a weighting scheme to calculate the number of errors. Since there is no reference in the literature on what a useful weighting scheme might be, we chose to use linearly decreasing weighting. Thus, if there are N profiles in the ranking order, the weights for errors that occur from the first position to the last position are (N-1), (N-2).....0.

This, then, means the following in relation to the previous example:

Subset {H}:

Number of errors caused by having aspect H in first position = 6

(Errors: AH>AS, AH >JS, JH>AS, JH>JS, JH> AD, JH >AC)

Store J ({H}) = 6, with H as optimal last aspect

Since the ranking order provided by the respondent is AS >JS> AH> AD > AC> JH > JD> JC, there are 6 violated pairs caused by having H in the first position. The original programme would store the number 6 as the number of errors for having aspect H in first position. There are 8 stimuli cards here, so the linearly decreasing weights are 7,6,5,4,3,2,1,0. So, if the error happens at the first position (AS), the weighted number of errors is 1*7=7. If the error happens at the second position (JS), the weighted number of errors is 1*6=6.If the error happens at the last position (JC), the weighted number of errors is 1*0=0. So the weighted number of errors by having H in first position = 7+6+7+6+4+3= 33. Number of weighted errors: AH>AS (1*7), AH >JS (1*6), JH>AS (1*7), JH>JS (1*6), JH> AD (1*4), JH >AC (1*3).

The weighted number of errors is stored for further analysis. And eventually, the program identifies the best lexicographic order as the order with smallest number of weighted errors. With the help of Michael Yee, the greedoid programming code was modified to incorporate linearly decreasing weights. (The finalised programming code for 'greedoid analysis' is presented in Appendix 4.)

Greedoid analysis: step 3

The lexicographic order for each respondent generated by the greedoid analysis was input into SPSS. Frequency analysis was run on the first lexicographic aspect for the whole sample to reveal the popular aspects that were used as the first choice criteria to make the selection. A hierarchical tree was made to present the commonly used structures of aspect orders. And the lexicographic aspects that were used to form the consideration set were identified by a 'Finding must-have aspects' program based on the results of the greedoid analysis (the programme code used for 'Finding the must-have aspects' is presented in Appendix 4.)

Two indicator instruments were used to evaluate the two choice heuristic models: accuracy of prediction on the hold-out data and the number of weighted errors. The test of predictability on the hold-out data-set was performed on both choice heuristic models. A few studies in marketing and consumer research have attempted to compare the predictive power of the compensatory choice heuristic model and the non-compensatory choice heuristic model and in these the indicator used was the accuracy of prediction on hold-out data (e.g. Kohli & Jedidi 2007; Yee et al. 2007; Dieckmann et al. 2009). The hold-out data are the data that are not used in the modelling of the choice heuristics, but that are used to assess the accuracy of these models.

As described, in this study, 10 stimuli destination cards were generated from an orthogonal design. Conjoint analysis requires the order of only the first 8 cards to make the estimation, including the utility scores of each attribute aspect for each respondent, while the preference order provided by the respondents on destination card 9 and destination card 10 are not used in the utility estimation process. Instead, they are used to control whether this analysis is accurate. The software would use the utility scores of each attribute aspect calculated by conjoint analysis to generate the utilities of destination card 9 and destination card 10 for each respondent and assess how frequently the predicted order of the two hold-out cards (based on their utilities) was consistent with the observed order in the rankings provided by the respondents.

However, the measurement that greedoid analysis uses to evaluate whether the analysis is accurate is not the prediction of the ranking of hold-out stimuli and the program processes the preference information for all 10 destination cards to generate the aspect order for each respondent. In order to make a fair comparison between the two methods of analysis, it was important that the greedoid analysis of the preference order of the 8 destination cards could, by omitting destination 9 and destination 10 from each respondent's rank order, remaining obtain A sorting solver was programmed in Java to sort the order of the two hold-out cards for each respondent based on the aspect order deduced from the 8 destinations analysed from a lexicographic by aspect perspective. This again allows a comparison of the observed rankings with an ordering predicted while holding out information about 2 destination cards. This made it possible to compare the predictive power of the conjoint and the greedoid analyses on an equal basis, with both analyses using only empirical information about 8 destination cards and holding out information from the remaining two, 10 and 9.

The weighted number of errors is the indicator that was developed in the course of this study to indicate to what extent the lexicographic heuristic was applied during the whole ranking process. The smaller the number of errors, the larger is the likelihood that the lexicographic heuristic is used. This indicator has now been incorporated in the greedoid program. The weighted number of errors resulting from analysing the data using the compensatory choice heuristic was calculated manually, in two steps.

Firstly, the conjoint analysis provided the utility score of each destination card for each respondent. The 10 destination cards were then ranked according to these scores. Secondly, the estimated ranking order of the 10 destination cards was compared with the actual observed ranking order. The violated pairs (errors) were identified by comparing the two ranking orders and each pair was multiplied by the weight according to the position where the error happened. The final number was obtained by the summing the weighted errors.

4.6 Conclusion

This chapter has outlined the methods used in this research. Within the first section, different kinds of research methods that can be used to investigate tourism destination choice were introduced and reviewed. Especially, the two estimation methods (conjoint analysis and greedoid analysis) adopted for this research were introduced in detail, since they are somewhat complicated and have not been widely used in studies of tourist decision-making Then, the justification of the approach and the methods used in this study was provided.

The empirical research had a two-stage data collection process, with both interview and questionnaire involved. The whole procedure of data collection was reported. Subsequently, the logic of the data analysis was described, with a special emphasis on the working of the greedoid algorithm, measures of fit, and ways to arrive at a fair comparison between the two different models. As far as we know, this is the first empirical study to explore and compare different estimation methods that can be used in the analysis of tourist destination choice and choice heuristics. The methodological approach used in this research is unique in tourism decision making studies and provided exciting new means to tackle the problem of non-compensatory heuristics which hadn't been available before. Additionally, this approach enabled a comparison of different analysis methods but based on the same data-set. Above all, besides the results generated from the data analysis, this chapter contributes methodological knowledge on its own.

The results and findings of this research are presented in the next two chapters. The first of these gives the findings of the interviews and the following chapter presents the modelling results of the survey data and in particular the rankings of destinations provided by respondents.

Chapter 5 Findings of the interview: the choice criteria

5.1 Overview of the chapter

The main purpose of this research is not to identify all the choice criteria used by Chinese tourists, but to explore how the choice criteria are used in the selection of a destination, in other words, the choice heuristics applied by Chinese long-haul outbound tourists. Thus interviews with six sales managers from different tour operators are used (1) to make sure the attributes evaluated in the survey stage of the research (see Chapter 4 and the results reported in Chapter 6) are the ones that are relevant and adequately represent actual destination choice criteria of Chinese long-haul outbound tourists and (2) to provide additional information for understanding the decision-making behaviour of the Chinese long-haul outbound tourists.

The findings of these semi-structured interviews are presented below in three parts. Section 5.2 provides some general information about Chinese long-haul outbound tourists, including: who they are, where they are from and where they prefer to travel to. In section5.3, the important attributes identified in the interviews are presented and illustrated, along with the cultural context that underpins them. Besides the choice criteria themselves, factors that may influence the choice criteria tourists employ were explored in the interviews; in particular, is a factor that emphasised by most of the informants as an influential factor were the travel arrangements, especially the composition of the party with which the tourist is travelling. This factor is also discussed in section 5.3 as well. The key findings of the interview are discussed in section 5.4 before the chapter concludes with section 5.5.

5.2 General information of Chinese long-haul outbound tourists

At the beginning of the interview, the six informants were asked to talk about what kind of people is inclined to take long-haul outbound leisure trips. Their answers reveal that, in general, these tourists have three things in common. Because we are investigating people who travel for leisure purposes, with their own money, relatively higher income or higher household income is regarded as the first common feature of these tourists. This feature has also been mentioned in previous studies of Chinese outbound tourists (Chinese Foreign Tourist Consumer Working Group, 2007; Ryan & Mo, 2002). It is extended here to higher household income because there are some younger outbound tourists who do not earn a lot but who are supported financially by their parents. Secondly, long-haul trips normally require 8–15 days, depending on the distance, which means the tourists need to have either flexible work or enough vacation days free to allow them to travel. The third commonality of this group of tourists perceived by the informants is that they must see travelling as an enjoyable activity since these people travel for leisure. This implies that these people probably have travelled before (although not necessarily to long-haul outbound destinations) and they stand a good chance to become repeat outbound tourists in the future.

During the interviews, almost every informant mentioned that young people (aged 18–35) account for the majority of outbound leisure trips. Three informants emphasised that a honeymoon is a great motivation for young people to take an outbound trip, while two informants mentioned that students who want to study abroad in the future may take a long-haul outbound trip to Europe or America as well. Compared to Western countries, relationships between parents and children in China are very close. Parents tend to provide unconditional help, including financial support, for their adult children. This is one reason why, although long-haul outbound travel is expensive, young tourists are still the majority of clients.

According to the research conducted by Chinese Foreign Tourist Consumer Working Group (2007), after young people, middle-aged people account for a large proportion of the outbound travellers as well. In that research, however, outbound travelling included business travellers and those going to visit their children studying abroad. However, middle-aged people were hardly mentioned by the present set of informants as undertaking for leisure trips. Informant 1 said 'Middle-aged people, especially the ones around 45 to 50, are normally quite occupied by their work so they don't have time for long term travel. But they may be willing to pay the trip for other family members such as their parents or children.'

In addition, four out of six informants mentioned the trend for retired people (aged around 55 to 70) to take a long-haul trip for leisure. As informant 1 explained: 'Because retired people have enough time and also the ability to pay, they would like to enjoy their life after many years of hard work.' Informant 2 said that 'Most old outbound tourists are retired from state-owned business with good welfare and high pensions and they are normally the group who ask the most questions when they are choosing a destination'.

Based on the interviewees' answers regarding which groups are most likely to take a long-haul leisure trip, we discerned four:(1) old people who have retired from a well-paid occupation; (2) young couples on honeymoon (or who just want to spend some time together); (3) students who want to study abroad in the future; (4) repeat tourists who love travelling.

Informant 5 was working at our operator located in Gansu, which is an economically less developed province. She indicated that 80% of her clients were business travellers, which means their travel was paid for by the government or their companies. Their preferences were different from those of people who had to pay for a trip. The difference in decision-making behaviour between business travellers and leisure travellers has been addressed in previous studies (Chen, 2000; Chu & Choi, 2000; Proussaloglou & Koppelman, 1999). According to Gungrui (2006) and Li et al. (2009), due to imbalanced economic development in China, most outbound leisure tourists are generated from the more affluent large cities – Beijing, Shanghai and Guangzhou. This implies that if we want to avoid the variance in destination preference that arises from differences in level of economic development. It is better to collect data within a single region. That approach was adopted for this research and we chose to collect data only in Beijing and Tianjin, as these large, developed cities provide a large number of long-haul outbound leisure tourists or potential outbound leisure tourists. Further, due to the complexity of the survey task, would be hard to get a sample big enough to generate the preference patterns of Chinese outbound tourists across different regions.

For the purpose of getting a general insight into the outbound destinations selected by Chinese tourists, the interviewees were asked to talk about popular destinations and the differences between groups of clients in this respect. The details provided by informants included cost of travel, visa applications and the type of destination, and they are summarised below.

Europe is the most popular regional destination, for two main reasons: the convenience of Schengen visa (which enables tourists to travel to any Schengen countries); and the variety of destination countries, in terms of both natural sights and culture. It is easier to get a visa to Europe than to the USA or Canada. Moreover, the package tours to Europe from China are generally cheaper than those to America.

The USA and Canada are the most two popular countries in the Americas for Chinese tourists. These package tours, though, cost more than comparable tours to other regions. And the visa restriction is a large obstacle for Chinese tourists, especially first-time tourists to choose them as destinations. However, image of the USA 'the most developed country' is very attractive to Chinese tourists.

Oceania, including Australia and New Zealand, is famous for its natural scenery and all kinds of nature-related activities. The region seems to be preferred by younger people and the price of packages is relatively low. Also, it is very easy to get a travel visa to Australia and New Zealand.

Africa is the least popular region for first-time travellers. But Egypt, Kenya and South Africa are very popular for repeat tourists. Package prices start from £800 per person for an all-inclusive economy tour. Furthermore, the visa application is not a problem.

These findings are consistent with the results of previous studies. According to Sparks and Pan (2009), Europe accounts for the largest proportion of Chinese tourists, followed by Australia and New Zealand. At the country rather than regional level, besides popular destinations in Asia such as Japan and Singapore, the preferred destinations of Chinese tourists are France, followed by the USA, Australia, Egypt, Italy, Germany, Canada and Spain (Kim et al., 2005).

All this general information about Chinese long-haul outbound leisure tourists helps us to get a better understanding of who are our research subjects, where can we approach them and their preferred destinations, as reported by the staff of some key tour operators. The following sections present the main findings of the interviews, principally the attributes of destinations that are of common concern to Chinese long-haul outbound tourists, or that are commonly asked about by them, and the common values/options/aspects provided by these destinations.

5.3 Important attributes considered by Chinese long-haul outbound tourists

A (potential) traveller's evaluation of (potential) travel destinations is a multi-attribute assessment (Sparks & Pan, 2009). To understand the destination preferences of Chinese long-haul outbound tourists, we need to identify the attributes considered important – and used – by tourists in performing that evaluation. As mentioned in literature review (Chapter 2), two kinds of attributes are often considered by tourists: constraints and destination attributes. Based on the previous study (Seddighi & Theocharous, 2002), the constraints considered by tourists include distance, cost and transport, while the important destination attributes include natural beauty, safety, weather and shopping.

In the present study, the interviews were asked 'What kind of information do people ask for most during their selection of a destination?' and 'What attributes do you think are important to them?' After these open questions, the important attributes of destinations for Chinese tourists generated from previous studies but not mentioned by each informant were double-checked by asking the interviewees "What do you think about the role of these attributes in the selection of a destination?" The attributes are identified and presented below. The top five mentioned frequently or emphasised by the interviewees are listed first; attributes that were found important in previous studies but did not feature in the top five are included later.

Cost

In this context, cost means the price of the tour package. The price charged by the tour operator covers transport, visa application fee, accommodation and a tour guide. Four of the six informants gave the price as the first attribute they could think of. Informant 2 said 'Most long-haul outbound Chinese tourists are price sensitive and many of them still prefer a lower price level'. On the one hand, this might be because the cost of long-haul travel is still a barrier for many people on average income. On the other hand, it could due to the Chinese culture of advocating frugality. Informant 6 supplemented this: 'Recently, in the Tian Jin tourism market, although tourists prefer a low price level they will avoid the lowest level, since the lowest price level gives the impression of poor quality'. Similarly, informant 1 said 'Most Chinese tourists I encountered prefer to choose the middle price level, which might be because this price level make them feel the quality of the trip is guaranteed without being too expensive'. Low cost was included in the list of important attributes studied by Kim et al. (2005) but was found to be less important than destination attributes such as safety, beautiful scenery and well equipped facilities. This might be because the respondents were approached at an international airport, which means they were probably repeat tourists who gave more consideration to destination attributes than to constraints.

Moreover, according to the interviewees, trips to European Schengen countries start from £1200 per person for an all-inclusive tour package lasting from 8 to 15 days. Trips to America are more expensive, at around £2000 or more per person for an all-inclusive economy tour package. Tours to Australia and New Zealand start from £800 for a single country or£1300 for both. The price of most long-haul outbound trips is around £1000–£2000, and £900, £1300 and £1800 are regarded as typical low, middle and high prices. This range of package fees does not include 'VIP' trips (packages for small groups) or luxury trips and they reflect only the economy price range in the Beijing-Tianjin region.

Visa

Visa restrictions constitute another important attribute identified in the interviews. It can be difficult to get a visa for a destination country. Three of the six informants mentioned that the ease of obtaining a visa would influence the destination choice of tourists. For example, informant 2 said 'Tourists who have no outbound experience probably choose some destinations with low risk of visa rejection such as Australia or some European countries like France or Italy. But people who have already got a few visas successfully may think the visa is not a problem or they may even prefer a country with a high risk of visa rejection, for reasons of self-esteem'. Informant 4 also mentioned stated that 'The staff in tour operators provide information and advice for first-time tourists regarding the difficulty of visa application so that they can be aware of the possibility of visa rejection. Normally we don't recommend the US as the first destination for people who have never previously got any visa unless the tourists have made their decision.'

Generally speaking, among the popular destinations, the USA is deemed as presenting the highest risk of visa rejection, followed by the UK and then the Schengen countries in Europe. Australia and New Zealand are regarded as presenting the lowest risk of rejection. Visa applications were not included in many previous studies because they focused on Chinese tourists travelling to short-haul destinations such as Singapore, Japan and Korea, or destinations like Australia or New Zealand. There is rarely any problem in getting a visa to these destinations. In contrast, the visa application was a key factor for Chinese travellers deciding whether to visit the USA (Agrusa et al., 2011; Lai et al., 2013).

Time schedule

Unlike independent travel, the itinerary is relatively fixed for package tours. Therefore, whether the itinerary fits the preference of decision-makers will influence the final choice of destination to a large extent. Besides the preferred scenic spots within the itinerary, tourists also expect a proper balance between fixed visiting activities organised by tour operators and free time, to be spent autonomously. During the interview, three informants suggested the time schedule is very often an attribute used by tourists to select a destination (i.e. a particular package). Informant 1 indicated there is a trend for people to prefer less hectic schedules. He said 'In past days, when international travel was a luxury purchase for most people, people tended to go to six or eight European countries within one tour because they regarded it as a one-time opportunity and they would like to see as much as possible. But with the increase in purchase ability and tourism experience, international travel is not an uncommon thing anymore, so people have started to demand more comfort and a more autonomous schedule – normally one or two adjacent countries each time, or, for the Schengen area, about three countries for a first-time visitor'.

The time schedule is one of the most important attributes used by Hong Kong residents to choose package tours (Wong & Lau, 2001) and in the study of Chinese outbound tourists conducted by Zhu (2005), the time schedule was also an important attribute.

In addition, according to the interviewees, the preferred time schedule may vary with age. Here, however, opinions differed between informant 2 and informant 3. The former mentioned that 'Given their physical condition, older people don't like an intensive time schedule and they prefer more relaxed travelling with enough time to rest'. But the latter said that 'although older people prefer more visiting than participant activity such as hiking or climbing, they still like a schedule with less free time since they may not know what to do by themselves or they feel it is a kind of waste if they don't visit enough scenic spots during the trip'. These responses are particularly interesting because differences in preferences about time schedule among different age groups have so far not been highlighted in earlier studies of Chinese travellers.

Fame of the destination

When the informants were asked about what attributes tourists give consideration during the selection of a destination, informants 1 and5 said something very similar, which is 'Sometimes, they don't think a lot: they just choose America or France because these countries are famous'. After an enquiry about the exact meaning of 'famous', it was summarised as being well known by the Chinese public and, furthermore, well known either for advanced economic development or for beautiful scenery. Beautiful scenery and advanced economic development level were previously identified in the literature (Kim et al., 2005; Sparks & Pan, 2009) as important destination attributes. However, just as informant 5 said, "For tourists who want to travel to a beautiful destination but don't have enough information to evaluate which destination is more beautiful, one credible means of evaluation is to select a destination the beauty and beautiful image of which is generally acknowledged by the public'.

It is important to note that in the present context 'famous' is different from a good destination image, in that it not only requires a good destination image but more importantly requires the destination to enjoy a high level of popularity. 'Famous' destinations might be popular with long-haul travellers because in the Chinese culture people care very much about what other people think of them and they are eager to have someone else's recognition and affirmation. And to some extent, international travel, especially to economically developed countries such as the USA or the UK, is something that indicates wealth and status – it gives those travellers the feeling of 'having face'. 'Having face' in Chinese culture involves dignity, a good reputation and prestige (Hofstede & Bond, 1988). Another reason for a preference for famous destinations might be a social-psychological tendency to conformity, which is also very common in Chinese culture (since it is a popular destination and everyone wants to go there, I would like to go there too).

Shopping

Shopping, especially shopping for brands such as Boss, Louis Vuitton or Clarkes, is a feature of Chinese tourists portrayed by Western media (see a few examples in Box 5.1). But the opinions provided by the interviewees were not consistent in this respect. Informants 2 and 4 said that shopping is a very common activity during the trip abroad and many destination itineraries include a stop for shopping. They suggested two reasons for this. Firstly, Chinese people tend to pay great attention to courtesy, so that they think it is important to bring presents back for their families and friends and Western-made products like cosmetics, purses or clothing are felt to make a respectable present. Secondly, Chinese people sometimes purchase globally recognised products because they think wearing them or owning them is a symbol of social standing. Nonetheless, informants 1 and 3 both indicated that there are tourists who dislike shopping very much. The principal reason for this, they felt, was that these tourists thought shopping reduced the time available for visiting attractions.

Box 5.1.Shopping as a feature of Chinese tourists according to Western media
'Britain braced for influx from China as wealthy tourists make a beeline for bargains in high-end shops.'
—Tania Branigan and Mark Tran, *Guardian*, 3 February 2011
'Though luxury brands started opening stores in Beijing and Shanghai years ago, Chinese shoppers still spend more on luxury products abroad than they do at home, according to the consulting firm Frost &Sullivan. Price is the major reason: Because of China's taxes, luxury products are about a third cheaper in the United States and elsewhere.'
— Stephanie Clifford, www.mb.com.ph, 20 April 2012
'Brand-hungry Chinese tourists boost luxury sales.... Chinese are among the top five nationalities shopping at Rivoli's stores.'
— Global Travel Industry News, 2012

The literature is also inconsistent regarding the importance of shopping for Chinese tourists. Some cultural studies (e.g Huang, 2010; Wang, 2011) claim that Chinese tourists are inclined to spend a lot of money on souvenirs or luxury brand products. In addition, Wang et al. (2010) indicated that the high prevalence of counterfeit goods in the domestic Chinese retail industry could encourage Chinese people to shop overseas. However, Kim and Guo (2005) reported that a 'good place for shopping' was the second least important attribute for Chinese outbound tourists among 10 suggested attributes (inexpensive travel cost, level of economic development, beautiful scenery, safety, good place for shopping, different cultural and historical resources, good weather, good leisure and recreation facilities, easiness to arrange travel plans, and well equipped tourism facilities). In the study be Sparks and Pan (2009) shopping was also not deemed very important by Chinese outbound tourists to Australia.

Thus, it is still uncertain whether shopping is important for Chinese outbound tourists, which means further investigation is needed. This uncertainty was manifest in both the interviews and in the literature. It might be due to simply to a lack of clarity in what exactly is meant by 'shopping' – what kind of shopping and how much shopping? For example, a 'good place for shopping', as an attribute used in the study by Kim and Guo (2005), could mean purchasing small local products such as chocolate and postcards or purchasing luxury products such as cosmetics or jewellery. Or it could also mean outlet shopping, with a focus on discounted internationally famous products. Tourists' attitudes could vary greatly between different kinds of shopping and how much time is scheduled for shopping in the itinerary. Therefore, if the attribute 'shopping' is going to be investigated as a choice criterion for Chinese tourists in selecting a destination, it should be specified in some detail for the respondents.

Other possible evaluation attributes

Sparks and Pan (2009) found that 'beautiful scenery' is the most important destination attribute for Chinese outbound tourists and 'natural beauty' had the highest mean rating for importance in the study by Kim and Guo (2005). However, it is arguable that these two attributes are not very helpful for tourists trying to 'filter' alternative destinations, since probably every travel destination would have some sort of claim to beautiful scenery or natural beauty. For first-time travellers especially, it may be hard to judge which destinations would better fit their standard of beauty, or their preference for specific types of scenery, as they are likely to have rather limited information, chiefly from friends or advertisements.

In the interviews, a possibly better construct for an attribute was found that could cover both scenery and natural beauty –which is the 'type of destination'. Informant 1 mentioned that 'tourists may choose a destination by type, according to their individual preference'. Generally, destinations can be categorised along these lines as those predominantly featuring: historical and cultural interest; natural sights; tours of islands; or nature-related activities such as snow skiing or hiking. Furthermore, informant 3 said 'For physical reasons, older people prefer sightseeing rather than participant activities on their package tours. For example, if scuba diving is the main activity in the itinerary for Australia, you may not see many older people considering it.' 'Type of destination' was in fact initially included as an attribute for the survey stage of the present research (see Chapter 6). But, as mentioned in Chapter 4, on methodology, the pre-test indicated that survey respondents would likely face information overload if they were asked to process more than five attributes. Therefore, given the lesser importance attached to this attribute in the interviews, it was removed from the final multi-attributes assessment task.

Another possible attribute is destination safety. This was reported to be the most important destination attribute by Chinese outbound tourists in the research by Kim et al. (2005).The importance of 'safety' perceived by Chinese outbound tourists was also reported by (Yu & Weiler, 2001) and Sparks and Pan (2009). Safety issues considered by tourists mainly include natural disaster and political acts such as riot. According to the interviews here, peaceful protest and strikes are not considered as a threat by Chinese tourists. I Informant 5spontaneously mentioned safety as a critical attribute in response to an open question. The other informants agreed that safety is very important for Chinese tourists. But it is more of a requirement for a package tour rather than a choice criterion for tourists. According to informant 4 'safety is like the basic condition for a package tour, which means the tour operators would automatically exclude those destinations which are experiencing safety problems'. And informant 3 said 'We would not promote a destination which just had an earthquake or where a civil war was going on. Besides, travelling with a group of Chinese people would automatically increase the feeling of safety for the tourists.' Given that the survey respondents in the present study were looking at taking a package tour that had been carefully planned by large tour operators, it was not included in the survey questionnaire.

Further attributes mentioned in previous studies included means of transport, local weather, local facilities and food, but these were not brought up by our informants. We double-checked these attributes by asking the informants what they thought of the roles of these specific issues. Informant 4 mentioned that 'for tourists who lives in small cities where there is no international airport, they may need to travel to the nearest big city first and then take an international flight to their outbound destinations'. In this regard they might consider the convenience of the transport to their destinations. And informant 3 said 'Some tourists may consider the local weather of the destinations. For example, if the destination is too cold or too humid, it may not suitable for people with serious arthritis'. Since most clients of informant 5 were business travellers, she said 'They care about the rating of the hotel and the quality of the food more than leisure tourists do, since they don't need to worry about the money.' But according to other informants, for the self-funded leisure outbound travellers, local facilities and food were not their primary concerns when selecting a destination. Generally speaking, confirmation of the importance of these attributes by the interviewees was lacking. As a result, they are not included in further investigation of this research.

The influence of travel companions

Besides demographic characteristics of travellers, we try to identify whether any other variables influence what attributes are considered by tourists in their selection of a destination. When we asked the interviewees to talk about this, one thing commonly mentioned was the composition of the party of travellers (i.e. who the decision-makers would be travel with). Different types of travelling companion might shift the attention of the decision-maker from some attributes to others. For instance, informant 2 said that people travelling with their whole family may pay more attention to the visa application than people who travel by themselves because if a visa were to be rejected all the other family members might feel it necessary to cancel the whole trip. Another example, given by informant 1, was 'People who want to take their children to see the world may consider the fame of the country especially important'. Therefore, this factor is considered during the survey and the respondents were asked to indicate who probably they would be travelling with on their next long-haul trip.

5.4 Discussion of the key findings and conclusion

The key findings of the interview comprise the answers to the research question 'What are the important attributes (choice criteria) considered by Chinese outbound tourists when selecting long-haul destinations?' Although six is a small sample, the interviewees were all very well informed about Chinese outbound tourists and some new insights as well as promising theoretical hypotheses were generated.

Firstly, the interview proved to be necessary because it provided additional information on Chinese long-haul outbound tourists. For example, due to the close family bond between parents and children, many young people are able to take a long-haul outbound trip financially supported by their parents. So rather than 'higher income' described in previous studies of Chinese outbound tourists (Chinese Foreign Tourist Consumer Working Group, 2007; Ryan & Mo, 2002), 'higher household income' is more appropriate as an indicator of 'having money' for travel. Actually, middle-aged people, especially those aged around 45–50 years, who have a higher income often simply do not have time for long-distance leisure trip. But they are willing to pay for a trip for other family members, such as their parents or children. This issue, revealed in the interviews, is helpful for us to understand why the majority of the sample are young people who may not have a high income at present. The profile of the Chinese long-haul outbound tourists revealed by the interview is also important for marketers to locate their target group more accurately and adjust their advertising campaigns accordingly.

Secondly, the choice criteria considered by tourists may differ between (potential) first-time tourists and repeat tourists. As mentioned in Chapter 3, on the theoretical context, China's long-haul tourism market is an emerging market, and the majority of clients are first-time tourists. The attributes considered most important by the tourists identified by the interviewees can be classified as constraints, such as price and visa restrictions. However, in previous studies (e.g. Kim, et al., 2005; Ryan & Mo, 2002; Yu & Weiler, 2001), destination attributes such as 'safety', 'beautiful scenery' and 'well-equipped facility' were shown to be more important than constraint attributes. These studies, however, approached the respondents at the airport or at a certain destination (i.e. Australia or New Zealand), which means the samples are likely to have contained a larger proportion of repeat outbound tourists.

The inconsistency of the findings of the interview and previous studies suggests the possibility that first-time tourists may pay more attention on constraint attributes, while repeat tourists focus more on destination attributes. In addition, as ample of respondents from a certain destination cannot represent the whole population of Chinese long-haul outbound tourists. For example, visa restrictions were not an important attribute revealed in studies (Ryan & Mo, 2002; Yu & Weiler, 2001) whose sample was collected in Australia or New Zealand but was a key constraint for tourists visiting the USA (Agrusa et al., 2011; Lai et al., 2013). Actually, ease of visa application has been found to be an important variable to increase travel (Goh & Law, 2002; Qu & Lam, 1997) and it was also mentioned by most of the interviewees. Therefore, this attribute should be included as a choice criterion for the general decision-making of Chinese long-haul outbound tourists.

Thirdly, due to the intangibility of tourism products, prospective tourists have to imagine the experience on offer. Choosing the destination for a holiday is not so much the selection of a product but the selection of an expected set of experiences. Therefore, the choice criteria tend to focus less on the quality of the facilities, say, but more on a desired experience or impression, such as whether the visa application is complicated, whether there are good places for shopping, or whether the destination is famous. These choice criteria are more abstract than the ones used to select normal products such as the colour of a cell phone or the amount of computer memory. As a result, a more careful identification and clarification of these choice criteria and their values is required to avoid misunderstanding during the data collection and to minimise any inconsistency in the findings.

For instance, one of the choice criteria used by the Chinese long-haul outbound tourists identified in previous studies is shopping (e.g Huang, 2010; Kim, et al., 2005; Sparks & Pan, 2009; Wang, 2011). But the degree of importance of shopping reported is inconsistent across studies. As noted above, shopping can cover anything from the acquisition of souvenirs to the purchase of luxury products (Sparks & Pan, 2009). Tourists who like getting souvenirs while on holiday may dislike shopping for luxury products. Thus a much greater degree of specification may be needed than simply 'good opportunity for shopping' to get a more accurate understanding of what exactly tourists prefer. In some of the Western media, Chinese tourists are shopaholics keen to acquire brand products; this was also mentioned as an attribute considered by Chinese tourists in the interviews. Therefore in the present research this attribute was included, but it was specified further as whether the destination is good for brand product shopping.

Finally, culture will influence tourist decision-making behaviour but how exactly culture plays a role requires further quantitative studies. The influence of culture on tourists' decisions and behaviour has been investigated in many studies (e.g. Hofstede & Bond, 1988; Huang, 2010; Pizam & Reichel, 1996; Wang, 2011;

Wang et al., 2010). According to Pizam and Reichel (1996), tourist behaviour differs among nations. Therefore, in order to better understand the destination choice of Chinese outbound tourists, the influence of Chinese culture should be further investigated. Although the present research does not aim to study the influence of culture on the destination choice of Chinese long-haul outbound tourists, some of the findings from the interviews do have some implications for cultural studies.

Hofstede (1988) introduced a model with five cultural value dimensions to understand and explain cross-cultural differences in human behaviour. These five dimensions were: individualism versus collectivism; power distance; masculinity versus femininity; uncertainty avoidance; and Confucian dynamism (long-term versus short-term orientation). As mentioned in the literature review (Chapter 2), a few researchers have sought to reveal the influence of culture on the decision-making of Chinese outbound tourists (Arlt, 2006; Mok & Defranco, 2000) based on this culture dimension model. As for the cultural dimensions, Chinese society is relatively high power distance, is more collectivist and has a low level of uncertainty avoidance. Due to the high collectivism, compared with Western tourists, they prefer to travel in groups and to purchase a package tour with all the arrangements settled by the tour operator, especially for travel to an unfamiliar environment (Armstrong & Mok, 1995). In selecting a destination, they tend to prefer places where everybody goes, to do typical things (Mok & Defranco, 2000). These propositions from previous studies were confirmed in the interviews.

However, there are some popular hypotheses generated by previous studies that may not prove to be true. For instance, the low level of uncertainty avoidance suggests that Chinese outbound tourists prefer flexibility in planning and executing travel arrangements (Mok & Defranco, 2000).But this is not always the case, since some tourists (identified by the interviewees) prefer compact travel schedules rather than schedules with more free time. And the low level of uncertainty avoidance seems to contradict the fact (reported in the interview) that many Chinese tourists are very sensitive to the risk of being rejected on a visa application. These issues need to be tested and examined further.

In conclusion, this chapter provides qualitative insights into Chinese long-haul outbound tourists. The information includes who represent the largest groups of outbound tourists, where they are from and what their preferred destinations are. By knowing the characteristics of long-haul outbound Chinese tourists, we can better understand why particular attributes a reconsidered by them in their selection of a holiday destination. Further, the classification of the Chinese long-haul outbound tourists provides a direction for a later segmentation study. By understanding where the long-haul outbound tourists are from, the appropriate respondents can be located more efficiently.

The popular destinations chosen by Chinese outbound tourists and the characteristics of these destinations, as revealed in the interviews, were useful for the next stage of the research, the results of which are reported in Chapter 6, to provide experimental materials which reflect actual destinations; for example, the price ranges provided for the survey respondents were based on real price ranges. Moreover, the major function of the interviews was to identify, among so many attributes potentially involved in tourists' decision-making, which are most relevant and are used most often as choice criteria by Chinese long-haul outbound tourists to eliminate alternative destinations and to make a final decision. Only if we know the actual attributes that Chinese outbound tourists use to evaluate the destinations can we further investigate the relative importance of these attributes and how they are used.

Eventually, five attributes were revealed from the interviews and selected for the further multi-attributes assessment task in the survey stage of the research: cost, visa restrictions, time schedule, famous destination, and famous brand product shopping. The complexity of the questionnaire task limits the number of attributes that we could present to respondents. Three additional reasons for using these five attributes are: (1) compared with other attributes, they were more often emphasised by the interviewees; (2) there are debates or inconsistency in the literature or in interviews regarding the attitudes of Chinese tourists to these attributes, so that further investigation is needed; (3) some of the attributes, such as brand shopping and the visiting of famous destinations, seem to distinguish Chinese tourists from tourists from other countries regarding the choice of destination and so invite further exploration of the influence of culture in future studies.

As a matter of fact, finding the attributes considered important by Chinese long-haul outbound tourists is the first step to understand their decision-making process. However, more importantly, we need to know the details of how these choice criteria are used. For example, now that we know that Chinese tourists generally consider the cost of the tour package to be an important attribute of a destination, we need to know which price level is preferred by Chinese tourists and to what extent a preferred price level will determine that a particular destination is chosen. If a tour operator marketing a particular destination cannot reduce the price to the preferred level, is it possible to still retain clients by improving the value of other attributes? In order to answer such questions, we need to explore the choice heuristics used by Chinese long-haul outbound tourists so that deeper insights regarding their choice of destination can be obtained. The next chapter provides the answers to these questions, by estimating the destination preference of Chinese long-haul outbound tourists based on different choice heuristics and the fitness of different models.

Chapter 6 Findings of the survey: choice heuristics

6.1 Overview of the chapter

This chapter provides the detailed results of the survey. In section 6.2, the respondents' profile is presented, mainly in terms of their demographic characteristics, previous travel experiences and travel companions.

Section 6.3 presents the results of the conjoint analysis of the tourists' destination preferences based on a weighted compensatory choice heuristic model. The results consist of the overall preferences of the whole sample, the differences in preference between various demographic subgroups and a further cluster analysis to identify any clusters of respondents with similar preference patterns.

The results of the greedoid analysis are reported in section 6.4, which reveals the preference estimates based on a lexicographic choice heuristic model. Firstly, the aspect order for each respondent is summarised; this is followed by the comparison of subgroups in terms of the first attribute used to in the selection of a destination. Then the preferences of the 20 respondents whose preferences could be fully predicted by the lexicographic heuristic model are presented, as well as the preferences of the17 respondents who could not provide a full ranking order of the destination cards. At the end of the section, a hierarchical tree is depicted to indicate the most commonly used aspect orders for destination selection.

Section 6.5 presents the results regarding the formation of consideration sets, including the size of the consideration set of Chinese long-haul outbound tourists and the non-compensatory aspects (values or options)of the attribute that are used to form the consideration set.

Section 6.6 discusses the fit of the two choice heuristic models for Chinese long-haul outbound tourists. The predictive power of each choice heuristic model (tested on the hold-out data described in Chapter 4) and their power to replicate the observed preference order are reported.

6.2 Respondents' profile

By the end of the survey, 201 useful questionnaires were collected: 184 respondents provided a full ranking of the 10 stimuli destination cards, while the remaining17 respondents were able only to provide a partial ranking of the destination cards. Since the conjoint analysis used in this research cannot make estimations based on a partial ranking, only the 184 full ranking orders are analysed by conjoint analysis. In contrast, the greedoid analysis can deal with partial ranking, so that all the ranking data from all201 respondents were processed by greedoid analysis.

Of the 201 participants, 78 were recruited at the CAISSA tour operator while they were enquiring about information on outbound trips or while they were soon due to take an outbound trip; the other 123 respondents were recruited by snowball sampling. The criteria for inclusion in the snowball sample were that respondents needed to have the necessary financial resources and also the desire to take an outbound trip in the near future. The recruitment of both CAISSA respondents and snowball respondents allowed a check on whether any preference bias would be generated if the tourists were accessed only from a particular tour operator.

Within the sample, there were 90 males and 111 females, which proved sufficient to evaluate any preference differences between genders. The respondents are categorised by age into three groups: young (below 35), middle aged (between 35 and 55) and older (above 55). In the sample, 155 (77%) respondents were under 35, 29 (14%) between 35 and 55, and 17 (9%) over 55. In China, these age groups approximately correspond with particular stages in the life cycle: most Chinese people start to have their stable career after the age of 35 and normally by then their children are old enough to go to primary school, while the retirement age in China starts at 55.To some extent, the three groups can also be regarded as strivers, achievers and retirees. The young age group accounts for the majority of the sample for two reasons. Firstly, young people are the main market for outbound tourism. Secondly, younger respondents were easier to approach during the data collection and seemed readier to undertake the task. Although the proportions of respondents in the age groups are uneven, there are sufficient numbers for us to explore the differences in preferences between age groups.

Occupations were diverse, with a large proportion (89%) of respondents having professional careers (in finance, education, engineering, media and IT etc.). One interesting thing noticed during the data collection was that people working in the IT industry were easier to approach and more patient in completing the questionnaire task.

More than half (111) of the respondents did not have any experience of self-funded outbound leisure trips, whether long- or short-haul, and this figure increased to 71% (143) for long-haul outbound travel (which excludes Asian countries). This implies that the preference and choice heuristics that we will derive from the data are particularly relevant for first-time Chinese long-haul outbound tourists.

Since travel companions are an important factor influencing tourists' preferences regarding destination (revealed during the interviews – see Chapter 5), the composition of the travelling party was included in the survey. More than 40% of the respondents (85/201) indicated that they would like to go on their next long-haul outbound leisure trips only with their spouse or partner. This is consistent with what the interviewees said –that many tourists travel for honeymoon or just want to spend some time with each other. Another 36% of respondents would like to travel with family members (73/201), which is a reflection of the close family bond in Chinese culture. Another 28respondents

(13.9%) would like to go with their friends. And only 15people (7.5%) would like to go by themselves. This distribution could demonstrate the collectivism evident in Chinese culture.

The remainder of this chapter provides the results and findings on the preferences of Chinese long-haul outbound tourists in their selection of a destination. Two choice heuristics are tested and how demographic characters may influence these preferences is also reported.

6.3 Preference estimation based on a compensatory choice heuristic

A compensatory choice heuristic, to be more specific the weighted compensatory choice heuristic, assumes that a decision-maker will assign a utility value to each attribute (or more specifically to its level or aspect or option) and sum the total utility value of each alternative and then select the one with the highest utility value. The utility value assigned to a specific attribute represents the influence it will has on the selection of a product: a higher utility value implies a greater preference (for a product with that attribute). Therefore, if a compensatory choice heuristic is used in tourists' decision-making, we need to know the part-worth utilities so that we can sum the total utility for each alternative destination and predict tourists' destination preference. The higher utility a destination has for a tourist, the higher the probability that it is preferred/selected by this tourist. We estimate the utility of each value of the various attributes by conjoint analysis.

Conjoint analysis is based on the assumption that all decision-makers use a compensatory choice heuristic; the method calculates the part-worth utility, which is the utility score of each value/aspect of each attribute for each respondent based on their ranking of the stimuli. It then averages the part-worth utilities of each respondent to yield the part-worth utilities of the whole sample. This aggregated utility information is valuable for us to understand the general preference of the sample. Thus conjoint analysis is adopted in this research to investigate Chinese long-haul outbound tourists' preferences for each 'value' of the five attributes that play an important part in the selection of a destination.

Basically, conjoint analysis conducts a regression analysis on each respondent's ranking data as the dependent variable and the profile design as the independent variable. The beta coefficients of the regression are the utility contributions of each value of each attribute. The command syntax to generate the orthogonal design and the conjoint analysis are presented in Appendix. The results of conjoint analysis are presented below. Again, these relate to the overall preferences of the whole sample. Difference in preferences between various demographic groups is also reported.

6.3.1 Overall preferences based on a compensatory choice heuristic model

From the data of the 184 respondents who provided a full ranking of the destination cards, the averaged part-worth utilities are estimated. These utility scores are reported in Table 6.1. As can be seen, in general, a low level price, an easy visa application, a famous destination, more free time during the trip and a good place for brand product shopping have positive utility (part-worth) scores, which means that, all else being equal, destinations with these characteristics are preferred over other ones. Apparently, price around 9000 RMB (0.69), a visa that is easy to get (0.51) and a famous destination (0.44) are the top three attribute aspects appreciated by respondents. Unlike the image portrayed by Western media, brand product shopping contributes relatively little to the overall preference for a destination. This may be because most of the respondents were first-time tourists who want to spend more time on sightseeing and experiencing a foreign culture. Moreover, they were self-funded and price sensitive, which means they may not be rich enough to purchase expensive brand products.

One thing to be noticed is these utility scores are interval data, which means they can be added and subtracted and that the difference between two values is meaningful and interpretable. But this kind of data does not allow division and multiplication. For example, we could say that by reducing the destination package price from RMB13,000 to RMB9,000, the average utility assigned to this destination within the whole sample would increase by 0.56 (0.69-0.13) units. But we cannot say that RMB9, 000 is about 5-fold (0.69/0.13) over RMB13, 000.

Moreover, the zero point for interval data is arbitrary and is not a natural zero. For instance, if a destination with no opportunities for brand product shopping suddenly opened a series of malls for that purpose, the overall preference would increase 0.04 (0.02-(-0.02)) units. We can, though, legitimately compare the preference increase caused by the price reduction (0.56 units)with the preference increase deriving from the availability of a suitable place for brand product shopping, which is 0.04 units (unlike comparisons of absolute utility values for different attributes).

During the calculation, the utility contributions are scaled to sum to zero within each attribute. But since these utility scores do not have an absolute value, a negative utility value (such as for a price level of RMB18, 000 see Table 6.1) does not mean that this price level is not acceptable to tourists. It just means that, everything else being equal, destinations with lower price level (RMB9, 000 or RMB13, 000) are more attractive to this group of tourists.

Utility is used to measure the influence of each attribute (in terms of level/aspect) on the overall preference of decision-makers. Given a set of utility values, we would know how to make a product (destination) more attractive to the average member of the sample (average tourist) by assembling attribute values with higher utility scores. However, the overall utility scores does not provide enough information to judge the importance of each attribute.

Table 6.1 Part-worth utilities for the whole sample

		Utility estimate
Package price (RMB)	9,000	.69
	13,000	.13
	18,000	-.82
Visa	Easy	.51
	Risk of failed application	-.51
Shopping	Brand shopping	.02
	No brand shopping	-.02
Time schedule	Compact	-.23
	Free time	.23
Famous destination	Famous	.44
	Not famous	-.44

For example, if half of our respondents prefer a famous destination while the other half prefer a less well known destination, then the utility value for 'famous destination' will take a positive value for half the sample, but for the other half the utility value for 'famous destination' would be negative. Then the average utility value for 'famous destination' (or conversely non-famous destination) across the sample would be zero. But obviously, this does not mean famousness is not important in the decision-making of this tourist sample. It would accurately indicate the lack of an overall preference, but it would fail to indicate the presence of two groups with counter-preferences. If we could segment these two groups, this attribute would be seen to play a huge role indecision-making.

Importance value is a measurement that can be used to supplement the overall utility scores, since it can indicate the largest preference difference a single attribute could make by changing its value. If we know the importance value, we can knowhow (much) people's preferences will change if we move, on a certain attribute, from one value to another (whether the change would be dramatic or hardly noticeable). To some extent, the importance value reflects the impacts of each attribute within a certain range on decision-makers' choices. It is calculated by taking the utility range for each attribute and dividing by the sum of the utility ranges for all attributes. The values thus represent percentages and have the property that they sum to 100.

The calculations are done for each subject independently and then the results are averaged. This indicator is able to suggest whether a low average utility score for one aspect of an attribute is because this attribute is really not important or it is because there are different subgroups within the sample who have counter-preferences for this attribute, as in the example in the previous paragraph. The results (see Table 6.2) show that price is the most important attribute on the change of preference, which means there is a large difference in preference between destinations at RMB 9,000 and those atRMB18, 000. Time schedule also plays an important role but not as important as price, followed by visa and fame of destination.

Here we use the comparison between time schedule and visa restriction as another example to further explain the relationship between overall utility and importance value. According to the overall utility score, if we change the time schedule from 'compact' to 'more free time', the overall utility of one destination for the whole sample would increase by 0.46 (0.23-(-0.23)), which is much less than if we change the aspect of visa application from 'easy' to 'risk of rejection' (0.51-(-0.51) =1.2 units). But according to the importance value, the averaged preference change (18.94) of each individual due to the change of time schedule is even larger than the averaged preference change (17.29) due to the change of aspect for the visa application. It does not mean the importance values are in conflict with the results of overall utilities. It instead suggests that if we treat the whole sample as a target group, then the change of time schedule (from compact to more free time) would make a destination more attractive for the entire group, but less so than a change of visa application (from easy to risk of rejection).

This is not because people do not care about the change of time schedule: rather, it is because, within the sample, people's preferences regarding the time schedule are not necessarily in the same direction (some would prefer a change to more free time, while others would not), whereas, presumably, none of the sample would prefer to have a risky visa application. The results suggest there are different groups within the sample that hold opposite opinions on how the time schedule should be arranged and therefore a segmentation of the sample would be desirable, to explore subgroups.

Table 6.2 Importance value of each attribute for the whole sample

Package price	32.48
Visa application	17.29
Brand shopping	14.22
Time schedule	18.94
Famous destination	17.08

Brand product shopping is the least important influence on tourists' decision-making, based on the averaged utility score for this attribute. But, as can be seen, the averaged importance value is much higher than might be expected from the overall utility score. What this indicates in practice is that, if we are looking at the whole group, whether a destination can offer brand product shopping will barely increase its attractiveness (as reflected in the low utility scores); nonetheless, there are some people in the group who greatly care about this attribute and who would change their preference for a destination if this attribute were to change (as reflected in the relatively high importance value). This raises the question whether these people share common characteristics, and how we might identify them. These questions will be answered in the next section.

6.3.2 Preference differences among various demographic groups

Because different groups may have different utility values for each attribute aspect, it is necessary to further investigate whether there is any significant difference between/among groups. *T*-tests and one-way ANOVAs were used to test for any significant preference differences in terms of gender, age, previous travel experience, travel companions of the trip and where the data were collected (travel agency versus snowball sampling). A summary of the tests performed are presented in Table 6.3. Cells with "ns" indicate there is no significant difference regarding the utility value of each attribute aspect between/among groups. For the cells where significant differences exist, the p value are reported followed by the means of the utility values of each group for this attribute aspect. Detailed illustrations regarding each significant difference are provided in the following context and tables.

Table 6.3 Summary of the comparison tests on utility values of different demographic groups

	Package price			Visa application		Brand shopping		Time schedule		Famous destination	
	9000	13000	18000	No risk	risky	Good	Not good	More free time	compact	Famous	Not famous
Gender (T-test)	ns			ns		ns		ns		ns	
Age groups (ANOVA)	ns			ns		ns		P<0.05		ns	
Young (Means of the utility)								0.26	-0.26		
Middle-aged								0.45	-0.45		
Senior								-0.69	0.69		
Travel companion (ANOVA)	ns			ns		ns		ns		P<0.05	
Travel only with spouse										0.46	-0.46
Travel with family										0.51	-0.51
Travel with friends										0.38	-0.38
Travel alone										-0.11	0.11

Table 6.3 Continued

Travel experience (T-test)	ns			ns	ns	P<0.1		P<0.05	
First time long-haul tourists						0.18	-0.18	0.49	-0.49
Repeat long-haul tourists						0.35	-0.35	0.38	-0.38
Data collection channel (agency vs. snowball) (T-test)	**P<0.05**	ns	ns	ns	ns	ns		ns	
Collected at the agency	0.53								
Snowball sampling	0.78								

Based on the results of the ANOVA, age has a significant effect on the preference for a particular time schedule. Both young people and middle-aged people prefer a schedule with more free time, and this is most pronounced for middle-aged people (utility value 0.45 compared with 0.26 for young people). The senior group (utility value -0.69), however, prefer a compact schedule with more scenic spots but less free time. The utility score for compact time schedule for the senior group reaches 0.69, while the other two age groups have a negative utility score for this aspect. The significant *F* value from the ANOVA indicates that there are differences in the means, but it does not indicate where those differences are.

For example, group 1's mean might be significantly different from group 2's mean but not significantly different from group 3's mean. In order to find which mean utility scores for the time schedule among the three age groups are statistically different from each other, a post hoc (Tukey) test was conducted. It is a multiple comparison of the means. It shows that the difference of the means for the middle-aged group and the young group is not significant (details can be found in Appendix 3), but the differences between the older group and both the other groups are significant ($p<0.05$). So we could say the older group prefer compact time schedule, while the middle-aged group and the young group prefer a time schedule with more free time. This difference in preference between the age groups was expected by the tour operator staff and the result confirmed the opinion of informant 3, who indicated that older people like to see as much as possible on holiday, more than do the younger groups. Also, seniors might have fewer options of activity if none is scheduled.

The preference on brand product shopping is very different between middle-aged group and the older group. The middle-aged group prefer a destination with good opportunities for brand product shopping and the utility score they assigned to this aspect is (0.16), which is higher than the average utility score for this aspect (0.02). In contrast, the older group has an emphatically negative attitude to brand product shopping, with a utility score of -0.31. Although the ANOVA test suggests this difference is not significant (p=0.2), that maybe because the number of the respondents within these two groups (middle-aged group and older group) is not large enough; this is therefore a promising hypothesis for testing on a larger sample.

In addition, a supplementary finding is that the importance value for this attribute had the second highest value (see Table 6.4) for the middle-aged group, at 20.85. Compared with the importance value (14.22) of this attribute for the whole sample, we could say that whether a destination is good for brand product shopping has a big impact on the preference of the middle-aged group. And this finding provides some answers to a question that came up earlier – do the people who care about brand product shopping have any common characteristics? Middle age is very likely a demographic characteristic that this group shares.

Table 6.4 Importance value of each attribute for different age groups

	Young	Middle-aged	Senior
Package price	33.37	31.88	22.59
Visa application	17.82	14.23	16.47
Brand shopping	13.09	20.85	15.52
Time schedule	18.61	16.56	27.64
Famous destination	17.11	16.49	17.78

Outbound travel experience also influences people's preferences, particularly with respect to fame of the destination and time schedule of the trip. Firstly, comparison was conducted between the group of people who had never been on an outbound leisure trip and the group of people who did have outbound travel experience. There is a significant difference ($p<0.05$) in the utility score for fame of the destination between these groups. First-time outbound tourists assigned a higher utility score (0.49) for famous destination while repeat outbound tourists assigned a lower utility score (0.38) for this attribute. This difference reflects that, in general, people who have not travelled to an outbound destination before prefer to go to a famous country more than those who do have experience of outbound travel.

A further comparison was conducted between the group of people who had never been on a long-haul outbound leisure trip (outside Asia) and the group of people who did have such experience. Besides the difference regarding their attitude to the fame of the destination country, another significant difference (at the $p<0.1$ level) is found: first-time long-haul outbound tourists assigned less utility (0.18) to 'more free time during the trip' while repeat long-haul outbound tourists assigned more utility (0.35) to this aspect. This may suggest that the more travel experience tourists have, the more confidence they are in spending time on their own.

We assumed (as set out above) that the composition of the travelling party (travel alone, with family, with family, or with spouse or partner) would influence the consideration of attributes to some extent. This was confirmed in the analysis. The single statistically significant difference across these groups concerned the preference for a famous destination country. Further, according to the post hoc test, the difference was significant only between those travelling with the family and those travelling alone, at the $p<0.05$ level, and between those travelling with a spouse or partner and those travelling alone, at the $p<0.1$ level.

Apparently, people will go with the whole family and their partners if they have a preference for famous destinations, whereas people who travel by themselves would rather go to some destinations which are not famous (See Table 6.3). This might be because those who travel alone are more adventurous. The fact that people who travel with their family prefer famous destinations more than any other groups confirmed the information obtained from interviews with the staff at the tour operators.

Earlier we indicated the need to control for a possible preference bias generated by the selection of the clients of one specific tour operator. Out of the total sample of 201 respondents, 123 were approached (via a snowball sampling technique) before they chose to use any specific travel agency. The preferences of this group of respondents were compared with those of the 78 respondents approached at the CAISSA travel agency. A significant difference (p<0.05) was found regarding preferences on package price.

The 123 respondents from the snowball sampling had a higher utility score (0.78) for the lowest price level than those approached at the tour operator (0.53). There are maybe two reasons for this. Firstly, some respondents recommended by friends might not be familiar with the price range of international trips. For example, a respondent interviewed at the tour operator would know that, normally, the price of a trip to the USA would have to be well over RMB9000, while a respondent who had not been to a tour operator may not know this. Secondly, some respondents recommended by friends might need more time than other respondents to save enough money for a trip, which implies that they would prefer a lower price at the time of being interviewed and performing the destination sorting task.

To sum up, for the whole sample, the most important attributes that determine people's preference for a destination are, in order of influence (averaged across the whole group) the price, time schedule of the trip, the visa application and fame of the destination country. More specifically, at the level of attribute aspect, a lower price level, an easy visa application and a famous destination country are the top three aspects that would generate high utility. So, destinations characterised by these aspects should be more attractive to Chinese long-haul outbound tourists than destinations that do not. In terms of preference differences among subgroups, age and previous travel experience have a significant impact on tourists' preference for the time schedule. Previous travel experience and the composition of the travel party on the trip influence how much tourists care about the famousness of the destination country. Brand product shopping is particularly desired by the middle-aged group.

There are not so many significant preference differences between the group of tourists accessed at CAISSA and the group of tourists accessed through snowball sampling, except the latter group prefers a lower price a bit more than the former group. These findings provide detailed insights into the criteria used by Chinese long-haul outbound tourists in selecting a destination. As can been seen in Table 6.3, there are rather few significant differences between the various groups regarding the five attributes. To some extent, this demonstrates that, for most of the destination attributes studied in this research, subgroups do not differ significantly from one another. This implies that marketers can advertise and improve their destination packages efficiently for the Chinese long-haul outbound tourists by using the destination preferences identified for the whole sample.

Rather than just telling which attributes Chinese tourists care about, conjoint analysis reveals much more information regarding what level/aspect of each attribute are preferred, how a change of one attribute can be compensated by a change in another attribute, whether it is worth exploring subgroups within the whole sample and how demographic characteristics might influence people's preferences.

Since there are a few significant preference differences between different demographic groups, in order to know if there are any distinctive subgroups who share similar preference patterns, a subsequent cluster analysis was conducted to explore possible market segmentation. Although the sample size (184) used for cluster analysis is not large enough to arrive at strong conclusions, it is sufficiently large for an exploratory segmentation analysis, the results of which may well be of value for further studies.

6.3.3 Market segmentation based on cluster analysis

The aim of the analyses reported in this section is to explore possible market segmentation solution based on utility values derived from the conjoint analyses. As a first step, a hierarchical cluster analysis was conducted to explore the possible cluster solutions. The dendrogram resulting from a hierarchical cluster analysis suggested the sample can be divided into either three clusters or four clusters. Since the hierarchical cluster analysis performed by the software (SPSS 20) is more focused on exploring the right number of clusters and does not provide the detailed utility patterns for each cluster group, a K-mean cluster analysis was instead performed to see which solution is more interpretable. The number of clusters needs to be specified for K-mean cluster analysis. A three-cluster solution was chosen due to its higher interpretability. The result is presented in Table 6.5.

There are 71 respondents in cluster1, 60 respondents in cluster 2 and 53 respondents in cluster 3. The first cluster consists of people who have strong preference for a low price (1.86) and an easy visa application (0.69) and who have the least concern (0.06) about whether the destination is good for brand product shopping. The second cluster includes people who do not prefer the lowest price (-0.45) but who do prefer (1.10) more free time during the trip. And they prefer good opportunities for brand product shopping (0.25) more than the other two clusters. People who belong to cluster 3 have a moderate preferences for lower prices (0.41) and a compact trip schedule (0.68). But they emphatically want to travel to a famous destination (1.06). And, unlike the other two clusters, they have a generally negative attitude (-0.31) to brand product shopping.

Table 6.5 K-mean cluster analysis (three-cluster result)

	Cluster		
	1 (n=71)	2 (n=60)	3 (n=53)
RMB9,000	1.86	-.45	.41
RMB13,000	-.01	.25	.20
RMB18,000	-1.85	.20	-.61
Visa easy	.69	.57	.21
Risk of visa rejection	-.69	-.57	-.21
Brand shopping	.06	.25	-.31
No brand shopping	-.06	-.25	.31
Compact schedule	-.16	-1.10	.68
More free time	.16	1.10	-.68
Famous destination	.12	.27	1.06
Not famous destination	-.12	-.27	-1.06

In order to explore the demographic difference among clusters, the cross-tabulation analysis was conducted to reveal possible association between each demographic variable and the "Cluster" variable. And then chi-square tests were used to identify the statistical significance of the observed association in each cross-tabulation. For the cross-tabulations conducted, only one significant association (The association between Age and Cluster) was found according to the chi-square tests. However, since the aim of this section is to explore useful information for possible market segmentation rather than providing solid conclusion, another two associations that were found not significant but close to P=0.1 level are also reported here (The association between Travel experience and Cluster; The association between Travel companions and Cluster). The results are presented by Table 6.6-6.8.

Firstly, as shown in Table 6.6, the proportion of young people decreases progressively from cluster 1 to cluster 3 while the proportion of seniors increases progressively from cluster 1 to cluster 3 ($p<0.05$). And 9 out of 12 seniors (retirees) belong to cluster 3, while almost half (10 out of 23) of the middle-aged people are located in cluster 2. It has been noticed that due to the small size of the senior group, there are two cells do not meet the minimum expected count, which might decrease the accuracy of the chi-square test.

However, the classification of the age group is based on the cultural characters of Chinese society. In this case, the senior group includes the people whose age is above 55 which is the legal age for retirement in China. The classification would be less meaningful if we amend it to increase the number of respondents belonging to senior group. Moreover, as mentioned above, the aim of this section is not for providing statistically significant findings but rather to reveal promising hypotheses for potential marketing segmentation that can be checked and confirmed by further study with larger sample. Because of this exploratory purpose minor infelicities in the application of the chi-square test (i.e., the insufficient number of expected observations in two of the cells) are irrelevant in this instance.

Secondly, Table 6.7 indicates a huge number of first-time long-haul outbound tourists in cluster 1, while both cluster 2 and cluster 3 have more repeat long-haul outbound tourists($p=0.12$). In cluster 1, 80% of respondents are first time long-haul outbound tourists, while only 70% of respondents are first-time long-haul outbound tourists in cluster 3 and the proportion decreases to 43% in cluster 3. Accordingly, the preferences of repeat tourists have a bigger influence in cluster 3 and the biggest influence in cluster 2.

Table 6.6 Cross-tabulation for Age and Cluster

			Cluster1	Cluster2	Cluster3	Total
Age	Young	Count	63	48	38	149
		%	42.3%	32.2%	25.5%	100.0%
	Middle	Count	7	10	6	23
		%	30.4%	43.5%	26.1%	100.0%
	Senior	Count	1	2	9	12
		%	8.3%	16.7%	75.0%	100.0%
Total		Count	71	60	53	184
		%	38.6%	32.6%	28.8%	100.0%

Chi-Square =0.01;df=4; P<0.05. The minimum expected count is 3.46

Table 6.7 Cross-tabulation for Travel experience and Cluster

			Cluster1	Cluster2	Cluster3	Total
First-time long-haul	First-time	Count	57	39	37	133
		%	42.9%	29.3%	27.8%	100.0%
	Repeat	Count	14	21	16	51
		%	27.5%	41.2%	31.4%	100.0%
Total		Count	71	60	53	184
		%	38.6%	32.6%	28.8%	100.0%

Chi-Square =0.13; df=6. The minimum expected count is 14.69

Thirdly, regarding the composition of the travel party, the percentage of people who would like to travel with their spouse or partner decreases from cluster1 to cluster 3 and the percentage of people who would like to travel with the whole family increases from cluster 1 to cluster 3. Those who would like to travel by themselves are mostly located in clusters 1 and 2, especially cluster 2 (see Table 6.8).

Table 6.8 Cross-tabulation for Travel companions and Cluster

			Cluster1	Cluster2	Cluster3	Total
Travel companions	Alone	Count	5	6	3	14
		%	35.7%	42.9%	21.4%	100.0%
	Whole family	Count	18	23	25	66
		%	27.3%	34.8%	37.9%	100.0%
	Friends	Count	9	9	7	25
		%	36.0%	36.0%	28.0%	100.0%
	Spouse/partner	Count	39	22	18	79
		%	49.4%	27.8%	22.8%	100.0%
Total		Count	71	60	53	184
		%	38.6%	32.6%	28.8%	100.0%

Chi-Square = 0.17; df=2. The minimum expected count is 4.03

Based on the cluster analysis and the information found by the cross-tabulations, a possible market segmentation is summarised in Table 6.9. One thing to be noticed is that the relatively small sample size restricts the accuracy and quality of the solution. And based on how distinctive each cluster is (compared with the others), there are three levels to judge the quality of the cluster solution, which are poor, fair and good. The quality here is just above fair. But the findings are nonetheless interesting and this possible market segmentation should be able to provide some useful suggestions for further studies and practitioners as well.

The three groups identified can be tentatively labelled and interpreted as follows: 'journey beginners', 'consumption enjoyers' and 'prestige pursuers'. Journey beginners are the ones who have not been to any foreign countries before. They are probably young and would like to go on a romantic trip with a partner. Their being young implies that they have not yet had the time to build up savings and so have to be sensitive to cost – they prefer a cheaper trip and may not have extra money for brand product shopping. Since it is probably their first long-haul leisure trip with the money they have been saving for a long time, they would not want to take any risk of a visa application being rejected. And within their budget, if the destination country is famous and there is some free time on the package tour for them to enjoy the company of their partner, it would be perfect.

Consumption enjoyers, on the other hand, are usually the ones who do not have to worry about money. They are either middle-aged or young people from a rich family and some of them already have experience of long-haul outbound travel. They seek to enjoy the trip by taking a high-quality but somewhat expensive package tour. They prefer a flexible time schedule with more free time to consume by themselves. And they enjoy brand product shopping at the destination country.

The prestige pursuers pay much attention to the fame of the destination country. They want to go somewhere that is well known by the Chinese public as a developed country with beautiful scenery and they want to see as many attractions and landmarks as possible, so that they do not feel their time is wasted. And apparently, they do not want to waste their time on brand product shopping when they could be sightseeing. Many of the older people within the sample fit the characters of prestige pursuers.

Table 6.9 A Possible market segmentation based on cluster analysis

	Cluster		
Preference of the attributes	Journey beginner	Consumption enjoyer	Prestige pursuer
Price	Low	Middle/high	Middle
Visa application	Very easy	Easy	Easy
Brand product shopping	Not important	Like shopping	Dislike shopping
Time schedule	Moderate free time	More free time	Compacted
Famousness	Moderate	Moderate	High
Demographic characteristics			
Age**	Young	Middle-age	Old
Travel experience	First time	Repeat	First time/repeat
Travel companions	Spouse/partner	Whole family/Alone	Whole family

Additionally, besides the useful information on possible marketing segmentation, the results of the cluster analysis can also shed light on possible correlations between attributes. For example, people who prefer a low package price may tend to prefer an easy visa application as well, or people who want to go to a famous destination may prefer a compact trip schedule. Such correlations would be very useful for tour operators, as they would allow them to design their packages by delivering appropriately bundled (correlated) attributes for various destinations.

This section above reveals Chinese long-haul outbound tourists' preferences for destinations based on the assumption that they make their choice using a compensatory choice heuristic. It implies that improving the overall strength of a destination and increasing its overall utility is the most efficient way of attracting more tourists. Conjoint analysis provides the utility score of each attribute level/aspect for a certain group of people so that: (1) we know how to combine attributes in order to generate high utility and gain high preference; and (2) we get some insights into the preferences of a target group for existing destination packages.

However, the compensatory choice heuristic is not the only way in which people may arrive at their choices. When tourists tend to apply a non-compensatory choice heuristic such as lexicographic by aspects (LBA) to select their destinations, the destination identified by conjoint analysis as having the highest utility score may not be the final choice – the final choice may instead be the destination that meets the non-compensatory requirements of tourists. Where the LBA choice heuristic is applied, the destination that provides the best performance on the most important attribute(s) will be selected. We cannot rule out the possibility that a non-compensatory choice heuristic might be applied in selecting a destination. Therefore, it is worth exploring how to estimate tourists' preferences based on a non-compensatory choice heuristic, so that additional information can be obtained and the predictive power of different choice heuristic models can be compared. The next section presents the results and findings of Chinese long-haul outbound tourists' destination preferences based on a non-compensatory (LBA) choice heuristic model.

6.4 Preference estimation based on a non-compensatory (LBA) choice heuristic

As mentioned in Chapter 3, a compensatory choice heuristic requires a lot of effort to assess the information of each level of each attribute for each alternative destination. It may therefore not be used in destination choice or in some stages of the choice process. Choices can also be derived from a simpler, non-compensatory choice heuristic, which may lead to different decisions. This research explores how to estimate tourists' destination preferences based on a non-compensatory choice heuristic and assesses whether different destinations are selected than when a compensatory choice heuristic is used. This study focuses on a specific non-compensatory heuristic, known as 'lexicographic by aspect' (LBA) which is generally regarded as the most commonly used non-compensatory heuristic for choices with a relatively large number of attributes but where each attribute binary or only has few levels (Yee et al., 2007).

6.4.1 Overall results of the greedoid analysis

To analyse the destination rankings provided by our participants from the LBA perspective, the greedoid dynamic computer program was used, which was introduced by Yee et al. (2007). The LBA choice heuristic assumes that decision-makers do not assign a utility score to each attribute level but instead that they consider these attribute levels in terms of importance, from the most important attribute to the least important. During the comparison and selection of choice options, a decision-maker would start from the most important attribute, so that the choice alternatives possessing the desired attribute level are selected. If there are ties, the decision-maker would continue the comparison based on the second most important attribute and select the options possessing the second most important attribute level. This process is repeated until all alternative destinations are sorted, and the top-ranked destination should be the final choice. The hierarchical preference order of these attribute levels/aspects is hereafter referred to as the 'aspect order'.

This greedoid dynamic program is based on the mathematical implications of the lexicographic choice heuristic described above. By providing the empirically observed ranking order of the 10 destination cards of each respondent, the program deduces the aspect order. The destination cards are actually 10 combinations of attribute aspects. The five attributes and the 11 aspects are presented in Table 6.10, while the 10 sets of stimuli presented on the destination cards are shown in Table 6.11.

Table 6.10 The 5 attributes (choice criteria) and the 11aspects

Attribute1 Price	Aspect1	Price RMB9,000
Attribute1 Price	Aspect2	Price RMB13,000
Attribute1 Price	Aspect3	Price RMB18,000
Attribute2 Visa	Aspect4	Easy visa application
Attribute2 Visa	Aspect5	Risk of visa rejection
Attribute3 Shopping	Aspect6	Good for brand shopping
Attribute3 Shopping	Aspect7	Not good for brand shopping
Attribute4 Schedule	Aspect8	Time schedule with more free time
Attribute4 Schedule	Aspect9	Compact time schedule
Attribute5 Famousness	Aspect10	Famous destination
Attribute5 Famousness	Aspect11	Not famous destination

Consider the following as an example: an observed ranking of the 10 destination cards is (6>4> 10> 8> 3>2> 1> 7>9>5). From this rank order (see Table 6.12), greedoid analysis would be able to deduce an 'aspect order' solution, which is (Aspect4>Aspect1>Aspect2>Aspect10>Aspect8; cost 0). This means that, for this tourist, the most important aspect is 4 (easy visa application), the second important aspect is 1 (price at RMB9,000), followed by 2 (price at RMB13000), 10 (famous destination country) and 8 (compact trip schedule). If we use this aspect order to replicate the order for the 10 destination cards, we will get exactly the same destination order that this respondent provided, which means this respondent followed a perfect LBA choice heuristic. The 'cost' is the number of pairs of the cards whose observed order is violated by the predicted order. This cost/error rate is used to quantify the predictive power of the greedoid solution, assuming that participants actually do use the LBA choice heuristic. In the case of the example just discussed, the cost is 0, which means the replicated order is the same as the empirically observed choice order; this result suggests that this tourist applies the LBA heuristic for the entire ranking process.

Not everyone would necessarily use a lexicographic choice heuristic during the whole ranking process. For participants who do not, no aspect order can be deduced from the observations that will replicate the observed ordering.But we may still assess whether an aspect order exists that replicates the observed order as closely as possible. The greedoid algorithm would find such a 'best' aspect order, while reporting the number of errors (i.e., the number of pairs of cards for which the observed and predicted order is different). For example, assume the observed preference order on the 10 cards given by a respondent differs only for the last two stimuli, and is not (6>4> 10> 8> 3>2> 1>7>9>5) but instead it (6>4> 10> 8> 3>2> 1>7>5>9).

Based on this order, the program would generate the aspect order as (Aspect4>Aspect1>Aspect2>Aspect10>Aspect8; cost 1),with an indicator as 'cost

1'.This means if we follow the aspect order deduced by the greedoid dynamic programme to replicate the observed order, there will be one pair of cards for which the observed choice order and the predicted order differ, and this violated pair is (5>9). The 'best' aspect order in this research means the aspect order with the minimum weighted number of errors to replicate the observed preference order. The process of how the greedoid dynamic programming finds the 'best' aspect order was illustrated in Chapter 4 (see Table 4.1).

Table 6.11 The presentation of the 10 stimuli destination cards

Destination cards	Price	Visa	Shopping	Schedule	Famousness
1	Price RMB9,000	Risk of visa rejection	Not good for brand shopping	More free time	Not famous destination
2	Price RMB9,000	Risk of visa rejection	Good for brand shopping	Compact	Not famous destination
3	Price RMB 18,000	Easy visa application	Not good for brand shopping	Compact	Not famous destination
4	Price RMB9,000	Easy visa application	Not good for brand shopping	More free time	Famous destination
5	Price RMB 18,000	Risk of visa rejection	Good for brand shopping	More free time	Famous destination
6	Price RMB9,000	Easy visa application	Good for brand shopping	Compact	Famous destination
7	Price RMB13,000	Risk of visa rejection	Not good for brand shopping	Compact	Famous destination
8	Price RMB13,000	Easy visa application	Good for brand shopping	More free time	Not famous destination
9	Price RMB 18,000	Risk of visa rejection	Not good for brand shopping	Compact	Famous destination
10	Price RMB9,000	Easy visa application	Not good for brand shopping	Compact	Not famous destination

Table 6.12 An observed ranking order of the 10 destination cards

Destination cards	Price	Visa	Shopping	Schedule	Famousness
6	Price RMB9,000	Easy visa application	Good for brand shopping	Compact	Famous destination
4	Price RMB9,000	Easy visa application	Not good for brand shopping	More free time	Famous destination
10	Price RMB9,000	Easy visa application	Not good for brand shopping	Compact	Not famous destination
8	Price RMB13,000	Easy visa application	Good for brand shopping	More free time	Not famous destination
3	Price RMB18,000	Easy visa application	Not good for brand shopping	Compact	Not famous destination
2	Price RMB9,000	A bit risk of getting visa	Good for brand shopping	Compact	Not famous destination
1	Price RMB9,000	Risk of visa rejection	Not good for brand shopping	More free time	Not famous destination
7	Price RMB13,000	Risk of visa rejection	Not good for brand shopping	Compact	Famous destination
9	Price RMB18000	Risk of visa rejection	Not good for brand shopping	Compact	Famous destination
5	Price RMB18,000	Risk of visa rejection	Good for brand shopping	More free time	Famous destination

Although the greedoid algorithm can estimate aspect orders with incomplete data, we can make comparisons with the results from the conjoint analysis only for complete data, as the latter procedure requires complete data. Therefore the incomplete ranking data (17 respondents who did not rank all 10 cards) were excluded at this stage, and the analysis is conducted on the same 184 respondents included in the conjoint analysis. The results (see Table 6.14) of the greedoid analysis demonstrate that the first (most important) aspect used by respondents to rank the destination cards most often was the lowest price (RMB9, 000), which was used by 21.7% of participants. In other words, for one out of five respondents the low price (RMB9, 000) aspect was the most important criterion on which to evaluate alternative destinations. For these respondents, all destinations not meeting this criterion would be put aside, no matter how attractive they are in terms of other attributes.

For 17.9% of respondents, free time during the trip was the most important criterion, and for yet another 16.8% an easy visa application was the single most important attribute. The fourth most frequently used first criterion used by the respondents was famous destination country (13.6%). The proportions of the respondents who used the other seven aspects as their first evaluation criterion are relatively small (no more than 10% for each aspect). These findings are displayed graphically in Figure 6.1.

Figure 6.1 Bar chart for Table 6.13

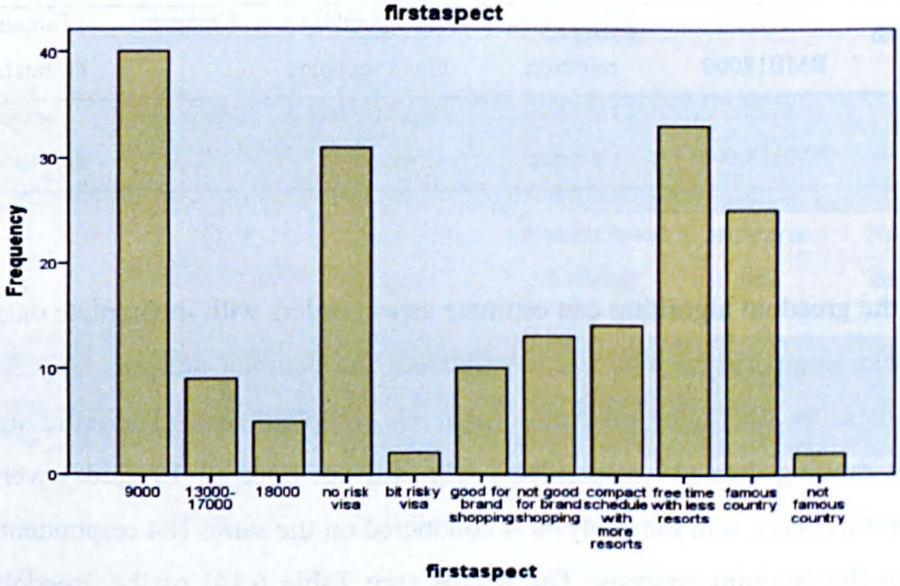


Table 6.13 Frequencies of first aspect used by tourists

Attribute aspects	Frequency	Percent
RMB9,000	40	21.7
RMB13,000	9	4.9
RMB18,000	5	2.7
Easy visa application	31	16.8
Risk of visa rejection	2	1.1
Good for brand shopping	10	5.4
Not good for brand shopping	13	7.1
Compact schedule	14	7.6
Tree time	33	17.9
Famous country	25	13.6
Not famous country	2	1.1
Total	184	100.0

So far, the findings from the greedoid analysis are in concordance with the findings from the conjoint analysis, which assumed a compensatory choice heuristic. Both methods diagnose the same three aspects as being important. The conjoint analysis showed that the overall utility scores of low price (RMB9, 000), easy visa application and famousness of the destination country for the respondents were much higher than those for other aspects, which means destinations having these three aspects would be more attractive. And these same three attributes are the most frequently used by tourists as their first choice criterion, which demonstrates their importance from another angle.

The overall utility score estimated by the conjoint analysis for 'more free time' was not high for the whole sample (see Table 6.1), which means that a change of the time schedule from compact to more free time would not make a big change in the overall preference for a destination. But the importance value for time schedule was the second highest value among the five attributes (see Table 6.2), which suggests people do care about this attribute, but that further segmentation or analysis is required to understand how this attribute is preferred. The greedoid analysis here reveals that 'having more free time during the trip' is the second most popular aspect used by tourists as their first choice criterion. This information complements the results found by conjoint analysis. If we want to go one step further and assess what kind of people tend to use 'having more free time' as their first choice criterion, we need to look at the common characteristics of these people. The following analysis addresses this question.

Almost 70% of the respondents use one of the four aspects (lowest price, more free time, easy visa application and famousness of the country) as their first choice criterion. This fourfold distinction was cross-tabulated with the available demographic variables. The chi-square test shows there is one significant difference ($p<0.05$), namely between first-time long-haul outbound tourists and tourists with previous long-haul outbound travel experience (see Table 6.14). First-time long-haul outbound tourists tend to use constraint attributes (i.e. price and visa application) as their most important aspect to evaluate alternatives. Indeed,65% of first-time long-haul outbound tourists use either price at RMB9,000or easy visa application as their first choice criterion, while for their counterparts, the repeat long-haul outbound tourists, more free time during the trip or famous destination country is usually their first choice criterion.

This difference can be easily understood, since people who can afford a long-haul outbound trip repeatedly will generally have enough money not to have to use budget as their most important criterion, and repeat outbound travel experience is likely to increase their confidence of getting the necessary visa. Therefore, when these travellers choose a destination, they pay attention to what they want to do or experience during the trip rather than to constraining factors. This finding is also consistent with the preference revealed by conjoint analysis, where the results indicate (see Table 6.3) that the utility scores for having more free time during the trip and famousness of the destination country are high for repeat long-haul outbound tourists.

Table 6.14 Differences in the first aspect used by first-time/repeat tourists

Long-haul travel experience	First aspect				
	RMB9000	Easy visa	More free time	Famous country	Total
0(None)	36	31	20	16	103
	35.0%	30.1%	19.4%	15.5%	100.0%
1(had)	6	5	19	10	40
	15.0%	12.5%	47.5%	25.0%	100.0%

6.4.2 Respondents with perfect LBA choice heuristic

Among the 184 respondents, there were 20 (10%) whose observed rankings could be perfectly reproduced (or predicted) by the LBA choice heuristic. Although the number of the respondents within this group is too small to produce any significant findings, it still worth looking at the characteristics of this group, since it may provide useful directions for further study to investigate the decision-makers who tend to use LBA heuristics. A frequency analysis was run on the first important aspect (see Table 6.15). Instead of lowest price, the most frequently (7) used first aspect by these perfect LBA decision-makers was more free time during the trip. But there is still quite a number of people (6) who used lowest price as their first choice criterion. A descriptive analysis was run on the demographic variables for the 20 respondents and an interesting trend was found regarding the gender of the respondents. Among the 184 respondents, there are 83 males (41%) and 101 females (50%) in total. But among the 20 perfect LBA decision-makers, there are 12 males (60%) and 8females (40%).This result may suggest that male tourists tend to use a non-compensatory choice heuristic more than female tourists. This result is further tested and discussed in Section 6.6.

Table 6.15 First aspect of the 20 perfect LBA respondents

	Frequency	Valid Percent
RMB9,000	6	30.0
Easy visa application	3	15.0
Compact schedule	1	5.0
More free time	7	35.0
Famous country	2	10.0
Not famous country	1	5.0
Total	20	100.0

6.4.3 Partial data results (17 people)

Since we wanted to compare the fit of the compensatory choice heuristic model and non-compensatory choice heuristic model, the 17 respondents who did not provide the full ranking for the 10 destination cards (conjoint analysis requires a full ranking) were not included in the greedoid analysis reported above. There are generally two reasons why respondents could not rank all 10 destination cards. Firstly, some indicated that the sorting task contained too much information to process and they wanted to simplify the process by ranking only the first a few destinations that were attractive to them. Secondly, some respondents were able to select the destinations they wanted to consider, but for the destinations they do not like they did not feel able to distinguish preferences. However, it would be a waste to ignore these partial preference data. As a matter of fact, most of these respondents effectively used a non-compensatory choice heuristic in eliminating those destination cards that they felt they could not rank. For example, one respondent provided preferences only for the five destination cards indicating an easy visa application. He said he would not consider any of the other destinations because of the higher risk of a visa application being rejected. This is clear evidence of a non-compensatory heuristic.

We analysed these partial data in two steps. The first step looked at attribute aspects used by the respondents to eliminate some of the destination cards. For this purpose a 'must-have aspect' program was written in Java so that if there is any attribute aspect(s) that exists on all the ranked destination cards for one respondent, this aspect would be indicated as the 'must-have aspect' for this respondent. And the 'must-have aspect' is regarded as the non-compensatory choice criterion used by this respondent to select the destinations cards he would consider. For 14 out of 17 respondents with incomplete data such a 'must-have aspect' could be detected, which suggests these 14 respondents probably used a non-compensatory choice heuristic during the formation of their consideration set. The remaining 3 respondents may have just randomly picked some destination cards to rank to reduce the workload of the task.

Seven of the 14 respondents (50%) used 'more free time during the trip' as their 'must-have' aspect, which means they were interested only in destinations with more free time during the trip. And from the analysis of the 20 respondents who followed a perfect LBA heuristic for the selection (see Table 6.15), more free time during the trip was the most frequently used first aspect as well. This consistency implies time schedule of the package tour to a destination tends to be used as a non-compensatory choice criterion by Chinese long-haul outbound tourists. Additionally, four respondents used 'easy visa application' to make the first-stage elimination. The remaining six respondents used 'price at RMB9, 000 RMB, 'not good for brand product shopping' and 'famous destination country' as their must-have aspects.

The second step of the analysis was to conduct a greedoid analysis to establish the aspect order for the destinations that were considered in the ranking. Because the must-have aspect means every remaining destination card has this aspect presented, this aspect was not used during the ranking of the remaining destinations and the aspect order provided by the greedoid analysis does not include the must-have aspect. From the 'must-have' analysis we do know, however, that this is the first aspect the respondents used. Therefore, for the 14 respondents for whom a must-have aspect could be found, their must-have aspects were added at the beginning of the aspect order obtained from the greedoid analysis. The final aspect orders of the 17 respondents with missing data were combined with the results of the 184 respondents to construct a hierarchical preference tree, as described below

6.4.4 Preference hierarchical tree

Greedoid analysis is a preference estimation method based on non-compensatory choice heuristic (in our case the LBA choice heuristic); it reveals the aspects order for each respondent. Unlike the indicator of overall utility, which is central in conjoint analysis, we cannot average aspect orders to obtain a description of preferences in the whole sample. Instead, we can summarise the commonly used aspect orders. Among the 201 respondents (184 with full ranking data, plus 17 with partial ranking data), the popular aspects used as their first choice criterion were price at RMB9, 000, easy visa application, more free time during the trip and the famous destination country. The numbers of respondents that used these four aspects respectively were 42, 36, 40 and 26. And for the other seven aspects, the number of respondents using any of them as the first choice criterion was less than 20 (10% of the whole sample), owing to which they are not included in the simplified hierarchical preference tree, which describes the seven popular aspect orders used to select a destination by the respondents(see Figure 6.3). These hierarchical preference orders are:

1. Price RMB9, 000> Price RMB13, 000>Easy visa application>More free time during the trip > Good for brand product shopping

2. Price RMB9, 000> Price RMB13, 000> Famous destination country>Easy visa application

3. Easy visa application> More free time during the trip

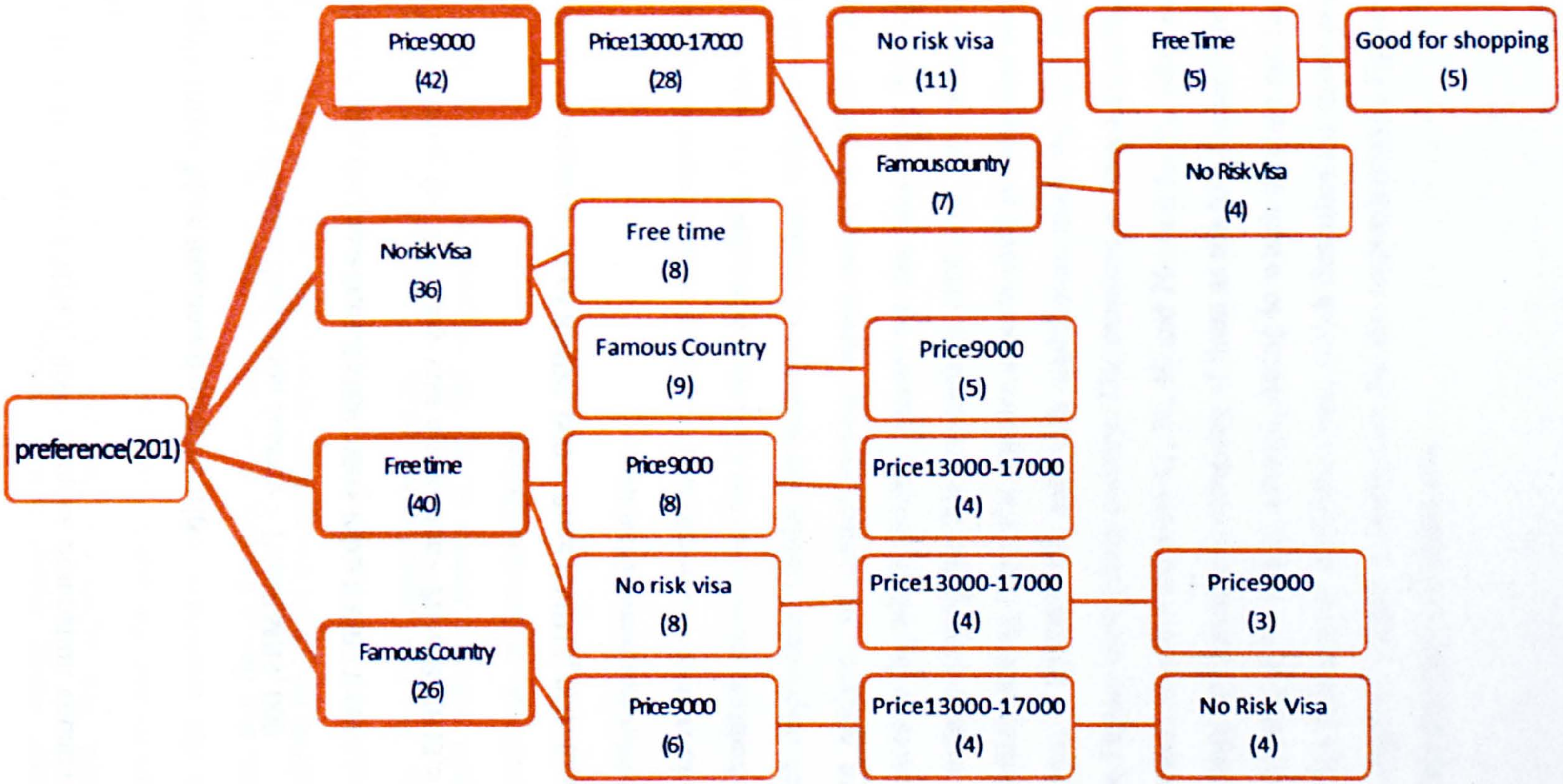
4. Easy visa application>Famous destination country > PriceRMB9, 000

5. More free time during the trip >Price RMB9, 000> Price RMB13, 000

6. More free time during the trip>Easy visa application> Price RMB13,> Price RMB9, 000

7. Famous destination country> Price RMB9, 000 > Price RMB13, 000>Easy visa application.

Figure 6.2 Hierarchical Tree



6.5 Choice-set formation

As mentioned in the literature review (Chapter 2), for making the final choice from many alternative destinations, tourists need to eliminate a large number of destinations first so that they can focus on the destinations they would like to consider further. Therefore a two-stage decision-making process is widely regarded as most realistic by many scholars. The first stage is to form a consideration set and the second stage is to further compare the destinations within the consideration set and then make a final choice. The goal of the first stage is to narrow down the options, while the purpose of the second stage is to find the one that is best. Since the purposes of the two stages are different, the attributes used as choice criteria may also be different in the two stages. Some attributes may be used to form the consideration set and others may be used to further compare the destinations within that set. Thus, how each attribute is used and preferred at different choice stages by decision-makers could be critical to get a clear picture of the entire process and a more accurate understanding of decision-makers' preferences. This research tries to provide some answers to this question for Chinese long-haul outbound tourists.

During the survey, after the sorting task of the destination cards, the respondents were asked to indicate which destinations they would consider as the destination for their next trip, so that we would be able to identify the consideration set among the 10 alternative destinations for each respondent. Frequency analysis was done on the size of the consideration set (expressed as the number of options for further consideration) for each respondent (see Table 6.16). Almost 98% of the respondents would consider no more than seven destinations out of the 10 described on the cards. The size of the consideration set for the majority (76%) of the respondents was between two and six alternatives, while the mode was three (used by 23% or respondents)

Table 6.16 How many destinations would you consider for your next trip?

Number of destinations	Frequency	Percent
1	12	6.0
2	31	15.4
3	45	22.4
4	39	19.4
5	31	15.4
6	22	10.9
7	11	5.5
8	2	1.0
9	3	1.5
Total	196	97.5
Missing	5	2.5
Total	201	100.0

Based on the size of the consideration set for each respondent, the 'must-have aspect' program was used to identify, for each respondent, whether there are any attribute aspects that exist for all the destination cards this respondent would consider. This analysis cannot be performed for the12 respondents whose consideration set comprised only one destination and these respondents are not included in the further analysis. There were too few five respondents (only five in total) who retained eight or nine destination cards for further consideration to lead to stable results, and they were excluded from the analysis too. Finally, for five cases the information about the size of the consideration set was missing. Therefore the subsequent analysis was conducted on 179 (201-12-5-5) respondents. Any 'must-have' aspects identified in the consideration set were recorded as an Excel file for further analysis.

In total, 14 (8%) respondents do not appear to have any 'must-have aspect', which suggests they probably did not use an LBA choice heuristic to form the consideration set, while the rest of the respondents (92%) did use an LBA heuristic to select the destinations they would consider. A large number of them(114) used a single must-have aspect, which means their consideration set was formed by the presence of one aspect. All the destinations that did not have this aspect were discarded by them. Of the remainder, 33 respondents used two must-have aspects while 18 had three must-have aspects. Seventeen of these 18 would consider only the first two destinations for their next trip, while most of the respondents (27 out of 33) who had two must-have aspects had two or three destinations in their consideration set. Almost all the respondents who used only one must-have aspect considered at least three destinations, except for one respondent who had only two destinations in his consideration set. The pattern is thus that the smaller the size of the consideration set, the more non-compensatory criteria (must-have aspects) were required to form this consideration set.

The largest group (114) used only one aspect to form their consideration set. For them the most commonly used aspect was 'More free time during the trip' (used by 23 respondents) followed by 'Easy visa application' (18), 'Famous destination country' (15) and 'Price RMB9, 000' (15) (see Table 6.17). It is interesting to note that, although the lowest price (RMB9, 000) has the highest utility score in the conjoint analysis, it is not the most commonly used aspect to form the consideration set for this group. These results suggest that although price is the most important attribute in general (see the importance values in Table 6.1), it is not a non-negotiable aspect in destination choice. In other words, even respondents who prefer a price of RMB9, 000may still consider destinations at a higher price. However, people who prefer 'more free time during the trip' tend to use this as a non-compensatory criterion (as a must-have aspect) in their selection.

Table 6.17 Frequency of must-have aspects

	Frequency	Valid Percent
RMB9,000	15	13.2
RMB13,000	12	10.5
RMB18,000	4	3.5
Easy visa application	18	15.8
Risk of visa rejection	2	1.8
Good for brand shopping	6	5.3
Not good for brand shopping	7	6.1
Compact schedule	11	9.6
More free time	23	20.2
Famous country	15	13.2
Not famous country	1	0.9
Total	114	100.0

In conclusion, studying tourism decision-making based on a two-stage process can provide more insights into tourists' preferences. Based on the data, we could say the LBA heuristic was used by more than 90% of the respondents during their formation of a consideration set and the number of their must-have aspects used to form the set ranged mainly from one to three. The most popular aspect that was used to make the consideration set was 'More free time during the trip'. Price RMB9, 000 may have been used more often during the stage of destination evaluation rather than during the first stage of destination elimination.

So far, the preferences of Chinese long-haul outbound tourists have estimated and revealed from the perspectives of two different types of choice heuristics. Both seem to perform well in describing the preferences of a majority of the observations, and they seem to highlight similar criteria as important (or, conversely, they do not lead to contradictory results). However, the question remains which (if any) of the two choice heuristics models is more appropriate when trying to understand destination choice of Chinese long-haul outbound tourists? Therefore, the last section of this chapter will compare the two approaches in more detail.

6.6 Fit of the two different choice heuristic models

The choice heuristic is the way that choice criteria (attributes) are used to make a decision. Even with the same choice criteria, different choice heuristics may lead to different choices. This research used two choice heuristic models to analyse and estimate Chinese long-haul outbound tourists' preferences regarding destination. But which choice heuristic model is more suitable for understanding Chinese long-haul outbound tourists, or which one is more accurate in terms of predicating tourists' preferences? The literature seems to have little so say on this question. In the absence of well-established criteria, this research explores two possible ways to arrive at a comparative evaluation of different models, which includes (1) their predictive power on the hold-out data and (2) their power to replicate the observed preference order.

6.6.1 Estimation on predictive power on the hold-out data

A small number of studies in marketing and consumer research have tried to compare the predictive power between compensatory and non-compensatory choice heuristic models (e.g. Kohli and Jedidi 2007; Yee et al. 2007; Dieckmann et al. 2009). They used as a yardstick the predictive power of models on a set of hold-out data. The hold-out data are data collected not for analysis but to test whether the analysis is accurate. In this research, there are 10 stimuli destination cards generated from an orthogonal design. Conjoint analysis needs the order only of the first eight cards to estimate the utility scores of each attribute aspect for each respondent. The preference order provided by the respondents on destination card 9 and destination card 10 are not necessary for this, and can thus be used in a hold-out analysis.

For the 184 respondents with complete rankings, conjoint analysis (on the basis of estimated utilities) can predict about 80% (147) rank orders of the hold-out data correctly. Theoretically, it means that the preferred destination of 80% of respondents can be predicted based on the assumption that all of them use a compensatory (i.e. utility-maximisation) choice heuristic.

However, the measurement that greedoid analysis uses to evaluate whether the analysis is accurate is not the predictive power of the hold-out data, as the program processes the preference information of all 10 destination cards and generates the aspect order for each respondent. In order to make a fair comparison between the two analyses, destination 9 and destination 10 were taken out of each respondent's ranking order and the greedoid dynamic program was run on the orders for the other eight cards again, to get the aspect order for each respondent.

For example, if a respondent provided a ranking order for the 10 destination cards which is(6>4> 10> 8> 3>2> 1>7>9>5), the preference order of eight destination cards is(6>4> 8> 3>2> 1>7>5) and the preference order (10>9) was extracted as hold-out data. The attributes (aspects) for destination 9 are the price is RMB18, 000, there is a risk of the visa application being rejected and the destination country is famous, while for destination 10 the price is RMB9, 000, the visa application is easy and the destination country is not famous. The 'sorting' solver was used to examine the aspect order of each respondent generated by the eight ordered destination cards. If the aspect that belongs to destination 9 (and not to destination 10) was identified as more important in the aspect order than the aspect that belongs to destination 10 (and not to 9), then the predicted order for the hold-out stimuli is 9>10, and otherwise the predicted order is 10>9. This makes it possible to compare the estimated orders with the observed order for each respondent. In total, we found 44 violations, which means among the 184 respondents, 140 (184-44) respondents could be predicted well on the hold-out data. So the correct prediction percentage using hold-out data is thus 76% for the LBA model, which is below the 80% found for compensatory model.

This comparison of prediction rates using hold-out stimuli has a number of limitations. Only two destinations could be used as the hold-out data, as the conjoint analysis requires a minimum of eight stimuli. When using larger sets of stimuli, a larger number of hold-out stimuli can be applied, and that may lead to a clearer differentiation of the two models than is possible in our case (with only 10 stimuli and a maximum of two sets of hold-out data). Moreover, for all 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. Therefore, this study explores another possibility for comparing the two choice heuristic models, which is the power to replicate the observed preference order.

6.6.2 The power to replicate the observed preference order

For each of the two choice heuristic models, we can compare for each respondent the empirically observed preference order with the preference order predicted by the model. In order to use this comparison, we have to define a measure of similarity between the observed and predicted rank orders. Greedoid analysis judges this similarity by decomposing each rank order into a set of ranking pairs. If the ranking order contains N elements, then the total number of ranking pairs is $(N-1) + (N-2)...+1$. And then the number of non-concordant ranking pairs can be assessed. The smaller the number of non-concordantly ordered pairs, the more similar is the two ranking orders. Consider an example where the real ranking order is A>B>C>D and the estimated ranking order is B>A>C>D. Firstly, the real ranking order can be decomposed into six ranking pairs ((4-1) + (4-2) + (4-3) =6). They are A>B, A>C, A>D, B>C, B>D, C>D. And the estimated ranking order can be decomposed as B>A, B>C, B>D, A>C, A>D, C>D. As can be seen, there is only one violated pair (B>A is different from the real choice, A>B). So we could say there is one error between the estimated (or predicted) ranking order and the observed ranking order. This number of violated pairs is referred to as 'cost' in greedoid analysis. This 'cost' indicator can be used to evaluate which choice heuristic model predicts preference orders that are more similar to the observed ones.

This approach disregards, however, the fact that people tend to be more careful and spend more time in the ranking of those destinations they would place in their consideration set than for the ranking of destinations that are readily discarded. This suggests that the higher-ranked stimuli may be more indicative of respondents' real preferences than lower-ranked stimuli. In order to take this into account, a weighting scheme was applied during the calculation of the 'cost'. Since there was no standard about how should the weights being added, linearly decreasing weights were used here. If there are N elements in the real order, the weights for violated pairs from the first element to the last element were (N-1), (N-2).....0. Take the example above again. Since the mistake is at the first element, A (B>A is different from the real choice A>B), so the cost is accounted as 3 (1* (4-1)).

With the help of Michael Yee (the researcher who introduced greedoid analysis), this linearly decreasing weights scheme was added to the greedoid analysis software so that the final cost reported in the solution is the weighted sum of the number of violated pairs. If the real destination order is 1>2>3>4>5>6>7>8>9>10 and the estimated ranking order is entirely reversed. which is 10>9>8>7>6>5>4>3>2>1, then the cost is 9*9+8*8+...1*1=285. For 10 stimuli285 is the maximum cost.

Because there is no program to calculate the cost for each respondent based on the estimation of conjoint analysis, the (weighted) cost for the conjoint results was calculated manually and recorded for further analysis. The 10 stimuli destinations were ranked based on each destination's utility score for each respondent and then the estimated ranking order was compared with the observed preference order. The costs based on the estimation of the conjoint analysis for the 184 respondents were recorded to compare with the costs based on the estimation of the greedoid analysis.

Here, the results regarding the cost indicator for each choice heuristic model are presented. Table 6.18 shows the statistical comparisons between the costs of the two choice heuristic models for the whole sample. The average cost of the whole sample is 17.39 for the LBA heuristic model and 21.4 for the weighted compensatory heuristic 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 is more accurately reflecting the mean of the costs for the actual population (the Chinese long-haul outbound tourists). In another word, a smaller standard deviation indicates the individual costs vary less from the mean.

The maximum value of the cost within the whole sample is 84 for the LBA model and 134 for the weighted compensatory model. Since the theoretical maximum cost is 285, averaged percentages of costs for both models are 6.1% (17.39/285) and 7.5% (21.4/285). In other words, based on the estimation of the LBA heuristic model, 93.9% (1-6.1%) of observed preference orders of the whole sample can be replicated, and based on the estimation of weighted compensatory heuristic model, 92.5% (1-7.5%) of the observed preference orders of the whole sample can be replicated. Based on all of these statistics, we could say the LBA model performs better to replicate the observed ranking order than the weighted compensatory model.

It would be as well to get a clear picture of what exactly these two figures (93.9% and 92.5%) actually mean. If we randomly ranked the 10 destinations and compared the random ranking order with the observed preference of each respondent, how many costs (errors) would be generated. Twenty respondents were selected from the sample randomly and 20 randomly ranked orders for the 10 destinations were created. The cost for each respondent was calculated. And if we assume the 20 respondents did not follow any heuristic but randomly ranked all the destinations, the averaged cost is 133 (47%).This means if we assume the destination cards were ranked randomly by each respondent, only 53% (1-47%) of the observed preference orders would be replicated.

Table 6.18 Statistical comparison of costs between two heuristic 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

To further examine the suitability of each choice heuristic model at an individual level, for each respondent the choice heuristic model that produced the fewer errors (less cost) was assigned to him/her. The frequency statistics of the respondents assigned to the two choice heuristic models is presented in Table 6.19. There are 67 (36.4%) respondents predicted better by the weighted compensatory choice heuristic model and117 (63.6%) respondents predicted better by the LBA choice heuristic model. After assigning the choice heuristic model to each individual, we tested whether there are significant demographic differences between the two groups. As mentioned in section 6.4.2 a large portion of males was found within the group (20) of the tourists who followed a perfect LBA choice heuristic during the ranking. For furthering testing the hypothesis that male tourists prefer to use LBA more than female tourists, a cross-tabulation and a chi-square test was performed on gender and the type of the choice heuristics applied. However, there was no significant difference between the two groups regarding the gender distribution. The cross-tabulation was performed on other demographic characteristics (age, travel experience and travel companion) and the type of the choice heuristics applied and there was no significant difference found regarding the three characteristics.

Table 6.19 Frequencies of the respondents applying different choice heuristics

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

6. 7 Discussion of the key findings and conclusion

This chapter presents the main contribution of this research, which is the exploration of the destination choice based on different choice heuristic models. The answers to the research questions are summarised in the next chapter (the conclusion and discussion). This section focuses on the issues addressed from the key findings which need further discussion and consideration.

The reasons for consistent results

This research initially explores how to estimate tourists' preferences based on different choice heuristic models. Although the principles of the compensatory choice heuristic is different from or even contradictory tothe principles of the non-compensatory choice heuristics, most substantive results revealed by conjoint analysis and greedoid analysis seem in accordance with each other (e.g. the important attribute aspects and the preference difference among various demographic groups). One reason for this was mentioned in Chapter 3 (on methodology), namely that a weighted additive model can theoretically reproduce a non-compensatory decision process if, in the ordered set of weights, each weight is larger than the sum of all subsequent weights (Kohli & Jedidi, 2007; Wahab et al., 1976).

Another important possible reason for this accordance is the nature of the levels/aspects provided in the experimental design. For example, the price was presented at three levels (RMB9, 000, RMB13, 000 and RMB18, 000). If a tourist who actually applies a compensatory choice heuristic but feels that the difference between RMB9, 000 and RMB13, 000 is too big to be compromised by any change of the other attributes, then he/she would only consider the destinations that can be visited for RMB9, 000. So in his/her preference ranking order, all the destinations put into the consideration set are priced at RMB9, 000. In this case, the results of the estimation based on both the weighted compensatory choice model and the LBA choice model would be similar (highest utility assigned to RMB9, 000RMB based on the compensatory model and RMB9, 000 used as the first aspect based on the non-compensatory model) and both models can be used to accurately predict the choice of this tourist. However, if the price was presented in three levels with small differences (e.g. RMB9, 000, RMB9, 500, RMB10, 000), for the same tourists, his/her preference ranking order might be quite different. The compensatory process can be detected easily. In this case, the predictive power of the weighted compensatory model would be better than that of the LBA choice heuristic model.

Previous decision-making studies have tried to explore the influence of the circumstances on the use of the choice heuristic model, such as whether the informant is paid (Bröder, 2000; Rieskamp & Otto, 2006), whether there is a time pressure (Rieskamp & Hoffrage, 2008) or whether the number of the alternatives is big (Yee et al., 2007). The selection of the attribute aspects and how the spread of the levels/aspects influences the use of different choice heuristics have not been well investigated or discussed. In fact, the fit of each choice heuristic depends critically on the given spread of the levels/aspects of the experiment.

One factor in particular requires special consideration in the design of an experiment that involves the presentation of a set of attributes to respondents, as in the present study. If the aim of the research is to predict the actual choice of the decision-makers (the preferred destination of the Chinese outbound tourists in this case), the attributes and the aspects of the attributes presented to the respondents should be the ones that reflect the real performance of the available destinations. This is why an interview was conducted prior to the survey to make sure the attributes and the aspects are genuinely relevant to the actually outbound destinations. But if the aim of the research is to investigate the use of difference choice heuristics, researchers may use other standards to design the spread of attribute aspects, which is not the issue investigated in this research.

Understanding the preference based on different choice heuristic models

In this research, the same data-set from the survey was analysed by different estimation methods (conjoint analysis and greedoid analysis). Unlike previous studies of tourist decision-making, in which compensatory preference is always implied (e.g. Papatheodorou, 2001; Seddighi & Theocharous, 2002; Um & Crompton, 1990), the integration of different analysis methods based on different choice heuristic models provides alternative explanations of Chinese long-haul outbound tourists' preferences from different angles. The results of conjoint analysis reveal the utilities of each choice criterion, which emphasise the trade-off between different attribute aspects. Alternatively, the results of greedoid analysis provide the hierarchical ranking order of each choice criterion, with a focus on the priority of influence for each choice criterion.

For instance, time schedule is one of the most important attributes used by Hong Kong residents in choosing a package tour (Wong & Lau, 2001) and in the study of Chinese outbound tourists conducted by Zhu (2005) time schedule was also an important attribute. The importance of the time schedule was confirmed by the present research too. But much more insight into how this attribute is preferred and used by Chinese long-haul outbound tourists was provided from the estimation of both conjoint analysis and greedoid analysis. The part-worth utility of each aspect of this attribute is provided by the conjoint analysis, so that we are able to know what kind of time schedule is preferred by the whole sample (compact schedule vs. schedule with more free time).

In addition, the importance value of this attribute provides an indication on whether there is a need to further segment the sample into different groups with different preferences for this attribute. A significant preference difference was found for this attribute between different age groups. The greedoid analysis reveals that having more free time during the trip is the second popular aspect used by tourists as their first choice criterion and this aspect is used most frequently by the respondents to form their consideration set. This is information that complements the insights revealed by the conjoint analysis. As can be seen, the results revealed by the two methods of analysis provide much deeper insights into Chinese tourist's preference for this attribute and how this attribute is used during their selection of a destination.

Moreover, since conjoint analysis and the greedoid analysis estimate tourists' preferences on the basis of different heuristic principles, the results of the two methods of analysis can be used to serve different functions or to tackle different research questions. The conjoint analysis allows demographic segmentation based on the part-worth utilities of individuals, so that we would be able to know whether there is any advantage in further segmenting the sample and, if there is, which demographic attributes should be used to make the segmentation. Alternatively, the greedoid analysis provides the aspect order for each respondent, so that the must-have aspects that are used to form the consideration set can be spotted. This information would be useful to investigate the role of each attribute played during the different stages of the decision-making process. In addition, greedoid analysis can deal with incomplete data, which cannot be estimated by the conjoint analysis, which is particularly useful if the data are missing because of the imposition of a must-have aspect (which itself is strongly indicative of the use of non-compensatory heuristics).

Issues for investigating the fit of different choice heuristic models

There is no standard criterion regarding how to evaluate the fit of different choice heuristic models. This study explores two possible measurements for model evaluation. There are a number of issues that require more attention or further development. Firstly, the cost indicator was added as a measurement along with predictive power on the hold-out data to evaluate the two choice heuristic models. The inclusion of this indicator is necessary and important during the investigation of the choice heuristic because it can help us to spot those individuals whose destination preference can be predicted perfectly by a certain choice heuristic (the cost is 0).And even for those tourists who are not using a certain choice heuristic consistently, this indicator is able to suggest to what extent a certain choice heuristic is applied based on the number of costs. In this study, the choice heuristic model that costs less (has fewer errors) was assigned to each individual, which allows further comparisons between the tourists using different choice heuristics. No significant demographic difference was found between the respondents applying different choice heuristic models. This may because a choice heuristic was assigned to each individual as long as it costs less (fewer errors) than the other one, which means this is not a strict comparison between perfectly weighted compensatory decision-makers and LBA decision-makers. Actually, there are 20 respondents who can be predicted by the LBA model with zero cost while there are 8 respondents who can be predicted by the weighted compensatory model with zero cost. If a larger sample can be collected in a future study, a comparison of the groups who perfectly follow a certain choice heuristic may generate more interesting findings.

Secondly, how to calculate the cost is another issue addressed in this research. Yee et al. (2007) and Kohli and Jedidi (2007) introduced greedoid analysis to infer a non-compensatory choice heuristic independently. Although the programmes they used to generate the non-compensatory aspect are differed, the principles they used to identify the 'best' aspect order are the same, which is finding the aspect order that generates the minimum number of violated pairs (costs). This principle does not consider the fact that the importance may vary when the violated pair occurs at different positions of the observed ranking order, although the weighted minimum number of costs was discussed in the thesis of Michael Yee. In general, the rankings at the front are more important; in other words, they better reflect the real preferences of the respondents than the rankings at the end. So the calculation of the cost was modified with the help of Michael Yee to incorporate a weighting scheme in the cost calculation. A linearly decreasing weighting was used in this research. However, whether a linearly decreasing weighting is the most appropriate way to reflect tourist preference is a question that needs to be further analysed. An alternative weighting scheme could give larger weights for all the alternatives within the consideration set and smaller weights for all the other alternatives.

Thirdly, another challenge regarding the fit evaluation between difference choice heuristic models is how to make the comparison fair. As mentioned above, theoretically, the weighted compensatory model estimated by conjoint analysis can approximate the outcomes of other kinds of decision rules. If we want to make sure the additive model is truly compensatory, the part-worth needs to be constrained so that the presence of other aspects can compensate for the lack of an important aspect (Yee et al., 2007). Additionally, since there is no mature software for greedoid analysis, the predictive power of this method of analysis on the hold-out data needs extra work to calculate (see 6.4.2), and may need further improvement. And similar problem was found during the comparison of the 'power to replicate the observed preference order'. The utilities calculated by the conjoint analysis are based on the preference information from eight cards, while the greedoid analysis deduces the aspect order based on the ranking of 10 cards. Therefore, despite the fact that the results indicate that the greedoid analysis performs better than the conjoint analysis to replicate the observed the preference order, we should keep in mind that the conjoint analysis used less information for the estimation in this case.

In conclusion, this chapter presents the results of the survey from two angles. The first part (section 6.1, 6.2 and 6.3) of the results reveals the destination preferences of Chinese long-haul outbound based on different choice heuristic models, which were estimated by conjoint analysis and greedoid analysis. The second part elaborates the results regarding the fit evaluation of the two analysis methods as well as the choice heuristic models. In general, the conjoint analysis and greedoid analysis were applied successfully and provided useful insights regarding both the Chinese long-haul outbound tourists' choice of destination and the comparison and evaluation of the choice heuristic models. The next chapter is the conclusion and discussion chapter, in which the main findings of this study are summarised, the limitations of the study are reported, and the theoretical, methodological and marketing implications are discussed. There are also some recommendations for future study.

Chapter 7 Conclusion and discussion

Based on the two essential concepts and the integrated theoretical background, several issues were investigated in this research to gain new insights on the decision-making processes of Chinese long-haul outbound tourists. They are: (1) identifying the choice criteria, (2) predicting their preferences (for particular types of destination) based on different choice heuristics, possibly used at different stages of the decision-making; and (3) comparing the fitness of different choice heuristic models. A semi-structured interview was used to identify the choice criteria of Chinese long-haul outbound tourists. An experimental survey was then conducted to quantify different choice heuristics within the context of the selection of a destination. The data collected from the survey were then subject to different methods of analysis (conjoint analysis and greedoid analysis) to estimate tourists' destination preferences according to these choice heuristics and the appropriate measures to evaluate the fit of different choice heuristic models were explored.

7.1 Summary of the key findings

Research questions

1. What are the important attributes (choice criteria) considered by Chinese outbound tourists when they select long-haul destinations?
2. How is each such attribute evaluated when a particular choice heuristic is used by these tourists?
3. What methods can be used to analyse the different types of choice heuristic used?
4. How can the fitness and predictive power of different choice heuristic models be estimated?

Main findings for the research questions

1 Important attributes (choice criteria) considered by Chinese outbound tourists

Five important attributes were identified from the desk research and the interviews: the cost of the trip, the risk of the visa application being rejected, the fame of the destination, the opportunities for shopping, and the schedule for the trip.

Since the tourists investigated in this research are package tourists, the cost here refers to the price of a tour package that tourists need to pay in advance to tour operators. This price covers the transport during the trip, visa application fees, accommodation and the service of a tour guide. And the common price levels for outbound destinations are around RMB 9,000, RMB 13,000 and RMB 18,000 among tour operators in the Beijing-Tianjin region.

For the tourists who travel to short-haul destinations or mid-range destinations such as Australia or New Zealand, obtaining a visa very rarely a problem. But for long-haul destinations more generally, this is an important attribute for Chinese tourists.

The schedule for the trip was characterised as 'compact' (i.e. more visits and activities prearranged) or with more free time to spend autonomously.

Fame of the destination means whether the destination is well known by the Chinese public and, furthermore, whether it is well known either for its advanced economic development or for its beautiful scenery.

The opportunity to go shopping is a somewhat uncertain attribute, as there is no consensus on its importance in either previous studies or in the interview data in this study. For clarification, the opportunity to do brand product shopping was investigated in this research.

2. How the attributes are preferred when the weighted compensatory heuristic applies

The weighted compensatory choice heuristic assumes that a decision-maker will assign a utility value to each attribute level/aspect and sum the total utility value of each alternative and then select the one with the highest utility value. Therefore, each respondent will assign the part-worth utility to the attribute aspects based on their preferences, and then sum them in order to selection a destination. The averaged part-worth utilities of the whole sample for the 11 aspects of the five attributes are price around RMB 9,000 (0.96), price around RMB 13,000 (0.13), price above RMB 18,000 (-0.82), easy visa application (0.51),good for brand shopping (0.02), more free time (0.23) and famous destination (0.44). Since the last four attributes are presented in a binary form, the utilities of their counter-aspects have the same value but are negative. Price around RMB 9,000, easy visa application and famous destination are the top three attribute aspects; in contrast, good for brand shopping contributed relatively little to the overall preference for a destination.

In addition, the results of the importance values of each attribute show that price is the most important attribute that would lead to a change of preference. The second most important attribute is the time schedule, followed by visa and fame of destination. The results of the averaged part-worth utilities and the importance value of the time schedule attribute suggests that if we treat the whole sample as a target group, then a change in time schedule (from compact to more free time) would not make a large difference, since there are subgroups within the sample who have contradictory preferences on this one attribute. Further analysis indicates that older people prefer a compact schedule while younger people prefer to have more free time.

There are a few more preference differences between different demographic groups. First-time outbound tourists assign a higher utility score for famous destination while repeat outbound tourists assign a lower utility score for this aspect ($p<0.05$). First-time long-haul outbound tourists assign less utility (0.18) to more free time while repeat long-haul outbound tourists assign more utility(0.35) to this aspect ($p<0.1$). The importance value of the opportunity to do brand shopping is much higher for the middle-aged group than for the young group or older group, which suggests although the influence of this attribute on the overall preference of the sample is small, brand product shopping is nonetheless particularly desired by the middle-aged group.

3 How the attributes are preferred when the lexicographic by aspect choice heuristic applies

The lexicographic by aspect (LBA) choice heuristic assumes that decision-makers do not assign a utility score to each attribute level but instead they consider these attribute levels/aspects by a hierarchical fashion. A decision-maker would start from the most important attribute aspect, so that only alternatives possessing the desired attribute level are selected for further consideration. If there are ties, (s)he would continue the comparison based on the second most important attribute aspect and select the options possessing the second most important attribute level. This process is repeated until all alternative destinations are sorted, and the top ranked destination should be the final choice. The hierarchical preference order of these attribute levels/aspects is the 'aspect order' for making an LBA selection.

According to the results of the greedoid analysis, the lowest price (RMB 9,000) was used by 21.7% of participants as the most important criterion to evaluate alternative destinations. For these respondents all destinations not meeting this criterion would be put aside, no matter how attractive they are in terms of other attributes. For another 17.9% respondents, free time during the trip was the most important criterion, and for yet another 16.8% an easy visa application was the single most important attribute. The fourth most frequently used first criterion used by the respondents was famous destination country (13.6%). The proportions of the respondents who used the other seven aspects as their first evaluation criterion are relatively small. Besides, further tests reveal that first-time long-haul outbound tourists tend to use constraint attributes (i.e. price and visa application) as their most important aspect, while for their counterparts, the repeat long-haul outbound tourists, more free time during the trip or famous destination country are usually their first choice criterion.

There are seven popular aspect orders used by the Chinese long-haul outbound tourists:

1. Price RMB 9,000> Price RMB 13,000>Easy visa application>More free time during the trip > Good for brand product shopping

2. Price RMB 9,000> Price RMB 13,000> Famous destination country>Easy visa application

3. Easy visa application> More free time during the trip

4. Easy visa application>Famous destination country > Price RMB 9,000

5. More free time during the trip >Price RMB 9,000> Price RMB 13,000

6. More free time during the trip>Easy visa application> Price RMB13,>Price RMB 9,000

7. Famous destination country> Price RMB 9,000> Price RMB 13,000>Easy visa application.

As for the formation of the consideration set, almost 98% of the respondents would consider no more than seven destinations out of the 10 described on the cards. The size of the consideration set for the majority (76%) of the respondents as between two and six alternatives, while the mode was three (used by 23% or respondents). Most of the respondents (114 out of 179) used only one aspect to form their consideration set. For them the most commonly used aspect was more free time during the trip (used by 23 respondents) followed by easy visa application (18), famous destination country (15) and price at RMB9,000 (15).

These results suggest that although price is the most important attribute in general, it is not a non-negotiable aspect in choice of destination. In other words, even respondents who prefer price level at RMB 9,000 may still consider destinations at a higher price. However, people who prefer more free time during the trip tend to use this as a non-compensatory criterion in their selection.

4. Methods that can be used to analyse different choice heuristic models

This study applied both conjoint analysis and greedoid analysis to estimate tourists' preferences based on different choice heuristic models. The conjoint analysis was invented for modelling compensatory heuristics, especially additive weighted heuristics (Gabbott & Hogg, 1994). Greedoid analysis is based on a so-called greedy algorithm and was developed by Kohli and Jedidi (2007) and Yee et al. (2007) to infer non-compensatory heuristics including: conjunctive heuristics; disconjunctive heuristics; lexicographic-by-features and lexicographic-by-aspects heuristics. Since most of the choice criteria identified from the interviews were categorical variables, the cut-off points used in disconjunctive and conjunctive heuristics are not applicable in this study. And lexicographic-by-features is a special kind of lexicographic-by-aspect heuristic.

Therefore, only the lexicographic-by-aspect heuristic model was investigated in this study, as a representative of the non-compensatory choice heuristic models, to be compared with the weighted compensatory choice heuristic model. Both analysis methods worked successfully on the data and were able to provide useful information on the destination preference of Chinese long-haul outbound tourists. Additionally, the combination of cluster analysis and conjoint analysis enabled us to explore possible segmentation solutions within the sample, based on respondents' utility scores. And the combination of 'finding the must-have aspect' program and the greedoid dynamic program enabled us to find the non-compensatory choice criteria aspects that are commonly used to form the consideration set.

5. Measurements used to evaluate the fit of different choice heuristic models

Two indicator instruments were used to evaluate the fit of the two choice heuristic models: their predictive power on the hold-out data and the number of costs (weighted errors). For the 184 respondents with complete rankings, conjoint analysis can predict about 80% (147) of the rank orders of the hold-out data correctly, while 140 (76%) orders can be predicted accurately on the hold-out data by the greedoid analysis. Therefore, we could say the weighted compensatory model has a slightly higher predictive power on the hold-out data than the LBA model. However, this measurement has a few limitations. Firstly, only two destinations could be used for the hold-out data, to ensure the number of the stimuli was not too much for the respondents. When using larger stimuli sets, a larger number of hold-out stimuli can be applied, and that may lead to a clearer differentiation of the two models than is possible in our case, with only 10 stimuli and a maximum of 2 hold-outs. Secondly, for the respondents for whom both models gave accurate predictions on the hold-out data, it is not possible to provide a verdict about which of the two models is more appropriate.

Therefore, this study explores another possibility for comparing the two choice heuristic models, which is the power to replicate the observed preference order. This measurement is based on the calculation of the costs generated by assuming a certain type of choice heuristic model is applied. The average cost of the whole sample is 17.39 (6.1%) for the LBA heuristic model, while the number is 21.4 (7.5%) for the weighted compensatory heuristic model. In other words, based on the estimation from the LBA heuristic model, 93.9% (1-6.1%) of the observed preference orders of the whole sample can be replicated, while based on the estimation of the weighted compensatory heuristic model, 92.5% (1-7.5%) of the observed preference orders of the whole sample can be replicated. Besides, during the investigation of the formation of consideration sets, the LBA heuristic can be used to predict the choice set of more than 90% of respondents. Above all, the LBA model estimated by the greedoid analysis has proven itself to be in any case useful, certainly not inferior to the weighted compensatory model estimated by the conjoint analysis, while having a number of advantages (e.g. dealing with missing data, identifying must-have aspects for formation of the consideration set) not possible in conjoint analysis.

In addition to the findings that answer the research questions directly, there are some other findings which are of particular interest. Besides the demographic characteristics, another factor was found to have an influence on the selection of choice criteria, and that was the composition of the travel party. During the interview, the informants suggested that different travelling companions would shift the attention of the decision-makers from some evaluation attributes to others. The results of the survey confirmed the influence of this factor. The results suggest that people who travel with the whole family or only their partners have a preference for famous destinations, whereas people who travel by themselves would rather go to some destinations which are not famous.

Based on the part-worth utilities of each individual, a cluster analysis was able to identify three interesting clusters that were tentatively labelled 'journey beginners', 'consumption enjoyers' and 'prestige pursuers'. Journey beginners are the ones who have not been to any outbound countries before. Most of them are young and first-time tourists. They are sensitive to cost; that is, they prefer a cheaper trip. They do not care too much for brand product shopping and they would not want to take any risk of being rejected in the visa application process. Consumption enjoyers, on the other hand, usually do not worry about money. They are either middle-aged or young people from a high net-worth family and some of them already have long-haul outbound experiences. They expect high quality but are willing to pay for a more expensive tour package. They prefer a flexible time schedule with more free time. And they enjoy the brand product shopping at the destination country. The prestige pursuers pay more attention to the famousness of the destination country. They desire to go somewhere that is well known by the Chinese public as a developed country with beautiful scenery and they want to see as many attractions and scenic spots as possible. And they dislike brand product shopping. Many of the older people within the sample fit the characteristics of the prestige pursuers.

The main findings of this research has provided important new knowledge that has contributed to the literature. The next section addresses the main contributions of this research from theoretical, methodological and practical perspectives followed by a detailed discussion of the implications from the three perspectives.

7.2 Contribution of the research

Theoretical contribution

Through the investigation of Chinese outbound tourists' decision-making, especially the different choice heuristics used for the process, this research makes theoretical contributions to general decision making as well as to tourist decision making. At the level of general decision making, this research provides additional insights on (1) how the concept of choice heuristics can be used to better understand the process of decision making and (2) how choice heuristics are used for the selection of complicated intangible services, tourism destinations in this case. Although there are some studies in consumer decision making that have investigated the choice heuristics used by consumers to form consideration-sets (e.g. Brisoux & Laroche, 1981 Crompton & Ankomah, 1993; Parkinson & Reilly, 2002), these are limited in scope and dated. Information regarding how choice heuristics might be used by consumers to make the final decision among alternatives in the consideration-set is missing from these studies. Only three studies were found (Dieckmann et al., 2009; Kohili and Jedidi, 2007; Yee et al., 2007) that had explored which choice heuristic model is more predictive during the whole process of alternative products evaluatin and selection.

However, these previous studies only focused on the comparison of the predictabilies of different choice heuristic models. They did not go a further, logical step to use the information generated from different heuristic models to describe, explain and better understand the preference of the target group. Besides the exploration of the possible indicators to campare predictabilities of different choice heuristic models, this study has explored how to present tourists' preferences based on different choice heuristic models and has evaluated the different uses of the preference information generated from different models. Therefore the investigation of the choice heuristic in this thesis is not only used to understand the mechanism of decision making but also to generate deeper and more comprehensive insights on decision-makers' preference as well as to increase the power of prediction.

In addition, the selection of a particular choice heuristic depends on the nature and context of the decision (Hauser et al., 2009), so even amongst the studies that tested tangible consumer products, there is no agreed conclusion regarding the predictability of different choice heuristic models. Therefore, different studies based in different contexts are required to obtain a relatively comprehensive picture about the selection and use of choice heuristics for consumer decision making. However, apart frot the article of Decrop and Kozak (2009), which briefly discussed the possible kinds of choice heuristics used for destination choice, there have been no previous empirical studies conducted that have estimated and evaluated different choice heuristic models used in tourism destination choice, which represents an important omission in the literature. This research fills the knowledge gap by quantifying two different choice heuristic theories within the context of tourism destination choice.

In terms of the theoretical contribution to tourists decision-making studies, this research clarifies and integrates two concepts (choice criteria and choice heuristics) to investigate tourists decision making and rigorously adapted theories from other disciplines that are suited to the special characters of tourism products. Since different disciplines adopt different perspectives and study different issues connected to decision-making, the knowledge produced tends to be independent of each other. Such isolated pieces of knowledge are not enough to give a comprehensive picture of tourist decision-making. In recent years, with the introduction of a more thoroughgoing interdisciplinary approach in tourism (Tribe, 1997) scholars have started to appreciate the importance of knowledge integration for tourism studies, which requires elements to be assembled, concepts to be unified and theories to be connected and circulated (Belhassen & Caton, 2009; Darbellay & Stock, 2012). This research initially clarifies two essential concepts for the investigation of tourism decision making which are referred as different terms in different studies. And for a more comprehensive insight on these two concepts, theories from different disciplinary approaches are adopted and modified accordingly to gain a better understanding. The details on theory adaptation in tourism research are further discussed later in the section of theoretical implications.

Methodological contribution

In order to estimate two different choice heuristic models, this research explores different estimation methods (conjoint analysis and greedoid analysis). In the marketing research field, conjoint analysis has been widely used by scholars but the greedoid analysis was first introduced to infer consumers' non-compensatory preference only recently in 2007 (Kohli and Jedidi 2007; Yee, Dahan et al. 2007). The few empirical studies that adopted this method investigated decision making for tangible products such as laptops (Kohli and Jedidi, 2007), cell phones (Yee et al., 2007) and skiing jackets (Decrop, 2010). Therefore, the implementation and empirical studies of greedoid analysis requires further exploration. This is the first study to apply greedoid analysis in an investigation of consumers' preference in intangible products (tourism destination), which is a new attempt to apply this method in a relative new research area. And during the implementation of the greedoid analysis, some technical issues were addressed and discussed (See section 4.5) which are of use for further improvement in future studies.

Moreover, this research provides two possible estimation methods to evaluate the predictability of different choice heuristic models. One is the predictability test on hold-out data while the other one is the power to replicate the real preference order named the "the number of cost". The former one is widely used by previous studies but the later one is introduced by this research as another indicator to suggest to what extent each choice heuristic is applied by the decision makers through the whole process of ordering alternatives. The inclusion of this indicator is necessary and important during the investigation of the choice heuristic because this indicator can help us to spot those individuals who can be predicted perfectly by a certain choice heuristic. And even for the tourists who do not use a certain choice heuristic consistently, this indicator is able to suggest to what extent a certain choice heuristic is applied. These information are crucial for understanding tourists' preference based on the choice heuristic they tend to use and to treat each one separately.

Another contribution of this research concerns the modifications made to the analytical methods. Firstly, combination of analytical methods are used in this study to gain deeper insights. The results of conjoint analysis was further analysed by a cluster analysis to detect possible marketing segmentation for the whole sample. The greeodid analysis provides the aspect order based on the ranking orders of the stimuli destination cards. But it cannot indicate which aspect(s) is used to form the consideration set. "Finding the must-have aspect" programme was integrated to further analyse the results of the greedoid analysis so that the attribute aspect(s) that only exist within the consideration set is pointed out. These aspects are the ones tourists used to form their consideration set. Secondly, the way of calculating "the cost" in the original greedoid programming does not take the weight into the consideration so that the error that happened at the beginning of the ranking is just as bad as the one that happened at the end of the ranking. However, this does not reflect the real situation. People tend to be more careful and spend more time for the ranking of the destinations they would consider at the beginning of the task. So the calculation of the cost was modified based on a weighting scheme to increase the accuracy.

Practical contribution

As for the practical contribution, despite the fact there has been a growing interest in Chinese outbound tourists, the majority of the studies on Chinese outbound tourists (e.g.Ryan and Mo 2002; Kim, Guo et al. 2005; Li, Harrill et al. 2009; Sparks and Pan 2009; Agrusa, Kim et al. 2011; Li, Lai et al. 2011) stays at the stage of identifying the important attributes concerned for this market. Further information regarding how each attribute affects the decision-making is still unknown. However, through the advanced analysis methods adopted by this research, the preference estimation based on different choice heuristic models is able to reveal much more information regarding how these choice criteria are preferred, the specific importance values of each attribute aspect and the role that each attribute plays during the whole process of the destination choice.

This information is of great importance for tourism destination marketers and suppliers. The trade-off relationships among different choice criteria revealed by the compensatory heuristic model will enable practitioners to make proper adjustments regarding each important attribute. The hierarchical importance of each attribute estimated by non-compensatory heuristic model provides a priority list of the attributes so that the suppliers can start from the most important attributes and make the improvements to their products (tour packages) more efficiently. And the information on whether an attribute is used more often to form the choice-set or to facilitate the final selection is helpful for marketers to understand the position of their destinations amongst competitors. Further discussions can be found in the section of marketing implications of this study below.

7.3 Discussion of the implications

Implications for (tourism) decision-making theories

Due to the complexity of tourism, tourism decision-making has been studied by different disciplinary approaches. Different concepts and theories are described and developed from each disciplinary perspective to understand and explain tourism decision-making. It is good to look into tourism decision-making from a variety of angles but it is also important to enable a combination of the different perspectives into a coherent whole, especially when different terms are used by the various disciplinary approaches to describe the same thing and when a theory from one perspective cannot explain a phenomenon very well. In such cases, unifying the concepts (Belhassen & Caton, 2009) and integration of the theories (Darbellay & Stock, 2012) becomes critical for knowledge production in tourism research.

Based on an extensive literature review, this thesis clarifies two essential concepts for the investigation of tourism decision-making, which are referred to differently in different studies. For a more comprehensive insight into these two concepts, theories from different disciplinary approaches are adopted in order to gain a better understanding. The two important concepts are: choice criteria (also termed evaluation criteria, determinants, characteristics and decision-making variables) and choice heuristics (also termed as preference functions and choice strategies). Although the terms used to describe these two concepts differ, the essentials are the same. These two concepts enable us to understand tourists' preferences for alternative destinations and enable us to predict choice of destination.

In this research, the choice criterion is defined as any attribute of a destination that might be evaluated and compared by a decision-maker, and the choice heuristic is defined as the way of processing the information about the attributes to decide on a destination. Theories from different disciplinary approaches are integrated to facilitate the investigation, including the theory of reasoned action from the social-psychological approach, characteristic theory and theories of preference function from the economic approach, compensatory and non-compensatory choice heuristic theories from the psychological approach and choice-set theory from marketing and consumer behaviour approaches.

The concepts used to describe choice criteria and choice heuristics were reviewed and summarised. Different terms, though, appear as their key words, such as determinants (Um & Crompton, 1990), variables (Bigne et al. 2001), strategies (Wright, 1975; Rieskamp & Otto, 2006) and rules (Adelbratt & Montgomery, 1980). However, the integration of the theories from different disciplinary perspectives enables a comprehensive understanding of a single phenomenon. The theory of reasoned action (Ajzen & Fishbein, 1980) states that if a person intends to perform a behaviour, then it is likely that the person will do it. This theory is the foundation for this research, so that for the potential long-haul tourists who have not made their final choice of destination, we are still able to investigate their decision-making, based on their stated intentions. And the characteristic theory introduced by Lancaster (1966) suggests that destination choice can be decomposed into the choices of a set of attributes, and in fact these attributes are the choice criteria used by the tourists to make the evaluation.

The choice heuristics were explored based on two economic theories, namely compensatory preference theory and the lexicographic preference theory introduced by Georgescu-Roegen (1954). Further, the consideration-set theory (Crompton, 1992; Crompton & Ankomah, 1993) was incorporated into the research and found to be useful to understand the actual destination choice process of the tourists.

To sum up, as an interdisciplinary research field, the investigation of tourism decision-making requires greater communication and knowledge exchange among different disciplinary perspectives. A unification of the concepts can be a start for better dialogue and integration of the theories which could be used to explain interdisciplinary phenomena such as destination choice.

This study tries to use classic decision-making theories and methods from other disciplines to understand and estimate the destination choice of Chinese long-haul outbound tourists. However, it is not a simple process of quantifying the theories of general consumer decision-making in another context, but a process of careful knowledge adaption and reflection, based on the special characteristics of tourism products. In this research, two issues were raised in the process of knowledge adaption: the nature of choice criteria and the influence of some unique factors of tourism (i.e. the composition of the travel party and experience). The nature of the choice criteria has been discussed in section 5.4. Due to the intangibility of tourism products, the destination choice is not so much a selection of an object as a selection of an expected set of experiences. Therefore, the choice criteria used by tourists tends to focus less on the quality of the product and more on the desired experience or impressions, such as whether the visa application is complicated, whether there are good places for shopping or whether the destination is famous. These choice criteria are more abstract than the ones used to select everyday products, such as the colour of a cell phone or the amount of computer memory. As a result, a more careful identification of these choice criteria and their values is required to avoid misunderstandings.

The second issue addressed in this research to distinguish destination choice from normal product decision-making are some unique factors that influence tourists' decision-making, including the composition of the travel party and previous travel experience. A leisure trip, especially a long-haul leisure trip, is not like the purchase of shampoo or a cigarette. It is a big decision for the decision-makers. And especially when they are going to travel with someone else, they need to consider their needs, so that the choice can be influenced by the composition of the travel party. Joint decision-making (Nichols and Snepenger 1988) and the influence of children (Thornton, Shaw et al. 1997), family (Fodness 1992; Wang, Hsieh et al. 2004; So and Lehto 2007) and friends (Gitelson and Kerstetter 1995) on destination choice have been included in many studies of tourist decision-making. So and Lehto (2007) indicate that Japanese family travellers are different from those who travel with friends, or alone. The influence of the travel companions was also emphasised during the interviews in this research as an important factor that may tilt tourists' preference. Therefore, this factor was included in the survey for further test. And the results prove the hypothesis. People who travel with their family prefer famous destinations more than any other groups, which confirm the information obtained from the interviews. But people who travel by themselves prefer to go to some destinations which are not famous.

Another factor is previous travel experience. Although previous experiences in purchasing a normal product can also influence the next purchase, the directions of the influences are slightly different. Previous purchase experience of a certain product such as a cell phone would enable the consumer to gain more knowledge of how to select a good cell phone next time. But besides the information gained from previous travel experience, the more important influence of previous travel experience is to increase the confidence of the travellers to explore new destinations, especially those ones that present a certain risk (Belhassen and Caton 2009).And this is confirmed by the findings of this research. Tourists who have long-haul travel experience pay less attention to constraint attributes such as risk of a visa application being rejected but more attention to the amount of free time during the trip, while the first-time long-haul outbound tourists tend to give greater consideration to the constraint attributes such as price and visa application.

Methodological implications

In this study, the interview and the survey are not parallel studies that provide findings independently of each other but a necessary combination to ensure the validity of the investigation. The interview provided the context and background for understanding the destination choice of Chinese long-haul outbound tourists and, more importantly, allowed the relevant choice criteria (important attributes) to be identified that tend to be used by the target group during their real choice of destination and the common values/aspects of each attribute provided by the real long-haul destinations. Therefore, the data generated in the interviews were not only for obtaining a general impression of the preferences of Chinese long-haul outbound tourists but also for making sure the design of the survey fitted the real situation. Thus the stimuli destination cards presented to the respondents cover the choice criteria that are actually used by Chinese long-haul outbound tourists and the values/aspects of each attribute presented to the respondents reflect those of real destinations. The findings prove the usefulness of such a combination. For example, the visa application is an important attribute revealed during the interviews but was not emphasised in previous similar studies. This attribute might not have been included in the stimuli if the design had been based only on desk research, but the results of the survey confirms that a large number of respondents care a lot about this attribute and 18% respondents even used it as the most important choice criterion. These important findings might have been missed if the interview had not been conducted.

Moreover, the same data-set of the survey was analysed by different estimation methods, namely conjoint analysis and greedoid analysis. Unlike previous tourism decision-making studies in which compensatory preference is always implied, the integration of different methods of analysis based on different choice heuristic models provides alternative explanations of Chinese long-haul outbound tourists' preferences, from different angles. The combination of analysis methods is used in this study to gain more insight. Conjoint analysis is used to estimate the utility scores for each attribute aspect of each respondent, assuming compensatory choice heuristic is applied. Although we are able to know the averaged utility scores of each attribute aspect for the whole sample, we cannot detect whether there are subgroups who share the similar pattern of utility scores. By applying a further cluster analysis based on the results of the conjoint analysis, three groups are identified. Within each group, the respondents show similar preferences for each attribute. And the results of the cluster analysis can be very useful for further market segmentation.

The greeodid analysis provides the aspect order based on the ranking orders of the stimuli destination cards. But it cannot indicate which attributes are used to form the consideration set. 'Finding the must-have aspect' program was used to further analyse the results of the greedoid analysis so that the (sole) attributes used to form the consideration set is identified. These aspects are the ones tourists used to form their consideration sets. In conclusion, the mixed research methods and combined analysis methods can be used as the best approach to tackle complicated research questions such as the exploration of the choice heuristics, and the power of this methodological approach was proved by the research.

Unlike normal products, destination choice is not a decision that we make every day, especially for long-haul destinations. In previous studies of consumer decision-making, student respondents are commonly used (Kohli & Jedidi, 2007; Yee et al., 2007; Dieckmann et al., 2009) due to ease of access and high response rates. The choices of those students concerning products like skiing jackets, smart phones or computers, so students are suitable respondents since they are the users and they need to make such decisions. However, in this study, this is not the case. The information might be biased or less accurate if the respondents were not real tourists or potential tourists who actually want to and have the ability to take a long-haul leisure trip.

Therefore, in this research the respondents were selected and accessed carefully. One group the respondents were recruited at the CAISSA tour operator as they were enquiring about information on outbound trips or were soon due to take an outbound trip, while the other group of respondents were accessed through a snowball sampling technique; they nonetheless had the necessary financial resources and also the desire to take an outbound trip in the near future. The preference comparison between the tourists approached at the tour operator and the tourists accessed through a snowball sampling indicated that although there were slight differences in their preferences on price, the rest of their preferences were similar to each other and, given the convenience of snowball sampling, this could be adopted by further studies to investigate tourists' long-haul destination choice.

Marketing implications

Another reason that destination may different from normal product is a number of characteristics/attributes of destination products are given such as weather, beach, historical-buildings etc. so that the destinations cannot really do anything about them, whilst other characteristics can be adapted to tourists' preference within the budget (van Raaij 1986). Therefore, the choice criteria used by tourists should be treated as two categories for a destination. One is the criteria that this destination cannot provide the desired value/aspect required by the tourists such as a beach for a destination that does not have one. For the tourists who use this kind of criteria, the destination could shift the tourists' preference to something they have by smart advertising or deselect this group of tourists as the target group. The other types of criteria that the destination can control and improve are those such as the service quality at the attraction. For this type of criteria, the destination should make enough efforts to meet the desired expectation based on the extent of the importance of these criteria for their target group.

In this study, the price range of the trip is relatively fixed for each destination due to the price of the flight. The restriction of the visa is relatively fixed due to the policy of each country. Although they are not definitely fixed, they are the attributes that not every destination can change within a short time. Whether the destination is famous is an impression of tourists, they can be changed through effective advertising, however this requires a great deal of effort while the time schedule of the trip and whether it is good for brand product shopping can be changed more easily. By noticing the different nature of these choice criteria, the destination marketing organizations and the tour operators would be able to react efficiently according to the preference revealed.

Beside the insights on the choice criteria used by the Chinese long-haul outbound tourists, the exploration of their preference based on different choice heuristic models provides much more valuable information for tourism suppliers to design and improve their destination products. The overall utility scores of the conjoint analysis and the summarization of the first aspect deduced by the greedoid both point to the importance of the lower price level, low risk to get a visa and famous destination country. More importantly, within the whole sample, the preferences do not vary a lot except for a few significant differences regarding the attribute toward one or two aspects such as the difference on the preference of time schedule between age groups. It demonstrates that the Chinese long-haul outbound tourists can be treated as a target group since they show similar preference patterns.

However, if there is a need to further segment the Chinese long-haul outbound tourists, a few significant differences found among different demographic groups and the three clusters identified by the cluster analysis can be used as a possible solution. Additionally, besides the useful information on possible marketing segmentation solution, the results of cluster analysis can also shed light on possible correlations between attributes' aspects. For example, people who prefer low-level package price may tend to prefer easy to get a visa as well or people who desire famousness of the destination country may be more inclined to favour a compacted trip schedule. And these correlations are very useful for tour operators to improve their destination packages by always delivering the bundle of correlated attributes' aspects.

As for the destination marketing, it is known that advertising primarily affects demand by changing tastes and creating brand loyalty (Shaughnessy & Shaughnessy, 2003). In particular, advertising tries to shift consumer's attention from weak to strong sides of the product (Piana, 2005). Therefore, the real success of destination advertising is to make people who disliked the destination like it and who liked the destination only like it. Take the UK as an example in order to compete with all other rivals and develop the potential China tourism market for the UK, we might go through two steps to enlarge the China outbound tourism market. Firstly, make Chinese tourists prefer to or at least consider visiting the destinations in the UK rather than other European countries. Secondly, increase the extent of favourableness of Chinese tourists' perceptions on UK to a greater extent so that Chinese tourists would like to visit UK repeatedly.

For the first step, we need to know the attributes and the aspects used by Chinese long-haul outbound tourists to form their consideration set. Finding the must-have aspect based on the greedoid analysis allow us to identify the non-compensatory attributes' aspects used by the Chinese long-haul outbound tourists to form their consideration-set (e.g. more free time during the trip, famous destination, little risk of getting visa and lower price level). For the second step, besides knowing the choice criteria used by the Chinese long-haul tourists, we still need to explore which choice heuristic is more suitable and predictable for Chinese long-haul outbound market or one step further, which choice heuristic is more suitable for which group of this market. Therefore, the most efficient advertising campaign can be provided accordingly. Although there are no significant results found in this research to distinguish the different groups applying different choice heuristics, it provides a promising method to identify the suitability of a certain choice criteria for each individual (see section 6.4). Larger sample with more control variables may generate more interesting findings in the future.

7.4 Limitations of the study and recommendations for future study

There are a number of limitations of this study which mainly include the methodological limitations and the limited research focus. Based on the methodological limitations and especially the limited research focus, recommendations are made for future studies.

The methodological limitations

As an exploratory study, there are some limitations of the study regarding the research methods. Firstly, instead of a random sample, a convenience sample was collected either at a certain tour operator or through a snowball sampling. The convenience sampling may not produce representative results for the whole population which limits generalizability of the study's findings (Acker 1999; Park 2004; Trzesniewski, Donnellan et al. 2008). In this sample of this research, the profile of respondents was skewed towards the younger demographic profile due to the high response rate of this group. Although there is sufficient number of mid-aged and older respondents to further explore the preference difference among different age groups, the overall destination preference revealed may be partial to the preference of the younger tourists. However, there are two reasons that drove a convenience sampling approach for this research which are (1) the difficulties encountered in locating actual long-haul outbound tourists or potential long-haul outbound tourists and (2) the exploratory purpose of the study .

Since unlike normal consumers, long-haul outbound tourists cannot be easily located at a shopping mall, the venue used to recruit respondents or location process needs to be considered and selected to find the respondents who are actual long-haul outbound tourists or would actually take a long-haul trip in the near future. In order to locate as many respondents as possible within a certain time and financial budget, big international tour operators were selected as appropriate venues to locate long-haul outbound tourists. However, only one tour operator (CAISSA) provided permission to access their customers. In order to control the bias that may generated due to the selection of a particular tour operator, the snowball sampling was used as an alternative way to approach potential respondents. Additionally, although convenience sampling may be weak regarding statistical inferences relating to the population outside the sample, it can be very useful for identifying issues, exploring promising hypotheses or for the collection of other sorts of non-inferential data (Fricker and Schonlau 2002). And the main purpose of the study was to explore the destination choice of Chinese long-haul outbound tourists based on different choice heuristic models rather than the generation of generalizable statistical conclusions. Although there are limitations of convenience sampling, it was still useful as a way to collect data in this research. Therefore, for future studies, of the types of respondents needed and the purpose of the research should be key considerations in the selection of different sampling methods.

Another limitation of the study is the number of attributes and aspects presented in the experimental design. In total, five attributes with eleven aspects was used to generate the stimuli destination cards. And four out of five attributes are binary ones. However this is not the ideal number of the attribute and levels/aspects intended for this study in the initial phase. There were a few additional important attributes such as the type of destination and safety of the destination and more aspects of the attributes such as whether it is good for outlet shopping or whether it is good for souvenir shopping that were also worthy of further exploration. However, the pre-test (6 respondents) of the ranking task with 18 cards (6 attributes with 17 aspects) was not successful due to information overload (see details in section 4.3). This factor necessitated that a simplified sorting task with 10 cards was chosen as the maximum number of attribute/aspects. The limited number of attributes and aspects raised some challenges. For example, the intention to use a compensatory heuristic could not be examined due to the limited available aspects and the distinctive difference between two levels could not be explored, so that the results seems like an non-compensatory heuristic was applied.

The limited number of attributes and aspects is actually because the full-profiled conjoint analysis requires the ranking data on all the stimuli which would cause information overload if we had presented many stimuli to the respondents. However, the greedoid analysis was able to analyze consider-then-rank data so that under circumstances where relatively large numbers of attribute/aspects needs to be investigated, the greedoid analysis is more suitable. For future studies of Chinese long-haul outbound tourists, there are two ways to overcome this limitation. It was found that the lexicographic by aspect choice heuristic model can predict equally well as the weighted compensatory model in this study. So further studies could only use greedoid analysis to explore a greater range of attributes regarding the destination preferences of Chinese long-haul outbound tourists by providing them with a relatively larger number of stimuli, and allowing the respondents to provide a partial order. Or alternative forms could be adopted to present the stimuli in a more attractive and interesting way rather than a simple descriptive destination. For example, the stimuli could be presented as designed brochures, rather than describing all the attributes and aspects as text, some of the attributes can be depicted in pictures such as the type of the destination, since visual representation has been found easier to be processed than the textual description (Shneiderman 1996; Walther, Slovacek et al. 2001)

Limitations of the research and future studies

Although there is an extensive literature in tourism decisions making and even destination choice, the study of choice heuristic is rare so that a whole range of issues need to be explored. However, this thesis can only focus on a limited range of issues. In this study, the decision making process is examined prior to the trip, the target group is the Chinese long-haul outbound tourists and only two popular choice heuristic models were explored and compared. There are three directions that can be further identified for further study.

Since the respondents were approached before the destination decision being made, they could be considered to be at the early consideration or awareness set stage of the process of decision-making. Studies which try to understand consumer's choice processes at different stages are very rare, and whilst this study may have limitations, it has attempted to shed some light on the decision criteria and important attributes considered by consumers at this particular stage. It would be useful to undertake longitudinal research on the same sample at different stages of the decision process to understand how early preferences inform or influence the later stages. In addition, the destinations investigated are not real destinations but stimuli which contain different combinations of destination attributes' aspects. A further link between stimuli with actual destinations should be made. For example, whether it is easy to get a visa is relatively fixed for each destination country so that the stimuli with aspect "easy to get a visa" should represent countries such as Australia or New Zealand rather than the USA.

This thesis focuses on Chinese long-haul outbound tourists. The influence of Chinese culture has been discussed in section 5.4. Some of the tourism decision making behaviours of Chinese tourists seems consistent with their cultural characteristics such as the adoption of packaged tours as opposed to free independent travel could be a reflection of collectivism, or the pursuit of famous destinations may derived from the "face" culture or conformity. However, some of the behaviours might not be explained well by cultural characteristics. This study did not provide any quantitative test regarding the influence of culture. How these cultural characteristics influence Chinese tourists' selection of the choice criteria and even choice heuristics should be examined in the future in addition to cross-cultural comparison.

The inference of non-compensatory choice heuristic has not been well explored in tourism decision making studies. The greedoid analysis method was introduced in this study and proved a useful approach to explore non-compensatory preference and provide important insights on tourists' destination choice. But this is an emergent method which requires further development such as the weighting scheme for the cost calculation and the estimation of other types of non-compensatory choice heuristic models. In addition, since there is no mature software to perform greedoid analysis, lots of extra works needs to be done manually for further tests such as the predictability on the hold-out data and to find the must-have aspect for consideration-set formation. More importantly, how to apply greedoid analysis to other tourism decision makings (e.g. choice of travel mode, hotel or tour operators etc.) and how to make appropriate modifications based on the special characters of the tourism products requires further exploration.

To sum up, this research is an exploratory study of making use of advanced analysis methods to understand the dynamic mental process of destination choice. It requires the interdisciplinary knowledge integration and the technical support of computer programing. This research was able to apply two estimation methods successfully to infer two different choice heuristic models and to get comprehensive information on the destination preference of Chinese outbound tourists. However, as aforementioned, it is just a start point in terms of the approach and the methods used to estimate and understand tourism decision making phenomena. Following-up research based on the three dimensions pointed above are important and necessary to further develop the knowledge missing from existing literatures and to stimulate more interest on the research field of tourism decision making.

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Appendix 1 Questionnaires

Pre-test Version a

问卷调查

尊敬的受访者

您好!

这是英国诺丁汉大学商学院博士项目的一个课题。这份问卷调查的目的是收集一些关于中国旅游者到远距离国家（如欧洲或美洲的国家）旅游的偏好信息。下面的问题大约会占用您5分钟的时间，但是您的回答将会对我们的研究起到十分重要的作用。我们不要求您提供姓名或是联系方式等信息，所以您的回答将会是匿名并且受到隐私保护的。

非常感谢您的参与和支持。

第一部分 旅游目的地偏好

1 请问您以前有过几次以休闲为目的并且是自费的出国旅游经历____，在这些经历中有几次是长距离旅游(非东亚国家)___.

2. 请设想一下您下一次的长距离出国旅游（不包括亚洲的周边国家），请问您最有可能会跟谁一起去？

○ 就我一个人

○ 全家人

○ 朋友

○ 和我的爱人

3. 假设您可以和上题所选的人出国旅游一次，有以下 18 个 旅游目的地线路（大约 8 到 15 天的行程）可供您选择 (分别罗列在 18 张卡片上)，每一条线路不涉及具体的国家名称,只包括了选择线路所需要的各种信息的不同组合，这些信息分别是：

（1）旅游目的地线路的价格

包括四种价位，9000 元左右，13000 左右，17000 左右和 21000 左右

（2）签证的难易程度

包括不存在拒签的风险，有少许拒签的可能和很有可能被拒签

（3）旅游线路的类型

包括以自然观光为主和以人文体验为主

（4）景点的著名程度

包括熟悉的国家和熟悉的景点，熟悉的国家但景点不太熟悉和不熟悉的国家不熟悉的景点

（5）名品购物

包括名品店较多，名品折扣店较多和不适合名品购物

（6）行程的安排

包括行程紧凑景点多和行程宽松景点少

3.1 请根据您的偏好,在这 18 条旅游目的地线路中选出您一定不会考虑的线路

____

3.2 请根据您的偏好,在剩下的旅游目的地线路中选出您一定会考虑的线路

____

3.3 请根据您的偏好,对您一定会考虑的线路进行排序

____

3.4 请根据您的偏好,对您一定不会考虑的线路进行排序

____

3.5 请根据您的偏好,对剩下的一组线路(不一定会考虑的线路)进行排序

____

第二部分 基本信息

4. 性别: ○ 男 ○ 女

6. 年龄____

5. 职业 ____

再次感谢您的协助!

如果您有任何疑问或建议请在下面的空白处留言或者与我们联系.

____

____

____

____

联系方式: lixcl23@nottingham.ac.uk

Pre-test Version b

问卷调查

尊敬的受访者

您好!

这是英国诺丁汉大学商学院博士项目的一个课题。这份问卷调查的目的是收集一些关于中国旅游者到远距离国家（如欧洲或美洲的国家）旅游的偏好信息。下面的问题大约会占用您 5 分钟的时间，但是您的回答将会对我们的研究起到十分重要的作用。我们不要求您提供姓名或是联系方式等信息，所以您的回答将会是匿名并且受到隐私保护的。

非常感谢您的参与和支持。

第一部分 旅游目的地偏好

1 请问您以前有过几次以休闲为目的并且是自费的出国旅游经历____, 在这些经历中有几次是长距离旅游(非东亚国家)___.

2. 请设想一下您下一次的长距离出国旅游（不包括亚洲的周边国家），请问您最有可能会跟谁一起去?

❍ 就我一个人

❍ 全家人

❍ 朋友

❍ 和我的爱人

3. 假设您可以和上题所选的人出国旅游一次, 有以下 18 个 旅游目的地线路（大约 8 到 15 天的行程）可供您选择 (分别罗列在 18 张卡片上), 每一条线路不涉及具体的国家名称,只包括了选择线路所需要的各种信息的不同组合，这些信息分别是:

（1）旅游目的地线路的价格

包括四种价位，9000 元左右，13000 左右，17000 左右和 21000 左右

（2）签证的难易程度

包括不存在拒签的风险，有少许拒签的可能和很有可能被拒签

（3）旅游线路的类型

包括以自然观光为主和以人文体验为主

（4）景点的著名程度

包括熟悉的国家和熟悉的景点，熟悉的国家但景点不太熟悉和不熟悉的国家不熟悉的景点

（5）名品购物

包括名品店较多，名品折扣店较多和不适合名品购物

（6）行程的安排

包括行程紧凑景点多和行程宽松景点少

请根据您的偏好，对这 18 条线路进行评价打分

旅游目的地线路 1

价格：13000 元左右

签证：没有拒签风险

旅游线路类型：以人文体验为主

著名景点：熟悉的国家不熟悉的景点

名品购物：名品折扣店较多

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分，

请问这条线路可以打多少分____(0-100)

旅游目的地线路 2

价格：9000 元左右

签证：没有拒签风险

旅游线路类型：以自然观光为主

著名景点：熟悉的国家熟悉的景点

名品购物：名品店较多

行程安排：行程紧凑景点多

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分，

请问这条线路可以打多少分____(0-100)

旅游目的地线路 3

价格：21000 元左右

签证：少许拒签风险

旅游线路类型：以自然观光为主

著名景点：熟悉的国家熟悉的景点

名品购物：名品折扣店较多

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分，

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 4

价格：17000 元左右

签证：没有拒签风险

旅游线路类型：以人文体验为主

著名景点：熟悉的国家熟悉的景点

名品购物：名品店较多

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分，

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 5

价格：17000 元左右

签证：少许拒签风险

旅游线路类型：以人文体验为主

著名景点：熟悉的国家不熟悉的景点

名品购物：名品店较多

行程安排：行程紧凑景点多

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分，

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 6

价格：17000 元左右

签证：较大拒签风险

旅游线路类型：以自然观光为主

著名景点：熟悉的国家熟悉的景点

名品购物：名品折扣店较多

行程安排：行程紧凑景点多

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分，

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 7

价格：13000 元左右

签证：较大拒签风险

旅游线路类型：以人文体验为主

著名景点：熟悉的国家熟悉的景点

名品购物：不适合名品购物

行程安排：行程紧凑景点多

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好,待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是100 分,

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 8

价格：13000 元左右

签证：少许拒签风险

旅游线路类型：以自然观光为主

著名景点：不熟悉的国家不熟悉的景点

名品购物：名品店较多

行程安排：行程紧凑景点多

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好,待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是100 分,

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 9

价格：17000 元左右

签证：没有拒签风险

旅游线路类型：以自然观光为主

著名景点：不熟悉的国家不熟悉的景点

名品购物：不适合名品购物

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是100 分，

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 10

价格：21000 元左右

签证：没有拒签风险

旅游线路类型：以自然观光为主

著名景点：熟悉的国家不熟悉的景点

名品购物：不适合名品购物

行程安排：行程紧凑景点多

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是100 分，

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 11

价格：9000 元左右

签证：少许拒签风险

旅游线路类型：以人文体验为主

著名景点：熟悉的国家熟悉的景点

名品购物：不适合名品购物

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好,待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分,

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 12

价格：21000 元左右

签证：没有拒签风险

旅游线路类型：以人文体验为主

著名景点：熟悉的国家熟悉的景点

名品购物：名品店较多

行程安排：行程紧凑景点多

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好,待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分,

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 13

价格：13000 元左右

签证：没有拒签风险

旅游线路类型：以自然观光为主

著名景点：熟悉的国家熟悉的景点

名品购物：名品店较多

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是100 分，

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 14

价格：9000 元左右

签证：较大拒签风险

旅游线路类型：以自然观光为主

著名景点：熟悉的国家不熟悉的景点

名品购物：名品店较多

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是100 分，

请问这条线路可以打多少分

____(0-100)

旅游目的地线路 15

价格：21000 元左右

签证：较大拒签风险

旅游线路类型：以人文体验为主

著名景点：不熟悉的国家不熟悉的景点

名品购物：名品店较多

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是100分，

请问这条线路可以打多少分____(0-100)

旅游目的地线路 16

价格：9000 元左右

签证：没有拒签风险

旅游线路类型：以人文体验为主

著名景点：不熟悉的国家不熟悉的景点

名品购物：名品折扣店较多

行程安排：行程紧凑景点多

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好，待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是100分，

请问这条线路可以打多少分____(0-100)

旅游目的地线路 17

价格：17000 元左右

签证：没有拒签风险

旅游线路类型：以人文体验为主

著名景点：熟悉的国家熟悉的景点

名品购物：名品折扣店较多

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好, 待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分,

请问这条线路可以打多少分____(0-100)

旅游目的地线路 18

价格：21000 元左右

签证：没有拒签风险

旅游线路类型：以自然观光为主

著名景点：不熟悉的国家不熟悉的景点

名品购物：不适合名品购物

行程安排：行程宽松景点少

评价 A 一定不会考虑这条线路

B 一定会考虑这条线路

C 没有特殊偏好, 待定

请选择您对这条线路的评价____

评分 假设您最理想的目的地线路是 100 分,

请问这条线路可以打多少分 ____(0-100)

第二部分 基本信息

4. 性别: ❍ 男 ❍ 女

6. 年龄_____

5. 职业 _____

再次感谢您的协助!

如果您有任何疑问或建议请在下面的空白处留言或者与我们联系.

____

____

____

____

联系方式: lixcl23@nottingham.ac.uk

Final Questionnaire (English Version)

Questionnaire

Dear Sir/Madam

This is a research conducted by a PhD student of Business School, Nottingham University in the UK. The purpose of this questionnaire is to gather information about Chinese tourists' preference on long-haul destinations. The following questionnaire may take you only around five minutes, but it will be very valuable for us. And the information you provided will be treated in a confidential and anonymous manner.

Thank you very much for your participation.

Part I About your experience of outbound tourism

1 How many leisure trips abroad have you made at your own expense before, how many long-haul (non-East Asia country) among them?

2. Imagine your next long-haul international trip, who will you go with for your next international trip?

☐ Just myself

☐ Family

☐ Friends

☐ My partner

3. Please imagine you will have a long-haul international trip with the persion(s) you choose above, which takes about 8-10 days. There are 10 destinations listed below as your options (spread out in 10 cards). It doesn't mention country information in each destination, only includes combination of the necessary travel elements for each destination.

3.1 According your preference and concern on different elements, please rank these destinations from the most possible to the least possible you will travel.

____

____

.2 Please point out which destinations fit your expectation, and you will consider them more than others.

____

____

Part II Basic Information

4. Sex: ☐ Male ☐ Female

5. Age_____

6. Occupation _____

Thanks for your cooperation again!!

If you have any inquires or suggestion, please leave your comments in the blank below or contact us by email

____

____

____

____

Contact: lixcl23@nottingham.ac.uk

The 10 destination tour cards

Destination Tour 1

Price: RMB9000 per person

Visa: a bit risky to get a visa

Shopping: not good for brand product shopping

Time schedule: more free time

Famous: not well-known destination

Destination Tour 2

Price: RMB9000 per person

Visa: a bit risky to get a visa

Shopping: good for brand product shopping

Time schedule: compacted schedule

Famous: very well-known destination

Destination Tour 3

Price: RMB18000 per person

Visa: not risky to get a visa

Shopping: not good for brand product shopping

Time schedule: compacted schedule

Famous: not very well-known destination

Destination Tour 4

Price: RMB9000 per person

Visa: not risky to get a visa

Shopping: not good for brand product shopping

Time schedule: more free time

Famous: very well-known destination

Destination Tour 5

Price: RMB18000 per person

Visa: a bit risky to get a visa

Shopping: good for brand product shopping

Time schedule: more free time

Famous: very well-known destination

Destination Tour 6

Price: RMB9000 per person

Visa: not risky to get a visa

Shopping: good for brand product shopping

Time schedule: compacted schedule

Famous: very well-known destination

Destination Tour 7

Price: RMB13000-17000 per person

Visa: a bit risky to get a visa

Shopping: not good for brand product shopping

Time schedule: compacted schedule

Famous: very well-known destination

Destination Tour 8

Price: RMB13000-17000 per person

Visa: not risky to get a visa

Shopping: good for brand product shopping

Time schedule: more free time

Famous: not very well-known destination

Destination Tour 9

Price: RMB18000 per person

Visa: a bit risky to get a visa

Shopping: not good for brand product shopping

Time schedule: compacted schedule

Famous: very well-known destination

Destination Tour 10

Price: RMB9000 per person

Visa: not risky to get a visa

Shopping: not good for brand product shopping

Time schedule: compacted schedule

Famous: not very well-known destination

Appendix 2 Syntax for Conjoint analysis

1. Syntax for orthogonal design of conjoint analysis

```
ORTHOPLAN
  /FACTORS=
price (1 '9000RMB' 2 '13000RMB-17000RMB' 3 'above18000RMB')
 visa (1 'esay' 2 'a bit risky')
shopping(1 'brand shopping' 2 'not for brand shopping')
time schedule (1 'compacted with more scenic spots' 2 'more free time less scenic spots')
famousness(1 'famous destination' 3 'not famous')
  /REPLACE
  /MINIMUM 2
  /HOLDOUT 2
  /MIXHOLD NO.
_DATASET NAME questionnaire.
```

2. Ten Destination stimuli cards generated from the orthogonal design

1	2	2	2	2
1	2	1	1	2
3	1	2	1	2
1	1	2	2	1
3	2	1	2	1
1	1	1	1	1
2	2	2	1	1
2	1	1	2	2

3 2 2 1 1

1 1 2 1 2

3. Syntax for Conjoint analysis

```
/*conjoint analysis

/*the data set has to be opened - the design does not have to be opened

compute cnum=$casenum.

execute.

CONJOINT

/PLAN 'D:\... \design_b.sav'

   /FACTORS

                  Price (discrete)

                    Visa(discrete)

                    Shopping (discrete)

                    Time schedule (discrete)

                    Famousness (discrete more)

   /subject cnum

   /SCORE P to Y

   /print all

   /utility='D:\... \util_l.sav'.

get file file= "D:\... \util_l.sav".

execute.

/*calculate percentage values (importance value)

compute Price=max(Price1,Price2,Price3)+abs(min(Price1,Price2,Price3)).
```

```
compute Visa=abs(visa1)+abs(visa2).

compute Shopping=abs(shopping1)+abs(shopping2).

compute Time schedule=abs(timeschedule1)+abs(timeschedule2).

compute Famousness=abs(Famousness1)+abs(Famousness2).

compute p100=sum(Price,Visa,Shopping,Time schedule,Famousness).

compute Price=Price*100/p100.

compute Visa=Visa*100/p100.

compute    Shopping=Shopping*100/p100.

compute Time schedule=Time schedule*100/p100.

compute Famousness=Famousness*100/p100.

EXECUTE .
```

Appendix 3 Outputs for differences of different groups

1. Gender utility T-test

Group statistics

	sex	N	Mean	Std. Deviation	Std. Error Mean
9000	male	81	.5514	1.38760	.15418
	female	103	.7961	1.21826	.12004
13000	male	81	.1872	.90653	.10073
	female	103	.0874	.82647	.08143
18000	male	81	-.7387	1.29447	.14383
	female	103	-.8835	1.15354	.11366
Easy visa	male	81	.4383	.75780	.08420
	female	103	.5680	.78917	.07776
a bit risky visa	male	81	-.4383	.75780	.08420
	female	103	-.5680	.78917	.07776
Brand shopping	male	81	-.0216	.79372	.08819
	female	103	.0437	.80320	.07914
no brand shop	male	81	.0216	.79372	.08819
	female	103	-.0437	.80320	.07914
Compact	male	81	-.3426	.98063	.10896
	female	103	-.1311	1.01209	.09972
free time	male	81	.3426	.98063	.10896
	female	103	.1311	1.01209	.09972
Famous country	male	81	.3580	.82627	.09181
	female	103	.5097	.77880	.07674
not famous	male	81	-.3580	.82627	.09181
	female	103	-.5097	.77880	.07674

Independent Samples Test

Equal variances assumed	Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
9000	.770	.382	-1.272	182	.205	-.24468	.19238	-.62426	.13491
13000	.129	.720	.780	182	.437	.09986	.12810	-.15289	.35261
18000	.226	.635	.801	182	.424	.14481	.18081	-.21194	.50156
esayvisa	1.501	.222	-1.126	182	.262	-.12969	.11517	-.35694	.09756
a bit risky	1.501	.222	1.126	182	.262	.12969	.11517	-.09756	.35694
brandshopping	.000	.982	-.550	182	.583	-.06529	.11866	-.29943	.16884
no brandshop	.000	.982	.550	182	.583	.06529	.11866	-.16884	.29943
compact	.004	.948	-1.427	182	.155	-.21152	.14827	-.50407	.08102
free time	.004	.948	1.427	182	.155	.21152	.14827	-.08102	.50407
Famous country	.043	.836	-1.277	182	.203	-.15168	.11881	-.38610	.08273
not famous	.043	.836	1.277	182	.203	.15168	.11881	-.08273	.38610

2 Age utility One way ANOVA

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
9000	Between Groups	1.012	2	.506	.298	.742
13000	Between Groups	.848	2	.424	.568	.568
18000	Between Groups	3.661	2	1.830	1.241	.292
esayvisa	Between Groups	.112	2	.056	.092	.912
a bit risky	Between Groups	.112	2	.056	.092	.912
brandshop	Between Groups	1.793	2	.896	1.416	.245
no brand shop	Between Groups	1.793	2	.896	1.416	.245
full	Between Groups	11.332	2	5.666	5.958	.003
free time	Between Groups	11.332	2	5.666	5.958	.003
Famous country	Between Groups	.122	2	.061	.094	.910
not famous	Between Groups	.122	2	.061	.094	.910

Multiple comparison (Tukey HSD)

Dependent Variable	(I) age1	(J) age1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
More free time	young35	midage55	-.18223	.21846	.682	-.6985	.3340
		old	.95092*	.29261	.004	.2594	1.6424
	midage55	young35	.18223	.21846	.682	-.3340	.6985
		old	1.13315*	.34725	.004	.3125	1.9538
	old	young35	-.95092*	.29261	.004	-1.6424	-.2594
		midage55	-1.13315*	.34725	.004	-1.9538	-.3125

3. Travel companions utility ANOVA

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
9000	Between Groups	10.435	3	3.478	2.103	.101
13000	Between Groups	2.063	3	.688	.925	.430
18000	Between Groups	9.729	3	3.243	2.237	.086
esayvisa	Between Groups	.955	3	.318	.524	.666
a bit risky	Between Groups	.955	3	.318	.524	.666
brandshop	Between Groups	1.134	3	.378	.590	.622
no brand shop	Between Groups	1.134	3	.378	.590	.622
full	Between Groups	1.554	3	.518	.512	.674
free time	Between Groups	1.554	3	.518	.512	.674
famous	Between Groups	5.278	3	1.759	2.821	.040
not famous	Between Groups	5.278	3	1.759	2.821	.040

Multiple comparison (Tukey HSD)

Dependent Variable: famous country

(I) who will you go with for your next longhaul leisure trip	(J) who will you go with for your next longhaul leisure trip	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
only myself	whole family	-.66775*	.23236	.023	-1.2703	-.0652
	friends	-.48714	.26360	.254	-1.1707	.1964
	my lover	-.56917	.22899	.066	-1.1630	.0246
whole family	only myself	.66775*	.23236	.023	.0652	1.2703
	friends	.18061	.18545	.764	-.3003	.6615
	my lover	.09858	.13169	.877	-.2429	.4401
friends	only myself	.48714	.26360	.254	-.1964	1.1707
	whole family	-.18061	.18545	.764	-.6615	.3003
	my lover	-.08203	.18121	.969	-.5519	.3879
my lover	only myself	.56917	.22899	.066	-.0246	1.1630
	whole family	-.09858	.13169	.877	-.4401	.2429
	friends	.08203	.18121	.969	-.3879	.5519

4 Travel experience (outbound experience and long-haul outbound experience) T-test

Group Statistics (First-time outbound tourist)

	First-time tourists	N	Mean	Std. Deviation	Std. Error Mean
9000	.00	107	.8660	1.21474	.11743
	1.00	77	.4416	1.37484	.15668
13000	.00	107	.0810	.82706	.07995
	1.00	77	.2013	.90839	.10352
18000	.00	107	-.9470	1.21666	.11762
	1.00	77	-.6429	1.20131	.13690
esay	.00	107	.5327	.79584	.07694
	1.00	77	.4805	.75193	.08569
a bit risky	.00	107	-.5327	.79584	.07694
	1.00	77	-.4805	.75193	.08569
brandshop	.00	107	.0421	.77664	.07508
	1.00	77	-.0227	.82934	.09451
no brand shop	.00	107	-.0421	.77664	.07508
	1.00	77	.0227	.82934	.09451
full	.00	107	-.2196	.98975	.09568
	1.00	77	-.2305	1.02338	.11663
free time	.00	107	.2196	.98975	.09568
	1.00	77	.2305	1.02338	.11663
famous	.00	107	.4860	.72508	.07010
	1.00	77	.3831	.89827	.10237
not famous	.00	107	-.4860	.72508	.07010
	1.00	77	-.3831	.89827	.10237

Independent sample test

	Levene's Test for Equality of Variances		t-test for Equality of Means						
Equal variances assumed	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
9000	1.259	.263	2.212	182	.028	.42449	.19189	.04588	.80309
13000	.971	.326	-.934	182	.352	-.12030	.12881	-.37446	.13385
18000	1.777	.184	-1.682	182	.094	-.30418	.18087	-.66105	.05268
Esay visa	.262	.609	.449	182	.654	.05219	.11624	-.17715	.28153
a bit risky	.262	.609	-.449	182	.654	-.05219	.11624	-.28153	.17715
brandshop	.214	.644	.543	182	.588	.06478	.11941	-.17083	.30040
no brand shop	.214	.644	-.543	182	.588	-.06478	.11941	-.30040	.17083
compact	.374	.542	.073	182	.942	.01089	.15003	-.28513	.30691
free time	.374	.542	-.073	182	.942	-.01089	.15003	-.30691	.28513
Famous country	4.169	.043	.858	182	.392	.10286	.11985	-.13360	.33933
not famous	4.169	.043	-.858	182	.392	-.10286	.11985	-.33933	.13360

Group Statistics (First-time long-haul outbound tourist)

	First-time long haul	N	Mean	Std. Deviation	Std. Error Mean
9000	.00	133	.8571	1.22769	.10645
	1.00	51	.2484	1.38218	.19354
13000	.00	133	.0902	.84705	.07345
	1.00	51	.2386	.89830	.12579
18000	.00	133	-.9474	1.18521	.10277
	1.00	51	-.4869	1.24492	.17432
esayisa	.00	133	.5658	.79944	.06932
	1.00	51	.3676	.69884	.09786
a bit risky	.00	133	-.5658	.79944	.06932
	1.00	51	-.3676	.69884	.09786
brandshop	.00	133	.0263	.77071	.06683
	1.00	51	-.0147	.87094	.12196
no brand shop	.00	133	-.0263	.77071	.06683
	1.00	51	.0147	.87094	.12196
compact	.00	133	-.1767	.96961	.08408
	1.00	51	-.3480	1.07944	.15115
free time	.00	133	.1767	.96961	.08408
	1.00	51	.3480	1.07944	.15115
famouscountry	.00	133	.4831	.74949	.06499
	1.00	51	.3382	.92307	.12926
not famous	.00	133	-.4831	.74949	.06499
	1.00	51	-.3382	.92307	.12926

Independent Samples Test

Equal variances assumed	Levene's Test for Equality of Variances		t-test for Equality of Means						
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
								Lower	Upper
9000	1.044	.308	2.906	182	.004	.60878	.20950	.19541	1.02214
13000	.002	.964	-1.046	182	.297	-.14834	.14188	-.42828	.13160
18000	.051	.821	-2.326	182	.021	-.46044	.19796	-.85102	-.06986
esay	1.383	.241	1.556	182	.121	.19814	.12733	-.05310	.44938
a bit risky	1.383	.241	-1.556	182	.121	-.19814	.12733	-.44938	.05310
brandshop	.364	.547	.312	182	.756	.04102	.13168	-.21879	.30084
no brand shop	.364	.547	-.312	182	.756	-.04102	.13168	-.30084	.21879
full	2.828	.094	1.039	182	.300	.17135	.16486	-.15394	.49664
free time	2.828	.094	-1.039	182	.300	-.17135	.16486	-.49664	.15394
famous	4.049	.046	1.098	182	.274	.14485	.13192	-.11543	.40513
not famous	4.049	.046	-1.098	182	.274	-.14485	.13192	-.40513	.11543

5 Channel of the data collection T-test

Group statistics

	where the data was collected	N	Mean	Std. Deviation	Std. Error Mean
9000	travel agency	63	.5344	1.48655	.18729
	friends	121	.7686	1.18622	.10784
13000	travel agency	63	.1892	.87467	.11020
	friends	121	.1012	.85690	.07790
18000	travel agency	63	-.7235	1.32108	.16644
	friends	121	-.8698	1.16059	.10551
esay	travel agency	63	.5675	.78572	.09899
	friends	121	.4814	.77269	.07024
a bit risky	travel agency	63	-.5675	.78572	.09899
	friends	121	-.4814	.77269	.07024
brandshop	travel agency	63	-.0952	.81000	.10205
	friends	121	.0723	.78822	.07166
no brand shop	travel agency	63	.0952	.81000	.10205
	friends	121	-.0723	.78822	.07166
full	travel agency	63	-.0595	1.01869	.12834
	friends	121	-.3099	.98532	.08957
free time	travel agency	63	.0595	1.01869	.12834
	friends	121	.3099	.98532	.08957
famous	travel agency	63	.4048	.69912	.08808
	friends	121	.4628	.85187	.07744
not famous	travel agency	63	-.4048	.69912	.08808
	friends	121	-.4628	.85187	.07744

Independent Samples Test

Equal variances assumed	Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
9000	4.597	.033	-1.163	182	.246	-.23420	.20141	-.63160	.16319
13000	.245	.621	.656	182	.513	.08791	.13408	-.17663	.35246
18000	.713	.400	.773	182	.440	.14629	.18918	-.22697	.51955
esay	.015	.904	.713	182	.477	.08606	.12074	-.15217	.32429
a bit risky	.015	.904	-.713	182	.477	-.08606	.12074	-.32429	.15217
brandshop	.001	.970	-1.355	182	.177	-.16755	.12362	-.41147	.07637
no brand shop	.001	.970	1.355	182	.177	.16755	.12362	-.07637	.41147
full	.006	.941	1.617	182	.108	.25039	.15487	-.05517	.55596
free time	.006	.941	-1.617	182	.108	-.25039	.15487	-.55596	.05517
famous	2.598	.109	-.465	182	.642	-.05805	.12477	-.30423	.18814
not famous	2.598	.109	.465	182	.642	.05805	.12477	-.18814	.30423

Appendix 4 Programming codes

Programming codes[2] for "Greedoid analysis"

```
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package bestlex.dp;

import java.util.HashMap;
import java.util.LinkedList;
import java.util.Map;
import java.util.Queue;

import bestlex.util.CostManager;

public class ForwardDynamicSolver {

    private int[][] design;
    private int[][] partialOrder;
    private double[][] weights;
    private int numProfiles;
    private int numAspects;
    private double bestSoFar;
    private long bestSolutionKey;
    private Map<Long, TableEntry> table;
    private long numComputations;

    public ForwardDynamicSolver(int[][] design, int[][] partialOrder, double[][]
weights, double bestSoFar) {
        this.design = design;
        this.partialOrder = partialOrder;
        this.weights = weights;

        this.numProfiles = design.length;
        this.numAspects = design[0].length;

        this.bestSoFar = bestSoFar;
        this.bestSolutionKey = -1;

        // initialize table

        table = new HashMap<Long, TableEntry>();
    }

    public ForwardDynamicSolver(int[][] design, int[][] partialOrder, double[][]
```

[2] The codes for greedoid analysis was provided by Michael Yee (2007), a few modifications (e.g.finding the must-have aspect and weighted errors calculation) and program running was helped by my friend Yijun Xue.

```
weights) {
		this(design, partialOrder, weights, Double.MAX_VALUE);
	}

	public ForwardDynamicSolver(int[][] design, int[][] partialOrder) {
		this(design, partialOrder,
CostManager.generateUnitWeights(partialOrder.length), Double.MAX_VALUE);
	}

	public void solve() {
		// initialize queue

		Queue<Long> queue = new LinkedList<Long>();

		// initialize stats

		numComputations = 0;

		// add singletons to table and queue (if better than incumbent)

		for (int a = 0; a < numAspects; a++) {
			long key = (1L << a);

			CostManager costManager = new CostManager(design);

			double cost = costManager.cost(partialOrder, weights, a, true);
			numComputations++;

			if (cost < bestSoFar) {
				TableEntry tableEntry = new TableEntry();

				tableEntry.setCostManager(costManager);
				tableEntry.setNumErrors(cost);
				tableEntry.setBestLastAspect(a + 1);

				queue.add(key);
				table.put(key, tableEntry);
			}
		}

		// process queue until empty

		while (queue.size() > 0) {
			long key = queue.remove();
			TableEntry currentEntry = table.get(key);

			for (int a = 0; a < numAspects; a++) {
				if ((key & (1L << a)) == 0) {
					double tempScore = currentEntry.getNumErrors() +
currentEntry.getCostManager().cost(partialOrder, weights, a, false);
					numComputations++;
```

```
                        if (tempScore < bestSoFar) {
                            long tempKey = key + (1L << a);

                            // create update tempKey if necessary

                            TableEntry tempEntry;

                            if (table.containsKey(tempKey)) {
                                // see if this aspect beats current best last aspect

                                tempEntry = table.get(tempKey);

                                if (tempScore < tempEntry.getNumErrors()) {
                                    tempEntry.setNumErrors(tempScore);
                                    tempEntry.setBestLastAspect(a + 1);
                                }
                            } else {
                                // add new table entry to table and queue

                                CostManager costManager = new
CostManager(currentEntry.getCostManager());
                                costManager.cost(partialOrder, weights, a, true);

                                tempEntry = new TableEntry();

                                tempEntry.setCostManager(costManager);
                                tempEntry.setNumErrors(tempScore);
                                tempEntry.setBestLastAspect(a + 1);

                                table.put(tempKey, tempEntry);

                                // only add to queue if not totally differentiated
yet

                                if (tempEntry.getCostManager().getNumClasses()
< numProfiles) {
                                    queue.add(tempKey);
                                }
                            }

                            // see if totally differentiated and better than
bestSoFar

                            if (tempEntry.getCostManager().getNumClasses() ==
numProfiles) {
                                bestSoFar = tempScore;
                                bestSolutionKey = tempKey;

                                //System.out.println("new bestSoFar : " +
bestSoFar);
```

```
                                        //System.out.println("new bestSolutionKey : " +
bestSolutionKey);
                                        //System.out.println("new bestSolutionKey : " +
key2binary(bestSolutionKey));

                                        //System.out.println("bestSoFar : " + bestSoFar +
" (after " + numComputations + " computations)");
                                    }
                                }
                            }
                        }
                    }

                    //System.out.println("table size : " + table.size());
                    //System.out.println("computations : " + numComputations);
            }

            public double getNumErrors() {
                    return bestSoFar;
            }

            public int[] getAspectOrder() {
                    if (bestSolutionKey != -1) {
                            /*
                             System.out.println("bestSolutionKey : " + bestSolutionKey);
                             System.out.println("bestSolutionKey : " +
key2binary(bestSolutionKey));
                             */

                            int[] temp = new int[numAspects];

                            int size = 0;

                            long key = bestSolutionKey;

                            while (key > 0) {
                                    TableEntry entry = table.get(key);

                                    int lastAspect = entry.getBestLastAspect();

                                    temp[size] = lastAspect;

                                    size++;

                                    // convert to a 0-based aspect label

                                    if (lastAspect < 0) {
                                            lastAspect *= -1;
                                    }

                                    lastAspect--;
```

```
                    // update key

                    key -= (1L << lastAspect);
                }

                int[] aspectOrder = new int[numAspects];

                for (int i = 0; i < size; i++) {
                    aspectOrder[i] = temp[size - i - 1];
                }

                return aspectOrder;
            } else {
                return new int[numAspects];
            }
        }

        /*
         private String key2binary(int key)
         {
         String temp = "";

         for (int i = 0; i < numAspects; i++)
         {
         if ((key & (1L << i)) > 0)
         {
         temp += "1";
         }
         else
         {
         temp += "0";
         }
         }

         return temp;
         }
         */
        public void setBestSoFar(int bestSoFar) {
            this.bestSoFar = bestSoFar;
        }

        public long getNumComputations() {
            return numComputations;
        }

        public long getTableSize() {
            return table.size();
        }
    }
```

Cost manager solver


```
public CostManager(CostManager that)
  {
     this.design = that.design;

     int numProfiles = that.design.length;

     this.profileOrder = new int[numProfiles];
     this.newClassMarker = new boolean[numProfiles];

     for (int i = 0; i < numProfiles; i++)
     {
        this.profileOrder[i] = that.profileOrder[i];
        this.newClassMarker[i] = that.newClassMarker[i];
     }

     this.numErrors = that.numErrors;
     this.numClasses = that.numClasses;
  }

  public double cost(int[][] partialOrder, double[][] weights, int aspect, boolean
update)
  {
     int left = 0;
     int nextLeft = 1;

     int cost = 0;

     while (nextLeft < profileOrder.length)
     {
        if (newClassMarker[nextLeft])
        {
           if (nextLeft - left >= 2)
           {
              cost += classCost(left, nextLeft - 1, partialOrder, weights, aspect,
update);
           }

           left = nextLeft;
           nextLeft = left + 1;
        }
        else
        {
           nextLeft++;
        }
     }

     // boundary cases
```

```
        // (1) T F F T : done since next to last group already scored and last
group/singleton can't cause error
        // (2) T F F F : need to score whole last group

        if (!newClassMarker[profileOrder.length - 1])
        {
            cost += classCost(left, profileOrder.length - 1, partialOrder, weights,
aspect, update);
        }

        if (update)
        {
            numErrors += cost;
        }

        return cost;
    }

    private double classCost(int leftIndex, int rightIndex, int[][] partialOrder,
double[][] weights, int aspect, boolean update)
    {
        //System.out.println("(left, right) : " + leftIndex + ", " + rightIndex);

        int cost = 0;

        // sort class by new aspect

        int currentIndex = leftIndex;
        int firstZeroIndex = rightIndex + 1;

        while (currentIndex < firstZeroIndex)
        {
            if (design[profileOrder[currentIndex]][aspect] == 0)
            {
                firstZeroIndex--;

                int temp = profileOrder[currentIndex];
                profileOrder[currentIndex] = profileOrder[firstZeroIndex];
                profileOrder[firstZeroIndex] = temp;
            }
            else
            {
                currentIndex++;
            }
        }

        // score newly differentiated pairs according to partialOrder table

        for (int i = leftIndex; i < firstZeroIndex; i++)
        {
```

```
            for (int j = firstZeroIndex; j <= rightIndex; j++)
            {
                int p1 = profileOrder[i];
                int p2 = profileOrder[j];

                if (partialOrder[p1][p2] == -1)
                {
                    // cost++;
                    cost += weights[p1][p2];
                }
            }
        }

        // update class markers if necessary

        if (update)
        {
            if (firstZeroIndex > leftIndex && firstZeroIndex <= rightIndex)
            {
                newClassMarker[firstZeroIndex] = true;
                numClasses++;
            }
        }

        return cost;
    }

    public int getNumClasses()
    {
        return numClasses;
    }

    public void displayClasses()
    {
        for (int i = 0; i < profileOrder.length; i++)
        {
            System.out.print((profileOrder[i] < 10 ? " " : "") + profileOrder[i] + " ");
        }
        System.out.println();

        for (int i = 0; i < profileOrder.length; i++)
        {
            System.out.print(newClassMarker[i] ? " T " : " F ");
        }
        System.out.println();

        /*
        for (int i = 0; i < profileOrder.length; i++)
        {
            System.out.print((i < 10 ? " " : "") + i + " ");
        }
```

```
        System.out.println();
        */
    }

    public double getNumErrors()
    {
        return numErrors;
    }
}
```

Finding must-have aspect

By Yijun xue

```
public static void testme() {
        int[][] design = {
            {1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1},
            {1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1},
            {0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1},
            {1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0},
            {0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0},
            {1, 0, 0, 1, 0, 1, 0, 1, 0, 1, 0},
            {0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0},
            {0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1},
            {0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0},
            {1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1}};

        int[][] design2 = {
            {24, 2, 6, 4},
            {32, 2, 8, 4},
            {36, 2, 4, 3},
            {5, 3, 4, 6, 10},
            {6, 3, 6, 2, 10},
            {8, 3, 2, 4, 6},
            {19, 3, 6, 7, 4},
            {26, 3, 4, 1, 8},
            {30, 3, 4, 6, 8},
            {31, 3, 8, 2, 6},
            {33, 3, 4, 6, 10},
            {38, 3, 9, 7, 5},
            {47, 3, 6, 2, 8},
            {195, 3, 8, 4, 6},
            {199, 3, 5, 8, 2},
            {23, 7, 4, 10, 6, 1, 2, 3, 7},
            {35, 7, 6, 10, 4, 8, 3, 1, 2},
            {73, 7, 6, 2, 4, 10, 8, 1, 5},
            {200, 7, 9, 3, 8, 10, 4, 1, 7}
        };
        int numDesign = 11;//design.length ;
        int numDesign2 = design2.length;
        int listlength = 13; // bignum and small number so +2

        for (int i = 0; i < numDesign2; i++) {
            int[] alist = design2[i];
            int bignum = alist[0];
            int smallnum = alist[1];
            int alistlength = alist.length;
            int[][] result = new int[numDesign2 + 1][listlength + 1];

            int[] initlist = {0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0};
            for (int j = 2; j < alistlength; j++) {
                int d1 = alist[j] - 1;
```

```
            int[] temp = design[d1];
            for (int u = 0; u < numDesign; u++) {
                int xx = initlist[u] + temp[u];
                initlist[u] = xx;
            }
        }
        int[] areadylist = new int[listlength];
        areadylist[0] = bignum;
        areadylist[1] = smallnum;
        for (int y = 0; y < numDesign; y++) {
            areadylist[y + 2] = initlist[y];
        }
        result[i] = areadylist;
        System.out.println("solution : " + array2string(areadylist));
    }

}
```