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# Market Segmentation using Bagged Fuzzy $C$ -Means (BFCM): Destination Image of Western Europe among Chinese Travellers

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## Abstract

Market segmentation offers several strategic and tactical advantages to marketers. Hierarchical and non-hierarchical segmentation methods have several weaknesses but remain widely applied in tourism studies. Alternative segmentation methods such as fuzzy, mixture models, and Bagged Clustering are relatively less popular. In this study, we propose a novel method, the Bagged Fuzzy  $C$ -Means (BFCM) algorithm, for segmenting tourism markets. A sample of 328 Chinese travellers revealed the existence of four segments (Admirers, Enthusiasts, Moderates, and Apathetics) of perceived images for Western Europe. BFCM is able to identify stable clusters, inheriting this feature from Bagged clustering method. Furthermore, fuzzy allocation allows to identify travellers whose profiles match with more than one cluster. Destination marketers need to proactively manage the image of Western Europe to attract the increasingly discerning Chinese traveller. Information provision and on-line presence strategies will be critical for destination success.

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# 1 Introduction

Market segmentation is critical for developing effective and engaging customer centric strategies. Effective segmentation leads to competitive advantage, recognition and exploitation of new market opportunities, selection of the appropriate target market, enhanced differentiation and positioning, and increased profitability (Dibb and Simkin, 2009; Dolnicar and Leisch, 2003, 2010; Tuma et al., 2011). Despite the appealing strategic and tactical benefits of market segmentation, there is much controversy surrounding the most commonly used methods and algorithms to segment consumer markets. Cluster analysis remains the most favoured method (Dolnicar, 2002; Jain, 2010; Wedel and Kamakura, 2000). The basic idea of cluster analysis is to divide a heterogeneous consumer market into homogeneous sub-groups (Punj and Stewart, 1983). This approach is typically representative of data driven segmentation methods (Dolnicar, 2002, 2004). Cluster analysis has been criticized for its overestimation of the validity of the segmentation results (Dolnicar, 2002; Dolnicar and Lazarevski, 2009) and no single clustering algorithm achieves satisfactory clustering solutions for all types of data sets (Ghaemi et al., 2009). The resulting clusters have been termed “convenient fictions” (Babinec, 2002), a marketing term that refers to the fact that no “natural groupings” and some information is inevitably lost when objects are grouped. Information loss is not problematic *per se*, but it can result in the wrong conclusions (Franke et al., 2009). Hence, there is no successful segmentation without an appropriate clustering algorithm (Dolnicar, 2003; Dolnicar and Leisch, 2010). In fact, the key to using cluster analysis is to know when the identified groups are “real” and not merely imposed on the data by the clustering method (Aldenderfer and Blashfield, 1984). Every clustering algorithm has advantages and drawbacks and has to be chosen with awareness of its characteristics and limitations (Dolnicar, 2002; Tuma et al., 2011). Several parameters, such as number of clusters chosen, the distance measure chosen, and the variables included, of the clustering computation can impact heavily on the final solution (Dolnicar and Lazarevski, 2009; Tuma et al., 2011). Furthermore, different clustering algorithms produce different solution (Dimitriadou et al., 2002b; Venugopal and Baets, 1994) and present different aspects of the data (Leisch, 2006).

Clustering methods are generally split into three groups: non-overlapping, overlapping

and fuzzy algorithms. In a non-overlapping algorithm, each element to be grouped belongs to a single segment only (Tuma et al., 2011). In overlapping algorithms, an object may belong to more than one cluster (Wedel and Kamakura, 2000). In contrast, fuzzy algorithms assign each object a degree of membership in a segment (Franke et al., 2009; Tuma et al., 2011).

Hierarchical (agglomerative) and non-hierarchical (iterative partitioning) methods are two common non-overlapping algorithms that permeate the marketing and tourism literature (Dolnicar, 2002, 2003; Dolnicar and Leisch, 2004; Tuma et al., 2011).

Ward's method remains popular among agglomerative hierarchical algorithms (Dolnicar, 2002; Tuma et al., 2011). Hierarchical methods typically become difficult with increasing sample sizes (Dolnicar, 2002; Dolnicar and Leisch, 2004; Venugopal and Baets, 1994) and like other data driven segmentation methods, the computational requirements demand the researcher to make several decisions (e.g. the choice of a measure of dissimilarity between units). The decisions accentuate the possibility of potential misinterpretations or choosing suboptimal procedures (Dolnicar and Grün, 2008). The application of hierarchical methods is not always justified in market segmentation given that it presupposes an underlying hierarchy among the objects or respondents to be clustered (Tuma et al., 2011).

Among iterative partitioning methods,  $k$ -means remains the most popular (Arimond and Elfessi, 2001; Dolnicar, 2002; Lilien and Rangaswamy, 1998; Tuma et al., 2011). "Iterative partitioning methods start with a random splitting of the observations and the reallocation of the respondents in order to optimize a pre-defined criterion" (Dolnicar, 2002, p. 9). Partitioning methods such as  $k$ -means suffer from: (1) identifying equally sized clusters when in reality such patterns rarely exist in empirical data; (2) the clustering solution is dependent on the starting solution and the possibility of building a marketing strategy based on weak data analysis is high; (3) the outcome of cluster analysis is much dependent on the characteristics of the data set but such characteristics are not always accounted for; (4) repeated computations typically lead to different grouping of respondents suggesting that solutions may be irreproducible; (5) the lack of published rules about how large the sample size should be in relation to the number of segmentation variables used leads to deceptive and uncritical partitioning exercises (Dimitriadou et al., 2002a; Dolnicar,

2003; Dolnicar and Leisch, 2004; Dolnicar et al., 2012; Jain, 2010). In a typical  $k$ -means segmentation study, a researcher begins essentially “blind” (Arimond and Elfessi, 2001).

Accordingly, alternative methods such as Neural Networks (Bloom, 2004; Kim et al., 2003; Mazanec, 1995), the family of finite mixture models (Wedel and Kamakura, 2000), including latent class analysis (Alegre et al., 2011; Mazanec and Strasser, 2007), and rough clustering (Voges, 2007), amongst many others, have been proposed to overcome some of the limitations of hierarchical and partitioning methods.

Furthermore, the exploratory nature of clustering can also be strengthened by combining the strengths of individual clustering algorithms (Ghaemi et al., 2009). An early example of this approach is the two-stage clustering (Punj and Stewart, 1983) that integrates a hierarchical method, such as Ward’s method, along with a non-hierarchical method, such as the  $k$ -means, in order to obtain a better solution respect to the application of each method individually. More recently, Kuo et al. (2002) suggested a modify version of the two-stage clustering in which a Self-Organizing Map (SOM) (Kohonen, 1989) is used in order to determine the number of clusters to use in the  $k$ -means algorithm, which is then applied in order to find the final solution.

In the last years also the “ensemble methods” (Strehl and Ghosh, 2002), among which the most popular are the voting approach (Dimitriadou et al., 2002b) and the Bagged Clustering (Leisch, 1999; Dolnicar and Leisch, 2003, 2004; Dolnicar et al., 2008), have been successfully applied in different ways to enhance the performance of unstable or weak clustering algorithms (Leisch, 1999). In fact, these approaches outperformed single clustering algorithms on *robustness* (better performance across domains and datasets), *novelty* (finding a combined solution unattainable by any single clustering algorithm), *stability* (clustering solutions with lower sensitivity to outliers or sampling variations), and *parallelization* (parallel clustering of data subsets with subsequent combination of results) (Ghaemi et al., 2009; Leisch, 1999; Topchy et al., 2005; Voges, 2007).

Yet, no clustering methods can be superior across data sets (Jain, 2010; Punj and Stewart, 1983; Tuma et al., 2011; Wedel and Kamakura, 2000). The chosen algorithm should allow for the suspected clusters to be identified, effective in this identification, insensitive to error, and appropriate for the data at hand (Everitt et al., 2001). Given the prevalence of partitioning and hierarchical methods in marketing (Jain, 2010; Voges,

2007) and tourism studies (Dolnicar et al., 2012), researchers have applied these methods uncritically, often without acknowledging the limitations of the chosen algorithms (Dolnicar and Grün, 2008). Hence, the main objective of the study is to apply a novel segmentation method, Bagged Fuzzy  $C$ -Means (BFCM), to derive market segments and to illustrate how this method overcomes some of the weaknesses of traditional methods. BFCM is applied on a sample of Chinese travellers' perceived images of Western Europe. By doing so, the contributions of the study are threefold. First, BFCM is a clustering ensemble method that combines the strengths of single algorithms. For example, the application of bagging to cluster analysis can substantially improve clustering accuracy and the algorithm is more robust than traditional methods (Leisch, 1999; Dolnicar and Leisch, 2004). That is, the accuracy of the bagging algorithm is less sensitive to the number and type of variables used in the clustering (Ghaemi et al., 2009). As a result, the derived segments are more robust and stable than traditional segmentation methods (Ghaemi et al., 2009; Topchy et al., 2005). Second, tourism image segmentation and the use of cluster analysis to understand image perceptions are popular topics in the literature (Pike, 2002; Gallarza et al., 2002). However, the widespread use of hierarchical and non-hierarchical methods in many image segmentation studies (e.g., Ahmed, 1996; Leisen, 2001; Prayag, 2010, 2012) cast doubt on the stability and reproducibility of the identified clusters. By using BFCM to segment images of Western Europe, we offer clusters that are stable and reproducible, and thus, of managerial significance for destination marketers and service providers interested in tracking destination image. Third, tourism market segmentation in general relies on the inherent assumption that respondents can only belong to one cluster (Li et al., 2013) and the most common way to capture destination image is via Likert scales (Dolnicar and Grün, 2013; Gallarza et al., 2002). Recent studies challenge these assumptions by demonstrating that destination image is best captured using binary formats rather than Likert scales (Dolnicar and Grün, 2013) and allowing segments to overlap can offer valuable information on destination attributes for positioning (Li et al., 2013). Image evaluations on Likert scales can be transformed into fuzzy data, to take into account the uncertainty and inaccuracy due to subjective evaluation. Extending the above mentioned studies, this transformation prior to clustering does not affect stability of the solutions. In addition, the use of fuzzy clustering in market segmentation relaxes the assumption of exclusiveness,

that is, a respondent can belong to several clusters without negatively impacting on their managerial usefulness. In a review of 210 articles, inclusive of marketing and tourism studies, Tuma et al. (2011) found only 2% of segmentation studies use fuzzy methods. The use of fuzzy *C*-means (FCM) for segmentation has many advantages. First, each data point can be a member of multiple clusters with a membership value (Jain, 2010) and this concept of partial membership is more appealing and flexible than classical clustering procedures (McBratney and Moore, 1985; Wedel and Kamakura, 2000). Furthermore, the fuzzy clustering models are computationally more efficient because dramatic changes in the value of cluster membership are less likely to occur in estimation procedures (McBratney and Moore, 1985). Finally, the fuzzy clustering has been shown to be less afflicted by local optima problems in the estimation procedures (Heiser and Groenen, 1997).

## 2 Theoretical Background

### 2.1 Destination image

Destination image has been the subject of considerable academic interest in the last four decades. To date, there is no accepted definition of destination image (Bigné et al., 2009; Pike, 2002; Gallarza et al., 2002; Tasci et al., 2007) but the literature converges around image being both a personal and social construction (Chen et al., 2012; Espelt and Benito, 2005; Kanemasu, 2013; Tasci and Gartner, 2007). For the purpose of this study, we focus on the personal construction of destination image and define it as the sum of beliefs, ideas, and impressions that a person has of a destination (Crompton, 1979). Destination image is constructed on the basis of a few selected impressions among a flood of impressions (Fakeye and Crompton, 1991), which may include prejudice, imaginations and emotional thoughts (Lawson and Bond-Bovy, 1977). Destination image has direct effects on pre, during and post trip tourist behaviour (Tasci and Gartner, 2007) and has been studied from three perspectives: image components, competitive analysis, and segmentation (Bigné et al., 2009, 2001; Gallarza et al., 2002; Pan and Li, 2011). Studies on the image components generally conclude a tri component structure (cognitive, affective, and conative) prevails, whereby the cognitive component influences the affective and conative (Gallarza et al., 2002; Pike and Ryan, 2004; Tasci et al., 2007). Alternatively, Baloglu and McCleary (1999) suggest



that the cognitive and affective components contribute to form an overall image of destination, also known as the composite image (Ahmed, 1996; Bigné et al., 2001). Likewise, Echtner and Ritchie (2003) suggest a three-dimensional image model of common/unique, functional/psychological, and holistic/attribute-based that fits the multiple-attribute measurement approach commonly used in tourism studies. More recently, Lai and Li (2012) propose a two dimensional model of core and periphery structure of destination image that highlights the complex, pluralistic, and constructed nature of mental structures. This approach confirms that destination image is complex, relativistic, dynamic and of multiple nature (Gallarza et al., 2002; Stepchenkova and Mills, 2010).

The second perspective of competitive analysis seeks to identify the image of a destination vis-à-vis its competitors (Bigné et al., 2009, 2001; Gallarza et al., 2002) and assesses destination competitiveness (Andrades-Caldito et al., 2013). Typically, a list of destination attributes is evaluated for one or more competitors and recommendations for image positioning are offered (Calantone et al., 1989; Cracolici and Nijkamp, 2009; Dolnicar and Grabler, 2004; Kim et al., 2005; Gartner, 1989; Pike and Ryan, 2004). The common image attributes identified allow the destination to establish point-of-parity associations, while the unique image attributes can be used to establish point-of-difference associations (Keller, 2003; Prayag, 2012). For competing destinations, the “uniqueness image” provides destination marketers with the most meaningful and relevant attributes for destination positioning in each targeted segment (Stepchenkova and Morrison, 2008). Overall, competitive analysis research suggests that images can be influenced, manipulated, and even (re)created to position a destination favorably in consumers’ minds (Ashworth and Goodall, 1990; Dolnicar and Grün, 2013).

### **2.1.1 Image segmentation**

The third perspective, image segmentation is the focus of our study. Within image segmentation studies, two distinct approaches exist: a priori (e.g., Crompton, 1979; Castro et al., 2007; Fakeye and Crompton, 1991; Joppe et al., 2001; Obenour et al., 2005; Ryan and Cave, 2005; Stepchenkova and Li, 2012) and post-hoc (e.g., Baloglu, 1997; Beerli and Martin, 2004; Leisen, 2001; Prayag, 2012; Schroeder, 1996). The segmentation of images is not only prevalent in tourism studies but has also been related to benefit segmentation.

Researchers have used the push and pull attributes of destinations for benefit segmentation (Frochot, 2005; Jang et al., 2002; Park and Yoon, 2009). While the push attributes generally refer to motives for travel, the pull attributes are related to the features, attractions, and other attributes of the destination itself (Klenosky, 2002). The pull attributes have also been described as images (Baloglu and McCleary, 1999; Prayag and Ryan, 2011) and hence, segmented in an effort to evaluate perceptions of place (e.g., Kau and Lim, 2005; Li et al., 2013; Prayag, 2010; Sarigöllü and Huang, 2005; Tkaczynski et al., 2010). Visitors' evaluation of the pull attributes inevitably consists of an internal assessment of the cognitive, affective and holistic components of destination image (Prayag and Ryan, 2011). Yet the majority of image studies evaluates only cognitive images (Pike and Ryan, 2004), because such images are more easily recalled by visitors than affective ones (Baloglu and McCleary, 1999; Ryan and Cave, 2005). The focus on image identification from cognitive processing and the use of self-reported measures is not without limitations (Yang et al., 2012).

Existing studies on segmentation of destination images or pull attributes have relied on a variety of techniques including, cluster analysis (Bieger and Laesser, 2002; Prayag, 2012; Prayag and Hosany, 2014; Tkaczynski et al., 2010), factor-cluster analysis (Kau and Lim, 2005; Kim et al., 2003; Leisen, 2001; Prayag, 2010; Sarigöllü and Huang, 2005), factor analysis and *t*-test/ANOVA (Baloglu, 1997; Beerli and Martin, 2004; Schroeder, 1996), factor analysis and regression (Jang and Wu, 2006), rough clustering (Voges, 2007), discriminant analysis (Obenour et al., 2005), canonical correlation analysis (Li et al., 2013), and multi-dimensional scaling (Gartner, 1989). The use of a factor-cluster approach for segmentation in general has been heavily criticized in the marketing and tourism literature (see Dolnicar and Grün, 2008; Tuma et al., 2011), often leading to irreproducible clusters. The *k*-means algorithm is prevalent in most of the studies utilizing cluster analysis but its limitations and the stability of identified results are almost never discussed. The use of a structured list of destination attributes for measurement purposes is also heavily criticized (Dolnicar and Grabler, 2004; Dolnicar and Grün, 2013; Stepchenkova and Li, 2012). Stepchenkova and Mills (2010) highlight the need for newer methods to understand destination image. Using the concept of image diversity (richness, evenness and dominance indices), Stepchenkova and Li (2012) explored inter-group perceptions of image based on

qualitative information. While this approach is certainly useful, the value (stability, robustness, and reproducibility) of traditional segmentation approaches using structured lists of attributes can be enhanced by using ideas borrowed from other approaches including machine learning and knowledge discovery, computational intelligence, pattern recognition, fuzzy sets, and Bayesian techniques (Jain, 2010; Voges, 2007).

## **2.2 Chinese Travellers Images of Western Europe**

Understanding Chinese outbound tourists' expectations and perceptions of the west is still in its infancy (Li et al., 2010, 2011). With the euro zone crisis and austerity measures crimping travel budgets in Europe, Western Europe is looking outside its traditional source markets for revenues (Bryan and Kane, 2013). Chinese travel in Europe remains well ahead of economic growth, with the majority of European destinations reporting double digit increases in terms of arrivals and overnight stays (European Travel Commission, 2013). While the number of arrivals is growing, Europe's share of the Chinese outbound travel market is slightly but steadily declining. A better understanding of the profile and needs of Chinese travellers, together with a critical review of legal and cultural barriers to travel are necessary to tap into this market (European Travel Commission, 2012). In particular, understanding the perceived image of Europe among potential Chinese travellers is necessary for effective destination marketing. While Chinese tourists perceptions of western countries such as United States (Li and Stepchenkova, 2012; Stepchenkova and Li, 2012), Australia (Li and Carr, 2004; Sparks and Pan, 2009; Yu and Weiler, 2001), and New Zealand (Ryan and Mo, 2002) have been researched, fewer academic studies are devoted to understanding the image of Western Europe and/or individual countries within this region (Corigliano, 2011). In fact, Cai et al. (2008) meta review of the Chinese outbound travel market confirms that Europe is an under-researched context. In contrast, a prolific trade literature on the Chinese market has emerged in recent years from various sources (e.g., VisitBritain, Euromonitor, European Travel Commission, TUI Think Tank, Financial Times, etc.), but these do not always assess perceived images of the region of Western Europe. A study by the Boston Consulting Group (BCG) in 2011 revealed that the Chinese outbound market consists of three distinct segments: the inexperienced, the experienced mass market, and the experienced affluent travellers. Each segment has

different push and pull motivations. For example, the inexperienced travellers are driven by the need for sightseeing and perceive travel as a life time dream. In contrast, the experienced mass traveller perceives travel as an indication of status and special occasions, with sightseeing and relaxation being important trip activities. For the experienced affluent travellers, entertainment, shopping, and luxury accommodations are more important than overscheduled sightseeing (BCG, 2011).

Within Western Europe, Chinese travellers have strong preferences for particular countries. Kim et al. (2005), for example, comparing the preferences of Chinese tourists for overseas travel found that France (ranked first), Italy (ranked sixth), Germany (ranked seventh), and Spain (ranked tenth) were among the most preferred destinations. More recently, a survey of Chinese middle income outbound tourists by the Financial Times in 2012, found the most popular intended travel destination in 2013 would be France, UK, Italy, Germany, and Switzerland (VisitBritain, 2013). France and Italy are closely associated with romance and lifestyle while Germany is perceived as the gateway to Europe (VisitBritain, 2013). Early studies suggest that Chinese travellers tend to prefer spectacles rather than seek authenticity (Shepherd, 2009) but recent studies show that an authentic cultural experience is valued highly by such visitors (VisitBritain, 2013). The Chinese outbound market to other western countries shows that travellers highly value scenic beauty, safety, value for money, infrastructure, quality food, and quality accommodation. For example, Chinese tourists to Australia rated local infrastructure (e.g., safety and quality of accommodation) and natural beauty/climate as the most important destination attributes but evaluated local culture and social characteristics of the destination (e.g., western food, nightlife and evening entertainment etc.) as the least important (Sparks and Pan, 2009). For a pleasure trip, they also typically like to visit famous attractions, experience different cultures, and obtain good service in hotels/restaurants (Yu and Weiler, 2001). Chinese tourists travelling to the US are concerned about the inadequate facilities of hotels/accommodations (e.g., hot water for drinking) and availability of Chinese food (Li et al., 2011). Food related attributes such as variety and diversity of food and tourists' own food culture have an impact on Chinese tourists' evaluations of their travel dining experience (Chang et al., 2011). They expect convenient transportation and opportunities for shopping (Li et al., 2011). Travel to Europe is mainly for the cultural experience and

shopping (VisitBritain, 2013). However, similar to the US (Lai et al., 2013) visa requirement to Western Europe is perceived as a major constraint by Chinese travellers. In 2012, the French and German governments created a joint visa office in Beijing to further fast track Chinese visitors' applications for a Schengen visa (Samuel, 2013). European countries need to focus less on beach holidays and more on history, landscape, and even poetic trees to take advantage of growing numbers of tourists from China. Chinese tourists want to visit places with historical relevance to their own culture and want to escape the smog back home (Bryan and Kane, 2013). Hence, Chinese tourist perceptions will most likely include stereotypical, affective and unique images of Western Europe as were found in the case of the US (Li and Stepchenkova, 2012).

### **3 The case study**

#### **3.1 Data Collection and Sample Characteristics**

Data for this study were collected from a survey in Beijing as part of a larger study on Chinese perceptions of Western Europe. Beijing is known for its high propensity to travel and its trend setting status in lifestyle (Hsu et al., 2010). Two trained interviewers approached potential respondents outside convenient locations such as high street shopping centers, leisure centers, tourist attractions, and local universities, following a procedure adapted from the study of Hsu et al. (2010) on the Chinese market. A screening question, adapted from Li et al. (2013) and Pan and Li (2011), on the potential respondent intention to travel to Western Europe was used to identify the correct target population of 18 to 44 years old. Intention to travel may not accurately reflect actual behaviour (McKercher and Tse, 2012), but can be used as a reliable indicator to understand tourism outbound markets (Li et al., 2013; VisitBritain, 2012). The target population of 18 to 44 years old is not only the largest group, but also has the highest propensity for outbound travel (Euromonitor, 2011). Within this group, the 30 to 44 years old is a well-educated segment in their prime earning years (Tse and Hobson, 2008). The younger segment of the target population is also more autonomous (Sparks and Pan, 2009) and is already travelling as students in Western Europe (Euromonitor, 2011). Likewise, the 21 to 35 years old are well educated and part of an emerging independent travel segment (Chen et al., 2013). Hence, the focus on the

age group of 18 to 44 years old potentially captures visitors with diverse travel orientations (group vs. independent travel) and perceptions. Of the 600 questionnaires distributed, 328 were usable, representing a response rate of 54.6%. The demographic profile of the sample indicates more female (57%) than male respondents, mostly single (60%), less than 26 years old (51%), with some university/college degree (59%) or postgraduate degree (36%), and earning an average monthly income of less than RMB 7,000 (67%). Of the respondents, 54% had a full time job while 43% described themselves as students. Respondents will travel for holiday (84%) and studying purposes (19%) mostly. First-time visitors (75%) to Western Europe would constitute the majority.

### 3.2 Survey Instrument

To capture Chinese travellers' perceptions, 21 image attributes measured the tourism product generally offered to Chinese travellers such as attractive scenery and natural attractions and cultural/historical attractions (Corigliano, 2011; Kim et al., 2005; Li et al., 2011; Sparks and Pan, 2009; Su, 2011; Yu and Weiler, 2001), and the more general images of Western Europe such as cities with modern technology, quality accommodation, and quality tourist services (BCG, 2011; Shepherd, 2009; TUI Think Tank, 2012; VisitBritain, 2013). The items were measured on a bipolar 7-point Likert scale anchored on [1] *Offers very little* and [7] *Offers very much*. Demographics, including gender, marital status, age, level of education, and income, as well as traveling characteristics, such as type of preferred accommodation, proposed length of stay on a trip to Western Europe, countries most likely to visit, and information sources most likely to use to plan a trip were also measured. The survey instrument originally designed in English was translated in Chinese. Back translation was used to assess the accuracy of meaning and content of the Chinese version. The translated version was further verified by one Chinese professor proficient in both languages. The questionnaire was pilot tested in Beijing among 20 respondents from the targeted group and revealed only minor problems that were subsequently amended in the final version. Figure 1 displays the percentage distribution for each image attribute measured. Typically, "attractive scenery and natural attractions" is the perceived image offered the most by Western Europe to Chinese travellers. Attributes such as "Festivals, events, and shows", "Quality shopping experiences", and "Language barriers" are perceived

as “lesser” offered by Western Europe.

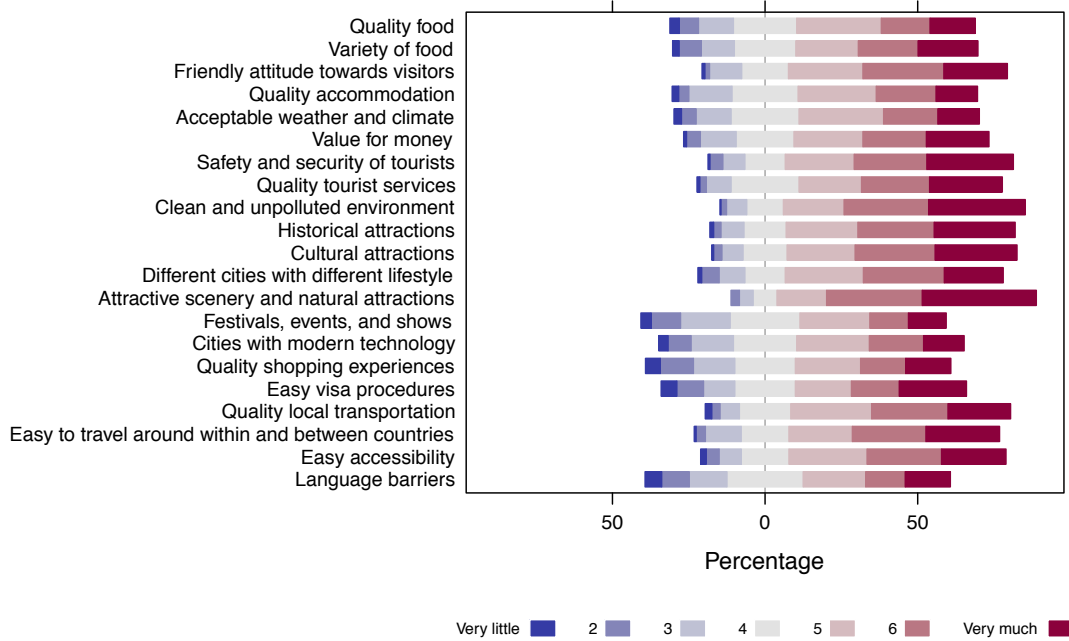


Figure 1: % distribution for each image attribute.

### 3.3 The Clustering Methodology

Clustering is subject to several sources of uncertainty concerning, amongst others, the assignment of units to clusters and imprecision/vagueness of observed features (Coppi et al., 2012; Dolnicar, 2003). The assignment of units to clusters can be improved by adopting a fuzzy approach. Fuzzy clustering is a classification method that allows units to belong to more than one cluster simultaneously, as opposed to traditional clustering which results in mutually exclusive clusters (Bezdek, 1981). Units are assigned to each cluster with a membership degree that represents a measure of the level of uncertainty (vagueness) in the assignment process. Conversely to crisp clustering in which the membership degrees can assume values 1 if the unit belong to the cluster observed, or 0 otherwise, in fuzzy clustering membership degrees can assume values between 0 and 1. The greater the membership degree of the unit to a given cluster, the greater is the confidence in assigning the unit to that cluster. This approach has the advantage of capturing the vague (fuzzy) behaviour of particular units (Kruse et al., 2007). This is not unreasonable in market segmentation given that customers may share some characteristics to more than one segment (Hruschka, 1986).

Hence, assigning a customer to only one cluster entails a loss of information (Chiang, 2011). In addition, fuzzy clustering methods have other advantages such as the algorithm is less affected by local optima issues (D’Urso, 2007; Heiser and Groenen, 1997) in comparison to more traditional (crisp) methods. It is also computationally more efficient, since significant changes of cluster membership rarely occur in the classification procedure (Coppi et al., 2012; McBratney and Moore, 1985).

In machine learning and knowledge discovery, researchers tend to analyze “precise” (non-vague) data, as exact results of observations and/or of measurements. However, in many real-life situations the observations may be defined vaguely and measurements may be imprecise (D’Urso, 2007; Hung and Yang, 2005). Furthermore, linguistic expressions are often used in order to formulate both scientific propositions and empirical data (Coppi et al., 2012). For example, information gathered in marketing and tourism is often referred to attitudes, emotions, opinions, feelings, satisfactions, and descriptions of people’s environment. Such information is usually collected using Likert-type scales. In destination image research, for example, Likert scales are the predominant answer format (Dolnicar and Grün, 2013). The widespread use of Likert scales is related to the ease of developing and administering them. A significant drawback of linguistic expressions on a Likert scale is that it represents subjective knowledge (D’Urso, 2007; D’Urso et al., 2013; Hung and Yang, 2005). The use of such scales incorporates a certain degree of imprecision, ambiguity, and uncertainty, due to the subjective meaning that each individual attributes to each value of a rating scale (Benítez et al., 2007; D’Urso, 2007). To cope with this uncertainty, we formalize the empirical information gathered in this study in a fuzzy framework. In particular, “imprecise” data are represented by fuzzy numbers, which are able to capture and measure the uncertainty and the heterogeneity of the individual evaluation (Benítez et al., 2007; Coppi and D’Urso, 2002; Sinova et al., 2012). Furthermore, fuzzy numbers have a very intuitive meaning, which can be easily grasped by potential users. Fuzzy numbers can also be adapted to a wide range of imprecise data, due to the richness of the scale of fuzzy numbers (including real and interval values as special elements) (Sinova et al., 2012).



A general class of fuzzy data, called  $LR_2$  fuzzy data, can be defined as follows:

$$\tilde{\mathbf{X}} \equiv \{\tilde{x}_{ik} = (c_{1ik}, c_{2ik}, l_{ik}, r_{ik})_{LR} : i = 1, \dots, N; k = 1, \dots, K\}, \quad (1)$$

where  $\tilde{x}_{ik} = (c_{1ik}, c_{2ik}, l_{ik}, r_{ik})_{LR}$  denotes the  $LR$  fuzzy variable  $k$  observed on the  $i$ th object;  $c_{1ik}$  and  $c_{2ik}$  indicate the left and right center;  $l_{ik}$  and  $r_{ik}$  represent the left and right spread. A particular case of  $LR_2$  fuzzy data are the  $LR_1$  fuzzy data, in which  $c_{1ik}, c_{2ik} (i = 1 \dots, N; k = 1 \dots, K)$ .

For the  $LR_2$  fuzzy data (1), we can consider the following membership functions:

$$\mu_{x_{ik}}(u_{ik}) = \begin{cases} L\left(\frac{c_{1ik} - u_{ik}}{l_{ik}}\right) & u_{ik} \leq c_{1ik} (l_{ik} > 0) \\ 1 & c_{1ik} \leq u_{ik} \leq c_{2ik} \\ R\left(\frac{u_{ik} - c_{2ik}}{r_{ik}}\right) & u_{ik} \geq c_{2ik} (r_{ik} > 0) \end{cases} \quad (2)$$

where  $L$  (and  $R$ ) is a decreasing “shape” function from  $\mathfrak{R}^+$  to  $[0, 1]$  with  $L(0) = 1$ ;  $L(z_{ik}) < 1$  for all  $z_{ik} > 0$ ,  $\forall i, j$ ;  $L(z_{ik}) > 0$  for all  $z_{ik} < 1$ ,  $\forall i, j$ ;  $L(1) = 0$  (or  $L(z_{ik}) > 0$  for all  $z_{ik}$  and  $L(+\infty) = 0$ ).

A particular case of  $LR_2$  fuzzy data is the “trapezoidal” one, with the following membership function:

$$\mu_{x_{ik}}(u_{ik}) = \begin{cases} 1 - \frac{c_{1ik} - u_{ik}}{l_{ik}} & u_{ik} \leq c_{1ik} (l_{ik} > 0) \\ 1 & c_{1ik} \leq u_{ik} \leq c_{2ik} \\ 1 - \frac{u_{ik} - c_{2ik}}{r_{ik}} & u_{ik} \geq c_{2ik} (r_{ik} > 0). \end{cases} \quad (3)$$

The Fuzzy  $C$ -Means (FCM) algorithm for fuzzy data introduced by Coppi et al. (2012) allows us to effectively address both issues mentioned at the beginning of the section.

The objective function to be minimized is the following:

$$\left\{ \begin{array}{l} \min : \sum_{i=1}^N \sum_{c=1}^C u_{ic}^m d_F^2(\tilde{\mathbf{x}}_i, \tilde{\mathbf{h}}_c) \\ \sum_{c=1}^C u_{ic} = 1, \quad u_{ic} \geq 0, \\ w_C \geq w_S \geq 0; w_C + w_S = 1 \end{array} \right. \quad (4)$$

where:  $m > 1$  is a weighting exponent that controls the fuzziness of the obtained partition;  $u_{ic}$  indicates the membership degree of the  $i$ th unit in the  $c$ th cluster;  $d_F^2(\tilde{x}_i, \tilde{h}_c)$  represents the suggested dissimilarity measure between the  $i$ th unit and the prototype of the  $c$ th cluster; the fuzzy vector  $\tilde{\mathbf{h}}_c \equiv \{\tilde{h}_{ck} = (h_{ck}^{C_1}, h_{ck}^{C_2}, h_{ck}^L, h_{ck}^R)\}$  represents the fuzzy prototype of the  $c$ th cluster.

The dissimilarity  $d_F^2$  is measured by comparing the fuzzy data observed on each unit, i.e. considering the distances for the centers and the spreads of the fuzzy data and using a suitable weighting system for such distance components. By considering the  $i$ th and  $i'$ th units, Coppi et al. (2012) proposed the following squared (Euclidean) distance measure:

$$d_F^2(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_{i'}) = [w_C^2 (\|\mathbf{c}_{1i} - \mathbf{c}_{1i'}\|^2 + \|\mathbf{c}_{2i} - \mathbf{c}_{2i'}\|^2) + w_S^2 (\|\mathbf{l}_i - \mathbf{l}_{i'}\|^2 + \|\mathbf{r}_i - \mathbf{r}_{i'}\|^2)], \quad (5)$$

where  $\tilde{\mathbf{x}}_i \equiv \{\tilde{x}_{ik} = (c_{1ik}, c_{2ik}, l_{ik}, r_{ik})_{LR} : j = 1, \dots, K\}$  denote the fuzzy data vector for the  $i$ th object;  $\mathbf{c}_{1i} \equiv (c_{1i1}, \dots, c_{1ik}, \dots, c_{1iK})'$ ,  $\mathbf{c}_{2i} \equiv (c_{2i1}, \dots, c_{2ik}, \dots, c_{2iK})'$ ,  $\mathbf{l}_i \equiv (l_{i1}, \dots, l_{ik}, \dots, l_{iK})'$  and  $\mathbf{r}_i \equiv (r_{i1}, \dots, r_{ik}, \dots, r_{iK})'$ ;  $\|\mathbf{c}_{1i} - \mathbf{c}_{1i'}\|^2$  and  $\|\mathbf{c}_{2i} - \mathbf{c}_{2i'}\|^2$  are the squared Euclidean distances between the left and right centers, respectively;  $\|\mathbf{l}_i - \mathbf{l}_{i'}\|^2$  and  $\|\mathbf{r}_i - \mathbf{r}_{i'}\|^2$  are the squared Euclidean distances between the left and right spread, respectively;  $w_C, w_S \geq 0$  are suitable weights for the center component and the spread component of (5). Note that in (4) the weights are endogenously detected, during the optimization process.

The distance (5) is a weighted sum of the centers and of the spreads distances. To ensure that the centers distance plays a more relevant role (at the most an equivalent role) than the spreads distance, we set the following conditions on the weights:  $w_C + w_S = 1$  (*normalization condition*) and  $w_C \geq w_S \geq 0$  (*coherence condition*) (Coppi et al., 2012).

Let indicate with  $\mathbf{h}_c^{C_1} \equiv (h_{c1}^{C_1}, \dots, h_{ck}^{C_1}, \dots, h_{cK}^{C_1})$ ,  $\mathbf{h}_c^{C_2} \equiv (h_{c1}^{C_2}, \dots, h_{ck}^{C_2}, \dots, h_{cK}^{C_2})$ ,  $\mathbf{h}_c^L \equiv (h_{c1}^L, \dots, h_{ck}^L, \dots, h_{cK}^L)$  and  $\mathbf{h}_c^R \equiv (h_{c1}^R, \dots, h_{ck}^R, \dots, h_{cK}^R)$  the  $K$ -dimensional vectors whose

$k$ th element refers to the  $k$ th variable, which denote, respectively, the (left and right) centers and the (left and right) spreads of the  $c$ th fuzzy prototype.

Solving the constrained optimization problem (4) by means of the Lagrangian multiplier method, the local optimal solutions are (Coppi et al., 2012):

$$u_{ic} = \frac{[w_C^2[d^2(\mathbf{c}_{1i}, \mathbf{h}_c^{C_1}) + d^2(\mathbf{c}_{2i}, \mathbf{h}_c^{C_2})] + w_S^2[d^2(\mathbf{l}_i, \mathbf{h}_c^L) + d^2(\mathbf{r}_{2i}, \mathbf{h}_c^R)]]^{-\frac{1}{m-1}}}{\sum_{c'=1}^C [w_C^2[d^2(\mathbf{c}_{1i}, \mathbf{h}_c^{C_1}) + d^2(\mathbf{c}_{2i}, \mathbf{h}_c^{C_2})] + w_S^2[d^2(\mathbf{l}_i, \mathbf{h}_c^L) + d^2(\mathbf{r}_{2i}, \mathbf{h}_c^R)]]^{-\frac{1}{m-1}}}, \quad (6)$$

$$\mathbf{h}_c^{C_1} = \frac{\sum_{i=1}^N u_{ic}^m \mathbf{c}_{1i}}{\sum_{i=1}^N u_{ic}^m}, \quad \mathbf{h}_c^{C_2} = \frac{\sum_{i=1}^N u_{ic}^m \mathbf{c}_{2i}}{\sum_{i=1}^N u_{ic}^m}, \quad \mathbf{h}_c^L = \frac{\sum_{i=1}^N u_{ic}^m \mathbf{l}_i}{\sum_{i=1}^N u_{ic}^m}, \quad \mathbf{h}_c^R = \frac{\sum_{i=1}^N u_{ic}^m \mathbf{r}_i}{\sum_{i=1}^N u_{ic}^m}, \quad (7)$$

$$w_C = \frac{\sum_{i=1}^N u_{ic}^m [d^2(\mathbf{l}_i, \mathbf{h}_c^L) + d^2(\mathbf{r}_i, \mathbf{h}_c^R)]}{\sum_{i=1}^N u_{ic}^m [d^2(\mathbf{c}_{1i}, \mathbf{h}_c^{C_1}) + d^2(\mathbf{c}_{2i}, \mathbf{h}_c^{C_2}) + d^2(\mathbf{l}_i, \mathbf{h}_c^L) + d^2(\mathbf{r}_i, \mathbf{h}_c^R)]}, \quad (w_S = 1 - w_C) \quad (8)$$

A crucial assumption of this clustering model (4) is that the prototypes are of LR fuzzy type, inheriting their typology by the observed data. Coppi et al. (2012) remarked that prototypes are weighted means of the observed units, in which the system of weights is provided by the membership degrees. In such way, the extent to which each unit belongs to a given cluster is incorporated in the definition of the prototypes.

### 3.3.1 The Bagged FCM (BFCM) Algorithm

In this study we use a Bagged Clustering (BC) method to cluster potential Chinese travellers. The BC method combines partitioning and hierarchical clustering procedures, and has many advantages compared to more traditional clustering methods (Dolnicar and Leisch, 2004; Dolnicar et al., 2008; Leisch, 1999). BC results are less dependent on the initial solution, are more stable, allow for the identification of niche segments, and are managerially easier to interpret for the formulation of relevant marketing strategies. BC has been sporadically employed in tourism market segmentation (Dolnicar and Leisch, 2003, 2004; Dolnicar et al., 2008; D'Urso et al., 2013). As discussed previously, the image variables measured are treated as fuzzy variables to deal with the uncertainty and the heterogeneity in individual evaluations. In addition, in the partitioning step of the BC procedure, we make use of the Fuzzy  $C$ -Means (FCM) algorithm for fuzzy data as illus-

trated in the previous section. In this way, we are able to take into account the intrinsic complexity of the phenomena observed. Integrating the FCM method for fuzzy data in the BC procedure (Leisch, 1999), we obtain the Bagged FCM (BFCM) model for fuzzy data. The clustering procedure can be summarized as follows:

1. construct  $B$  bootstrap samples of  $N$  units,  $\tilde{\mathbf{X}}^1, \dots, \tilde{\mathbf{X}}^b, \dots, \tilde{\mathbf{X}}^B$ , where  $\tilde{\mathbf{X}}^b$  is a fuzzy data matrix obtained by drawing with replacement from the original fuzzy data matrix  $\tilde{\mathbf{X}}$ ;

2. run the FCM algorithm for fuzzy data (4), on each bootstrap sample;

From this procedure we obtain  $(B \times C)$  fuzzy prototypes:  $\{\tilde{\mathbf{h}}_1^1, \dots, \tilde{\mathbf{h}}_c^1, \dots, \tilde{\mathbf{h}}_C^1\}, \dots, \{\tilde{\mathbf{h}}_1^b, \dots, \tilde{\mathbf{h}}_c^b, \dots, \tilde{\mathbf{h}}_C^b\}, \dots, \{\tilde{\mathbf{h}}_1^B, \dots, \tilde{\mathbf{h}}_c^B, \dots, \tilde{\mathbf{h}}_C^B\}$ , where  $C$  is the number of prototypes detected in the partitioning step and  $\tilde{\mathbf{h}}_c^b$  is the  $c$ th fuzzy prototype of the  $b$ th bootstrap sample  $\tilde{\mathbf{X}}^b$  ( $b = 1, \dots, B; c = 1, \dots, C$ );

3. arrange all the fuzzy prototypes in a new dataset  $\tilde{\mathbf{H}}_{B \times C}$ ;

4. compute a distance matrix between the fuzzy prototypes in  $\tilde{\mathbf{H}}_{B \times C}$ , by using the distance for fuzzy data (5);

5. run a hierarchical cluster algorithm on  $\tilde{\mathbf{H}}_{B \times C}$ , in order to produce a family of partitions of the prototypes. The result is represented with a dendrogram and the best partition of  $P$  final clusters is obtained investigating the graphic, or by means of suitable criteria (see below);

6. the membership degree of unit  $i$  to each final cluster  $p$  ( $h = 1, \dots, P$ ) is obtained selecting the maximum membership degree of the unit to all the prototypes in the cluster. Let  $\tilde{\mathbf{h}}_{1[p]}, \dots, \tilde{\mathbf{x}}_{C^p[p]}$  be the  $C^p$  prototype classified in the  $p$ th final cluster  $\left(\sum_{p=1}^P C^p = B \times C\right)$ , and let  $u_{i1[p]}, \dots, u_{iC^p[p]}$  be the membership degrees of the unit  $i$  to the  $C^p$  medoids. Then the membership degree of the  $i$ th unit to the  $p$ th final cluster is defined as  $\hat{u}_{ip} = \max\{u_{i1[p]}, \dots, u_{iC^p[p]}\}$ ,  $p = 1, \dots, P$ ;

To detect the best partition in the dendrogram, we make use of the Average Silhouette width criterion proposed by Rousseeuw (1987)

In our context, let us consider a prototype  $\tilde{\mathbf{h}}_c$  belonging to the generic cluster  $p$ . Let the average distance of the prototype to all other prototypes belonging to cluster  $p$  be denoted by  $a_{cp}$ . Also, let the average distance of this prototype to all prototypes belonging to another cluster  $p' (p' \neq p)$ , be called  $d_{cp'}$ . Finally, let  $b_{ck}$  be the minimum  $d_{cp'}$  computed over  $p' (p' \neq p)$ , which represents the dissimilarity of the prototype  $\tilde{\mathbf{h}}_{c[p]}$  to its closest neighbouring cluster. Then, the silhouette width of the prototype is defined as follows:

$$S_c = \frac{b_{cp} - a_{cp}}{\max\{a_{cp}, b_{cp}\}}, \quad (9)$$

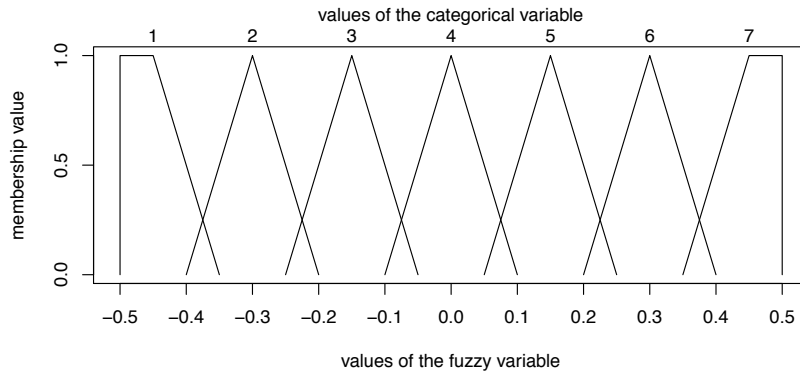
where the denominator is a normalization term.

The higher  $S_c$ , the better the assignment of  $c$ th prototype to the  $p$ th cluster. The Average Silhouette width ( $I_S$ ) defined as the average of  $S_p$  over all the prototypes is:

$$I_S = \frac{1}{B \times C} \sum_{c=1}^{B \times C} S_c. \quad (10)$$

The best partition is achieved when the crisp silhouette is maximized, which implies minimizing the intra-cluster distance ( $a_{cp}$ ) while maximizing the inter-cluster distance ( $b_{cp}$ ).

Since the image attributes, expressed in Bipolar 7-point Likert scales, were used as clustering variables in order to implement the BFCM algorithm, the recoding of these variables into  $LR_2$  fuzzy variables (1) was necessary. This was achieved by following the procedure for recoding suggested by Kazemifard et al. (2011) and illustrated in Figure 2.

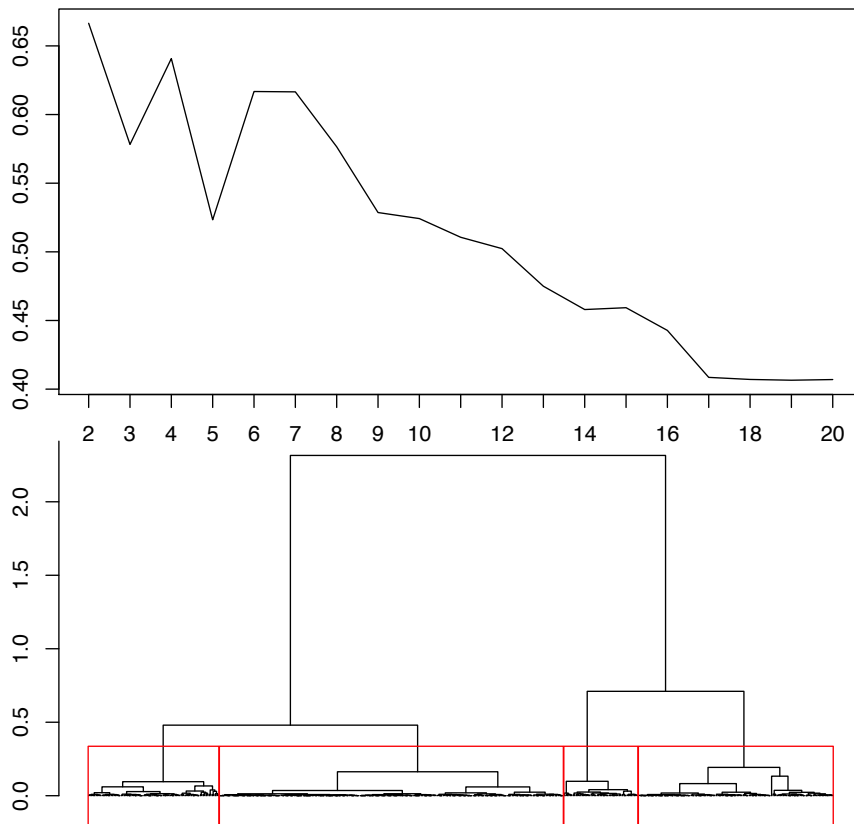


**Figure 2:** Fuzzy recoding of the 7-items Likert-type variable

## 4 Results

### 4.1 Identified Clusters

The result of the BFCM procedure is presented in Figure 3. The dendrogram (Figure 3, bottom panel) and the best partition of the units are obtained using the Average Silhouette width criterion, described in the previous section. The peak in the Silhouette series (Figure 3, top panel) suggests that the Chinese travellers can be segmented into four groups.



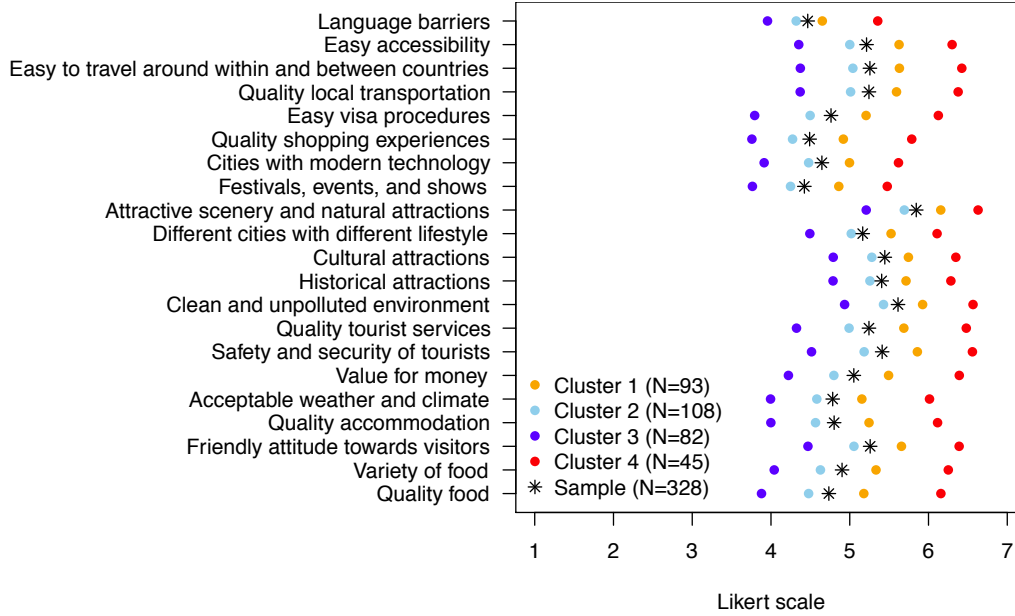
**Figure 3:** Values of the Silhouette index per each cluster partition from 2 to 20 (top panel) and dendrogram (bottom panel).

The weighted mean values of the image attributes are graphically displayed in Figure 4. The weighted mean value of the  $k$ th original segmentation variable ( $\mathbf{x}_k$ ) is calculated as follows:

$$wm_{kp} = \frac{\sum_{i=1}^N x_{ik} \hat{u}_{ip}}{\sum_{i=1}^N \hat{u}_{ip}} \quad (11)$$

The analysis of these values suggest that cluster 4, is a niche cluster ( $N = 43$ ) of “Admirers”. This cluster comprises Chinese travellers who believe more than the other travellers that Western Europe offers all the image attributes considered. However, they rated “festivals, events and shows” and “language barriers” lower and “attractive scenery and natural attractions” higher than the other attributes. At the opposite end, cluster 3 ( $N = 82$ ) groups the “Apathetics”. These are Chinese travellers who perceive more than the other travellers that Western Europe has little to offer on image attributes such as “easy visa procedures”, “quality shopping experiences”, “cities with modern technology”, “festival, events and shows”, and “quality food”. Yet, this group has somewhat positive perceptions of “attractive scenery and natural attractions”, “clean and unpolluted environment” and “friendly attitude towards visitors”. Cluster 1 ( $N = 93$ ), generally has positive perceptions of most attributes with “attractive scenery and natural attractions”, “clean and unpolluted environment”, “safety and security of tourists” and “friendly attitude towards visitors” rated the highest and “language barriers” rated the lowest. Consequently, this cluster was labeled “Enthusiasts”. Finally, cluster 2 ( $N = 108$ ), the largest cluster, grouped travellers who rated most of the image attributes as neither offering much nor offering little. This cluster was named the “Moderates”.

To further understand differences in perceptions, the 21 image attributes were ranked in ascending order for each cluster. The results (Table 1) show that clusters 1 and 4 perceive Western Europe to offer little in terms of language barriers in comparison to cluster 3. Cluster 4 perceives Western Europe to offer very much of “quality food” in comparison to the other clusters that ranked this attribute lower. Cluster 2 ranked highest the attribute “acceptable weather and climate”. The attribute “value for money” was ranked highest by cluster 4 and lowest for the attribute “different cities with different lifestyles”. Cluster 3 ranked lowest the attribute “easy visa procedures”. Cluster 4 also perceived Western Europe to offer “quality tourist services” more than clusters 2 and 3. The ranking of the attribute “historical attractions” and “cultural attractions” were ranked lowest by cluster 4. Overall, the results suggest that Western Europe offers relatively little of “festival, events



**Figure 4:** *Weighted mean of the segmentation variable, i.e. image attributes.*

and shows”, “language barriers” – except for cluster 3 –, “quality shopping experiences”, and “cities with modern technology”. All clusters perceived that Western Europe offers much of “friendly attitude towards visitors”, “safety and security of tourists”, “clean and unpolluted environment”, and “attractive scenery and natural attractions”.

## 4.2 Cluster Profiling

To further understand the other specific characteristics of the identified clusters, the socio-demographic (gender, age, income etc.) and travel characteristics of a possible trip to Western Europe (purpose, duration, destination, information source) were used to profile the clusters. Appendix A reports the complete list of the profiling variables with a brief description of each, while table 2 presents their percentage values in the whole sample and in each cluster identified.

The socio-demographic characteristics reveal that the percentages of women and of people having a University degree or less are higher in clusters 1 (“Enthusiasts”) and 4 (“Admirers”) compared to clusters 2 (“Moderates”) and 3 (“Apathetics”). The “Admirers” have the lowest level of income given that this cluster has the highest percentage of respondents who stated their individual monthly income is equal to RMB 7,000 or less. However, the “Admirers”, compared to the other groups, have the highest proportion of respondents



**Table 1:** Rank of the image attributes for each cluster

Image Attributes	Overall Sample	Rank	CL1 “Enthusiasts”	Rank	CL2 “Moderates”	Rank	CL3 “Apathetics”	Rank	CL4 “Admirers”	Rank
Festivals, events and shows	4.42	1	4.86	2	4.25	1	3.76	2	5.48	2
Language barriers	4.47	2	4.65	1	4.32	3	3.96	6	5.36	1
Quality shopping experiences	4.49	3	4.92	3	4.27	2	3.76	1	5.79	4
Cities with modern technology	4.65	4	5.00	4	4.48	5	3.91	5	5.62	3
Quality food	4.73	5	5.18	6	4.48	4	3.88	4	6.16	9
Easy visa procedures	4.76	6	5.21	7	4.50	6	3.79	3	6.12	8
Acceptable weather and climate	4.78	7	5.15	5	4.58	8	3.99	7	6.01	5
Quality accommodation	4.80	8	5.24	8	4.57	7	4.00	8	6.12	7
Variety of food	4.90	9	5.33	9	4.63	9	4.04	9	6.25	10
Value for money	5.05	10	5.49	10	4.80	10	4.22	10	6.39	16
Different cities with different lifestyle	5.16	11	5.52	11	5.02	14	4.49	16	6.11	6
Easy accessibility	5.21	12	5.63	13	5.00	12	4.35	12	6.30	12
Quality local transportation system	5.24	13	5.59	12	5.01	13	4.37	13	6.38	14
Quality tourist services	5.24	14	5.69	16	4.99	11	4.32	11	6.48	18
Easy to travel around within and between countries	5.26	15	5.63	14	5.04	15	4.37	14	6.42	17
Friendly attitude towards visitors	5.26	16	5.66	15	5.05	16	4.47	15	6.39	15
Historical attractions	5.41	17	5.71	18	5.26	18	4.79	18	6.28	11
Safety and security of tourists	5.41	18	5.18	17	5.18	17	4.51	17	6.56	19
Cultural attractions	5.45	19	5.74	19	5.28	19	4.79	19	6.35	13
Clean and unpolluted environment	5.61	20	5.93	20	5.43	20	4.93	20	6.57	20
Attractive scenery and natural attractions	5.84	21	6.16	21	5.69	21	5.21	21	6.63	21

having a partner and/or children (46.7% are single), are generally older (i.e. more than 26 years old), and the highest proportion of respondents employed full time (62.2%). An examination of the trip characteristics reveals that the “Enthusiasts” have the highest proportion (83.7%) of first-time visitors to Western Europe while the “Moderates” have the lowest (72.9%). The “Admirers” have the highest proportion (59.1%) of travellers preferring to stay in luxury hotels (i.e. hotel from 3 to 5 stars). Furthermore, the “Admirers” have the highest proportion of travellers staying less than two weeks on their next trip (64.4%) compared to the “Enthusiasts” (58.7%) and “Moderates” (62.9%). Regarding the main purpose of travel, the “Admirers” have the highest proportion (93.3%) of respondents travelling for holiday purposes while the “Moderates” have the highest proportion (9.3%) of those travelling for study purposes. The countries that Chinese travellers would most likely to visit on their next trip to Western Europe are France (72.6%), UK (55.5%), Italy (54.6%), Switzerland (53.1%) and Greece (50.3%). However, differences exist between the clusters. For example, the “Enthusiasts” have the highest proportion of respondents wanting to visit UK (64.5%). The “Moderates” have the highest proportion of respondents wanting to visit Netherlands (33.3%) and Spain (45.4%). The “Apathetics” have the lowest proportion of respondents wanting to visit UK (46.3%), Portugal (4.9%), Switzerland (46.3%), Germany (29.3%), Austria (14.6%) and Greece (37.8%). The “Admirers” have the highest proportion of respondents wanting to visit Belgium (20%), Portugal (13.3%), France (88.9%), Switzerland (68.9%), Germany (53.3%) and Greece (66.7%). Finally, regarding the information source that travellers are likely to use to plan their next trip to Western Europe, the “Enthusiasts” (51.6%) and “Admirers” (46.7%) have the highest proportion of respondents that prefer to use a travel agency. The “Moderates” have the highest proportion of respondents that will use guidebooks (44.4%). The “Enthusiasts” (84.9%) and “Apathetics” (76.8%) have the highest proportion of respondents that will use search engines on the Internet but the latter has also the lowest proportion of respondents (35.4%) that will use travel forums and blogs as a source of information.

**Table 2:** Characteristics and preferences of the travellers, and characteristics of the trip (percentage values).

Variables	Whole sample	CL1	CL2	CL3	CL4	$p$ -value
<i>Socio-demographic and economic characteristics</i>						
Female	57.32	63.44	54.63	43.90	75.56	***
Individual Monthly Income	67.08	64.13	65.42	68.29	75.00	
Marital Status	61.06	66.30	62.75	60.98	46.67	
Educational Level	62.46	69.57	58.49	56.10	68.89	
Age	51.53	56.52	51.40	52.44	40.00	
Employment Status	54.29	50.00	51.85	58.02	62.22	
<i>Trip characteristics</i>						
Preferred type of accommodation	42.64	44.57	35.19	41.46	59.09	*
Visitation status to WE	76.95	83.70	72.90	75.64	75.00	
Estimated duration of the next trip to WE	62.58	58.70	64.81	62.96	64.44	
Party group of the next trip to WE	60.37	50.00	64.49	63.29	66.67	
<i>Main Purpose of travel</i>						
VFR	3.96	2.15	4.63	3.66	6.67	
Study	19.21	21.51	20.37	19.51	11.11	
Work	5.18	4.30	9.26	2.44	2.22	
Holiday	83.54	84.95	82.41	78.05	93.33	
<i>What destinations are you most likely to visit?</i>						
UK	55.49	64.52	51.85	46.34	62.22	*
Italy	54.57	54.84	51.85	58.54	53.33	
Belgium	13.41	8.60	12.96	15.85	20.00	
Portugal	9.45	7.53	12.96	4.88	13.33	
France	72.56	74.19	65.74	70.73	88.89	**
Switzerland	53.05	51.61	52.78	46.34	68.89	
Ireland	17.99	16.13	20.37	14.63	22.22	
Netherlands	30.79	29.03	33.33	30.49	28.89	
Germany	39.63	41.94	39.81	29.27	53.33	*
Spain	39.33	37.63	45.37	32.93	40.00	
Austria	22.87	25.81	25.00	14.63	26.67	
Greece	50.30	56.99	47.22	37.80	66.67	***
<i>What information source are you likely to use to plan your trip to Western Europe?</i>						
TV or radio advertising	15.85	13.98	17.59	19.51	8.89	
Guidebook	33.84	29.03	44.44	24.39	35.56	**
Internet search engine	77.13	84.95	75.93	76.83	64.44	*
Travel agency	44.51	51.61	38.89	42.68	46.67	
Travel forums & blogs	47.56	53.76	50.00	35.37	51.11	*
Special magazine	29.88	31.18	32.41	26.83	26.67	

Notes: All Chi-square tests calculated are not significant unless indicated otherwise: \*\*\* Significant at  $p \leq 0.01$ , \*\* Significant at  $p \leq 0.05$ . \* Significant at  $p \leq 0.1$ .

## 5 Implications

The main objective of this study was to apply a novel segmentation method, BFCM, to understand Chinese travellers' images of Western Europe. The results reveal the existence of four clusters that can be differentiated on their images and socio-demographic characteristics. The results have both theoretical and managerial implications.

### 5.1 Theoretical Implications

Market segmentation is the cornerstone of marketing strategy. Over the years, the most commonly used method (cluster analysis) and algorithm ( $k$ -means) for segmenting markets have been heavily criticized (Dolnicar, 2003; Dolnicar and Grün, 2008; Dolnicar et al., 2012; Tuma et al., 2011). These criticisms pertain mainly to reproducibility of clusters, stability of clusters, sub-optimal procedures in assigning units to clusters, and selecting the number of clusters. BFCM as a clustering algorithm overcomes some of these limitations.

First, BFCM is reproducible, inheriting this feature from Bagged Clustering (Leisch, 1999).

Second, FCM as a clustering algorithm provides the best performance in stability criterion when compared to crisp methods (Chuang et al., 1999; Shin and Sohn, 2004; Wang et al., 2008). Therefore, also BFCM algorithm is a more stable method than crisp ones.

Third, BFCM allows respondents to belong to more than one cluster and hence more robust than traditional and overlapped clustering methods. Conceptually, one consumer higher statistical probability to belong to one segment does not necessarily mean that s/he only belongs to this segment (Arabie et al., 1981; Chaturvedi et al., 1997). A tourist may well desire more than one attribute or benefit from a destination and hence can belong to multiple groups (Li et al., 2013). For newly emerging outbound markets such as China, clear segments are yet to develop (Li et al., 2013) given that group and independent travel orientations coexist (VisitBritain, 2013). Hence, the creation and management of mutually exclusive segments is premature (Li et al., 2013). BFCM contrary to traditional clustering methods and overlapped clustering, permits the identification of the typical member of a segment, provides information on the strength of the membership, and the intersection of the segments. Overlapping classification only shows which member belong to multiple

competitive segments, while the fuzzy  $C$ -means partitioning indicates if the membership of an attribute in two segments is virtually equally strong or stronger in one segment than in the other (Hruschka, 1986).

Fourth, using the Bagged Clustering approach is not necessary to impose in advance the number of clusters in the FCM algorithm because the final partition is obtained investigating the results of the hierarchical algorithm. Instead of finding the final number of clusters only from the analysis of the dendrogram, the Average Silhouette index is proposed in this study.

Furthermore, by considering the FCM clustering method for fuzzy data in our BFCM clustering procedure, we inherit the benefits connected both to fuzzy clustering and to fuzzy formalization of imprecise information.

Adopting a fuzzy approach to cluster analysis offers several other advantages over classic clustering approaches (Hwang et al., 2007). First the fuzzy clustering methods are computationally more efficient because dramatic changes in the value of cluster membership are less likely to occur in estimation procedures (McBratney and Moore, 1985). Second, fuzzy clustering has been shown to be less affected by local optima problems (Heiser and Groenen, 1997). Finally, the memberships for any given set of respondents indicate whether there is a second-best cluster almost as good as the best cluster—a result which traditional clustering methods cannot uncover (Everitt et al., 2001). For other advantages see D’Urso (2014).

Recoding subjective evaluations or imprecise information into fuzzy data allows us to capture the imprecision or vagueness of the data. The BFCM clustering procedure is a fuzzy clustering for fuzzy data able to analyse segmentation problems in which the empirical information is affected by imprecision or vagueness.

Overall, BFCM offers a rigorous, visually simple, and alternative way of segmenting tourism markets that can be applied in order to deal with imprecise information and for the identification of niche markets.

## **5.2 Managerial Implications**

The results have several managerial implications for tapping into the Chinese outbound market. First and foremost, the study confirms increasing heterogeneity in the Chinese

outbound market as suggested by others (e.g., Ong and du Cros, 2012; TUI Think Tank, 2012). The study reveals the existence of four main segments of Chinese visitors based on their image perceptions. All the segments perceive Western Europe as offering much of attractive scenery and natural attractions, clean and unpolluted environment, safety and security, and cultural attractions. The positive perceptions of these attributes across the segments confirm that projected images of Western Europe in China have set realistic expectations. Europe is marketed in China using the region's rich cultural background and unique landscapes and will continue to be marketed as such given that these attributes resonate well with the Chinese market (TUI Think Tank, 2012). Just like other international travellers to Europe, the Chinese outbound market values destinations that offer a safe and secure environment. The recent attacks on Chinese tourists in Paris, for example, have not only highlighted the need for European destinations to provide tougher security measures around famous attractions and places of interests to Chinese visitors, but also the need to provide comprehensive guides on safety and complaint procedures in Chinese language (Huet, 2013). Chinese tourists are attracted by the perceived "cleanliness" of Europe compared to China (TUI Think Tank, 2012) and therefore the region's pristine environment should continue to feature prominently in destination advertising and promotion. A positive destination image certainly affects destination preference, tourists' intention to visit, and recommendation behaviour (Dolnicar and Grün, 2013).

In general, shopping remains an important pull factor for the Chinese outbound market (Kau and Lim, 2005; Li et al., 2011; TUI Think Tank, 2012; VisitBritain, 2013; Xu and McGehee, 2012), but as the findings indicate, it is not necessarily a strength of Western Europe. Clusters 2 ("Moderates") and 3 ("Apathetics") rated Western Europe as offering less of "quality shopping experiences" in comparison to other attributes. Plausible explanations for this occurrence can be found in studies of Chinese visitors to the United States (Li et al., 2011; Xu and McGehee, 2012) and Singapore (Kau and Lim, 2005). For example, Li et al. (2011) found that Chinese tourists did not want to visit regular shops or undertake "forced" shopping but rather preferred shopping areas with local flavor and the availability of international brands at good prices. Xu and McGehee (2012) found that Chinese visitors were disappointed when they found that the international brands bought were made in China or in other Asian countries. However, some visitors were interested in

purchasing products made in China but unavailable in China given that such products are perceived to be of higher quality. Both Kau and Lim (2005) and Xu and McGehee (2012) found that prices and the lack of communication in Chinese language were major sources of dissatisfaction with the shopping experience. Hence, for perceptions of high quality shopping experience for Chinese visitors, Western Europe must emphasize products made in Europe, offer customer assistance in the Chinese language, and provide value for money. It may also be necessary to create awareness of the shopping infrastructure in Western Europe, timing of sales promotion, and shopping festivals that can contribute to increase the perceived quality of the shopping experience. Signage in shopping malls in Chinese language can also improve the shopping experience (Xu and McGehee, 2012).

The attribute rated the least favorably by all the segments is “festivals, events and shows”. Trade reports (e.g., TUI Think Tank, 2012) suggest that the new generation of Chinese travellers will not necessarily follow the classic cultural-historical itineraries currently offered in Europe, but more likely to follow personal trails mounted from movies, music, sports or culture, and personal idols. Hence, marketing to the younger generation of Chinese tourists will require the promotion of festivals, events and shows that are of relevance to this generation such as the Cannes Film Festival, shooting location of popular movies, and the home/second home of popular Chinese celebrities (TUI Think Tank, 2012). Movies and music are likely to influence Chinese travellers to visit particular countries (VisitBritain, 2013). Hence, the European Tourism Council mandate of marketing Europe in China should seek to address the “less” favorable perception of “festivals, events and shows” of Western Europe. Li et al. (2011) confirm that Chinese visitors to the US are keen to experience local culture and customs through festivals, events and shows. Yet, the findings of this study also suggest that differences in perception exist between the segments on this attribute. Cluster 4 (“Admirers”) have the most favorable perception and cluster 3 (“Apathetics”) have the least, suggesting that potential visitors from the same outbound market may hold very different images of a country/region (Prayag and Hosany, 2014).

Visa requirements continue to be perceived as a significant constraint of travel for the Chinese outbound market (BCG, 2011; Lai et al., 2013; Sparks and Pan, 2009; VisitBritain, 2013; TUI Think Tank, 2012). Except for Cluster 3 (“Apathetics”), all the other clusters perceived Western Europe as offering much of easy visa procedures. In the last few years,

countries such as France and Germany have taken active steps to ease visa procedures for Chinese tourists (Samuel, 2013) but the tough visa requirements of countries such as UK has kept Chinese visitors away, often leading to significant loss in retail revenues (Anderson, 2013). Likewise, perceptions of significant language barriers when travelling in Western Europe persist (Euromonitor, 2011). Western Europe is perceived as offering much of language barriers by three of the four clusters, thereby confirming findings from previous studies (BCG, 2011; VisitBritain, 2013). Perceived language barrier is a significant deterrent of travel for the Chinese outbound market (Lai et al., 2013) but also impacts on behaviour in Europe. For example, Chinese tourists often miss out on tax refunds from shopping due to the perceived language barrier (China Times, 2013). If Western Europe wants to attract increasing numbers of Chinese visitors, service providers will have to train staff in not only speaking Chinese but also to understand the subtle cultural differences in behaviour. The MPCE (Mission Possible: Chinese for Europeans) is one of many projects supported by the European Commission to overcome the language and cultural barriers with China and enhance mutual understanding. The project is targeted at business companies, cultural organizations and educational institutions ([www.chinese-for-eu.eu](http://www.chinese-for-eu.eu)). This initiative should encourage service providers to adapt to Chinese customer requirements.

While variety of food was rated positively by all the segments, Western Europe is perceived as offering much of quality food by only three of the four segments. In general, considerable differences exist between cultures in terms of the perception of attractiveness of food from other cultures (Chang et al., 2011). Local food at a destination can be an impediment to travel (Cohen and Avieli, 2004). For Chinese consumers, food that is different in taste, culture and quality is fashionable and desirable (Eves and Cheng, 2007). However, not all Chinese visitors are eager to try local food. Tasting local food satisfies experiential needs but Chinese visitors to Australia did not want to consume local food for every meal. They prefer familiar flavors and cooking methods (Chang et al., 2010). Li et al. (2011), for example, found that Chinese visitors to the US do not like too many uncooked, fried food, and cold dishes, but appreciate meals that include more fruits and vegetables, more dish choices and menus available in Chinese. Trade reports (e.g., TUI Think Tank, 2012) confirm some of these tendencies such as Chinese visitors' preference for familiar



food and restaurants when travelling in Europe. The findings also suggest preferences for countries such as France, Italy and UK which conform to findings from the European Travel Commission. Countries such as Spain, Austria, Ireland, and Portugal may need to more proactively market to Chinese visitors. These countries have the lowest preference for travel among potential Chinese visitors. Surprisingly, Clusters 1 (“Enthusiasts”) and 4 (“Admirers”) are most likely to use travel agencies as an information source for travel to Western Europe. This contrasts to other studies (e.g., Sparks and Pan, 2009) suggesting that Chinese visitors are most likely to gather information from TV programs and friends. The preference for travel agencies may just reflect the information provision by travel agents on the Schengen visa. However, cluster 1 (“Enthusiasts”) has a high proportion of 18 to 25 years old and they are likely to use the Internet as a source of travel information. Therefore, on-line presence through websites in Mandarin and Chinese will be critical and such websites will need to be linked to search engines such as Baidu, as popular as Google among Chinese consumers (BCG, 2011; TUI Think Tank, 2012). Communicating with less experienced travellers is about building product awareness, thereby focusing on the cognitive attributes of a destination, whereas the communication strategy for more experienced travellers requires a focus on the emotional and unique aspects of a destination (Stepchenkova and Li, 2012).

Overall, the findings confirm the need for a more fine-tuned segmentation of the Chinese market. Indeed, different segments of Chinese visitors may hold different images of Western Europe and have different preferences for countries they want to visit. Understanding the expectations of the Chinese outbound market is critical for service provision (Li et al., 2011) and identifying the image of a region/country is critical for destination benchmarking and competitiveness analysis (Stepchenkova and Li, 2012). Hence, the results can be used to monitor the evolution of the image of Western Europe in China and assist destination marketers in selecting the appropriate image associations for destination differentiation and positioning purposes. For example the findings confirm scenery and natural attractions, safety and security, historical/cultural attractions, and clean/unpolluted environment as image strengths while quality of food, festivals, events and shows, language barriers, and quality shopping experiences are image weaknesses for some segments. The results also highlight the need for greater forms of cooperation between individual countries and a

more coordinated approach by the European Travel Council to market the region in China. International competition from the US and Asia may require Western Europe and Europe in general to be positioned differently for the Chinese market. This can be achieved by not necessarily developing new products and services for the Chinese market, but rather by delivering better services and managing expectations/perceptions in a more effective way. The marketing strategy for Europe should involve systematically expanding the use of existing digital services, the development of smart phone travel applications for the Chinese market, and online presence on social networks such as 51.com and Renren (TUI Think Tank, 2012). These can create a substantially different perception of the visitor experience and image of Europe in comparison to the US or Australia. This strategy is supported by trends such as the increasing ownership of mobile phones is approaching 600 per 1,000 (VisitBritain, 2013) and the popularity of self-organized sightseeing/independent travel from China (TUI Think Tank, 2012).

## **6 Limitations and Areas of Future Research**

The Chinese outbound market is undoubtedly a growth market for Western Europe. As this study showed, there is heterogeneity in the perceived image of Western Europe that will require marketing strategies to be adapted for each segment of potential visitors. The study also introduces a novel segmentation method (BFCM) that overcomes many of the limitations of traditional clustering methods. However, the study is not without limitations and these need to be acknowledged to better contextualise the findings.

First, as many clustering methods available in the literature, the BFCM clustering procedure could be afflicted by two problems: computational complexity and outlier sensitivity. Computational complexity and scalability are two important issues in clustering (Havens et al., 2012). The FCM algorithm considered in the BFCM clustering procedure with large datasets can be computationally too intensive and this could increase the computational complexity of the Bagged Clustering. A possible solution is to consider a “linearized” version of the FCM algorithm (D’Urso and Massari, 2013; Krishnapuram et al., 2001). In this way, the computational complexity of the BFCM clustering procedure could be significantly reduced. Another important issue in cluster analysis is the presence

of outliers in the data set. FCM algorithm is sensible to outliers (García-Escudero and Gordaliza, 1999). In order to neutralize and smooth the disruptive effects of possible outliers in the BFCM clustering procedure it would be useful to use robust versions of the FCM clustering algorithm (see, e.g. Wu and Yang, 2002).

Given that clustering ensemble like the one used in this study remain sparsely applied in tourism studies, future studies can consider other clustering ensembles such as Self-Organizing Maps (SOM) and FCM, SOM and  $k$ -means, and SOM and fuzzy clustering for segmenting tourism markets. These ensembles are likely to generate more stable results than traditional clustering methods (Budayan et al., 2009). Second, the sample of Chinese visitors was identified from Beijing and the results are pertinent to the outbound market from this city only. Research on the Chinese outbound market (Li et al., 2010, 2011, 2013) suggests that Shanghai and Guangzhou are also important generating markets and this study should be replicated in other locations within China. Third, the list of image attributes has mostly cognitive images. (Stepchenkova and Li, 2012) suggest that the Chinese outbound market is driven by cognitive and affective images, with less experienced travellers associating mainly cognitive images with a destination. Hence, it would be worthwhile for future studies to extend the list of attributes for Western Europe to include affective images and also to assess the image of individual countries such as Spain, Italy and France for competitive analysis. Fourth, this study focused on segmenting destination image but there is a need for novel qualitative and quantitative methods to understand the image construct and competitive images of destinations (Lai and Li, 2012; Stepchenkova and Li, 2012). Quantitative methods such as Bray-Curtis dissimilarity index and Electre II methods may be useful in achieving that (Andrades-Caldito et al., 2013).

## References

- Ahmed, Z. U. (1996). The need for the identification of the constituents of a destination's tourist image: A promotional segmentation perspective. *Revue du Tourisme*, 51(2):44–57.
- Aldenderfer, M. S. and Blashfield, R. K. (1984). *Cluster Analysis*. Beverly Hills: Sage Publications.
- Alegre, J., Mateo, S., and Pou, L. (2011). A latent class approach to tourists' length of stay. *Tourism Economics*, 32(3):555–563.
- Anderson, M. (2013). *Tourist visa hurdles cost UK millions*. Accessed 21.07.03 <http://uk.reuters.com/article/2013/07/25/uk-britain-visarestrictions>.
- Andrades-Caldito, L., Sánchez-Rivero, M., and Pulido-Fernández, J. I. (2013). Differentiating Competitiveness through Tourism Image Assessment: An Application to Andalusia (Spain). *Journal of Travel Research*, 52(1):68–81.
- Arabie, P., Carroll, J. D., DeSarbo, W., and Wind, J. (1981). Overlapping clustering: a new method for product positioning. *Journal of Marketing Research*, 18(3):310–317.
- Arimond, G. and Elfessi, A. (2001). A clustering method for categorical data in tourism market segmentation research. *Journal of Travel Research*, 39(May):391–397.
- Ashworth, G. and Goodall, B. (1990). *Marketing Tourism Places*. London: Routledge.
- Babinec, T. (2002). Editorial: Some musings on cluster analysis. *Journal of Targeting, Measurement and Analysis for Marketing*, 10(4):301–303.
- Baloglu, S. (1997). The relationship between destination images and sociodemographic and trip characteristics of international travellers. *Journal of Vacation Marketing*, 3(3):221–233.
- Baloglu, S. and McCleary, K. W. (1999). A model of destination image formation. *Annals of Tourism Research*, 26(4):868–897.

- BCG (2011). *Taking off travel and tourism in China and beyond*. The Boston Consulting Group, MA: Boston.
- Beerli, A. and Martin, J. D. (2004). Factors influencing destination image. *Annals of Tourism Research*, 31(3):657–681.
- Benítez, J. M., Martín, J. C., and Román, C. (2007). Using fuzzy number for measuring quality of service in the hotel industry. *Tourism Management*, 28(2):544–555.
- Bezdek, J. C. (1981). *Pattern Recognition with Fuzzy Objective Function Algorithms*. Kluwer Academic Publishers, Norwell, MA, USA.
- Bieger, T. and Laesser, C. (2002). Market segmentation by motivation: The case of switzerland. *Journal of Travel Research*, 41(1):68–76.
- Bigné, J. E., Garcia, I. S., and Blas, S. S. (2009). The functional-psychological continuum in the cognitive image of a destination: A confirmatory analysis. *Tourism Management*, 30(6):715–723.
- Bigné, J. E., Sanchez, M. I., and Sanchez, J. (2001). Tourism image, evaluation variables, and after purchase behaviour: Inter-relationship. *Tourism Management*, 26(6):607–616.
- Bloom, J. Z. (2004). Tourist market segmentation with linear and non-linear techniques. *Tourism Management*, 25(6):723–733.
- Bryan, V. and Kane, C. (2013). *Europe searches for charms to lure Chinese tourists*. Accessed 12.08.13 <http://www.reuters.com/assets>.
- Budayan, C., Dikmen, I., and Birgonul, M. T. (2009). Comparing the performance of traditional Cluster Analysis, Self-Organizing maps and Fuzzy C-means method for strategic grouping. *Expert Systems with Applications*, 36(9):11772–11781.
- Cai, L. A., Li, M., and Knutson, B. J. (2008). Research on China Outbound Market: A Meta-Review. *Journal of Hospitality & Leisure Marketing*, 16(1-2):5–20.
- Calantone, R. J., Di Benedetto, C. A., Hakam, A., and Bojanic, D. C. (1989). Multiple multinational tourism positioning using correspondence analysis. *Journal of Travel Research*, 28(2):25–32.

- Castro, C. B., Armario, E. M., and Ruiz, D. M. (2007). The influence of market heterogeneity on the relationship between a destination's image and tourists' future behaviour. *Tourism Management*, 28(1):175–187.
- Chang, R. C. Y., Kivela, J., and Mak, A. H. N. (2010). Food preferences of chinese tourists. *Annals of Tourism Research*, 37(4):989–1011.
- Chang, R. C. Y., Kivela, J., and Mak, A. H. N. (2011). Attributes that influence the evaluation of travel dining experience: When East meets West. *Tourism Management*, 32(2):307–316.
- Chaturvedi, A., Carroll, J. D., Green, P. E., and Rotondo, J. A. (1997). A feature-based approach to market segmentation via overlapping  $k$ -centroids clustering. *Journal of Marketing Research*, 34(3):370–377.
- Chen, C.-C., Lin, Y.-H., and Petrick, J. F. (2012). Social biases of destination perceptions. *Journal of Travel Research*, 52(2):240–252.
- Chen, G., Bao, J., and Huang, S. S. (2013). Segmenting chinese backpackers by travel motivations. *International Journal of Tourism Research*.
- Chiang, W.-Y. (2011). Establishment and application of fuzzy decision rules: an empirical case of the air passenger market in Taiwan. *International Journal of Tourism Research*, 13:47–456.
- China Times (2013). *Chinese visitors to Europe often miss out on tax rebates*. Accessed on 21.07.13 <http://www.wantchinatimes.com/news-subclass-cnt.aspx.20130521000084>.
- Chuang, K., Chiu, M., Lin, C., and Chen, J. (1999). Model free functional mri analysis using kohonen clustering neural network and fuzzy  $C$ -means. *IEEE Transactions on Medical Imaging*, 18(12):1117–1128.
- Cohen, E. and Avieli, N. (2004). Food in tourism: Attraction and impediment. *Annals of Tourism Research*, 31(4):755–778.
- Coppi, R. and D'Urso, P. (2002). Fuzzy  $k$ -mean clustering models for triangular fuzzy time trajectories. *Statistical Methods and Applications*, 11:21–24.

- Coppi, R., D'Urso, P., and Giordani, P. (2012). Fuzzy and possibilistic clustering for fuzzy data. *Computational Statistics & Data Analysis*, 56(4):915–927.
- Corigliano, M. A. (2011). The outbound Chinese tourism to Italy: The new graduates' generation. *Journal of China Tourism Research*, 7(4):396–410.
- Cracolici, M. F. and Nijkamp, P. (2009). The attractiveness and competitiveness of tourist destinations: A study of southern Italian regions. *Tourism Management*, 30(3):336–344.
- Crompton, J. (1979). An assessment of the image of Mexico as a vacation destination and the influence of geographical location upon that image. *Journal of Travel Research*, 17:18–23.
- Dibb, S. and Simkin, L. (2009). Implementation rules to bridge the theory/practice divide in market segmentation. *Journal of Marketing Management*, 25(3/4):375–396.
- Dimitriadou, E., Dolnicar, S., and Weingessel, A. (2002a). An examination of indexes for determining the number of clusters in binary data sets. *Psychometrika*, 67(1):137–160.
- Dimitriadou, E., Weingessel, A., and Kurt, H. (2002b). A combination scheme for fuzzy clustering. *International Journal of Pattern Recognition and Artificial Intelligence*, 16(7):901–912.
- Dolnicar, S. (2002). A review of data-driven market segmentation in tourism. *Journal of Travel & Tourism Marketing*, 12(1):1–22.
- Dolnicar, S. (2003). Using cluster analysis for market segmentation—typical misconceptions, established methodological weaknesses and some recommendations for improvement. *Australasian Journal of Market Research*, 11(2):5–12.
- Dolnicar, S. (2004). Beyond “commonsense” segmentation: A systematics of segmentation approaches in tourism. *Journal of Travel Research*, 42(Feb):244–250.
- Dolnicar, S., Crouch, G. I., Devinney, T., Huybers, T., Louviere, J., and Oppewal, H. (2008). Tourism and discretionary income allocation heterogeneity among households. *Tourism Management*, 29(1):44–52.

- Dolnicar, S. and Grabler, K. (2004). Applying city perception analysis (CPA) for destination positioning decisions. *Journal of Travel & Tourism Marketing*, 16(2/3):99–111.
- Dolnicar, S. and Grün, B. (2008). Challenging factor-cluster analysis. *Journal of Travel Research*, 47(Aug):63–71.
- Dolnicar, S. and Grün, B. (2013). Validly measuring destination image in survey studies. *Journal of Travel Research*, 52(1):3–14.
- Dolnicar, S., Kaiser, S., Lazarevski, K., and Leisch, F. (2012). Biclustering: overcoming data dimensionality problems in market segmentation. *Journal of Travel Research*, 51(1):41–49.
- Dolnicar, S. and Lazarevski, K. (2009). Methodological reasons for the theory/practice divide in market segmentation. *Journal of Marketing Management*, 25(3/4):357–373.
- Dolnicar, S. and Leisch, F. (2003). Winter tourist segments in Austria: Identifying stable vacation styles using bagged clustering techniques. *Journal of Travel Research*, 41(3):281–292.
- Dolnicar, S. and Leisch, F. (2004). Segmenting markets by bagged clustering. *Australasian Marketing Journal (AMJ)*, 12(1):51–65.
- Dolnicar, S. and Leisch, F. (2010). Evaluation of structure and reproducibility of cluster solutions using the bootstrap. *Marketing Letters*, 52(1):3–14.
- D’Urso, P. (2007). Clustering of fuzzy data. In De Oliveira, J. V. and Pedrycz, W., editors, *Advances in fuzzy clustering and its applications*, pages 155–192. J. Wiley and Sons.
- D’Urso, P. (2014). Fuzzy clustering. In Hennig, C., Meila, M., Murtagh, F., and Rocci, R., editors, *Handbook of Cluster Analysis*. Chapman and Hall.
- D’Urso, P., De Giovanni, L., Disegna, M., and Massari, R. (2013). Bagged clustering and its application to tourism market segmentation. *Expert Systems with Applications*.
- D’Urso, P. and Massari, R. (2013). Fuzzy clustering of human activity patterns. *Fuzzy Sets and Systems*, 215:29–54.



- Echtner, C. M. and Ritchie, J. R. B. (2003). The meaning and measurement of destination image. *Journal of Tourism Studies*, 2(2):2–12.
- Espelt, N. G. and Benito, J. A. D. (2005). The social construction of the image of girona: A methodological approach. *Tourism Management*, 26(5):777–785.
- Euromonitor (2011). *Impact of Chinese travellers in Europe*. Report by Euromonitor International.
- European Travel Commission (2012). *Europe: A unique destination for Chinese travellers*. Press Release on 27.11.12 by ETC, Brussels, Belgium.
- European Travel Commission (2013). *European tourism needs joint efforts to stimulate growth*. Press Release on 24.07.13 by ETC, Brussels, Belgium.
- Everitt, B. S., Landau, S., and Leese, M. (2001). *Cluster Analysis*. London: Arnold, 4th edition.
- Eves, A. and Cheng, L. (2007). Cross-cultural evaluation of factors driving intention to purchase new food products – Beijing, China and south-east England. *International Journal of Consumer Studies*, 31(4):410–417.
- Fakeye, P. and Crompton, J. (1991). Image differences between prospective, first-time, and repeat visitors to the Lower Rio Grande Valley. *Journal of Travel Research*, 29:10–16.
- Franke, N., Reisinger, H., and Hoppe, D. (2009). Remaining within-cluster heterogeneity: a meta-analysis of the “dark-side” of clustering methods. *Journal of Marketing Management*, 25(3/4):273–293.
- Frochot, I. (2005). A benefit segmentation of tourists in rural areas: a scottish perspective. *Tourism Management*, 26(3):335–346.
- Gallarza, M. G., G., S. I., and Garcia, H. C. (2002). Destination image: towards a conceptual framework. *Annals of Tourism Research*, 29(1):56–78.
- García-Escudero, L. Á. and Gordaliza, A. (1999). Robustness properties of k means and trimmed k means. *Journal of the American Statistical Association*, 94(447):956–969.

- Gartner, W. C. (1989). Tourism image: Attribute measurement of state tourism products using multidimensional scaling techniques. *Journal of Travel Research*, 28(2):16–20.
- Ghaemi, R., Sulaiman, N., Ibrahim, H., and Mustapha, N. (2009). A survey: Clustering ensembles techniques. *World Academy of Science, Engineering and Technology*, 29:636–645.
- Havens, T. C., Bezdek, J. C., Leckie, C., Hall, L., and Palaniswami, M. (2012). Fuzzy c-means algorithms for very large data. *IEEE Transactions on Fuzzy Systems*, 20(6):1130–1146.
- Heiser, W. J. and Groenen, P. J. F. (1997). Cluster differences scaling with a within-clusters loss component and a fuzzy successive approximation strategy to avoid local minima. *Psychometrika*, 62(1):63–83.
- Hruschka, H. (1986). Market definition and segmentation using fuzzy clustering methods. *International Journal of Research in Marketing*, 3(2):117–134.
- Hsu, C. H. C., Cai, L. A., and Li, M. (2010). Expectation, motivation, and attitude: A tourist behavioral model. *Journal of Travel Research*, 49:282–296.
- Huet, N. (2013). *Paris ramps up tourist security amid Chinese concerns*. Accessed 21.07.13 <http://www.reuters.com/article/2013/08/02/us-france-tourists>.
- Hung, W. L. and Yang, M. S. (2005). Fuzzy clustering on LR-type fuzzy numbers with an application in Taiwanese tea evaluation. *Fuzzy sets and systems*, 150(3):561–577.
- Hwang, H., Desarbo, W. S., and Takane, Y. (2007). Fuzzy clusterwise generalized structured component analysis. *Psychometrika*, 72(2):181–198.
- Jain, A. K. (2010). Data clustering: 50 years beyond  $k$ -means. *Pattern Recognition Letters*, 31:651–666.
- Jang, S., Morrison, A. M., and O’Leary, J. T. (2002). Benefit segmentation of Japanese pleasure travelers to the USA and Canada: Selecting target markets based on the profitability and risk of individual market segments. *Tourism Management*, 23(4):367–378.

- Jang, S. and Wu, C.-M. E. (2006). Seniors' travel motivation and the influential factors: An examination of Taiwanese seniors. *Tourism Management*, 27(2):306–316.
- Joppe, M., Martin, D. W., and Waalen, J. (2001). Toronto's image as a destination: A comparative importance-satisfaction analysis by origin of visitor. *Journal of Travel Research*, 39(3):252–260.
- Kanemasu, Y. (2013). Social construction of touristic imagery: case of Fiji. *Annals of Tourism Research*. DOI:<http://dx.doi.org/10.1016/j.annals.2013.06.004>.
- Kau, A. K. and Lim, P. S. (2005). Clustering of chinese tourists to singapore: an analysis of their motivations, values and satisfaction. *International Journal of Tourism Research*, 7(4-5):231–248.
- Kazemifard, M., Zaeri, A., Ghasem-Aghaee, N., Nematbakhsh, M. A., and Mardukhi, F. (2011). Fuzzy Emotional COCOMO II Software Cost Estimation (FECSCCE) using Multi-Agent Systems. *Applied Soft Computing*, 11(2):2260–2270.
- Keller, K. L. (2003). Brand synthesis: the multidimensionality of brand knowledge. *Journal of Consumer Research*, 29(1):595–660.
- Kim, J., Wei, S., and Ruys, H. (2003). Segmenting the market of West Australian senior tourists using an artificial neural network. *Tourism Management*, 24(1):25–34.
- Kim, S. S., Guo, Y., and Agrusa, J. (2005). Preference and positioning analyses of overseas destinations by mainland Chinese outbound pleasure tourists. *Journal of Travel Research*, 44(2):212–220.
- Kim, S. S., Lee, C., and Klenosky, D. (2003). The influence of push and pull factors at Korean national parks. *Tourism Management*, 24(2):169–180.
- Klenosky, D. B. (2002). The “pull” of tourism destinations: A means-end investigation. *Journal of Travel Research*, 40(4):396–403.
- Kohonen, T. (1989). *Self-Organizing and associative memory*. Berlin: Springer.

- Krishnapuram, R., Joshi, A., Nasraoui, O., and Yi, L. (2001). Low-complexity fuzzy relational clustering algorithms for web mining. *IEEE Transactions on Fuzzy Systems*, 9(4):595–607.
- Kruse, R., Döring, C., and Lesot, M.-J. (2007). Fundamentals of fuzzy clustering. In de Oliveira, J. V. and Pedrycz, W., editors, *Advances in Fuzzy Clustering and Its Applications*, pages 3–30. J. Wiley and Sons.
- Kuo, R. J., Ho, L. M., and Hu, C. M. (2002). Cluster analysis in industrial segmentation through artificial neural networks. *Computers and Industrial Engineering*, 42:391–399.
- Lai, C., Li, X., and Harrill, R. (2013). Chinese outbound tourists’ perceived constraints to visiting the United States. *Tourism Management*, 37:136–146.
- Lai, K. and Li, Y. (2012). Core-periphery structure of destination image: concept, evidence and implication. *Annals of Tourism Research*, 39(3):1359–1137.
- Lawson, F. and Bond-Bovy, M. (1977). *Tourism and Recreational Development*. London: Architectural Press.
- Leisch, F. (1999). Bagged clustering. Working paper 51, SFB Adaptive Information Systems and Modelling in Economics and Management Science, WU Vienna University of Economics and Business.
- Leisch, F. (2006). A toolbox for  $k$ -centroids cluster analysis. *Computational statistics & data analysis*, 51(2):526–544.
- Leisen, B. (2001). Image segmentation: the case of tourism destination. *Journal of Services Marketing*, 15(1):49–66.
- Li, J. W. J. and Carr, N. (2004). Visitor satisfaction: an analysis of mainland Chinese tourists on the Australian Gold Coast. *International Journal of Hospitality & Tourism Administration*, 5(3):31–48.
- Li, X., Harrill, R., Uysal, M., Burnett, T., and Zhan, X. (2010). Estimating the size of the Chinese outbound travel market: A demand-side approach. *Tourism Management*, 31(2):250–259.

- Li, X., Lai, C., Harrill, R., Kline, S., and Wang, L. (2011). When East meets West: An exploratory study on Chinese outbound tourists' travel expectations. *Tourism Management*, 32(4):741–749.
- Li, X., Meng, F., Uysal, M., and Mihalik, B. (2013). Understanding China's long-haul outbound travel market: An overlapped segmentation approach. *Journal of Business Research*, 66:786–793.
- Li, X. and Stepchenkova, S. (2012). Chinese outbound tourists destination image of America: Part i. *Journal of Travel Research*, 51(3):250–266.
- Lilien, G. L. and Rangaswamy, A. (1998). *Marketing Engineering: Computer Assisted Marketing Analysis and Planning*. Mass: Addison-Wesley.
- Mazanec, J. A. (1995). Competition among European tourist cities: A comparative analysis with multi-dimensional scaling and self-organizing maps. *Tourism Economics*, 1(1):283–302.
- Mazanec, J. A. and Strasser, H. (2007). Perceptions based analysis of tourism products and service providers. *Journal of Travel Research*, 45(4):387–401.
- McBratney, A. B. and Moore, A. W. (1985). Application of fuzzy sets to climatic classification. *Agricultural and Forest Meteorology*, 35(1):165–185.
- McKercher, B. and Tse, T. S. M. (2012). Is intention to return a valid proxy for actual repeat visitation? *Journal of Travel Research*.
- Obenour, W., Lengfelder, J., and Groves, D. (2005). The development of a destination through the image assessment of six geographic markets. *Journal of Vacation Marketing*, 11(2):107–119.
- Ong, C. and du Cros, H. (2012). The post-Mao gazes: Chinese backpackers in Macau. *Annals of Tourism Research*, 39:735–754.
- Pan, B. and Li, X. (2011). The long tail of destination image and online marketing. *Annals of Tourism Research*, 38(1):132–152.

- Park, D.-B. and Yoon, Y.-S. (2009). Segmentation by motivation in rural tourism: A Korean case study. *Tourism Management*, 30(1):99–108.
- Pike, S. (2002). Destination image analysis—A review of 142 papers from 1973 to 2000. *Tourism Management*, 23(5):541–549.
- Pike, S. and Ryan, C. (2004). Destination positioning analysis through a comparison of cognitive, affective and conative perceptions. *Journal of Travel Research*, 42:333–342.
- Prayag, G. (2010). Images as pull factors of a tourist destination: A factor-cluster segmentation analysis. *Tourism Analysis*, 15(2):213–226.
- Prayag, G. (2012). Paradise for who? Segmenting visitors' satisfaction with cognitive image and predicting behavioral loyalty. *International Journal of Tourism Research*, 14(1):1–15.
- Prayag, G. and Hosany, S. (2014). When Middle East meets West: Understanding the motives and perceptions of young tourists from United Arab Emirates. *Tourism Management*, 40(0):35–45.
- Prayag, G. and Ryan, C. (2011). The relationship between the push & pull attributes of a tourist destination: The role of nationality. an analytical qualitative research approach. *Current Issues in Tourism*, 14(2):121–143.
- Punj, G. and Stewart, D. W. (1983). Cluster analysis in marketing research: review and suggestions for application. *Journal of Marketing Research*, 20(2):138–148.
- Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, 20:53–65.
- Ryan, C. and Cave, J. (2005). Structuring destination image: A qualitative approach. *Journal of Travel Research*, 44(2):143–150.
- Ryan, C. and Mo, X. (2002). Chinese visitors to new Zealand—Demographics and perceptions. *Journal of Vacation Marketing*, 8(1):13–27.
- Samuel, H. (2013). *How France is benefiting from Chinese tourists over Britain*. Accessed 29.07.13 <http://www.telegraph.co.uk/news/worldnews/europe/france/10173805>.

- Sarigöllü, E. and Huang, R. (2005). Benefits segmentation of visitors to Latin America. *Journal of Travel Research*, 43(3):277–293.
- Schroeder, T. (1996). The relationship of residents’ image of their state as a tourist destination and their support for tourism. *Journal of Travel Research*, 34(4):71–73.
- Shepherd, R. (2009). Cultural preservation, tourism and “donkey travel” on China’s frontier. In Winter, T., Teo, P., and Chang, T. C., editors, *In Asia on Tour: Exploring the Rise of Asian Tourism*, pages 253–263. Routledge, London.
- Shin, H. W. and Sohn, S. Y. (2004). Segmentation of stock trading customers according to potential value. *Expert Systems with Applications*, 27(1):27 – 33.
- Sinova, B., Gil, M. Á., Colubi, A., and Van Aelst, S. (2012). The median of a random fuzzy number. the 1-norm distance approach. *Fuzzy Sets and Systems*, 200:99–115.
- Sparks, B. and Pan, G. W. (2009). Chinese outbound tourists: Understanding their attitudes, constraints and use of information sources. *Tourism Management*, 30(4):483–494.
- Stepchenkova, S. and Li, X. (2012). Chinese outbound tourists’ destination image of America: Part ii. *Journal of Travel Research*. DOI:10.1177/0047287512451137.
- Stepchenkova, S. and Mills, J. E. (2010). Destination image: A meta-analysis of 2000-2007 research. *Journal of Hospitality Marketing & Management*, 19:575–609.
- Stepchenkova, S. and Morrison, A. M. (2008). Russia’s destination image among american pleasure travelers: Revisiting Echtner and Ritchie. *Tourism Management*, 29(3):548–560.
- Strehl, A. and Ghosh, J. (2002). Cluster ensembles – a knowledge reuse framework for combining multiple partitions. *Journal of Machine Learning Research*, 3:583–617.
- Su, W. (2011). *Helsinki as a tourist destination for Chinese visitors*. PhD thesis, Haggä-Helia University of Applied Sciences, Finland.
- Tasci, A. D. A. and Gartner, W. C. (2007). Destination image and its functional relationships. *Journal of Travel Research*, 45:413–425.

- Tasci, A. D. A., Gartner, W. C., and Cavusgil, S. T. (2007). Conceptualization and operationalization of destination image. *Journal of Hospitality & Tourism Research*, 31:194–223.
- Tkaczynski, A., Rundle-Thiele, S., and Beaumont, N. (2010). Destination segmentation: a recommended two-step approach. *Journal of Travel Research*, 49(2):139–152.
- Topchy, A., Jain, A. K., and Punch, W. (2005). Clustering ensembles: Models of consensus and weak partitions. *IEEE Transaction on Pattern Analysis and Machine Intelligence*, 27(12):1866–1881.
- Tse, T. S. M. and Hobson, J. S. P. (2008). The forces shaping China’s outbound tourism. *Journal of China Tourism Research*, 4:136–155.
- TUI Think Tank (2012). *New Chinese Tourists in Europe from 2017*. Report by Trend Survey. Accessed 21.07.13 <http://www.tuigroup.com/en/innovation/thinktank/trendstravelmarket>.
- Tuma, M. N., Decker, R., and Scholz, S. W. (2011). A survey of the challenges and pitfalls of cluster analysis application in market segmentation. *International Journal of Market Research*, 53(3):391–414.
- Venugopal, V. and Baets, W. (1994). Neural networks and statistical techniques in marketing research: A conceptual comparison. *Marketing Intelligence & Planning*, 12(7):30–38.
- VisitBritain (2012). *China Market and Trade Profile*. Accessed 16.01.13 <http://www.visitbritain.org/research>.
- VisitBritain (2013). *Market and Trade Profile China*. Report by Visit Britain, UK.
- Voges, K. (2007). Rough clustering of destination image data using an evolutionary algorithm. *Journal of Travel & Tourism Marketing*, 21(4):121–137.
- Wang, Y. P., Gunampally, M., Chen, J., Bittel, D., Butler, M. G., and Cai, W. W. (2008). A comparison of fuzzy clustering approaches for quantification of microarray gene expression. *The Journal of VLSI Signal Processing*, 50(2):1–16.



- Wedel, M. and Kamakura, W. A. (2000). *Market Segmentation: Conceptual and Methodological Foundations*. Archives of Psychology, Dordrecht: Kluwer, 2nd edition.
- Wu, K.-L. and Yang, M.-S. (2002). Alternative c-means clustering algorithms. *Pattern recognition*, 35(10):2267–2278.
- Xu, Y. and McGehee, N. G. (2012). Shopping behavior of Chinese tourists visiting the United States: Letting the shoppers do the talking. *Tourism Management*, 33(2):427–430.
- Yang, J., He, J., and Gu, Y. (2012). The implicit measurement of destination image: The application of implicit association tests. *Tourism Management*, 33(1):50–52.
- Yu, X. and Weiler, B. (2001). Mainland Chinese pleasure travellers to Australia: A leisure behaviour analysis. *Tourism, Culture & Communication*, 3:81–91.

## Appendix A

**Table A1: Variables description**

<b>Independet variables</b>	<b>Descriptions</b>
<i>Socio-demographic and economic characteristics</i>	
Female	1= Female; 0= Male
Individual monthly income	1= Individual monthly income equal to RMB 7,000 or less; 0 = otherwise
Marital status	1 = Single; 0 = otherwise
Educational level	1 = University degree and less; 0 = Post-graduate degree
Age	1 = 18 and 25 years old; 0 = 26 years old and over
Employment Status	1 = Full-time employee; 0 = student or not employed
<i>Trip characteristics</i>	
Preferred Type of Accommodation	1= 3–5 star hotel; 0= otherwise (e.g. hostel, guest house)
Visitation Status to WE	1= First-timer in Western Europe; 0= otherwise
Estimated Duration of the Next Trip to WE	1= Less than 2 weeks in Western Europe; 0= otherwise
Party Group of the Next Trip to WE	1= Family or partner on the next trip to Western Europe; 0= otherwise
<i>Main Purpose of travel</i>	
VFR	1= visiting friends & relatives; 0= otherwise
Study	1= study; 0= otherwise
Work	1= work; 0= otherwise
Holiday	1= holidays; 0= otherwise
<i>What destinations are you most likely to visit?</i>	
UK	1= UK; 0= otherwise
Italy	1= Italy; 0= otherwise
Belgium	1= Belgium; 0= otherwise
Portugal	1= Portugal; 0= otherwise
France	1= France; 0= otherwise
Switzerland	1= Switzerland; 0= otherwise
Ireland	1= Ireland; 0= otherwise
Netherlands	1= Netherlands; 0= otherwise
Germany	1= Germany; 0= otherwise
Spain	1= Spain; 0= otherwise
Austria	1= Austria; 0= otherwise
Greece	1= Greece; 0= otherwise
<i>What information source are you likely to use to plan your trip to Western Europe?</i>	
TV or radio advertising	1= TV or radio advertising; 0= otherwise
Guidebook	1= Guidebook; 0= otherwise
Internet search engine	1= Internet search engine; 0= otherwise
Travel agency	1= Travel agency; 0= otherwise
Travel forums & blogs	1= Travel forums & blogs; 0= otherwise
Special magazine	1= Special magazine; 0= otherwise