Freie Universität Bozen
Libera Università di Bolzano
Free University of Bozen - Bolzano

Fakultät für Wirtschaftswissenschaften
Facoltà di Economia
School of Economics and Management

BEMPS –
Bozen Economics & Management Paper Series

NO 20 / 2014

Fuzzy segmentation in postmodern consumers

Pierpaolo D'Urso, Marta Disegna, Riccardo Massari, Linda Osti

Fuzzy segmentation in postmodern consumers

Pierpaolo D'Urso[a], Marta Disegna[b,*], Riccardo Massari[a], Linda Osti[b]

[a] *La Sapienza, Roma, Italy*

[b] *Faculty of Economics and Management, Free University of Bolzano, Italy*

Abstract

The aim of this paper is to create a nexus between postmodern consumer behaviour and fuzzy clustering, and to propose a suitable clustering method to segment postmodern consumers. From a methodological perspective, the main contribution of this paper is related to the use of the fuzzy theory from the beginning to the end of the process. Unlike other fuzzy-based applications, which use fuzzy theory only on some parts of the clustering process, the clustering technique we propose and apply is fuzzy in every single step of the clustering process. By totally embracing the fuzzy theory the procedure we propose is capable of analysing the uncertainty and vagueness that characterise the experiences and perceptions of postmodern consumers.

Keywords: Fuzzy clustering, Fuzzy numbers, Likert–type scale, Segmentation, Postmodernity.

*Corresponding author
Email addresses: pierpaolo.durso@uniroma1.it (Pierpaolo D'Urso), marta.disegna@unibz.it (Marta Disegna), riccardo.massari@uniroma1.it (Riccardo Massari), Linda.Osti@unibz.it (Linda Osti)

1 Introduction

Over the years in both the general marketing and the more specific tourism literature, a great debate, still open, has been generated over the clustering types and techniques to use in segmentation. Since the introduction of market segmentation in the late 1950s, the number and types of approaches to market segmentation have grown enormously (Dolnicar & Leisch, 2004; Liao, Chu, & Hsiao, 2012). In marketing and tourism literature, cluster analysis remains the most favoured method (Dolnicar, 2002; Wedel & Kamakura, 2000) even if has been criticized for its overestimation of the validity of the segmentation results (Dolnicar, 2002; Dolnicar & Lazarevski, 2009). Non-overlapping, overlapping, and fuzzy algorithms are the three groups in which clustering algorithms are generally divided. A non-overlapping (hard) algorithm allows each observation to belong to a single segment only (Tuma, Decker, & Scholz, 2011), an overlapping algorithm allows each observation to belong to more than one cluster (Wedel & Kamakura, 2000), while a fuzzy (or soft) algorithm assigns each observation to each cluster with a certain degree of membership (Tuma et al., 2011). Because different clustering algorithms produce different solutions (Grekousis & Thomas, 2012) and present different aspects of the data (Leisch, 2006), no single clustering algorithm achieves satisfactory clustering solutions for all types of data sets (Ghaemi, Sulaiman, Ibrahim, & Mustapha, 2009). Furthermore, clustering performance strongly depends on the characteristics of the data to be segmented (Grekousis & Thomas, 2012). Every clustering algorithm has advantages and drawbacks and has to be chosen with awareness of its characteristics and limitations (Dolnicar, 2002, 2003; Tuma et al., 2011).

In the discussion on the best algorithm to adopt, little attention has been paid on the customers (or tourists in this instance) that the investigator is trying to segment. In the early 90s the marketing and tourism literature has started to debate about and investigate a new type of consumer, which reflects the current postmodern era. Much has been discussed on the differences between the new “postmodern” consumer and the “modern” consumer. In tourism, “postmodern” tourists, in contrast to “modern” tourists, can be described as individuals who enjoy multiple experiences embracing different, sometimes contrasting, life values: travellers who may consume Mac Donald’s at the airport but choose to dine at organic restaurants at the destination; tourists who are looking for authentic cultural attractions but also visit Disneyland. Considering the differences between “modern” and “postmodern” tourists, the question arises whether the different clustering algorithms are interchangeable when it comes to such different behaviours. In this paper we are going to discuss that when it comes to postmodern tourists, the fuzzy algorithm seems to be the most suitable as it is able to capture the “undefined” tourists’ behaviour, preferences, emotions, or other feelings. The fuzzy theory (which includes fuzzy numbers, fuzzy sets, and fuzzy clustering), is capable to cope with the imprecision, uncertainty and vagueness that characterize each aspect and experience regarding real-life (Benítez, Martín, & Román, 2007; Coppi & D’Urso, 2002; D’Urso & De Giovanni, 2014; Hisdal, 1988; Ngai & Wat, 2003; Pérez-Gladish, Gonzalez, Bilbao-Terol, & Arenas-Parra, 2010; Sinova, Gil, Colubi, & Van Aelst, 2012; Y. Wang, Ma, Lao, & Wang, 2014; Zadeh, 1965), and that, in particular, characterize the experiences and perceptions of “postmodern” tourists. In addition, comparing the results obtained using fuzzy and non-fuzzy clustering algorithms on the same data it has been demonstrated (Ahmad & Richard, 2014; Hruschka, 1986) that fuzzy algorithms allow to obtain more insights than non-fuzzy algorithms in terms of market and segment information.

2 Research objectives

The aim of this paper is to propose a clustering procedure that is suitable to segment postmodern tourists and embraces the fuzzy theory from the beginning to the end of the process:

1. transforming the segmentation variables into fuzzy numbers;
2. adopting a fuzzy clustering algorithm;
3. profiling the clusters using the fuzzy membership degrees.

This procedure is suggested in order to conduct a segmentation analysis which is able to capture both the vagueness derived from the uncertainty in assigning units to each cluster and the vagueness in individual evaluation of linguistic terms. After a theoretical discussion of the nexus between postmodernity and fuzzy clustering, a fuzzy segmentation analysis is applied to international tourists visiting the province of Bolzano (Northern Italy) in 2010 and 2011. The analysis is based on the tourists' level of satisfaction with 10 different aspects of the destination and provides reliable results to destination managers and policy makers for the creation of future management and marketing strategies, and the development and maintenance of competitive advantage in the postmodern consumer era.

3 Postmodernism

In the last 30 years the term "postmodern" has been widely used and applied to a variety of disciplines including literature, arts, history, and also marketing. Postmodernism has been considered as a complex phenomenon, frequently paradoxical and multi-faced in nature, making it a hard concept to define. Under a philosophical point of view, postmodernism is the movement that poses a critique to modernity, the philosophical movement centred around "absolute reality" and universality, just antecedent to postmodernity. In the late 1960s and 1970s some of the most eminent postmodern philosophers –Lyotard, Foucault, Derrida and Baudrillard– put into discussion "absolute" realities and "universal" claims. Basing some of their discussions on the initial work by Kant, Nietzsche, Heidegger, and Kierkegard postmodernists introduced concepts like de-realisation, subjectivation, deconstruction and hyperreality. For

Lyotard (1979) de-realisation, or better “loss of meaning”, is the acknowledgment state of the limits of “meaningfulness” in narrative elements. The postmodern can therefore be described by the incredulity by human beings towards “meta-narratives” (mainly the progression of history and the totality and universalism of science). Subjectivity (Foucault, 1969) becomes, therefore, an essential element of the discussion, which entails the existence of a multiplicity of theoretical standpoints, for meta-narratives are inadequate to represent and contain the totality of human kind. Deconstruction, firstly introduced by Heidegger in relation to metaphysics, was further discussed by Derrida (1967) in relation to signifiers (words) and signified (the object that the word represents). Strictly linked to subjectivism and de-realisation the concept of deconstruction questions the unambiguity of texts and see the meaning of a signifier is the difference of the object with similar signifier in the language. Postmodernism can therefore be described as a time characterised by an increasing awareness of the complexity of the world whereby ambiguity and disorder are accepted, as there is no ultimate reality and no absolute truth. Styles and manners are mixed and copies exist without reference to an original due to the inability to distinguish between what is real and what is fiction Baudrillard (1981).

In the early 1990s postmodernism has started to pertain also marketing studies, where modernist approaches of marketing like the 4ps, the SWOT, and the general approach of analysis, planning, implementation and control were put into discussion (Brown, 1993). In marketing and consumer behaviour postmodernism has been mainly described by the following characteristics (Brown, 2006; Firat & Venkatesh, 1995): blurring of the distinction between real and non-real, multiple and disjointed consumption experiences; lack of commitment to any (central) theme, language as the basis for subjectivity, experiences that allow the coexistence of differences and paradoxes, postmodernism as a culture of consumption. In tourism postmodernism has been described by the enjoyment of tourists to move from one tourist experience to the other (Feifer, 1985; Uriely, 1997; N. Wang, 1999), the intermingling of different motivations (Maoz & Bekerman, 2010; Uriely, 1997), a nature which involves “both-and” rather than “either-or” (Munt, 1994). More recently, it has been further discussed that postmodern travellers cannot be classified under a rigid and subjective term, instead, if questioned, postmodern travellers describe themselves through terms that are subjective, fluid and open to change (Maoz & Bekerman, 2010). As stressed by Maoz and Bekerman (2010), in a postmodern era “each tourist has his/her small narrative to tell, and those small narratives replace the grand and universal narrative of the past” (p. 437). While in the late 1960s and early 1970s philosophers were discussing issues such as subjectivism and deconstruction, engineers had already realized that human needs and behaviours had become so complex that the binary code of “true or false” was not enough and that a new logic was needed Ghomshei, Meech, and Naderi (2008). In 1965 Zadeh presented his work on fuzzy sets –where elements of sets have degrees of memberships– and in 1973 fuzzy logic –where the true value may range between 0 and 1. Although born and developed independently, fuzzy numbers and postmodernism were providing an answer and a point of discussion to the changing needs, behaviours and believes of the consumer age. The nexus between postmodernism and fuzzy logic has been recently discussed by Balas and Balas (2009), Ghomshei et al. (2008), and Simon (2006) who explored the applicability of fuzzy (though rigorous) numbers to the uncertainty and ambiguity of postmodernism. In 2004, Ligorio (2004) based her work on Negoita (2002) and traced and highlighted the affinities and shared ideas that stand at the foundations of both fuzzy set theory and the philosophical postmodern movement. So far, whoever, no discussion has been open on the use of the fuzzy theory in postmodern marketing and its applicability in segmenting postmodern consumers.

4 Fuzzy theory

4.1 Fuzzy numbers

Oftentimes, information regarding opinions, satisfaction, emotions, and other aspects that involve a personal judgement are vaguely defined and captured through imprecise measurements (D'Urso, 2007). Individual judgements regarding an attribute depend on the prior expectations or beliefs of the respondents, and on the weight or importance that the attribute has for the respondent (Engel, Blackwell, & Miniard, 1995), thus these judgements are vague, or, in a word, "fuzzy", by definition. Nevertheless, most of the studies conducted in marketing, tourism, management, and business overlooked this relevant issue and assumed that this information is precise and consequently the related variables are treated as precisely measured, or "crisp", data.

In order to investigate these subjective perceptions, qualitative scales, such as Likert–type scales, are often used to formulate both scientific propositions and empirical data (Benítez et al., 2007; Coppi, D'Urso, & Giordani, 2012; Gil & González-Rodríguez, 2012; Li, Meng, Uysal, & Mihalik, 2013). Likert–type scales consist of a set of response categories labelled with linguistic terms (such as "satisfied" or "dissatisfied, "important" or "not important", "agree" or "disagree"). The widespread use of Likert–type scales is related to the ease of developing and administering them.

A significant drawback of linguistic expressions on a Likert–type scale is that they entail a source of vagueness and uncertainty in evaluation since they represent subjective knowledge (Benítez et al., 2007; Coppi & D'Urso, 2002; D'Urso, 2007; D'Urso, De Giovanni, Disegna, & Massari, 2013). As underlined by Lin and Yeh (2013), "consumer perception is an extremely complex process that involves degrees of uncertainty, imprecision or vagueness". The evaluation provided by a consumer is subjective, thus implying that consumers' perception on a unique aspect or object is different. For example, through the comparison between structured (5-point Likert scale) and unstructured (open ended) queries describing 19 image attributes of Kansas (USA), C. H. C. Hsu, Wolfe, and Kang (2004) demonstrated that consumers had a vague, and incorrect, tourist image of the destination. This concept is intimately related to the de-realisation, subjectivation, and deconstruction of postmodernism, and the coexistence of both "true" and "false" or the existence of an in-between value in the postmodern consumer experience.

Another important drawback that arises using Likert–type scales is that when respondents must express an opinion on a scale they automatically convert their opinion to scores, and this conversion can distort the original opinion that had to be captured (T.-H. Hsu & Lin, 2006). Therefore, Likert–type scales incorporates also a certain degree of imprecision, ambiguity and uncertainty, due to the subjective meaning that each individual attributes to each value of the rating scale (Benítez et al., 2007; D'Urso, 2007). In other word, the concept to be evaluated is unique but the mind of the consumer is fuzzy and vague (Lin & Yeh, 2013).

As underlined by Chou, Hsu, and Chen (2008), generally it is difficult to manage uncertain and/or vague data through traditional methods. Therefore, fuzzy sets, firstly proposed by Zadeh (1965), is commonly used in order to capture the imprecision or vagueness that characterize the aspects of the real-life (Y. Wang et al., 2014) and it provides a useful tool to make decisions based on imprecise and/or incomplete information Pérez-Gladish et al. (2010). The widespread development of fuzzy sets theory can be attributed to its ability to transform "inexact information and verbal variables into a mathematically well-defined way which simulates the processing of information in natural-language commutation" (Hisdal, 1988). A fuzzy set is defined by a function that assigns to each unit a membership degree. This membership degree indicates how much the unit is close, similar, or compatible with the concept expressed by the fuzzy set. Fuzzy numbers are convex and normalized fuzzy sets with a piecewise continuous membership function defined in $\mathbb{R}$. In other words, the membership function that characterizes a fuzzy number is continuous, it maps an interval $[a, b]$ to $[0, 1]$, and it monotonically increases (Zimmermann, 1996). In the literature, the use of fuzzy sets and fuzzy numbers has become increasingly greater for different reasons. Firstly because they are able to capture and measure the uncertainty of individual evaluations (Benítez et al., 2007; Coppi & D'Urso, 2002; Sinova et al., 2012). Secondly, fuzzy numbers have a very intuitive meaning, which can be easily grasped by potential users, and it is more comprehensive than other methods (Sohrabi, Vanani, Tahmasebipur, & Fazli, 2012). Thirdly, fuzzy sets can better describe complex processes of the real-life which are often difficult or ambiguous to model with traditional statistical methods (Sohrabi et al., 2012). Furthermore, fuzzy sets can be adapted to a wide range of imprecise data, due to the richness of the scale of fuzzy sets and in particular of fuzzy numbers, including real (trapezoidal and triangular fuzzy numbers) and interval fuzzy numbers (Sinova et al., 2012; Sohrabi et al., 2012; Y. Wang et al., 2014). Therefore, it is useful to formalize the linguistic variables in terms of fuzzy numbers before the adoption of a segmentation method.

4.2 Fuzzy clustering

Generally, market segmentation relies on the inherent assumption that consumers can only belong to one cluster (Li et al., 2013), but this is not always a reasonable hypothesis (Kotler, 1988). This is even more so if the units to be segmented are "postmodern" consumers, which enjoy multiple and at time contrasting experiences. In fact, it is reasonable to assume that an observation might belong to more than one cluster , because the customers may share some characteristics with more clusters (Hruschka, 1986). Conceptually, consumers which belong to one cluster with high probability do not necessarily have to be attributed solely to that segment (Chaturvedi, Carroll, Green, & Rotondo, 1997). At the same manner, a tourist may be satisfied with more than one attribute or element that characterize a destination and hence can belong to multiple groups (Li et al., 2013). Hence, assigning a customer to only one cluster entails a loss of information (Chiang, 2011) and, consequently, the creation and management of mutually exclusive segments is inappropriate (Li et al., 2013).

Following this line of reasoning, a fuzzy algorithm can be adopted. Fuzzy clustering is a classification method that allows units to belong to more than one cluster simultaneously, contrary to hard clustering which results in mutually exclusive clusters (Bezdek, 1981). Units are assigned to each cluster with a membership degree that represents the level of uncertainty (vagueness) in the assignment process. Conversely to hard clustering in which 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. Contrary to overlapped algorithms, fuzzy algorithms provide information on the strength of the membership. Overlapping classification only shows which member belong to multiple competitive segments, while fuzzy algorithms indicate if the membership of a unit in more segments is virtually equally strong or stronger in one segment than in the others (Hruschka, 1986).

The use of a fuzzy algorithm not only allows to capture the imprecision/vagueness with which units are assigned to each cluster, but has also many other advantages over more traditional cluster algorithms (D'Urso, 2014): 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 (Coppi et al., 2012); second, fuzzy clustering has been shown to be less affected by local optima problems in the estimation procedures (D'Urso, 2007); third, fuzzy clustering provides the best performance in stability criterion when compared to hard methods (Y. P. Wang et al., 2008).

However, despite fuzzy clustering allows each unit to belong to more than one cluster, it is important to underline that when a fuzzy clustering algorithm is applied, the membership degrees result from the procedure. Therefore, in order to conduct a profiling of the clusters, each unit is assigned to a cluster in a crisp, or "hard", way, i.e., by assigning the unit to the cluster with the highest membership degree, adopting a "defuzzification" procedure and/or specifying a cut–off point for membership degree (see Malinverni & Fangi, 2009 for an example). Although this is a common practice widespread in the literature (see for example Chiang, 2011; Lim, Kim, & Runyan, 2013; Malinverni & Fangi, 2009), this procedure is in itself contradictory since the segmentation phase is fuzzy, of "soft", but the profiling phase is hard.

4.3 Fuzzy numbers and clustering in tourism

Despite ample research regarding fuzzy sets was conducted in the past, less attention was paid to its applications in tourism. As underlined by Ngai and Wat (2003) and Sohrabi et al. (2012), until 2003 applications of fuzzy sets in hotel selection research was almost absent while recent study increasingly adopt this theory due to its inherent advantages. In the study of Ngai and Wat (2003), the Hotel Advisory System (HAS), a fuzzy expert system, has been developed and presented as a useful and effectively tool to assist tourists in the hotel selection process. T.-H. Hsu and Lin (2006) presented a fuzzy multi-criteria approach to measure the consumers' perceived risk on their travel, using data derived from the Kinmen National Park located in Kinmen island in the Taiwan Strait as an example. Benítez et al. (2007) analysed the quality of service of three hotels belonging to the LHR chain in Gran Canaria island. In doing this study, they suggested to fuzzify the linguistic information ("poor", "fair", "good", and "very good"), obtained from the 13 questions through which each hotel's performance was evaluated, into triangular fuzzy numbers. Sanna, Atzeni, and Spanu (2008) presented a ranking procedure, based on qualitative and quantitative variables expressed as fuzzy numbers, among different conservation projects that may be defined for an archaeological site in order to increase its cultural and tourism competitiveness. Chou et al. (2008) presented a fuzzy Multi-Criteria Decision Making (FMCDM) model for the location selection of hotels by international tourists in which the linguistic values are transformed into triangular fuzzy numbers. In order to identify the factors that influence the tourists' choice of a destination and to evaluate the preferences of tourists for destination, T.-K. Hsu, Tsai, and Wu (2009) proposed to transform the descriptions and judgements, expressed in linguistic term, into triangular fuzzy numbers before to adopt the TOPSIS method. The fuzzy number construction approach proposed by Cheng (1991) was adopted by Wu, Hsiao, and Ho (2010) to identify the sustainable indicators that characterize and distinguish urban ecotourism concept from urban tourism and ecotourism concepts. Lin, Chen, and Chang (2011) proposed the adoption of the Fuzzy Quality Function Deployment (FQFD) method to evaluate the performance of tourists' services offered by hospitality firms taking into account both external consumers' needs and internal service management requirements. In this study, the 120 tourists collected during the survey have been asked to rank the relative importance of each service attribute on a 9-point Likert–type scale, that has been transformed into triangular fuzzy number. Huang and Peng (2012) suggested a new approach: the Fuzzy Rasch model that combines the Rasch model with fuzzy theory, to analyse the Tourism Destination Competitiveness (TDC) of nine Asian countries. In order to select the most appropriate indicators that influence tourists to choose a hotel, Sohrabi et al. (2012) suggested to conduct first a factor analysis to obtain the main hotel selection factors and then to define a set of fuzzy membership functions for the extracted factors. Using a fuzzy logic approach and parameter weighting matrices, Rangel-Buitrago, Correa, Anfuso, Ergin, and Williams (2013) provided a scenic assessment of 135 sites long the Colombian Caribbean coast. Lin and Yeh (2013) introduced the use of Choquet Integral (CI) to model more accurately and closer to reality the Multiple-Criteria Decision-Making (MCDM) process for travellers that lead them to the selection of the hotel.

While the popularity of fuzzy sets and systems has grown over the last years, studies applying fuzzy clustering algorithms, in the context of tourism, are still few. Chiang (2011) segmented the air transport passenger market integrating the fuzzy $C-$means clustering method with the C4.5, a decision tree algorithm, to create fuzzy decision rules. Similarly, fuzzy $C-$means was adopted to segment passengers' travel behaviour before and after the use of the intercity High-speed rail from Beijing to Tianjin (Jian & Ning, 2012). Recently, D'Urso et al. (2013) proposed the use of a new fuzzy clustering algorithm, a fuzzy version of the Bagged Clustering algorithm introduced by Leisch (1999), to segment tourists based on their motivation to visit two different cultural attractions. The above mentioned studies provide a thorough review of the fuzzy approaches applied to tourism and, to the best of our knowledge, studies in which fuzzy numbers and fuzzy clustering algorithms are combined are not present in the tourism field. Furthermore, this paper proposes also an innovative technique to conduct a fuzzy profiling of the clusters.

5 The empirical study

To apply the theory of fuzzy numbers and fuzzy clustering discussed so far, this study focuses on the 997 international visitors, interviewed through the "International Tourism in Italy" survey (source *Banca d'Italia*), who spent a holiday in South–Tyrol (Northern Italy) in 2010 and 2011. Interviewees were requested to report their level of satisfaction with 10 different aspects, which were employed as segmentation variables. The investigation ranged from the overall satisfaction with the destination, to satisfaction with friendliness of local people, accommodation, food and beverage, art, landscape, prices and cost of living, quality and variety of products offered in stores, information, and safety. A 10–point Likert–type scale was used, where [1] was "Very unsatisfied" to [10] "Very satisfied".

Figure 1 displays the percentage distribution of the level of satisfaction per each observed item. The percentage of visitors who attributed a value lower than 6 to the different aspects of the trip is sharply low, with the exception of

“Prices”.

Finally, a list of the other information collected through the survey is reported in table 1.

6 Methodology

The fuzzy segmentation procedure proposed in this study incorporates the fuzzy theory from the beginning to the end of the process and it consists of three main steps, which can be briefly described as follows:

1. To represent the ambiguity and uncertainty arising in using the Likert–type scale, the items of the scale are formalized in terms of fuzzy numbers (Coppi & D'Urso, 2002) before conducting the fuzzy segmentation method. This transformation allows to capture the imprecision or vagueness of the data.
2. The fuzzy C–means algorithm for fuzzy data (FCM-FD) is used in order to capture the uncertainty that arise assigning each unit to each cluster. A suitable distance for fuzzy data is used in the FCM-FD algorithm. A suitable cluster validity index is adopted in order to detect the optimal number of clusters.
3. The vagueness raised assigning each unit to each cluster with a certain membership degree is finally used also to profile the clusters.

The adoption of FCM-FD allow us to analyse segmentation problems in which the empirical information is affected by imprecision or vagueness and this clustering procedure inherits the benefits connected both to fuzzy clustering and to fuzzy formalization of imprecise information.

6.1 From Likert variables to fuzzy numbers

A general class of fuzzy data, called LR fuzzy data, can be defined in a metric form following Dubois and Prade (1988):

$$\widetilde{\mathbf{X}} \equiv \{\tilde{x}_{ik} = (m_{ik}, l_{ik}, r_{ik})_{LR} : i = 1, \ldots, N;\ k = 1, \ldots, K\}, \tag{1}$$

where $\tilde{x}_{ik} = (m_{ik}, l_{ik}, r_{ik})_{LR}$ denotes the LR fuzzy variable k observed on the ith unit; m_{ik} indicates the center, i.e. the "core" of the fuzzy number; l_{ik} and r_{ik} represent the left and right spread, i.e. the vagueness of the observation. A common LR fuzzy datum is the *triangular* one, with triangular membership function:

$$\mu_{\tilde{x}_{ik}}(u_{ik}) = \begin{cases} 1 - \frac{m_{ik}-u_{ik}}{l_{ik}} & u_{ik} \leq m_{ik}\,(l_{ik} > 0) \\ 1 - \frac{u_{ik}-m_{ik}}{r_{ik}} & u_{ik} > m_{ik}\,(r_{ik} > 0). \end{cases} \tag{2}$$

The fuzzy recoding from the Likert–type scale to the fuzzy numbers is displayed in Figure 2.

For instance, to the value 1 in the Likert–type scale (*Very unsatisfied*) corresponds a fuzzy number in the range [1, 2]. It is important to underline that the degree of vagueness, i.e. the right and left spread, of the extreme linguistic terms, i.e. *very unsatisfied* (equal to 1) and *very satisfied* (equal to 10), is higher than the degree of vagueness of the other linguistic terms and that the degree of vagueness decreases more and more approaching to the central values, i.e. 5 and 6. In fact, it is common to think that a value below 5 indicates a negative evaluation while a value above 6 expresses a positive judgement. Therefore, respondents well know the difference between values 5 and 6, i.e. these values are little vague, but it is more difficult for them to understand/appreciate the difference between 1 and 2, or between 9 and 10, i.e. these values incorporate a higher degree of uncertainty.

Notice that *elicitation* and *specification* of the membership functions are two important issues connected with the representation of natural language by means of fuzzy data. As remarked by Coppi, Giordani, and D'Urso (2006) "as for the subjectivistic approach to probability, also the choice of the membership functions is subjective. In general, these are determined by experts in the problem area. In fact, the membership functions are context-sensitive. Furthermore, the functions are not determined in an arbitrary way, but are based on a sound psychological/linguistic foundation. It follows that the choice of the membership function should be made in such a way that a function captures the approximate reasoning of the person involved. In this respect, the elicitation of a membership function requires a deep psychological understanding." For what regards specification we can distinguish two approaches for the specification of the membership functions when dealing simultaneously with K variables, as is in our case: (a) the *conjunctive* approach and (b) the *disjunctive* approach (Coppi, 2003). In this work we follow the *disjunctive* approach. In the disjunctive approach our interest focuses upon the "juxtaposition" of the K, observed as a whole in the group of N objects. In this case, we have K membership functions and the investigation of the links among the K fuzzy variables is carried out directly on the matrix of fuzzy data concerning the NK-variate observations (Coppi, 2003; D'Urso, 2007). Another relevant issue is related to the imprecision associated with the use in the evaluation process of linguistic term-based scales. In our study we have dealt with the imprecision related to ordinal qualitative data by means of a fuzzy conversion scale, i.e. we employ a fuzzy version of Likert-type scales. As a final remark, it has to be noticed that robustness and stability of the results obtained from fuzzy data analysis are still open problems. We will investigate in deep these important research topics in our future studies.

subsectionThe fuzzy clustering method

To take into account at the same time the uncertainty related to the data at hand, and that related to the assignment of units to each cluster, we make use of the fuzzy C-means algorithm for fuzzy data (FCM-FD) proposed by Coppi et al. (2012):

$$
\begin{cases}
\min: & \sum_{i=1}^{N}\sum_{c=1}^{C} u_{ic}^{p} d_F^2(\tilde{\mathbf{x}}_i, \tilde{\mathbf{h}}_c) = \\
& \sum_{i=1}^{N}\sum_{c=1}^{C} u_{ic}^{p} \left[w_M^2 \left(\|\mathbf{m}_i - \mathbf{h}_c^M\|^2 \right) + w_S^2 \left(\|\mathbf{l}_i - \mathbf{h}_c^L\|^2 + \|\mathbf{r}_i - \mathbf{h}_c^R\|^2 \right) \right] \\
s.t. & \sum_{c=1}^{C} u_{ic} = 1, \qquad u_{ic} \geq 0, \\
& w_M \geq w_S \geq 0; \; w_M + w_S = 1
\end{cases}
\tag{3}
$$

where: $d_F^2(\tilde{\mathbf{x}}_i, \tilde{\mathbf{h}}_c)$ represents the squared fuzzy distance between the ith unit and the prototype of the cth cluster; $\tilde{\mathbf{x}}_i \equiv \{\tilde{x}_{ik} = (m_{ik}, l_{ik}, r_{ik})_{LR} : k = 1, \ldots, K\}$ denotes the fuzzy data vector for the ith unit observed on K fuzzy variables; $\mathbf{m}_i$, $\mathbf{l}_i$ and $\mathbf{r}_i$ are the vectors of the centers and of the left and right spreads, respectively; $\tilde{\mathbf{h}}_c \equiv \{\tilde{h}_{ck} = (h_{ck}^M, h_{ck}^L, h_{ck}^R)_{LR} : k = 1, \ldots, K\}$ represents the fuzzy prototype of the cth cluster; $\mathbf{h}_c^M$, $\mathbf{h}_c^L$ and $\mathbf{h}_c^R$ represent respectively, the center and the left and right spreads of the c-th fuzzy prototype; $\|\mathbf{m}_i - \mathbf{h}_c^M\|^2$ is the squared Euclidean distances between the centers; $\|\mathbf{l}_i - \mathbf{h}_c^L\|^2$ and $\|\mathbf{r}_i - \mathbf{h}_c^R\|^2$ are the squared Euclidean distances between the left and right spread, respectively; w_M, $w_S \geq 0$ are suitable weights for the center component and the spread component for the fuzzy distance considered; $p > 1$ is a weighting exponent that controls the fuzziness of the obtained partition; u_{ic} indicates the membership degree of the ith unit in the cth $(c = 1, \ldots, C)$ cluster. For the iterative solutions with respect to $\tilde{\mathbf{h}}_c$, u_{ic}, w_M and w_S see Coppi et al. (2012). Finally, as for the elicitation issue -see previous section- there is no need for *a priori* choice of the shape of the membership functions, since the squared distance measure adopted in (3) is defined considering only the centers and the spreads of the fuzzy data. Hence, the adopted squared distance measure and the connected clustering method are, as it were, "shape free".

6.2 Cluster validation and cluster profiles

The cluster validity index proposed by Xie and Beni (1991) -henceforth XB- was adopted in order to detect the optimal number of clusters. This index aims to quantify the ratio of compactness (and therefore the total variance within the clusters) to the separation of clusters. A smaller XB indicates that all the clusters are overall compact and separate to each other. Thus the goal is to find the fuzzy C-partition with the smallest XB. As stated in the theoretical part of the paper, the usual method to profile the clusters is done through a "defuzzification" procedure which consist in assigning the unit to the cluster according to the highest membership degree or by specifying a cut–off point. However, this contrasts with the very essence of the fuzzy theory and fuzzy clustering whereby individuals are allowed to belong to more than one cluster. This also contrasts with the postmodern consumer / tourist which are characterised by the absence of commitment in any single lifestyle. Therefore, in order to profile the identified clusters, other information, such as socio–demographic and travelling characteristics, collected through the survey can be used. In order to capture the vagueness raised assigning each unit to each cluster with a certain membership degree also in the profiling stage, the weighted percentage frequency ($\tilde{f}_{kjc}$) and the traditional weighted average, respectively adopted for qualitative and quantitative variables, can be used. The $\tilde{f}_{kjc}$, referring to the jth ($j = 1, \ldots, J$) modality of the kth original variable ($\mathbf{x}_k$) for the cth cluster, was calculated as follows:

$$\tilde{f}_{kjc} = \frac{\sum_{i=1}^{N} x_{kji} u_{ic}}{\sum_{c=1}^{C} \sum_{i=1}^{N} x_{kji} u_{ic}} \cdot 100. \tag{4}$$

7 Empirical results and discussion

7.1 The fuzzy clusters

Based on the Xie-Beni criterion, the best partition which allow a precise a detailed characterization of the market segments is the one with three clusters. The vectors of the centers for the final clusters solution, graphically displayed in Figure 3 (dotted lines represent the uncertainty in subjective evaluations), suggest that cluster 1 and 2 group, respectively, people less and more satisfied with the investigated aspects in comparison to the third cluster. Consequently, these two clusters were labelled respectively "Unfulfilled" and "Enthusiasts". Cluster 3 groups visitors who are neither much nor little satisfied. This cluster was named the "With reservations". To further understand differences in satisfaction among the three clusters, the 10 aspects were ranked in ascending order (from the least to the most satisfactory) for each cluster. The results (Table 2) show that all clusters are less satisfied in "Prices", "Products sold", and "Information"; similarly, all clusters rank "Landscape" in the first position. The most clear-cut difference among the three clusters lies in Cluster 2, which ranked as the most satisfying factor "Accommodation" and as the least satisfying "Friendliness" of local people.

7.2 Cluster profiles

Table 3 presents the percentage composition of the whole sample (first column) and the weighted relative frequencies per each profiling variable and cluster. The socio–demographic characteristics reveal that only the country of origin is significantly dependent belonging to different clusters. In particular, the percentage of Austrian people in Cluster 1 ("Unfulfilled") is higher compared to Cluster 2 ("Enthusiasts") and 3 ("With reservations"), the percentage of German people and people from other European countries is higher in Cluster 2, while Cluster 3 presents the highest percentage of people from countries outside Europe. An examination of the travelling characteristics reveals that the

"Unfulfilled" have the highest proportion of visitors who are travelling alone, while the "Enthusiasts" have the lowest. The "Unfulfilled" have the highest proportion of travellers visiting Italy for the first time, while the "Enthusiasts" have the highest proportion of travellers who had already visited Italy before. Regarding the main purpose of travel, the "Enthusiasts" have the highest proportion of respondents travelling for leisure purposes (82.63%) and undertaking mountain holidays, while the "Unfulfilled" have the highest proportion of people travelling for business. Finally, regarding the travel expenditure behaviour, the "Enthusiasts" have the highest proportion of visitors who spend on accommodation, transportation, food and beverage, and shopping, while the "Unfulfilled" have the lowest proportion in each of these expenditure item.

7.3 Discussion of the results

This study reveals that no matter whether visitors are enthusiastic about the destination or feeling unfulfilled, all of them perceive prices to be too high and inadequate. Destination managers and planners should therefore encourage tourism operators to justify prices through quality of the products. Moreover, the percentage of those travellers who do not find complete satisfaction with their experience in South–Tyrol is equal to 34%. Careful steps must be undertaken in order to turn these travellers into satisfied and potentially returning visitors. Interestingly, these visitors tend to travel alone, to visit Italy (and therefore South–Tyrol as well) for the first time and for business or other personal reasons. They also spend less frequently in all shopping categories than other visitors and they mainly come from Austria. A reason for this partial satisfaction can lie in the initial image they have about South–Tyrol, perhaps due to a comparison with the nearby home-region Tyrol or due to incorrect marketing campaigns done by the South Tyrolean Tourism Board in Austria. Furthermore, it is interesting to note that although "Enthusiasts" attribute a high score to the friendliness of local residents, they rank it as the fifth satisfying aspect of the destination. This cluster has a higher proportion of visitors from Germany who have visited Italy 5 or more times. This result should be further analysed with an ad–hoc survey to detect whether this is due to an underestimated cultural difference between Germans and Northern Europeans (as tourists) and South Tyroleans (as hosts), or by an expectation by those who have travelled to Italy before –but never to South–Tyrol– to find a "typical Italian" atmosphere in mountain villages where residents are predominantly of Austrian decent and culture.

8 Cconclusions

This paper has tried to create a nexus between postmodern consumer behaviour and fuzzy clustering. Its aim was to propose a suitable clustering method to segment postmodern consumers by theoretically discussing fuzzy numbers and clustering and by empirically applying the techniques suggested to a dataset of international tourists. The philosophical postmodern movement has put into discussion the absolute reality and universality of modernity offering a new perspective and point of discussion and analysis of people's behaviour, attitudes and values. Simultaneously fuzzy sets, which "encouraged the acceptance of uncertainty as a condition of everyday life" (Negoita, 2002, p. 1047), developed and made possible the manipulation of imprecise facts (or impressions) through the use of membership degrees (Negoita, 2002). This paper embraces the fuzzy theory to analyse the uncertainty and vagueness that characterise the experiences and perceptions of postmodern consumers. From a methodological perspective, the main contribution of this paper is related to the use of the fuzzy theory from the beginning to the end of the process. Unlike other fuzzy-based applications in tourism (Chiang, 2011; D'Urso et al., 2013; Jian & Ning, 2012) which make use of the fuzzy theory only on single steps of the analysis, the clustering technique we have proposed and applied is fuzzy in every step of the process: in the data used, in the clustering algorithm, and finally in the profiling of the clusters. In the first step of the process we adopted fuzzy numbers as a method to measure satisfaction level with a destination and to overcome the vagueness of concepts that are associated with subjective evaluations. The ambiguity of the texts, whereby the written mark loses its meaning to adopt a pure technical function, has been "corrected" through a triangular transformation of the values of satisfaction expressed by the respondents. In the second step of the process we adopted the FCM-FD algorithm as a method able to allocate each unit to each cluster in a more flexible manner. Postmodern consumers, with their multiple and disjointed consumption experiences which allow the coexistence of differences and paradoxes, by nature cannot be allocated to one (and only one) cluster. The FCM-FD algorithm has allowed us to allocate units to more than one cluster according to their membership degree (or better their similarity/dissimilarity degree with the clusters) and consequently it has been possible to account for the specific individualities of the units. This is a situation that cannot be detected with hard clustering methods. The third step of the process relates to the use of membership degrees not only in the creation of the clusters, but also in the profiling phase. A common practice in the literature is to assign each unit to a cluster in a crisp (or hard) way, adopting a "defuzzification" procedure and/or specifying a cut–off pint for membership. Postmodern consumers who, as described by Simmons (2008), "do not present a united, centered self and, therefore, set of preferences, but instead a jigsaw collage of multiple representations of selves and preferences even when approaching the same product category" need to be analysed in such a way that their fragmentation and absence of commitment in any single lifestyle is taken into consideration. Finally, some authors suggest that the most successful way to communicate to postmodern consumers and to analyse their behaviour is through micro marketing, neo–marketing, database marketing (for a full list see Brown, 1993) as these techniques allow the detection of specific individualities and creation of tailored–made responses. Although through the use of the Internet and mobile communication single firms can communicate with and market their products on a one–to–one base, destination mangers and planner still need to have a broader understanding of their visitors in an aggregate way in order to "allocate resources more effectively in attracting distinct and unique groups of travellers" (Kau & Lim, 2005), who spend more at the destination, return over the year, and spread positive word of mouth. To this end market segmentation has been increasingly adopted. In this paper we proposed a suitable market segmentation which allows to collect aggregate information about individuals but is also capable to deal with the vagueness, fragmentation and multiple preferences of postmodern consumers.

References

Ahmad, S. N., & Richard, M.-O. (2014). Understanding consumer's brand categorization across three countries: Application of fuzzy rule-based classification. *Journal of Business Research*, *67*(3), 278 - 287.

Balas, M. M., & Balas, V. E. (2009). Postmodernism and control engineering. In Seising, E. (Ed.), *Views on fuzzy sets and systems.* Berlin, Heiderberg: Springer Verlag.

Baudrillard, J. (1981). *Simulacres et simulation.* Paris: Galilée.

Benítez, J. M., Martín, J. C., & 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.

Brown, S. (1993). Postmodern Marketing? *European Journal of Marketing*, *27*(4), 19–34.

Brown, S. (2006). Recycling Postmodern Marketing. *The Marketing Review*, *6*(3), 211–230.

Chaturvedi, A., Carroll, J. D., Green, P. E., & Rotondo, J. A. (1997). A feature-based approach to market segmentation via overlapping *k*-centroids clustering. *Journal of Marketing Research*, *34*(3), 370–377.

Cheng, C. B. (1991). Fuzzy process control: construction of control charts with fuzzy numbers. *Fuzzy Sets and Systems*, *154*, 287–303.

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*, 447–456.

Chou, T.-Y., Hsu, C.-L., & Chen, M.-C. (2008). A fuzzy multi-criteria decision model for international tourist hotels location selection. *International Journal of Hospitality Management*, *27*, 293–301.

Coppi, R. (2003). *The fuzzy approach to multivariate statistical analysis* (Tech. Rep. No. 11). Rome, Italy: Dipartimento di Statistica, Probabilità e Statistiche Applicate, Sapienza Università di Roma.

Coppi, R., & D'Urso, P. (2002). Fuzzy k–means clustering models for triangular fuzzy time trajectories. *Statistical Methods and Applications*, *11*, 21–24.

Coppi, R., D'Urso, P., & Giordani, P. (2012). Fuzzy and possibilistic clustering for fuzzy data. *Computational Statistics & Data Analysis*, *56*(4), 915–927.

Coppi, R., Giordani, P., & D'Urso, P. (2006). Component models for fuzzy data. *Psychometrika*, *71*(4), 733–761.

Derrida, J. (1967). *De la grammatologie*. Paris: Les Éditions de Minuit, Collection Critique.

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., & Lazarevski, K. (2009). Methodological reasons for the theory/practice divide in market segmentation. *Journal of Marketing Management*, *25*(3/4), 357–373.

Dolnicar, S., & Leisch, F. (2004). Segmenting markets by bagged clustering. *Australasian Marketing Journal (AMJ)*, *12*(1), 51–65.

Dubois, D., & Prade, H. (1988). *Possibility theory*. Plenum press, New

York.

D'Urso, P. (2007). Clustering of fuzzy data. In J. V. De Oliveira & W. Pedrycz (Eds.), *Advances in fuzzy clustering and its applications* (pp. 155–192). J. Wiley and Sons.

D'Urso, P. (2014). Fuzzy clustering. In C. Hennig, M. Meila, F. Murtagh, & R. Rocci (Eds.), *Handbook of cluster analysis.* Chapman and Hall.

D'Urso, P., & De Giovanni, L. (2014). Robust clustering of imprecise data. *Chemometrics and Intelligent Laboratory Systems*, *136*, 58–80.

D'Urso, P., De Giovanni, L., Disegna, M., & Massari, R. (2013). Bagged clustering and its application to tourism market segmentation. *Expert Systems with Applications*, *40*(12), 4944–4956. doi: 10.1016/j.eswa.2013.03.005

Engel, J. F., Blackwell, R. D., & Miniard, P. W. (1995). *Consumer behavior.* TX: The Dryden Press: Forth Worth.

Feifer, M. (1985). *Going places.* London: Macmillan.

Firat, A. F., & Venkatesh, A. (1995). Liberatory postmodernism and the reenchantment of consumption. *Journal of Consumer Research*, *22*(3), 239–267.

Foucault, M. (1969). *L'archéologie du savoir.* Collection Bibliothèque des Sciences humaines, Gallimard.

Ghaemi, R., Sulaiman, N., Ibrahim, H., & Mustapha, N. (2009). A survey: Clustering ensembles techniques. *World Academy of Science, Engineering and Technology*, *29*, 636–645.

Ghomshei, M. M., Meech, J. A., & Naderi, R. (2008). Fuzzy logic in a postmodern era. In Nikravesh, et al. (Ed.), *Forging the new frontiers. fuzzy pioneers ii.* Berlin, Heiderlberg: Springer Verlag.

Gil, M. A., & González-Rodríguez, G. (2012). Fuzzy *vs. Likert Scale in Statistics*. In E. Trillas, P. P. Bonissone, L. Magdalena, & J. Kacprzyk (Eds.), *Combining experimentation and theory* (Vol. 271, p. 407-420). Springer.

Grekousis, G., & Thomas, H. (2012). Comparison of two fuzzy algorithms in geodemographic segmentation analysis: The Fuzzy C–Means and Gustafson–Kessel methods. *Applied Geography*, *34*, 125–136.

Hisdal, E. (1988). The philosophical issues raised by fuzzy set theory. *Fuzzy Sets and Systems*, *25*(3), 349–367.

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., Wolfe, K., & Kang, S. K. (2004). Image assessment for a destination with limited comparative advantages. *Tourism Management*, *25*, 121–126.

Hsu, T.-H., & Lin, L.-Z. (2006). Using fuzzy set theoretic techniques to analyze travel risk: an empirical study. *Tourism Management*, *27*, 968–981.

Hsu, T.-K., Tsai, Y.-F., & Wu, H.-H. (2009). The preference analysis for tourist choice of destination: a case study of Taiwan. *Tourism Management*, *30*, 288–297.

Huang, J.-H., & Peng, K.-H. (2012). Fuzzy Rasch model in TOPSIS: a new approach for generating fuzzy numbers to assess the competitiveness of the tourism industries in Asian countries. *Tourism Management*, *33*, 456–465.

Jian, L., & Ning, Z. (2012). Empirical research of intercity high-speed rail passengers' travel behavior based on fuzzy clustering model.

Journal of Transportation Systems Engineering and Information Technology, *12*(6), 100–105.

Kau, A. K., & Lim, P. S. (2005). Clustering of Chinese tourists to Singapore: An analysis of their motivations, values and satisfaction. *International Journal of Tourism Research*, *7*, 231–248.

Kotler, P. (1988). *Marketing management* (6th ed.). Prentice-Hall: Englewood Cliffs, NJ.

Leisch, F. (1999). *Bagged clustering* (Working paper No. 51). WU Vienna University of Economics and Business: SFB Adaptive Information Systems and Modelling in Economics and Management Science.

Leisch, F. (2006). A toolbox for k-centroids cluster analysis. *Computational statistics & data analysis*, *51*(2), 526–544.

Li, X., Meng, F., Uysal, M., & Mihalik, B. (2013). Understanding China's long-haul outbound travel market: An overlapped segmentation approach. *Journal of Business Research*, *66*, 786–793.

Liao, S. H., Chu, P. H., & Hsiao, P. Y. (2012). Data mining techniques and applications – A decade review from 2000 to 2011. *Expert Systems with Applications*, *36*, 11772–11781.

Ligorio, T. (2004). Postmodernism and fuzzy systems. *Kybernetes*, *33*(8), 1312–1319.

Lim, C. M., Kim, Y.-K., & Runyan, R. (2013). Segmenting luxe-bargain shoppers using a fuzzy clustering method. *International Journal of Retail & Distribution Management*, *41*(11/12), 848–868.

Lin, L.-Z., Chen, W.-C., & Chang, T.-J. (2011). Using FQFD to analyze island accommodation management in fuzzy linguistic preferences. *Expert Systems with applications*, *38*, 7738–7745.

Lin, L.-Z., & Yeh, H.-R. (2013). A means-end chain of fuzzy conceptualization to elicit consumer perception in store image. *International*

Journal of Hospitality Management, *33*, 376–388.

Lyotard, J. F. (1979). *La condition postmoderne – rapport sur le savoir.* Paris, Les Éditions de Minuit, Collection Critique.

Malinverni, E. S., & Fangi, G. (2009). Comparative cluster analysis to localize emergencies in archaelogy. *Journal of Cultural Heritage*, *10, Supplement 1*, e11–e19.

Maoz, D., & Bekerman, Z. (2010). Searching for Jewish Answere in Indian Resorts - The Postmodern Traveler. *Annals of Tourism Research*, *37*(2), 423–439.

Munt, I. (1994). The "Other" Postmodern Tourism: Culture, Travel and the new Middle Class. *Theory, Culture and Society*, *11*(3), 101–123.

Negoita, C. V. (2002). Postmodernism, cybernetics and fuzzy set theory. *Kybernetes*, *31*(7/8), 1043–1049.

Ngai, E., & Wat, F. (2003). Design and development of a fuzzy expert system for hotel selection. *Omega*, *31*(4), 275–286.

Pérez-Gladish, B., Gonzalez, I., Bilbao-Terol, A., & Arenas-Parra, M. (2010). Planning a TV advertising campaign: A crisp multiobjective programming model from fuzzy basic data. *Omega*, *38*(1–2), 84–94.

Rangel-Buitrago, N., Correa, I. D., Anfuso, G., Ergin, A., & Williams, A. T. (2013). Assessing and managing scenery of the Caribbean Clast of Columbia. *Tourism Management*, *35*, 41–58.

Sanna, U., Atzeni, C., & Spanu, N. (2008). A fuzzy number ranking in project selection for cultural heritage sites. *Journal of Cultural Heritage*, *9*, 311–316.

Simmons, G. (2008). Marketing to postmodern consumers: introducing the internet chameleon. *European Journal of Marketing*, *42*(3/4), 299–310.

Simon, D. (2006). Truth, American Culture, and Fuzzy Logic. In *Proceedings of the North American Fuzzy Information Processing Society Conference, Montreal, Canadaâ* (pp. 430–435).

Sinova, B., Gil, M. Á., Colubi, A., & Van Aelst, S. (2012). The median of a random fuzzy number. the 1-norm distance approach. *Fuzzy Sets and Systems*, *200*, 99–115.

Sohrabi, B., Vanani, I. R., Tahmasebipur, K., & Fazli, S. (2012). An exploratory analysis of hotel selection factors: A comprehensive survey of Tehran hotels. *International Journal of Hospitality Management*, *31*, 96–106.

Tuma, M. N., Decker, R., & 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.

Uriely, N. (1997). Theories of Modern and Postmodern Tourism. *Annals of Tourism Research*, *24*(4), 982–985.

Wang, N. (1999). Rethinking authenticity in tourism experience. *Annals of Tourism Research*, *26*(2), 349–370.

Wang, Y., Ma, X., Lao, Y., & Wang, Y. (2014). A fuzzy-based customer clustering approach with hierarchical structure for logistics network optimization. *Expert Systems with Applications*, *41*(2), 521–534.

Wang, Y. P., Gunampally, M., Chen, J., Bittel, D., Butler, M. G., & 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., & Kamakura, W. A. (2000). *Market segmentation: Conceptual and methodological foundations* (2nd ed.). Dordrecht: Kluwer:

Archives of Psychology.

Wu, Y.-Y., Hsiao, H.-L., & Ho, Y.-F. (2010). Urban ecotourism: defining and assessing dimensions using fuzzy number construction. *Tourism Management*, *31*, 739–743.

Xie, X., & Beni, G. (1991). A validity measure for fuzzy clustering. *IEEE Trans. Pattern Analysis and Machine Intelligence (PAMI)*, *13*(8), 841–847.

Zadeh, L. (1965). Fuzzy sets. *Information and control*, *8*, 338–353.

Zimmermann, H. J. (1996). *Fuzzy sets and its application* (3nd ed.). Norwell, MA: Kluwer Academic.

Figures

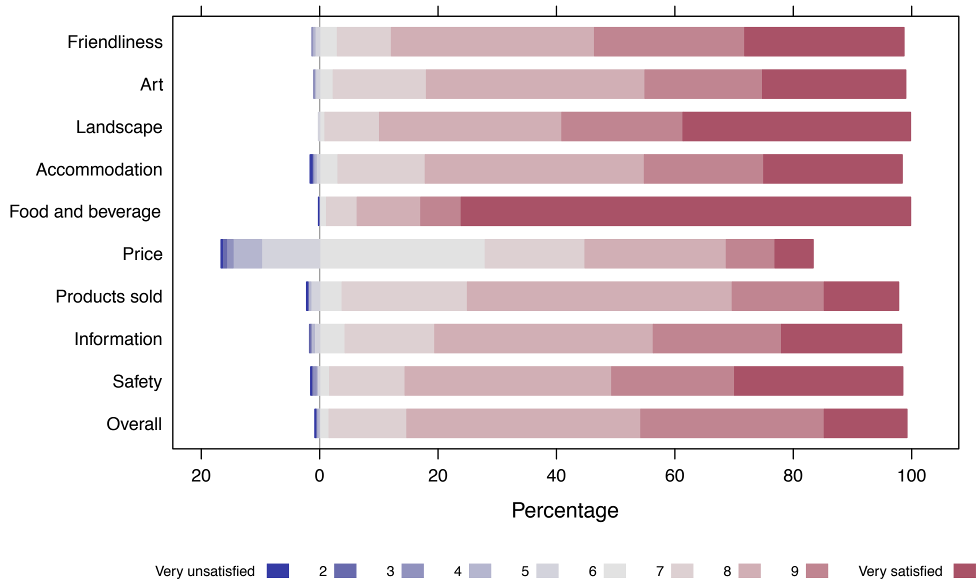

Figure 1: *% distribution for each aspect.*

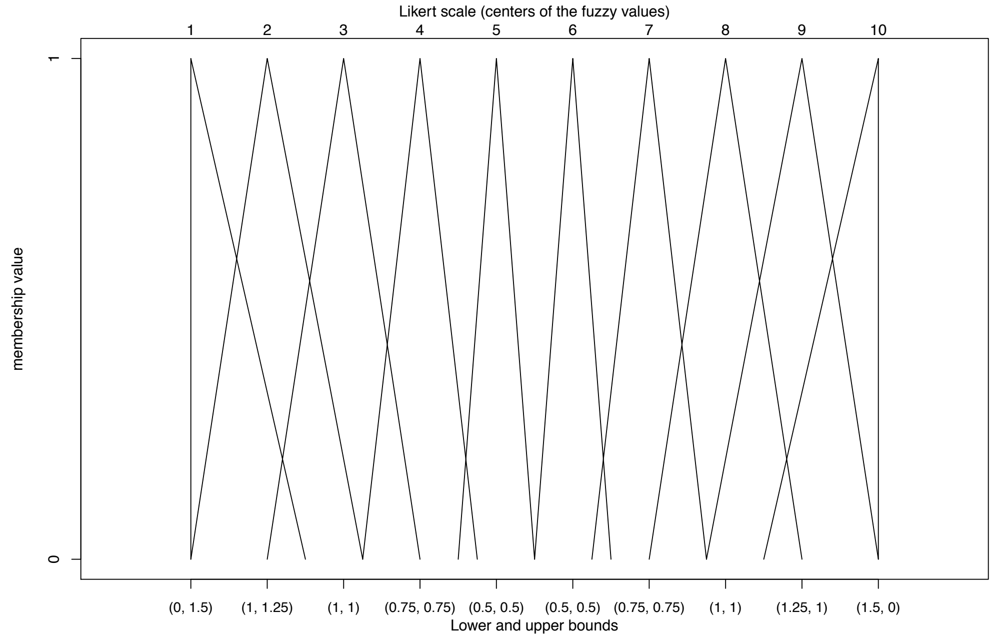

Figure 2: *Linguistic satisfaction terms in the form of fuzzy numbers.*

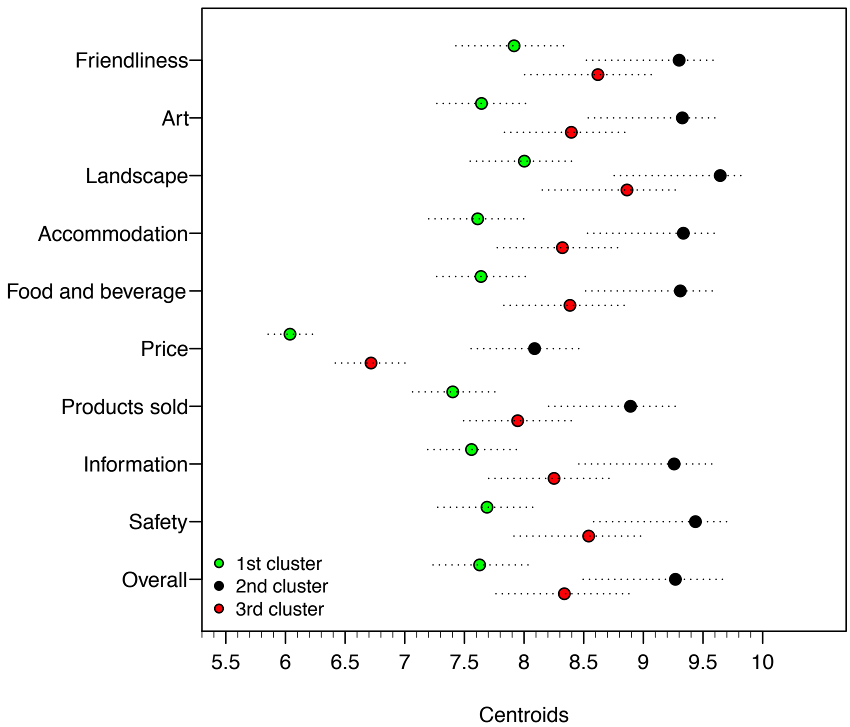

Figure 3: *The three clusters solution.*

Tables

Table 1: *Variables description*

Independet variables	Descriptions
Socio-demographic and economic characteristics	
Male	1= Male; 0= Female
Age	
Less than 35 years old	1 = ticked; 0 = not ticked
35-44 years old	1 = ticked; 0 = not ticked
45-64 years old	1 = ticked; 0 = not ticked
More than 65 years old	1 = ticked; 0 = not ticked
Employment status	
Self-employed	1 = ticked; 0 = not ticked
Office worker	1 = ticked; 0 = not ticked
Employee	1 = ticked; 0 = not ticked
Retired	1 = ticked; 0 = not ticked
Other employment status	1 = ticked; 0 = not ticked
Country of origin	
Austria	1 = ticked; 0 = not ticked
Germany	1 = ticked; 0 = not ticked
Other EU countries	1 = ticked; 0 = not ticked
Outside EU	1 = ticked; 0 = not ticked
Trip characteristics	
Visit alone	1 = The respondent makes the trip alone; 0 = otherwise
Only one cities visited	1 = Only one city visited in South-Tyrol during the trip; 0 = otherwise
Number of times in Italy before	
Zero	1 = The interviewee visits any city in Italy for the first time; 0 = otherwise
Up to 5 times	1 = Been in Italy from 1 to 5 times before the interview; 0 = otherwise
More than 5 times	1 = Been in Italy more than 5 times before the interview; 0 = otherwise
Main purpose of travel	
Mountain holiday	1 = ticked; 0 = not ticked
Cultural holiday	1 = ticked; 0 = not ticked
Other kind of holiday	1 = The respondent makes the trip for other holiday purposes (see, lake, sport, wine & food, etc.); 0 = otherwise
Other personal motivations	1 = The respondent makes the trip for a personal motivations (visiting friends & relatives, study, shopping, etc.); 0 = otherwise
Business	1 = ticked; 0 = not ticked
Expenditure behavior	
Accommodation	1 = Positive expenditure on accommodation; 0 = otherwise
Transportation	1 = Positive expenditure on transportation; 0 = otherwise
Food & Beverage	1 = Positive expenditure on food and beverage; 0 = otherwise
Shopping	1 = Positive expenditure on shopping; 0 = otherwise
Other services	1 = Positive expenditure on other services; 0 = otherwise

Table 2: *Rank of the different aspects of the visited destination for each cluster.*

Satisfaction	Cluster 1 "Unfulfilled"	Rank	Cluster 2 "Enthusiasts"	Rank	Cluster 3 "With Reservations"	Rank
Friendliness	7.916	9	9.300	5	8.619	9
Art	7.643	7	9.327	7	8.396	7
Landascape	8.002	10	9.644	10	8.863	10
Accommodation	7.611	4	9.335	8	8.321	4
Food & beverage	7.639	6	9.310	6	8.385	6
Prices	6.038	1	8.088	1	6.717	1
Products sold	7.402	2	8.892	2	7.946	2
Information	7.559	3	9.258	3	8.251	3
Safety	7.689	8	9.437	9	8.541	8
Overall	7.627	5	9.269	4	8.338	5

Table 3: *Socio–demographic characteristics of the visitors and travelling characteristics (percentage values).*

Variables	Sample	Cluster 1 "Unfulfilled"	Cluster 2 "Enthusiasts"	Cluster 3 "With Reservations"	p-value
Socio–demographic characteristics					
Male	68.91	70.74	66.13	69.60	
Age					
Less than 35 years old	21.16	22.39	19.74	21.25	
35-44 years old	28.59	26.57	31.07	28.33	
45-64 years old	36.41	35.52	37.22	36.54	
More than 64 years old	13.84	15.52	11.97	13.88	
Employment status					
Self–employed	11.57	11.38	11.61	11.68	
Office worker	16.20	14.67	17.74	16.52	
Employee	53.72	53.89	52.58	54.42	
Retired	12.47	14.07	11.29	11.97	
Other	6.04	5.99	6.78	5.41	
Country of origin					***
Austria	21.06	29.85	14.84	18.13	
Germany	50.85	42.99	56.45	53.26	
Other EU countries	21.46	20.59	22.58	21.25	
Outside EU	6.63	6.57	6.13	7.36	
Trip characteristics					
Visit alone	23.97	31.14	18.71	21.81	***
Only one cities visited	84.05	86.97	81.61	83.57	
Number of times in Italy before					***
Zero	23.97	31.14	17.10	23.23	
Up to 5 times	24.87	22.15	27.10	25.50	
More than 5 times	51.15	46.71	55.80	51.27	
Main purpose of travel					***
Mountain holiday	46.14	39.70	50.48	48.43	
Cultural holiday	18.86	19.40	19.29	17.95	
Other kind of holiday	11.03	9.55	12.86	10.83	
Other personal motivations	13.44	17.92	9.97	12.25	
Business	10.53	13.43	7.40	10.54	
Expenditure behavior					
Accommodation	84.25	73.05	93.55	86.67	***
Transportation	71.51	58.98	83.97	72.52	***
Food & Beverage	83.35	77.91	87.70	84.70	***
Shopping	72.52	68.66	76.77	72.44	*
Other services	35.31	31.94	37.10	36.93	

Notes: Significance of the Chi-square test was reported. All test results are not significant unless indicated otherwise: ***Significant at $p \leq 0.01$, **Significant at $p \leq 0.05$, *Significant at $p \leq 0.1$.