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Fuzzy segmentation of postmodern tourists

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HIGHLIGHTS

- Illustrates the nexus between postmodern tourist and fuzzy clustering.
- A procedure that embraced fuzzy theory from the beginning to the end is proposed.
- A procedure that is able to handle the uncertainty that characterize postmodern era.
- Levels of satisfaction with the destination are used to segment tourists.

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ABSTRACT

In postmodern tourism, the experiences of each tourist could not be summarized only through a unique perspective but multiple and disjointed perspectives are necessary. The aim of this paper is to create a nexus between postmodern tourist and fuzzy clustering, and to propose a suitable clustering procedure to segment postmodern tourists. 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 clustering process. Furthermore, the suggested procedure is capable of analysing the uncertainty and vagueness that characterise the experiences and perceptions of postmodern consumers. From a managerial perspective, fuzzy clustering methods offer to practitioners a more realistic multidimensional description of the market not forcing consumers to belong to one cluster. Moreover, the results are easy and comprehensible to read since they are similar to those obtained with more traditional clustering techniques.

1. Introduction

Over the years in both the general marketing and the more specific tourism literature a great debate has generated about the techniques to use in segmentation. In marketing and tourism literature, cluster analysis remains the most favoured method (Dolnicar, 2002; Wedel & Kamakura, 2000) despite the criticisms it has raised (Dolnicar, 2002; Dolnicar & Lazarevski, 2009). A clustering algorithm performs a multivariate description of the data therefore different clustering algorithms produce different solutions (Grekousis & Thomas, 2012) and no single clustering algorithm achieves satisfactory clustering solutions for all types of data sets (Ghaemi, Sulaiman, Ibrahim, & Mustapha, 2009).

A literature review in the tourism field suggests that the majority of segmentation studies used motivations, personal opinions/judgements, or other psychographic variables to segment tourists (see for example Konu, Laukkanen, & Komppula, 2011; Li, Meng, Uysal, & Mihalik, 2013; Prayag & Hosany, 2014). Oftentimes, these kinds of information are captured through qualitative scales, such as Likert-type scales. Despite these kind of scales are widely used in many different research fields, mainly thanks to the ease of developing and administering them, they allow to obtain only an imprecise measurement of the subjective perception of the respondent. To the best of our knowledge, few segmentation studies on tourism have taken into consideration the uncertainty and vagueness that generally characterize qualitative scales (D'Urso, De Giovanni, Disegna, & Massari, 2013, D'Urso, Disegna, Massari, & Prayag, 2015). Over the years it has been demonstrated that fuzzy theory (Zadeh, 1965) is capable to cope with uncertain and/or vague data in a better way than traditional methods (e.g. Coppi & D'Urso, 2002; Benítez, Martín, & Román, 2007; Sinova, Gil, Colubi, & Van Aelst, 2012; Wang, Xiaolei, Yunteng, & Yinhai, 2014; Chu & Guo, 2015). Hence, this study

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suggests to transform the information obtained by qualitative scales into fuzzy numbers before the adoption of any segmentation technique.

Another important issue that must be taken into consideration in the choice of the best algorithm to adopt, but on which little attention has been paid till now, regards the peculiar characteristics of the customers (or tourists in this instance). In the early 90s the marketing and tourism literature has started to debate about and to investigate a new type of tourist, which reflects the current postmodern era. “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 (that can be grouped in non-overlapping, overlapping, and fuzzy 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 algorithms seem to be the most suitable as they are able to capture the “undefined” tourists' behaviour, preferences, emotions, or other feelings, assigning each tourist to each cluster with a certain degree of membership (Tuma, Decker, & Scholz, 2011). Furthermore, fuzzy clustering methods seem to satisfy managerial needs of segmentation with a more realistic multidimensional description of the market place, in which consumers are not forced to belong to one cluster (Zhang, Prater, & Lipkin, 2013).

Accordingly, this study aims to adopt a clustering procedure able to segment postmodern tourists using personal opinions collected through qualitative scales as segmentation variables. The peculiarity of this procedure consists in embracing fuzzy theory from the beginning to the end of the process:

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

As such, this procedure is able to capture both vagueness in individual evaluation of linguistic terms and that derived from the uncertainty in assigning units to each cluster.

After a theoretical discussion of the nexus between postmodernity and fuzzy theory (Section 2), the fuzzy segmentation procedure is described (Section 3). In section 4 the case study is presented while section 5 shows and discusses the results, describing how they can be visualized and interpreted. The paper concludes discussing both academics and practitioners implications of the segmentation procedure suggested.

2. Literature review

2.1. Postmodernism and tourism

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 (Wang, Niu, Lu, & Qian, 2015; Uriely, 1997).

In the early 1990s, postmodernism has started to pertain also marketing studies, where traditional approaches were put into discussion (Brown, 1993) and new marketing approaches were proposed (e.g. Cova & Svanfeldt, 1993; Stern, 1994; Firat, Dholakia, & Venkatesh, 1995). Nowadays, postmodernism is considered to shape today's world society in preferences, choices, and behaviour (e.g. Wang et al., 2015; Goneos-Malka, Strasheim, & Grobler, 2014; Dunn & Castro, 2012; Riefler, 2012). 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 (Uriely, 1997; 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).

2.2. Postmodernism and fuzzy sets

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, & Naderi, 2008). In the same period, Zadeh presented his first work on fuzzy sets (Zadeh, 1965). Although born and developed independently, fuzzy theory and postmodernism were providing an answer and a point of discussion to the changing needs, behaviours, and believes of the consumer age.

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, as demonstrated for example in the study conducted by Hsu, Wolfe, and Kang (2004). In other words, the concept to be evaluated is unique but the mind of the consumer is fuzzy and vague (Lin & Yeh, 2013). This concept is intimately related to the deconstruction, subjectivation, and de-realisation of postmodernism (Derrida, 1967; Foucault, 1969; Lyotard, 1979), and the coexistence of both “true” and “false” or the existence of an in-between value in the postmodern consumer experience. Moreover, information regarding opinions, satisfaction, emotions, and other aspects involving a personal judgement are vaguely defined and captured with imprecise measurements (D'Urso, 2007). 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 et al., 2013). Unfortunately, using linguistic expressions to capture the complex mind of respondents produces inevitably vague and uncertain evaluations. Therefore, 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 (Coppi & D'Urso, 2002; D'Urso, 2007; Benítez et al., 2007; D'Urso et al., 2013). Another important drawback of Likert–type scales is when respondents must express an opinion on a scale: they automatically convert their opinion to scores, and thus possibly distorting the original opinion that had to be captured (Hsu & Lin, 2006). Therefore, Likert–type scales incorporate 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). 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 (Zadeh, 1965) are commonly used in order to capture the imprecision or vagueness that characterize the aspects of the real-life (Wang et al., 2014) and provide a useful tool to cope with opinions based on imprecise and/or incomplete information (Pérez-Gladish, Gonzalez, Bilbao-Terol, & Arenas-Parra, 2010).

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 (Coppi & D'Urso, 2002; Benítez et al., 2007; 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 (Hisdal, 1988; Sinova et al., 2012; 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 (Hisdal, 1988; Sohrabi et al., 2012). Finally, 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; Wang et al., 2014). Summarizing, "fuzzy numbers become a flexible and easy-to-use tool which enables us to exploit the subjectivity that is often involved in perceiving and expressing the available information" (Sinova et al., 2012).

2.3. Postmodernism and fuzzy clustering

So far no discussion has been opened on the use of the fuzzy theory in postmodern marketing and its applicability in segmenting postmodern consumers.

From an economic point of view, a fuzzy approach to segment postmodern consumers is justified by the emerging fuzzy perspective of the classical consumer theory. As remarked by Georgescu (2010), because of the insufficient information and human subjectivity the preferences of the individuals (consumers) are often not exact or not precise, i.e. fuzzy. For this reason, several authors have suggested a fuzzy conceptualization of the consumer theory and of the connected notions of preference and choice (see, e.g., Banerjee, 1995; Dasgupta & Deb, 1991; Fodor & Roubens, 1994; Georgescu, 2007; Kulshreshtha & Shekar, 2000; Orlovsky, 1978; De Wilde, 2004).

From a managerial and marketing perspective, 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 this kind of observation might belong to more than one cluster, since postmodern customers may share some characteristics with more clusters (Hruschka, 1986). Conceptually, consumers belonging to one cluster with a high membership degree do not necessarily have to be attributed solely to that segment (Chaturvedi, Carroll, Green, & Rotondo, 1997). At the same manner, a crisp assignment of data to clusters can be inadequate when units are almost equally distant from two or more clusters (Li et al., 2013). In these cases, 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).

These arguments support the adoption of a fuzzy algorithm to segment postmodern consumers since it relaxes the requirement that data points have to be assigned to one (and only one) cluster. Furthermore, the degrees of membership by which each unit belongs to the different clusters are provided using this kind of algorithm. The memberships of data points at the overlapping boundaries can express the ambiguity of the cluster assignment (Kruse, Döring, & Lesot, 2007) and, for any given set of respondents, the degrees of membership indicate whether there is a second-best cluster almost as good as the best cluster. This kind of information cannot be obtained using more traditional clustering methods (Everitt, Landau, & Leese, 2001) but this gradual cluster assignment is more appropriate since it reflects the hidden market structure, especially when clusters overlap, in a more realistic way. In fact, due to the difficulty of identifying a clear boundary between clusters in real world problems, the partial classification of fuzzy clustering appears more appealing and attractive than the deterministic classification of traditional (non-overlapping or crisp) clustering methods (McBratney & Moore, 1985; Wedel & Kamakura, 2000).

2.4. Fuzzy sets and fuzzy clustering in tourism

Despite ample research regarding fuzzy sets was conducted in the past, less attention was paid to its applications in tourism. Due to its inherent advantages, recent studies in tourism increasingly adopt fuzzy sets. Hsu and Lin (2006) presented a fuzzy multi-criteria approach to measure consumers' perceived risk of travelling. Benítez et al. (2007) analysed the quality of service of three hotels based on 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. The 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, has been developed by Chou et al. (2008). In order to identify the factors that influence the tourists' choice of a destination and to evaluate the preferences of tourists for destination, Hsu, Tsai, and Wu (2009) proposed to transform the descriptions and judgements, expressed in linguistic terms, into triangular fuzzy numbers before the adoption of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. The fuzzy number construction approach proposed by Cheng (1991) was recently 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, in which triangular fuzzy numbers are used, to evaluate the performance of tourists' services offered by hospitality firms taking into account both external consumers' needs and internal service management requirements. The Fuzzy Rasch model, that combines the Rasch model with fuzzy theory, has been suggested by Huang and Peng (2012) 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 along 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. The Similarity–Based Importance–Performance Analysis (SBIPA) has been suggested by Chu and Guo (2015) in order to overcome the inconsistencies that arise using the traditional Importance–Performance Analysis (IPA) and the vagueness of respondents' reported perceptions.

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 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. Similarly, D'Urso, Disegna, Massari, and Prayag (2015) proposed the Bagged fuzzy C-means clustering method for fuzzy data to segment Chinese travellers based on perceived images of tourist destination.

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, with the exception of D'Urso et al. (2013, 2015).

3. 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 capture 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) (Coppi et al., 2012) 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 to profile the clusters.

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

3.1. From Likert-type scale to fuzzy numbers

A fuzzy set is defined by a function that assigns a membership degree to each unit. 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).

A general class of fuzzy number, called LR fuzzy number, can be defined in a matrix form as follows (Dubois & Prade, 1988):

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

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 number is the triangular one, with the following membership function:

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

Alternatively, a fuzzy number can be expressed as $(m_{ik} - l_{ik}, \ m_{ik}, \ m_{ik} + r_{ik})$, where $m_{ik} - l_{ik}$ and $m_{ik} + r_{ik}$ are the lower and upper bounds of the fuzzy number, respectively.

Notice that elicitation and specification of the membership functions are two important issues connected with the representation of natural language by means of fuzzy numbers. Following the subjectivistic approach to probability, also the choice of the membership functions is subjective (Coppi, Giordani, & D'Urso, 2006). Furthermore, the membership function is not determined in an arbitrary way, because it must capture the approximate reasoning of the person involved. In this respect, the elicitation of a membership function requires a deep psychological understanding (Coppi et al., 2006). When dealing simultaneously with K variables, two approaches for the specification of the membership functions can be used: (a) the conjunctive approach and (b) the disjunctive approach (Coppi, 2003). In this work we follow the disjunctive approach in which the interest focuses upon the "juxtaposition" of the K variables observed as a whole in the group of N objects. In this case, K membership functions are considered 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).

3.2. The fuzzy clustering method

To simultaneously analyse the uncertainty related to both the data at hand and the assignment of units to each cluster, the fuzzy C–means algorithm for fuzzy data (FCM-FD) proposed by Coppi et al. (2012) is adopted. The FCM-FD can be expressed as follows:

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

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; $\tilde{\mathbf{x}}_i \equiv \{\tilde{x}_{ik} = (m_{ik}, l_{ik}, r_{ik})_{LR} : \ k = 1, \dots, K\}$ 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; $\tilde{\mathbf{h}}_c \equiv \{\tilde{h}_{ck} = (h^M_{ck}, h^L_{ck}, h^R_{ck})_{LR} : k = 1, \ldots, K\}$ represents the fuzzy prototype of the cth cluster; $\mathbf{h}^M_c$, $\mathbf{h}^L_c$ and $\mathbf{h}^R_c$ represent respectively, the center and the left and right spreads of the c-th fuzzy prototype; $\left\|\mathbf{m}_i - \mathbf{h}^M_c\right\|^2$ is the squared Euclidean distances between the centers; $\left\|\mathbf{l}_i - \mathbf{h}^L_c\right\|^2$ and $\left\|\mathbf{r}_i - \mathbf{h}^R_c\right\|^2$ 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 of the membership function, 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".

3.3. Cluster validation and cluster profiles

A measure of within–cluster variability (V_w) has been used in order to detect the clustering accuracy across clusters, i.e. the compactness of the clustering solution. Working with fuzzy data, the within–clusters variability is obtained as the sum between the variability due to the centers (V^M_w) and the variability due to the spreads (V^S_w).

$$
\begin{aligned}
V_w &= \frac{\sum_{i=1}^N \sum_{c=1}^C u^p_{ic} d^2_F\left(\tilde{\mathbf{x}}_i, \tilde{\mathbf{h}}_c\right)}{N} = \\
&= \frac{\sum_{i=1}^N u^p_{ic}\left[w^2_M\left\|\mathbf{m}_i - \mathbf{h}^M_c\right\|^2 + w^2_S\left(\left\|\mathbf{l}_i - \mathbf{h}^L_c\right\|^2 + \left\|\mathbf{r}_i - \mathbf{h}^R_c\right\|^2\right)\right]}{N} = \\
&= \frac{\sum_{i=1}^N u^p_{ic} w^2_M\left\|\mathbf{m}_i - \mathbf{h}^M_c\right\|^2}{N} + \frac{\sum_{i=1}^N u^p_{ic}\left[w^2_S\left(\left\|\mathbf{l}_i - \mathbf{h}^L_c\right\|^2 + \left\|\mathbf{r}_i - \mathbf{h}^R_c\right\|^2\right)\right]}{N} = \\
&= V^M_w + V^S_w
\end{aligned}
\tag{4}
$$

where V_w is the within–clusters variability, V^M_w is the variability due to the centers and V^S_w the variability due to the spreads. In particular, these indices allow to detect differences in the compactness across clusters and, if any, to individuate the main source of these differences.

The Xie and Beni cluster validity index (Xie & Beni, 1991) was adopted, and suitably adapted to the data at hand, in order to detect the optimal number of clusters. The Xie and Beni (XB) index can be expressed as:

$$
XB = \frac{\sum_{i=1}^N \sum_{c=1}^C u^p_{ic} d^2_F\left(\tilde{\mathbf{x}}_i, \tilde{\mathbf{h}}_c\right)}{\min\limits_{c \neq c'} d^2_F\left(\tilde{\mathbf{h}}_c, \tilde{\mathbf{h}}_{c'}\right)} \tag{5}
$$

This index aims to quantify the ratio of compactness 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 regards the profiling phase, the common approach is to assign each unit to a cluster in a crisp 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). Whereupon, other information, such as socio–demographic and travelling characteristics, collected through the survey are used to profile the clusters. Although this is a common practice widespread in the literature (see, for example Malinverni & Fangi, 2009; Chiang, 2011; Lim, Kim, & Runyan, 2013), it is in itself contradictory for different reasons: the segmentation phase is fuzzy but the profiling phase is crisp; it is in contrast with the very essence of the fuzzy theory and fuzzy clustering, since individuals can belong to more than one cluster simultaneously; and it is also in contrast with the idea behind the postmodern consumers which are characterised by the absence of commitment in any single lifestyle. In order to overcome these contradictions and to capture the vagueness raised assigning each unit to each cluster with a certain membership degree, the weighted percentage frequency and the traditional weighted average (in which the weight is the membership degree), respectively adopted for qualitative and quantitative variables, are suggested and used in the profiling stage.

4. The empirical study

To apply the fuzzy clustering procedure 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". Fig. 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.

5. Results and discussion

5.1. The fuzzified Likert-type scale

The fuzzy recoding from the Likert–type scale to the fuzzy

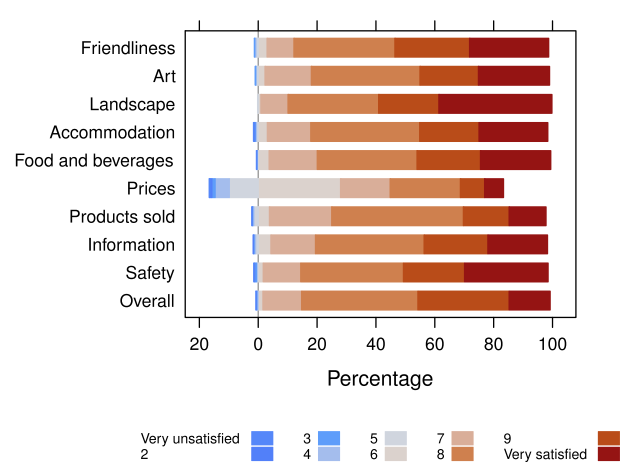

Fig. 1. % Distribution of the level of satisfaction for each aspect.

Table 1
Variables description.

Independent 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
Clerk	1 = ticked; 0 = not ticked
Other 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 = otrw
Only one cities visited	1 = Only one city visited in South-Tyrol during the trip; 0 = otrw
Number of times in Italy before	
Zero	1 = Never been in Italy before the interview; 0 = otrw
Up to 5 times	1 = Been in Italy from 1 to 5 times before the interview; 0 = otrw
More than 5 times	1 = Been in Italy more than 5 times before the interview; 0 = otrw
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 = otrw
Other personal motivations	1 = The respondent makes the trip for a personal motivations (visiting friends & relatives, study, shopping, etc.); 0 = otrw
Business	1 = ticked; 0 = not ticked
Expenditure behaviour	
Accommodation	1 = Positive expenditure on accommodation; 0 = otrw
Transportation	1 = Positive expenditure on transportation; 0 = otrw
Food & Beverages	1 = Positive expenditure on food and beverages; 0 = otrw
Shopping	1 = Positive expenditure on shopping; 0 = otrw
Other services	1 = Positive expenditure on other services; 0 = otrw

Note: otrw is the abbreviation of otherwise.

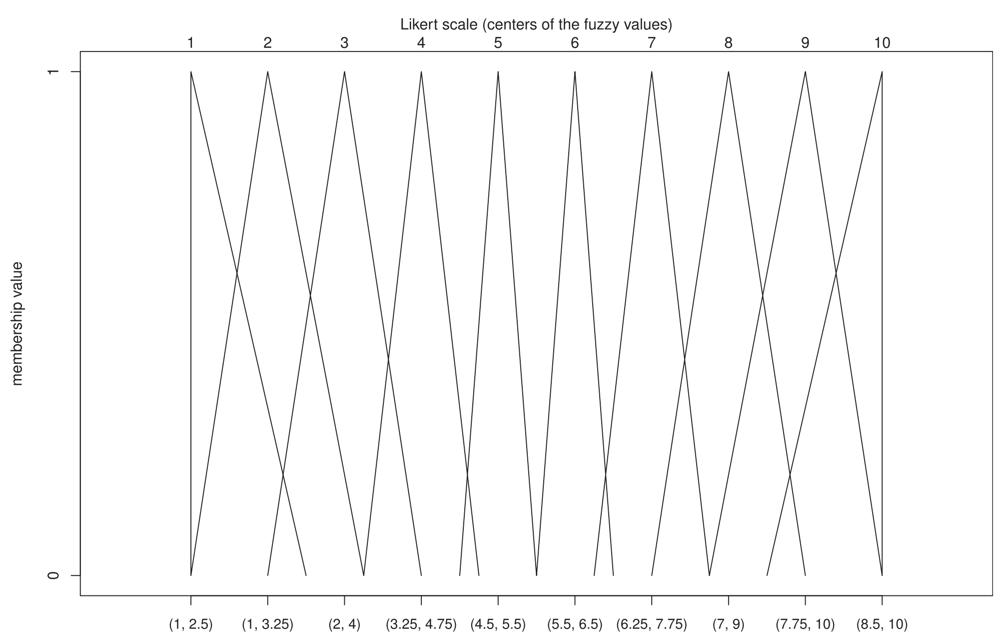

Fig. 2. Linguistic satisfaction terms in the form of fuzzy numbers.

numbers is displayed in Fig. 2. For instance, the value 1 in the Likert–type scale (i.e. “Very unsatisfied”) corresponds to a fuzzy number in the range [1, 2.5], while the value 5, which corresponds to mild dissatisfaction, corresponds to a fuzzy number [4.5, 5.5]. 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. Moreover, the more the central values (i.e. 5 and 6) are approached, the more the degree of vagueness decreases. 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 known 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.

5.2. The fuzzy clusters

Based on the *XB* index, international visitors to South Tyrol can be segmented into two groups. The second best option is the three-clusters solution. Since the value of the internal validity index must be interpreted as a guideline rather than an absolute truth (Vesanto & Alhoniemi, 2000), in this study the three-clusters solution will be considered. In fact, the three-clusters solution allows us to obtain a more precise and detailed characterization of the market segments in comparison to the two-clusters solution. Table 2 reports the within–clusters variability (V_w) of the three clusters, as well as the variabilities according to the centers and the spreads (respectively V_w^M and V_w^S). As it can be seen, there are very little differences between clusters indicating that all clusters are equally compact.

The three fuzzy centroids for the final clusters solution are displayed in Fig. 3 with radar plots, while their values are reported in Table 3. Notice that while a centroid is a vector of *K* values, in which *K* indicates the number of segmenting variables, a fuzzy centroid is a vector of *K* fuzzy numbers each of which, in our case, is described by three values, i.e. the lower, center, and upper value (see Section 3.1). The lower and upper bounds represent the uncertainty that characterizes subjective evaluations. In Fig. 3, the black solid line represents the centers of the fuzzy centroids, the dark grey dashed line represents the lower values (inner lines) and the light grey dashed line the upper values (outer lines) of the fuzzy centroids. By looking at the radar plots, we labelled the first and second clusters as “Unfulfilled” and “Enthusiasts”, since they are characterized respectively by people less and more satisfied with the investigated aspects. The third cluster groups visitors who are neither much nor little satisfied, therefore we labelled it as “With reservations”. As it can be observed, the “Unfulfilled” seem to have less uncertainty in the evaluations, followed by the “With reservations” and finally by the “Enthusiasts”. The aspect on which tourists have generally less uncertainty in the evaluation is “Prices” for which the left and right spreads are the smallest in every clusters. While the “Unfulfilled” and the “With reservations” are characterized by almost symmetric spreads, the “Enthusiasts” centroid is characterized by a higher uncertainty towards smaller value, i.e. left spreads are in general higher than right spreads. To

Table 2
Within variability of the fuzzy clusters.

Within variability index	“Unfulfilled”	“Enthusiasts”	“With reservations”
V_w	1.204	1.134	1.171
V_w^M	0.777	0.719	0.785
V_w^S	0.427	0.415	0.386

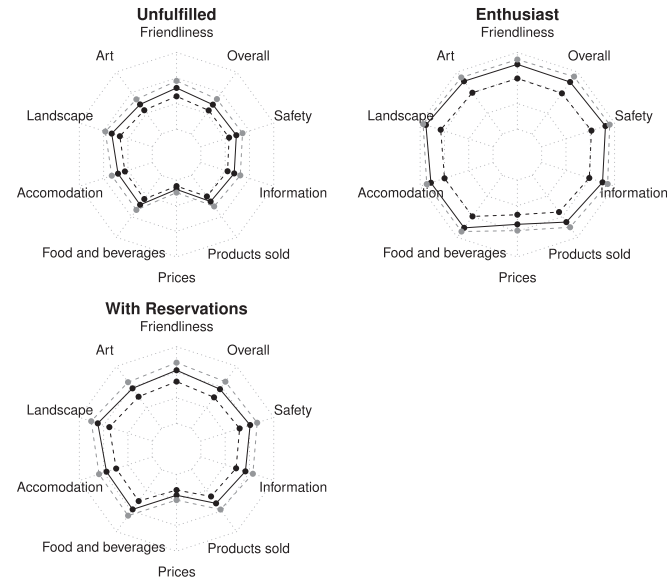

Fig. 3. Radar plots for fuzzy centroids.

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 3) show that all clusters are less satisfied with “Prices”, “Products sold”, and “Information”; similarly, all clusters rank “Landscape” in the first position; while the most clear-cut difference among the three clusters, in particular between the “Enthusiasts” and the other two clusters, lies in the evaluation of the “Accommodation” and the “Friendliness” aspects.

5.3. The fuzzy cluster profiles

The respondents are graphically displayed according to their membership degrees with the three resulting clusters using a suitable graph called ternary plot (Fig. 4). The ternary plot allows us to better understand how the respondents are distributed among the three clusters. In particular, it can been observed that there is a considerable group of respondents who belong to the “Enthusiasts” with a high membership degree (between 60% and 80%), and simultaneously to the “With reservations” with a membership degree between 10% and 30%, and to the “Unfulfilled” with a membership degree lower than 20%. Similarly, there is a group of respondents who mainly belong to the “Unfulfilled” (membership degree between 60% and 80%) and simultaneously belong to the “With reservations” and to the “Enthusiasts”, despite with a membership degree lower than 30%. As regards the “With reservations” cluster we can observe that only few respondents belong to this group with high membership degree (between 60% and 80%) indicating that there are only few undecided visitors in the sample. Finally, it can been observed that the particular shape of the distribution reflects the realistic composition of the vector of the membership degrees: nobody is observed in the unrealistic situation in which respondents simultaneously belong to the “Enthusiasts” and to the “Unfulfilled” with a high membership degree, while respondents simultaneously belong with a high membership degree to the two more realistic combinations represented by “Enthusiasts”–“With reservations” and “Unfulfilled”–“With reservations”. Table 4 presents the percentage composition of the whole sample (first column) and the weighted relative frequencies per each profiling variable and cluster. The weighted sample size of the

Table 3
Rank of the different aspects of the visited destination for each cluster.

Satisfaction	"Unfulfilled"	Rank	"Enthusiasts"	Rank	"With reservations"	Rank
Friendliness	(7.423, 7.916, 8.330)	9	(8.472, 9.300, 9.584)	5	(7.956, 8.619, 9.065)	9
Art	(7.223, 7.643, 8.012)	7	(8.492, 9.327, 9.599)	7	(7.791, 8.396, 8.844)	7
Landscape	(7.499, 8.002, 8.397)	10	(8.733, 9.644, 9.817)	10	(8.146, 8.863, 9.267)	10
Accommodation	(7.188, 7.611, 7.997)	4	(8.496, 9.335, 9.593)	8	(7.727, 8.321, 8.784)	4
Food and beverages	(7.219, 7.639, 8.010)	6	(8.479, 9.310, 9.577)	6	(7.782, 8.385, 8.839)	6
Prices	(5.845, 6.038, 6.226)	1	(7.525, 8.088, 8.458)	1	(6.412, 6.717, 7.001)	1
Products sold	(7.031, 7.402, 7.755)	2	(8.164, 8.892, 9.267)	2	(7.446, 7.946, 8.395)	2
Information	(7.149, 7.559, 7.935)	3	(8.439, 9.258, 9.573)	3	(7.675, 8.251, 8.711)	3
Safety	(7.244, 7.689, 8.072)	8	(8.572, 9.437, 9.697)	9	(7.893, 8.541, 8.976)	8
Overall	(7.209, 7.627, 8.033)	5	(8.448, 9.269, 9.663)	4	(7.746, 8.338, 8.879)	5

Note: in brackets are reported the lower bounds, the centers, and the upper bounds of the fuzzy data.

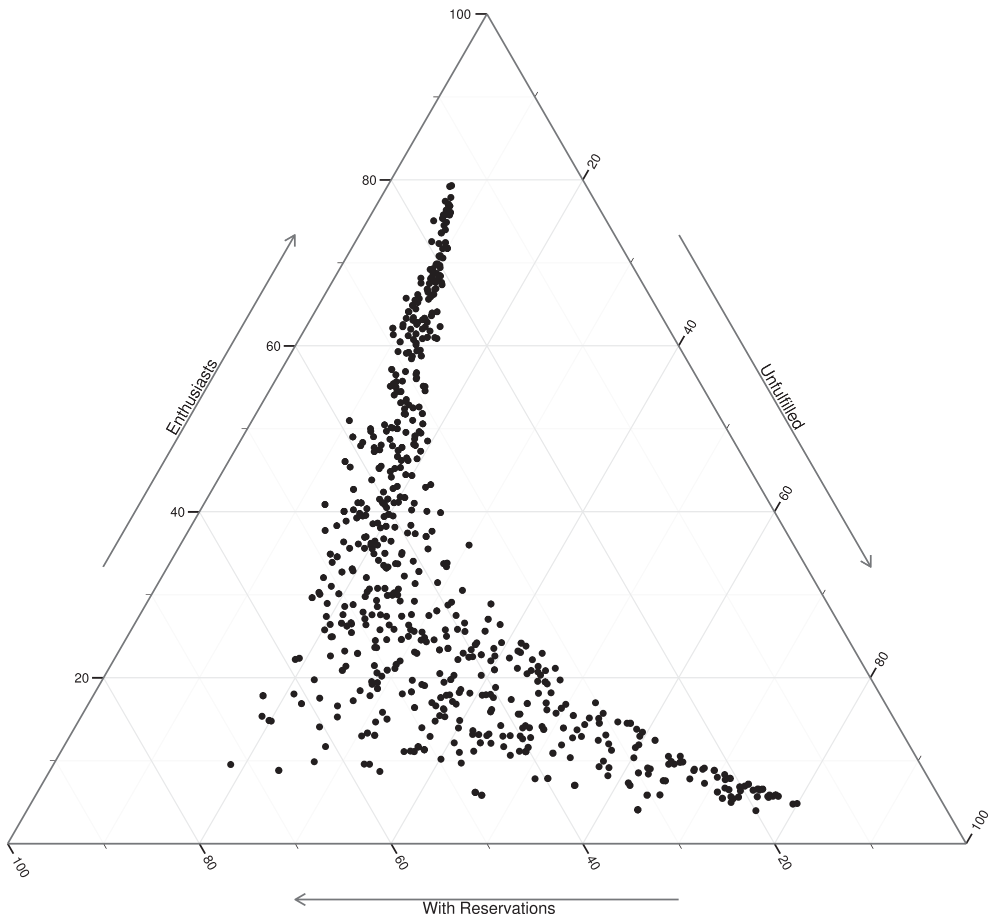

Fig. 4. Ternary plot.

three clusters is almost equal, indicating that the international tourists have been equally divided among "Enthusiasts" (35%), "With reservations" (31%), and "Unfulfilled" (34%). 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 the "Unfulfilled" is higher compared to the "Enthusiasts" and to the "With reservations", the percentage of German people and people from other European countries is higher in the "Enthusiasts" cluster, while the "With reservations" 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.

5.4. Discussion

This study reveals that no matter whether visitors are enthusiastic about the destination or feeling unfulfilled, all of

Table 4
Socio–demographic characteristics of the visitors and travelling characteristics (percentage values).

Variables	Sample	"Unfulfilled"	"Enthusiasts"	"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	
Clerk	16.20	14.67	17.74	16.52	
Other 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 behaviour					
Accommodation	84.25	73.05	93.55	86.67	**
Transportation	71.51	58.98	83.97	72.52	**
Food & Beverages	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	

Note: 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 $p \leq 0.1$.

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.

6. Conclusions

This paper is aimed to create a nexus between postmodern consumer behaviour and fuzzy clustering. Its main objective is to propose a revisited fuzzy clustering procedure to both academics and practitioners for the segmentation of 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; Jian & Ning, 2012) which make use of the fuzzy theory only on single steps of the analysis. Generally, the three steps by which a clustering process can be divided are: selection and transformation of the data; choice of the clustering algorithm; profiling of the clusters.

In the first step of the process we transformed the satisfaction levels with a destination into fuzzy numbers to overcome the vagueness of concepts that are associated with subjective evaluations. In particular, 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. 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 depth these important research topics in our future studies.

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 overlapping and non-overlapping clustering methods. Moreover, the FCM-FD algorithm is able to specifically take into account: the vagueness connected with the use of linguistic terms in the description of the real world; the imprecision deriving from the granularity of the terms utilized in the description of the physical world; the imprecision in measuring the empirical phenomena; the uncertainty related to the assignment process of observed data to different segments (clusters). As a consequence, the features of the postmodern consumer behaviour, which are usually vague (fuzzy), can be naturally treated by means of fuzzy clustering. In fact, we can notice that the postmodern tourist behaviour is thinking in terms of "degrees" of membership associated with each cluster rather than in terms of "total membership" versus "non-membership" to each cluster.

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 fuzzy clustering 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 point 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. This paper proposes to use the membership degrees to assign each unit to the clusters. This last profiling step merges common features of different postmodern consumers to create a "new" consumer characterising the cluster with an output similar to the one of a crisp algorithm. In this way, destination managers and policy makers obtain comprehensible and easy to read results since they appear similar to the results of other more traditional crisp clustering techniques. Therefore, practitioners can use the results given by such clustering technique for the creation of future management and marketing strategies, and the development and maintenance of competitive advantage in the postmodern consumer era.

Concluding, 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. Therefore, in order to obtain an aggregate description of the individuals while considering the vagueness, fragmentation and multiple preferences of postmodern consumers, suitable segmentation methods are needed and the FCM-FD method suggested in this paper is a first effort in this direction.

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