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Review

Soft computing applications in customer segmentation: State-of-art review and critique

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ABSTRACT

Segmentation has been taken immense attention and has extensively been used in strategic marketing. Vast majority of the research in this area focuses on the usage or development of different techniques. By means of the internet and database technologies, huge amount of data about markets and customers has now become available to be exploited and this enables researchers and practitioners to make use of sophisticated data analysis techniques apart from the traditional multivariate statistical tools. These sophisticated techniques are a family of either data mining or machine learning research. Recent research shows a tendency towards the usage of them into different business and marketing problems, particularly in segmentation. Soft computing, as a family of data mining techniques, has been recently started to be exploited in the area of segmentation and it stands out as a potential area that may be able to shape the future of segmentation research. In this article, the current applications of soft computing techniques in segmentation problem are reviewed based on certain critical factors including the ones related to the segmentation effectiveness that every segmentation study should take into account. The critical analysis of 42 empirical studies reveals that the usage of soft computing in segmentation problem is still in its early stages and the ability of these studies to generate knowledge may not be sufficient. Given these findings, it can be suggested that there is more to dig for in order to obtain more managerially interpretable and acceptable results in further studies. Also, recommendations are made for other potentials of soft computing in segmentation research.

1. Introduction

Segmentation was first introduced to the marketing literature by Smith (1956). Later, segmentation was mentioned as an alternative concept instead of product differentiation strategy (Beane & Ennis, 1987; Claycamp & William, 1968; Wind, 1978). The main idea of segmentation or clustering is to group similar customers. A segment can be described as a set of customers who have similar characteristics of demography, behaviours, values, and so on (Nairn & Berthon, 2003).

The selection of segmentation techniques has become more important due to the fact that the developments in information and communication technologies, especially database management systems and data mining have changed the way of marketing. The vast availability of data and the inefficient performance of traditional statistical techniques (or statistics-oriented segmentation tools) on such voluminous data have stimulated researchers to find effective segmentation tools in order to discover useful information about their markets and customers. Thus, knowledge discovery (KD) and data mining (DM) have been seen as a solution to this problem. Disciplines such as machine learning, statistics, artificial intelligence (soft and hard computing techniques), expert systems, data and knowledge management technologies are incorporated with KD and DM by making use of their theories and algorithms (Freitas, 2002; Mitra, Pal, & Mitra, 2002; Shaw, Subramaniam, Tan, & Welge, 2001; Tyndale, 2002). Marketing researchers are interested in the application of these technologies in marketing-related problems, such as forecasting, segmentation, knowledge-based marketing decision support systems, and so forth, especially in the frame of DM (Liao, 2003; Mitra et al., 2002; Pal, Talwar, & Mitra, 2002; Smith & Gupta, 2000; Vellido, Lisboa, & Vaughan, 1999).

Soft computing, as a family of data mining techniques, has been recently started to be exploited in the area of segmentation and it stands out as a potential area that may be able to shape the future of segmentation research. The significant usage of soft computing techniques in business-related problems, particularly in segmentation, makes segmentation problems more attractive, since these techniques are very effective and applicable. From this perspective, the objective of this article is to find out where the future of segmentation is heading towards in terms of being able to obtain effective segmentation results. In order to accomplish this objective, the current applications of soft computing techniques in

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segmentation problem are reviewed based on some critical factors including factors related to the segmentation effectiveness that every segmentation study should take into account.

The rest of this study is organised as the following. Critical methodological issues associated with segmentation are presented in Section 2. Section 3 includes background information regarding the soft computing technologies. The method followed in accomplishing the critical analysis of the empirical studies is presented in Section 4 while the results obtained through the critical analysis is shown in Section 5. Section 6 concludes the article by providing some discussions on the future of soft computing in segmentation research.

2. Critical issues in segmentation research

Although most segmentation research takes individual consumers into account as a unit of analysis, considerations in consumer segmentation studies have not been mentioned in the previous literature except for Wind's landmark article (1978) published 30 years ago. Moreover, researchers such as Goyat (2011), Myers and Tauber (1977), Wilkie and Cohen (1977), Beane and Ennis (1987), Dolnicar (2004), Yankelovich and Meer (2006), Sun (2009) and Tynan and Drayton (1987) provided ample reviews of segmentation research. Additionally, in order to give a comprehensive discussion regarding the methodological issues in segmentation research the structure in Wind's work (1978) will be expanded by reviewing additional literature. His structure was based on five main topics: (1) problem definition; (2) research design; (3) data collection; (4) analysis; and (5) implementation and interpretation of data and results. Since then, important developments have occurred particularly in research methodologies, including new bases and tools for segmentation (Wind, 1978). Nevertheless, the main considerations he highlighted are still contemporary and should be taken into account for today's segmentation studies.

Table 1 represents major considerations related to the five methodological issues mentioned above. Detail information will not be provided for all the considerations listed in the table, instead, only some of them will be described here since those are considered to be included as critical factors or variables in the critical analysis part. Since the critical analysis will be done for the academic empirical studies, their evaluations based on other considerations might be difficult. For example, considerations related to real-life practical issues such as budget constraints, information need of the company and the baseline for segmentation (this is about conducting either a one shot or continuous segmentation study) were not selected and were excluded as basis for the critical analysis. The reason for this is that these considerations are mainly company-specific and dependent on the practical conditions of a company. Likewise, considerations including operationalization of variables, segment stability, and issues related to the implementation and interpretation of results were not taken into account, as those are either not easy to be evaluated or usually not mentioned in academic studies. Hence, the discussion regarding the considerations taken into account will be brief and the findings from the literature will be summarised.

2.1. Conceptual segmentability

The term "segmentability" questions when it is possible to segment a market, and under what conditions this should be done. Young, Ott, and Feigin (1978) provided practical insights for different segmentation. Green and Carmone (1977) proposed a market segmentability measure in the componential segmentation framework that helps to develop a numerical segmentability index (called omega square measure) before a large-scale segmentation study is undertaken. Also, in a research conducted by Dolnicar, Freitag, and Randle (2005), they developed an investigation model based on a hypothetical simulation in order to understand the success of different segmentation strategies under varying marketing conditions, which may help one to decide whether to segment or not before undertaking a segmentation study.

Conceptually, there are other arguments regarding what characteristics an effective segmentation study should possess. Kotler (2003) points out that measurability, accessibility, substantiality, differentiability, and actionability are five criteria for effective segmentation. Having a measurable segment means that you have the ability to measure the variables in terms of the size, the purchasing power, and the profiles. Accessibility refers to whether the segments can be effectively reached and served. Also, segments obtained should be large or profitable enough to serve. Differentiability is the issue of being able to have segments which are conceptually distinguishable and respond differently to different marketing mix elements or programmes. Furthermore, the marketing activities should be designed for the segments that are actionable or worth considering in order to attract and serve them. Wedel and Kamakura (2000) omitted the criterion of measurability and added two additional criteria, namely, stability and responsiveness. Stability is a criterion that reflects whether the segments are stable over time or change their structure while responsiveness refers to the combination of the criteria of differentiability and actionability in the above definitions. Biggadike (1981) looked at the issue from the strategic management perspective and replaced the last three criteria of Kotler with defensibility, durability, and competitiveness. However, he used the term "accessibility" to refer to the meaning of actionability in Kotler's definition. According to him defensibility is a measure to check whether the cost of serving a particular segment is unique to it or not. Also, he used the term "durability" for understanding the differences between segments that are likely to endure or erode, and the term "competitiveness" for making sure that the organisation has a relative advantage in terms of the skills required to serve the segments. Furthermore, Raaij and Verhallen (1994) classified these criteria into four categories, namely, typifying the segments (including the criteria of identifiability, differentiability, and measurability), homogeneity (variation, stability, and congruity), usefulness (accessibility and substantiality), and strategic criteria (potentiality, profitability, and attractiveness) by adding some additional criteria.

There are some studies which considered this issue from the point of view of strategic management literature. For example, Goller, Hogg, and Kalafatis (2002) categorised these criteria into two main criteria: segmentability, which mainly includes Kotler's criteria of measurability, accessibility, and differentiability (homogeneity within and heterogeneity between); and target market selection (e.g., segment size and growth, market share), which consists of Kotler's criteria of substantiality and actionability. The most comprehensive study in that particular topic was conducted by Dibb (1995, 1999), and operationalises the criteria from two different dimensions by merging them into the segmentation process. The first dimension is criteria-oriented and includes two main criteria, namely, segment qualification (whether segments are operational or not) and segment attractiveness (includes a wide range of internal and external factors within the context of environmental conditions, available resources, and the level of competition). The second is a resource-oriented dimension that shows which different sources of thought take this issue into account and from what perspective. The variables associated with these criteria can be found in the related literature (Dibb, 1995, 1999; Dibb & Simkin, 1997, 2010).

As it can be seen, there are many classification efforts, but the literature does not have a comprehensive analysis of those criteria.

Table 1
Considerations about critical methodological issues.

Critical methodological issues	Major consideration
Problem definition related issues	Managerial requirements • Conceptual segmentability • Budget and other constraints • Total information needs of the firm The baseline for segmentation Segmentation variables and models • Classification of segmentation variables • Selection of segmentation basis • Choosing appropriate segmentation model
Research design issues	Unit of analysis Segmentation objective Sample design Data reliability Operationalization of variables Stability
Data collection related issues	Data type and source
Data analysis related issues	Segmentation techniques • Classification of segmentation methods and techniques • Selection of segmentation techniques Standardisation/normalisation Determining the number of clusters (or segments) Reliability and validity
Issues related to the implementation and interpretation of results	Selection of target segments Translating segmentation findings into marketing strategy

This could be because different researchers put those criteria into wider concepts or they interpret them differently. Furthermore, there is no clear guidance regarding how to measure those criteria in the literature. It can only be claimed that measurability, accessibility, differentiability, substantiality, and actionability are the five common criteria for effective segmentation as Kotler (2003) suggested. From the clustering point of view homogeneity can be added to this list.

2.2. Segmentation variables

Consumers have a variety of differences according to their characteristics. In consumer and industrial marketing literature, several segmentation variables can be found, such as geographic, demographic, firmographic, behavioural, decision making process-related variables, purchasing behaviour, situation factors, personality, lifestyle, psychographics, and so on (Bock & Uncles, 2002; Cheron & Kleinschmidt, 1985; Kotler, 2003; Walters, 1997). Kotler (2003) classifies market segmentation variables into four major areas, namely, geographic, demographic, psychographic, and behavioural variables. On the other hand, some other researchers give a classification based on the level of variables. One example of this kind of classification can be found in the study of Raaij and Verhallen (1994), who make a classification based on two main dimensions: the level of variables (general, domain-specific, brand specific) and the objectivity/subjectivity of variables. Wedel and Kamakura (2000) give the following classification schema below for segmentation bases:

- General observable variables (e.g., geographic, demographics, socio-economic variables)
- Product specific observable variables (e.g., usage frequency and loyalty)
- General unobservable variables (e.g., lifestyle, psychographics)
- Product specific unobservable variables (e.g., benefits, preferences and intentions)

Selection of variables suitable for the segmentation model is an important point to consider. Wind (1978) addressed this issue by giving two major considerations. His first consideration is about management's specific need for a segmentation study, while the second is the current state of the marketing and consumer information. He points out that even though all variables could be used as bases for segmentation, a consensus that some variables are better than others should be reached. Furthermore, from a practical point of view, Greenberg and McDonald (1989) stressed some important dimensions which should correlate with market behaviour, readable for product manipulation and development of communication strategies, and should give directions for media buying when choosing a base for segmentation. Additionally, another scholar Day (1990) suggests two different ways of identifying segment descriptors. The first way starts with the identifiers of consumers and then checks whether segments have distinct response profiles or not. The second works backward in order to find out if the segments have distinct response profiles and can be identified in respect of different characteristics.

Each of these variables has been used in segmentation studies and has advantages and disadvantages (Vriens, 2001). It is likely to have different segmentation schemas depending on the usage of different variables that are included in analysis (Segal & Giacobbe, 1994). For some specific marketing objectives, the guidelines on which variables should be considered can be found from the literature. For instance, a study conducted by Natter (1999) who suggested that benefit-related bases are the most meaningful types to use from the point of view of facilitating other marketing activities, such as product planning, positioning, and advertising. The article also points out that although lifestyle or psychographic variables are not problematic from the statistical standpoint, from the marketing perspective they are not helpful enough as they may not directly be associated with the actual consumer behaviours.

Furthermore, while general observable variables are easy to collect, in fact their reliability and validity are questionable. Some researchers agree that demographics and socio-economic variables are not sufficient for an effective segmentation study (Barnett, 1969; Dhalla & Mahatoo, 1976; Greenberg & McDonald, 1989; Haley, 1968; Peltier & Schribrowsky, 1997; Sharma & Lambert, 1994; Yankelovich, 1964). It is suggested that demographic variables provide little guidance for product development and communication strategies (Greenberg & McDonald, 1989). In addition to that, they have poor prediction capabilities for consumer behaviour (Haley, 1968), because customers who are in the same segment may want personalised products and services and might not exhibit similar behaviour, even if they have similar demographic features and lifestyles. However, although general unobservable variables are weakly related to purchasing behaviours they are also accessible and useful for marketers. The best evaluation of those variables can be found in the book of Wedel and Kamakura (2000). They make the evaluation based on six segmentation criteria which were mentioned in an earlier section when the issue of market segmentability was being discussed. According to them, compared to product-specific bases, general observable variables have higher potential on the criteria of identifiability, substantiality, accessibility, and stability. However, in terms of actionability and responsiveness criteria, they tend to have a lower potential. General unobservable bases are rated between high and low on most of the criteria.

Thirty years after Wind's (1978) original work, this issue still remains a problem, mainly because of a lack of systematicity and non-representativeness in academic studies. The most important point here is to determine the objective(s) of the segmentation study. After deciding the objective, one of the variables mentioned earlier or a combination of those variables can be used for a segmentation purpose. It should be noted that one of the most valuable pieces of information is customers' behavioural characteristics, especially past customer purchases and value-oriented attributes (Bayer, 2010; Kim, Jung, Suh, & Hwang, 2006; Wind & Lerner, 1979). In fact, customer analytics related technological advances have facilitated performing segmentation studies based on those characteristics (Bailey, Baines, Wilson, & Clark, 2009).

2.3. Segmentation models

When building a segmentation model, another crucial consideration is the selection of segmentation methods or techniques. In segmentation literature, several methods and modelling techniques have been proposed. However, the most well-known segmentation models can be found in industrial market segmentation literature and can be classified into three categories, single, two-stage (Wind & Cardozo, 1974) and multi-stage (aka nested approach) (Shapiro & Bonoma, 1984) models. This classification is mainly based on how many times the segmentation process works in respect of the variable bases used in the model. In consumer segmentation literature, most approaches are technique- or method-oriented, ranging from simple inferential statistics to artificial intelligence. It is possible to give a classification of segmentation techniques based on the literature, which were used as analytical techniques or methods for market/customer segmentation. For example, Wind (1978) identified four basic approaches for market segmentation. The first approach is "a priori" segmentation, which chooses some variables of interests and then classifies consumers based on that designation (Green & Krieger, 1991; Wind, 1978). However, in the second approach, called "post hoc" segmentation, the classification job in the segmentation process is based on clustering (Greenberg & McDonald, 1989). The "a priori" segmentation supposes that the number of segments or clusters, along with their dimensions and descriptions, are known. On the other hand, these characteristics are found in the "post hoc" approach after the segmentation process (Greenberg & McDonald, 1989). In the "post hoc" segmentation, multi-variate analytical techniques are commonly used. The third approach is called "flexible" segmentation. This is a dynamic approach and can develop and examine many alternative segments. The last approach is developed by Green (1977), and is an extended version of conjoint analysis, which can make predictions regarding which type of person will be most responsive to which type of products.

A second example in association with the classification of segmentation techniques can be the classification proposed by Wedel and Kamakura (2000), which is provided below:

- A priori descriptive methods
- A priori predictive methods
- Post-hoc descriptive methods
- Post-hoc predictive methods

The most important distinction in this classification is that the methods are classified as descriptive or predictive. In the descriptive methods, there is no difference between variables like being dependent or independent. However, the predictive methods suppose that one variable must indicate the dependent variable and the rest are defined as independent (Vriens, 2001). Different combinations of these methods in a single problem are also possible to find, as the conceptual examples regarding this can be found in Dolnicar (2004).

As the third example regarding this, Raaij and Verhallen (1994) classified methods into three basic approaches: forward, backward, simultaneous. The forward approach, which is a kind of analysis of customer response, assigns customers to groups on the basis of behavioural similarity response. In the backward approach, this similarity is based on one or more customer characteristics. The simultaneous approach takes its basis from the relationship between customer characteristics and behavioural responses.

2.4. Unit of analysis and objective of segmentation

Selection of a unit of analysis depends on two decisions (Sausen, Tomczak, & Herrmann, 2005). The first one is associated with companies' overall marketing strategies that lead them to come up different objectives with regards to market segmentation, while the second one is the ability to access to certain units of analysis. Segmentation literature includes a variety of possible segmentation objectives. Wind (1978) stated that segmentation is implemented through the intent of a company, which could be either strategy generation like identifying new markets or product-related decisions i.e., defining pricing policy and possible changes in existing products. According to Beane and Ennis (1987), the aid of segmentation can be either searching for new product opportunities or gaining a better customer understanding. Segmentation objectives can be extended via considering company's resources, customers and products. Then the list can include objectives such as customer acquisition, customer retention, profitability, customer satisfaction, resource allocation by designing marketing measures or programmes increasing, and customer value, etc. (Sausen et al., 2005). However, the organisations follow two main dimensions of segmentation strategies, namely, market-induced and customer-induced segmentation (Sausen et al., 2005). In the first dimension, the main objective is the identification and exploitation of new markets and customers by using an anonymous and aggregated unit of analysis. In the second dimension, the objective could be customer acquisition or retention by deploying a unit of analysis based on disaggregated and personalised customers. For customer segmentation this should be an individual customer. Within the scope of this study, the categorisation provided by Sausen and his friends (2005) is used; they comprehensively organised a workshop by inviting many marketing scholars and managers in order to identify main segmentation objectives and the capability of the units of analysis to accomplish these objectives. According to their synthesis, Table 2 presents five segmentation objectives and four aggregation levels of objects regarding market segmentation.

2.5. Sample design

For any scientific research, finding an appropriate sample design is crucial for the reasons of validity and reliability. The selection of an appropriate sample design is supposed to have a representative impact on the projectability of the results of a study to the research universe. The choice of a target population and the sampling frame are two key considerations related to this topic (Steenkamp & Hofstede, 2002). Regarding the sample design consideration, only "sample size" will be included in the critical analysis.

2.6. Data type and source

There are two main different data available for a segmentation study. One of them is primary data, which is commonly used by commercial research; the other one is secondary data, which is accepted as more academically oriented (Wind & Lerner, 1979). With the development of communication and Internet technologies, the problem of data collection or reaching compatible data is

Table 2
Segmentation objectives and units of analysis. Source: Vellido et al. (1999).

Segmentation objective	Unit of analysis
Exploitation of new customers potentials	Anonymous sub-markets
Development of existing customer potentials	Anonymous groups or typologies of customers
Increasing customer profitability	Personalised existing customers
Improving targeting of marketing measures	Personalised potential customers
Identification of new sub-markets	

diminishing. This study will take into account three different data types, namely, survey data (for the empirical studies that obtain the data through questionnaire), secondary data (for the studies that make use of data directly taken from a company database), and simulation data (for the studies that generate hypothetical data via simulation).

2.7. Segmentation techniques

For customer segmentation, a wide variety of data analysis techniques, cluster analysis (Alfansi & Sargeant, 2000; Allred, Smith, & Swinyard, 2006; Balakrishnan, Cooper, Jacob, & Lewis, 1996; Chaturverdi, Carroll, Green, & Rotondo, 1997; Dolnicar, 2003; Dolnicar, 2004; Dolnicar & New Zealand Marketing Academy Conference, 2002; Doyle & Saunders, 1985; Hruschka, Fettes, & Probst, 2004; Hruschka & Natter, 1999; Kuo, Ho, & Hu, 2002a; Lee, Lee, & Wicks, 2004, Li, Wang, & Xu, 2009; Liu & Shih, 2004, 2005; Shih & Liu, 2003; Shoemaker, 1994; Smith & Hirst, 2001; Smith, Willis, & Brooks, 2002; Wang, 2009; Xia et al., 2010), clusterwise regression (Bass, Tigert, & Lonsdale, 1968; Desarbo, Atalay, Lebaron, & Blanchard, 2008; Wedel & Kistemaker, 1989), AID/CHAID (Assael & Roscoe, 1976; Chen, 2003; Chung, Oh, Kim, & Han, 2004; Gensch, 1978; Gil-Saura & Ruiz-Molina, 2008; Jonker, Piersma, & Poel, 2004; McCarty & Hastak, 2007), multiple regression (Suh, Noh, & Suh, 1999), discrimination analysis (Fish, Barnes, & Aiken, 1995; Johnson, 1971; Mazanec, 1992; Tsiotsou, 2006), latent class structure (Green, Carmone, & Wachspress, 1976; Kontoleon & Yabe, 2006; Rajiv & Srinivasan, 1987) (Dias & Vermunt, 2007; Wu & Chou, 2011), inductive learning techniques (Leung, 2009) and soft computing techniques (the details of which will be provided in the following sections) have been used in marketing management.

Even though it is very difficult to provide a clear classification for segmentation techniques, Fig. 1 is proposed as a baseline scheme for the classification of those techniques. In this figure, while some techniques are classified under data preparation, others are considered as classification or clustering data analysis techniques, depending on the distinction of whether they are "a priori" or "post hoc" methods of approach or not. Besides traditional statistical data analysis techniques, such techniques based on fuzzy logic (FL), artificial neural networks (ANNs), rough set theory (RST) and evolutionary methods (EM) such as genetic algorithm (GA) are considered as soft computing tools, which are mostly supposed to be non-traditional artificial intelligence (AI) technologies. They have been considered in both data analysis and data preparation as techniques for segmentation. Among the soft computing techniques, supervised neural networks, GA, and RST have been used for classification, while unsupervised neural networks, FL, and GA are appropriate for clustering purposes. However, some of them (i.e., rough sets and GA) have also been considered as algorithms for data preparation purposes such as attribute reduction or selection.

For market segmentation purposes, many algorithms can be found in the literature, and it is a very challenging task to determine which techniques or algorithms perform better than the others. Most of them have their advantages as well as disadvantages (Kuo, Ho, & Hu, 2002b). Segmentation results mostly depend on algorithms that will be used for clustering or classification. Improper selection of segmentation techniques may cause a negative financial impact. To avoid this problem, the first decision is to determine what kinds of segmentation approaches are suitable for the current segmentation study. In other words, it should be decided whether the data in the segmentation study is appropriate for the "post hoc" approach or the "a priori" approach. The second issue that should be taken into consideration is the understanding of data characteristics. The characteristics can be based on the volume of the data (e.g., large or small) or its structure (e.g., ill-structured or not).

For segmentation problems, previous research suggests that hierarchical approaches do not perform very well with large data sets (Kuo et al., 2002a). Due to the fact that hierarchical methods build a tree structure using a dendogram, they are not able to provide a unique clustering because partitioning to cut the dendogram above a certain level becomes imprecise The process of cutting the dendogram is usually done by visualising the dendogram through taking into account the distance between cluster centres, which can be considered as an arbitrary process. Moreover, non-hierarchical or partitional methods work based on the assumption that the number of clusters and initial cluster points (not necessarily) are pre-defined, and this affects the final cluster solution (Lee, Lee, & Wicks, 2004). However, integration of hierarchical and partitional methods makes the clustering result powerful, especially in large databases (Kuo et al., 2002b).

In customer segmentation problem, there are only a few studies that combined two clustering methods together. Punj and Steward (1983) first introduced a two-stage clustering concept by combining a hierarchical (Ward's minimum variance) and a non-hierarchical technique (K-means). Here, initial clusters (the number of clusters) are determined by a hierarchical method, and then a partitional method is employed to find the final clusters. Similar to this methodology, another approach was proposed by Vesanto and Alhoniemi (2000), which initially was applied in a non-segmentation context, via changing the combination mentioned above by replacing Ward's minimum variance method with a self-organising maps (SOM) approach. This second methodology was implemented by other researchers (Al-Khatib, Stanton, & Rawwas, 2005; Chiu, Chen, Kuo, & Kun, 2009; Kuo et al., 2002a, 2002b; Lee, Lee, & Wicks, 2004; Lee, Suh, Kim, & Lee, 2004; Lien, Ramirez, & Haines, 2006) for the segmentation problem. In this approach, a set of initial cluster prototypes is formed before implementing k-means to obtain final clusters. Similar to Ward's method, the determination of cluster number is accomplished by visual inspection; however, this process in SOM method is much less arbitrary as SOM itself provides more insights about how to make the visualisation. Also, there are a few techniques developed for that purpose that can be found in the related literature, such as U-matrix, displaying the number of hits, and generic projection methods (Vesanto & Alhoniemi, 2000). Apart from being able to identify the initial cluster numbers, the main advantage of using SOM initially is that the complexity of the reconstruction task and noise can be effectively reduced. More technical benefits of this approach are well explained in the related literature (Lee, Lee, & Wicks, 2004; Vesanto & Alhoniemi, 2000). Furthermore, since the non-hierarchical methods require an initial solution and a specification of cluster number, it was better to first solve this problem by performing a hierarchical method.

2.8. Standardisation/normalisation

The first consideration related to data analysis issue is standardisation/normalisation of variables. As mentioned earlier,

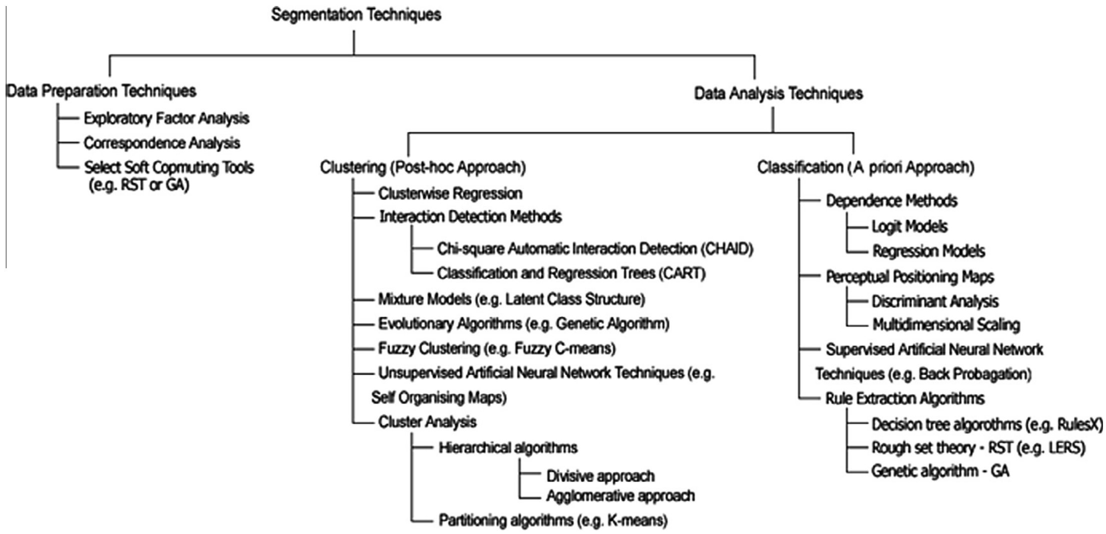

Fig. 1. A classification of segmentation techniques.

segmenting markets or customers can be performed either by employing a clustering or a classification technique. This issue should be taken into account especially when using a cluster analysis technique. In fact, this is not necessarily a prerequisite issue for every segmentation study. However, since the scope of the study does include the critical analysis of soft computing applications and some of soft computing techniques based on a clustering procedure, the standardisation/normalisation consideration will be addressed in the methodology part. Although, according to some researchers, standardisation/normalisation has no significant effects, some scholars think that standardisation/normalisation eliminates the potential effects on scale differences due to the fact that a subset of variables can dominate the definition of clusters (Ketchen & Shook, 1996). Therefore we took the advice of those who advocate that the standardisation/normalisation should be addressed on studies. Since results may differ solely based on standardisation/normalisation the evaluation base for this particular consideration will be based on the fact that whether a particular study employed any standardisation/normalisation procedure or not before performing the data analysis.

2.9. Determining the number of cluster (or segments)

Similar to the previous consideration this also is associated with studies that perform any clustering procedure. Clustering literature provides several techniques regarding the determination of number of clusters in data (Ketchen & Shook, 1996). For example, visualising the cut points on a dendogram, (which is a graph of the order that similar observations are joined), the agglomeration coefficient (a numerical value at which various observations are merged), and certain cluster validity measures (examples are presented in the validity section) are the common ones to name. In addition, as we discussed before, combining two clustering methods (the two-stage clustering procedure) is another approach to determine the number of clusters.

2.10. Reliability and validity

An important aspect concerning segmentation is associated with its validity and reliability. Even after obtaining a segmentation schema the researcher has no assurance of being able to obtain a meaningful and useful set of segments. One way of satisfying this condition is to conduct suitable reliability and validity tests. Reliability is a measurement of having stable, repeatable, and consistent results (Punj & Steward, 1983). Validity is a measurement of accuracy. There are mainly two types of classification to define the validity, namely external and internal validities (Shavelson, 1988). The former implies that findings of the study can be generalised or not, while the latter measures to which extent the outcomes of the study results from the variables and techniques being used.

In general, there are two possible approaches to assess reliability of a study (Ketchen & Shook, 1996). The first approach is based on the degree of consistency and can be performed via the clustering or classification task. It is possible to do that via altering the methods employed or carrying out the execution multiple times and discovering the consistency in solutions. The second approach, which is based on cross-validation, can be accomplished by splitting the data into two halves and conducting the analysis to come up consistency across sample halves. If a clustering procedure is employed then the second approach can be modified through obtaining cluster centroids from the first half and using them to define clusters in the second half. Cross validation is a more common approach compared to the first one. Pertaining to the cross validation discriminant measure of Wilk's Lambda (λ) and the Kappa index are the most popular ones used by the marketing researchers (Punj & Steward, 1983). When analysing the empirical studies we will just consider whether any form of reliability has been taken into account or not in those studies.

The external validity can be accomplished by showing that the results are useful in larger sense (Punj & Steward, 1983). A widely used procedure developed by Choffray and Lilien (1980) can be utilised for that purpose. As an alternative, analysis can be done on a hold-out sample or on a completely different data set to assess the similarity of the results (Ketchen & Shook, 1996). With regards to internal validity of the clustering or classification results, finding a criterion-related validity measure (either in the context of accuracy or in the form of homogeneity/clustering efficiency) can be helpful for evaluating and selecting an optimal clustering or classification schema. If the analysis is classification in nature then any form of classification accuracy measurements can be used. However, if segmentation is performed through a clustering procedure, there are two measurements referring to this, namely, compactness and separation (Kovacs, Legany, & Babos, 2005). The compactness measures how close are the members of a cluster to other clusters. The separation measures the distance between different clusters. In the related literature, many clustering indexes have been developed (particularly for the partitional methods) and they can be categorised into three groups (Dimitriadou, Dolnicar, & Weingessel, 2002). The first group of indexes consider the sum of squares within and between the clusters. The second group is based on the scatter matrix of the data points, which is the sum of the scatter matrices in each cluster. The last group consists of indexes that do not belong to the previous ones, such as Davies & Bouldin index, likelihood index, simple structure index, and cluster similarity index of C. Among those indexes, there are some measures that can also be applied to determine the number of fuzzy clusters in the data set. Interested readers can refer to related literature (Bezdek & Pal, 1998; Chou, Su, & Lai, 2004; Dimitriadou et al., 2002; Estivill-Castro, 2002; Hruschka, 1986; Kovacs et al., 2005; Punj & Steward, 1983; Shin & Sohn, 2004; Vesanto & Alhoniemi, 2000; Xie & Beni, 1991). Some of those indexes can also be used for comparing the results of different clustering methods (Bezdek & Pal, 1998; Estivill-Castro, 2002; Kovacs et al., 2005; Rand, 1971; Shin & Sohn, 2004; Vesanto & Alhoniemi, 2000). Another possible way to measure the criterion-related validity is to assess significancy with the external variables (Ketchen & Shook, 1996). These variables must not have been used in defining clusters but are theoretically related to the clusters. Categorisation associated with internal and external validities that were used to assess the empirical studies is presented in the methodology section.

3. An overview of soft computing technologies

Soft computing (SC) is mainly used in order to improve the performance of conventional traditional systems, which can be considered as hard computing. It can also be used for implementing novel intelligent and user-friendly features (Dote & Ovaska, 2001). Soft computing consists of technologies including FL, ANNs, RST, and EM. The history of the soft computing technologies goes back further than the history of soft computing itself (Dote & Ovaska, 2001; Mitra et al., 2002). This is partly because of the late realisation or awareness of using those technologies in a complementary manner due to them being seen as competing tools in the beginning. The definition of soft computing as "an evolving collection of methodologies, which aims to exploit tolerance for imprecision, uncertainty, and partial truth to achieve robustness, tractability, and low cost" shows that it deals with the problems that have ambiguity and vagueness in human thinking with real-life uncertainty (Dote & Ovaska, 2001). The concepts of uncertainty and vagueness characterise the situations that we regard as the phenomena surrounding us and are concerned with the amount of information available at our disposal (Novak, 1998). Both terms are the main constituents of soft computing. The first term is mathematically explained by probability theory and concerns the question of whether something occurs or not, while the latter can be formulised by fuzzy or other approximate sets and deals with what has or has not occurred (Novak, 1998). Zadeh (1994) defined soft computing as "not a body of concepts and techniques, [but] a partnership of distinct methods that in one way or another conform [to] its guiding principle", while some authors describe it by the opposite term of "hard computing" (Mitra & Hayashi, 2000; Wang & Tan, 1997).

However, definitions about soft computing are not completely satisfactory because there is a risk of epistemological confusion about related thoughts (Dubois & Prade, 1998). It can be said that the only consensus about soft computing is that it is a consortium of methodologies that work synergistically (Mitra & Hayashi, 2000; Mitra et al., 2002; Pal et al., 2002). This consortium is done in a cooperative, rather than a competitive manner (Mitra & Acharya, 2003). In addition to this consensus, the techniques mentioned above are the principal components of soft computing, where fuzzy tools enable us to work with vagueness and uncertainty, and EM can involve optimisation and searching processes, while ANNs and RST can solve classification and rule generation problems with their learning and discernability capabilities (Mitra et al., 2002; Pal et al., 2002). Only fuzzy systems work with a deductive logic; the others have inductive capabilities. Both fuzzy and RST can work with descriptive and numeric data, while ANN and EM can work only with numeric data (Duntsch & Gediga, 2000).

Soft computing technologies have recently been used for solving data mining problems (Craven & Shavlik, 1997; Kim & Street, 2004; Zhong & Skowron, 2001). In the related literature a guideline is given along with several dimensions (complexity of the task, dynamic modelling capability of each technique, the size of training data and data type, the capability of modelling uncertainty and handling noisy data, interpretability of the technique's results) regarding the decision of which technique to use when developing a soft computing application (Martinez, Magoulas, Chen, & Macredie, 2005). The suitability of each technique for different problems can be extracted from the literature. Classification of soft computing application within the scope of data mining is provided in Table 3. Considering the fact that segmentation is handled as either a classification or a clustering problem within the data mining, one can figure out which soft computing technologies are applicable for segmenting customers or markets.

Fuzzy sets are suitable for handling issues, such as understandability of patterns, incomplete and imprecise data, information fusion and linguistic information, deducing the knowledge, and finding approximate solutions (Pal et al., 2002; Pedrycz, 1998). Most of the fuzzy-oriented applications utilised fuzzy clustering (Crespo & Weber, 2005; Hruschka, 1986; Hu & Sheu, 2003; Ozer, 2001; Shin & Sohn, 2004; Wedel & Steenkamp, 1989) in order to segment customers. The fuzzy clustering methods partition a data set into a number of overlapping groups based on the similarity or the distance in a metric space between the objects in the data and the cluster prototypes (Setnes, 2000). Therefore, in FC, constructing clusters with uncertain boundaries by allowing one object to belong to some overlapping clusters to some degree of membership is possible.

ANNs are able to extract the embedded knowledge in trained networks usually in the form of symbolic rules, which helps to identify the classes or the predicted values of the observations and the importance of the attributes regarding the determination of those classes or class values in the data space (Mitra et al., 2002). Rule generalisation, clustering or classification of the objects, forecasting or prediction future behaviour, and modelling complex mathematical functions are the tasks that neuro-computing is able to deliver within the scope of data mining and knowledge discovery, especially for predictive marketing (consumer behaviour, market segmentation, purchase modelling, customer service support, prediction of bond rating, fraud detection, bankruptcy and corporate failure) (Zahavi & Levin, 1997). With regards to the application of ANN in the area of segmentation, solely the backpropagation algorithm (Bloom, 2005) was used for classification while the other ANN algorithms (e.g., self-organising maps – SOM) were used for clustering (Chiu et al., 2009; Diez, Coz, Luacez, & Bahamonde, 2008; Ha, 2007; Hung & Tsai, 2008; Kuo, An, Wang, & Chung, 2006; Lee & Park, 2005; Shin & Sohn, 2004). Moreover, Adaptive Resonance Theory, Hopfield ANN, Backpropagation, Frequency-Sensitive Competitive Learning Algorithm (FSCL) are other methods that have been used market/customer segmentation problem.

EM are capable of arriving at an optimal solution via a fitness function in a robust and efficient way where the search space is large as in data mining problems. Evolutionary methods (EM), as a member of soft computing techniques, consist of several computational models of evolutionary processes including evolutionary algorithms, genetic algorithms, evolution strategy, and evolutionary programming (Kusiak, 2000). It is also possible to find some applications of EM (particularly applications of genetic algorithms, which is the most common approach) in the marketing field, including customer targeting (Kim & Street, 2004; Kim, Street, & Menczer, 2001; Kim, Street, Russell, & Menczer, 2005), market modelling (Shiraz, Marks, Midgley, & Cooper, 1998), location analysis and market structuring (Hurley, Moutinho, & Stephens, 1995), acquiring marketing decision rules (Ghosh & Bhabesh, 2004; Terano & Ishino, 1995), and direct marketing applications (Bhattacharyya, 2000). Furthermore, strategic marketing initiatives, such as optimization of marketing resources, segmentation and other consumer behaviour modelling problems, can be considered by EM (Chan, 2008; Chiu, 2002; Hurley et al., 1995; Kim & Ahn, 2008; Kuo et al., 2006; Tsai & Chiu, 2004).

RST, which is based on mathematical computations and granular approximation, has been used for discovering hidden patterns in an uncertain environment like fuzzy sets (Mitra et al., 2002). Within the framework of data mining, some application purposes of RST can be found, such as attribute reduction and rule generation (Hu & Cercone, 1994; Hu & Cercone, 1996), prediction (Poel & Piesta, 1998), rule extraction (Lingras & Yao, 1998; Zhong & Skowron, 2001), rule induction (Griffin & Chen, 1998) and classification (Chan, 1998; Li & Wang, 2004). For marketing problems, it can be possible to find a few applications of RST, such as rule extraction, feature selection, customer retention and response modelling, segmentation and prediction (Changchien & Lu, 2001; Cheng & Chen, 2009; Komorowski, Polkowski, & Skowron, 1999; Poel & Piesta, 1998; Tseng & Huang, 2007; Voges, Pope, & Brown, 2003).

4. Method

The method which was followed in this article can be found in most of the literature studies that include the critical analysis of the current body of knowledge, particularly associated with examining the empirical studies of any literature. The identification of the relevant studies, establishing a coding procedure and maintaining the reliability of this coding procedure are the main constituents of the method. A description of these efforts is clearly explained below.

4.1. Identification of relevant studies

To identify the applications of soft computing techniques on segmentation problem, several journal articles were examined. The article selection procedure was based on several criteria. The first criterion is that the studies should be in empirical nature and consist of hypothetical (or simulated) or real-world data. The second one is related to the main purpose of using soft computing techniques; the technique or the techniques should be used in order to perform the segmentation either in clustering or classification form. The techniques that are supplementary to the segmentation process, such as data preparation or attribute reduction were excluded. The third criterion is that only articles where segmentation was the main purpose of the study were considered. Also, the excluded studies were those, whose main focus is not segmentation, but they may be doing something related to the segmentation process, such as predictive modelling or direct marketing. The last one is associated with the publication type. Only journal articles were examined, and publications in other forms, such as conference paper, book chapters and research reports were not included in the study. Hence, regardless of the publication date, all empirical studies were collected through the publication databases depending on the availability of the access to these databases. However, it can be said that the majority of the well-known science and social science journals were searched.

At the end of the searching process, a total of 42 studies were selected for critical analysis. The earliest date of these publications is in 1986, whilst the latest one is in 2012. The majority of the studies were published in science related journals, while only a few of those were in business and marketing related journals. The following section of this study will provide detail knowledge for the distribution of these studies in different journals and their publication periods.

4.2. Coding procedure

The critical factors described in the previous section served as the basis for the coding procedure. Specifically, each journal article was given an electronic code number and each of the factors used to examine the journal articles was coded respectively. The following table is given for elucidating the coding scheme for each factor.

As it can be seen from Table 4, a total of 18 factors or variables were taken into consideration, as the basis to examine the selected

Table 3
Soft computing applications in different data mining tasks. Adapted from Mitra et al. (2002) and Pal et al. (2002).

Soft computing technologies	Data mining tasks
Fuzzy sets	• Clustering • Association rules • Functional dependencies • Data summarisation • Time series analysis • Web mining (information retrieval) • Image retrieval
Artificial neural networks	• Rule extraction • Rule evaluation • Clustering • Regression • Web mining (information extraction and retrieval, personalisation)
Evolutionary methods	• Regression • Association rules • Web mining (search and retrieval, query optimisation, document representation, distributed mining)
Rough sets	• Decision rule induction • Data filtration (including attribute reduction) • Rule generation • Web mining (information retrieval, information fusion, handling multimedia data, document clustering, web usage mining)

articles. 13 out of 18 variables were explained via a specific categorisation. Some variables took values that include more than one categorisation, whilst for some of them one category was enough to carry out the task. In other words, some of the variables in certain articles were needed to be explained with more than one category. Variables, such as segmentability criteria, internal validity, and external validity etc. can be given as examples for this type of cases. However, as it can be seen from the table, some of the variables (year, journal name, SC technique, sample size, and industry) do not have any categorisation at all. This is due to the fact that either the values for those factors were difficult to be categorised or a categorisation might not have been necessary at all for them.

Regarding the explanation of each variable by referring to what was mentioned in the previous sections, the followings can be said. The objectives of segmentation in the studies were examined based on the five categories that were previously described in the study of Sausen and his friends (2005) and each study was assigned to one category only. At the end of the coding procedure, all five objectives were appeared in at least one journal article. For some articles, it was really hard to extract this information as these studies do not mention it clearly. It should be clarified that here "objective" does not refer the objective of the article as the objective of the article could be comparison of different techniques. Rather, it is an identification process that finds the most suitable segmentation objective category for the selected studies in terms of models that they were employed. In other words, which of the specified segmentation objective is the most suitable to describe the potential implication of the article. The unit of analysis were coded into five categories and similar to the previous factor the categorisation was taken from the same literature (Sausen et al., 2005). One extra category was added, labelled as "not available", to represent studies where the identification of the unit of analysis was impossible. It might be possible to see some articles where unit of analysis is not clearly mentioned in their methodology part. Also, the category coded with one did not appear at the end of the coding process.

Segmentation variable factor were categorised into four, namely, general observable, product-specific observable, general unobservable, and product-specific unobservable. This categorisation is based on a common classification scheme accepted by segmentation scholars and suggested by Wedel and Kamakura (2000). As we mentioned earlier for this category some of the studies had more than one category. Similarly, segmentation model categorisation is based upon industrial segmentation literature. As we expected, none of the studies were assigned to multi-stage model segmentation category.

Segmentation technology category was created to cover the major technologies of soft computing. There was no single study benefiting from rough computing in the selected literature. With regard to the segmentation technique no categorisation were created but typing of each technique was carefully done. For the studies where the soft computing technique is not named clearly, a categorisation of "not available" was used. A range of techniques from fuzzy clustering and genetic algorithm to self-organising maps and back propagation were obtained after finishing the coding process. The purpose of the usage of these segmentation techniques on segmentation problem is also another factor included in the critical analysis. Based on the experience of the author different categories associated with classification and clustering were created as represented in the table.

Sample size and industry are other variables included in the study. Studies that do not mention the number data available were labelled as "not available". However, from the majority of the studies it was possible to extract this information. Sample sizes from two digits to five and six digits numbers were available in the selected studies. Also, those studies are implemented into different industries such as manufacturing, banking, logistics, and charity etc. Moreover, the term "data source" indicates the origin or the source of the data.

The studies were examined based on six different segmentation criteria. As we discussed earlier, these are the criteria for an effective segmentation study. While there were studies that satisfy a few of them, some studies do not meet any of those criteria and they were labelled as "none" during coding procedure.

Apart from the factors or variables mentioned above the study also took into consideration some other issues related to technical aspects of those studies. The studies were examined depending on the availability of the information whether they include any normalisation or not. For some studies this information was unavailable and they were coded as "not available" for this variable. Also, the studies that are in clustering nature were examined if they use any method (these are coded as categories from 1 to 5) in order to determine the number of segments (or clusters). However, for some studies this information is "not applicable" and they coded as it so due to the fact that the technique(s) is(are) used for classification purpose in those studies.

Finally, there are variables associated with reliability and validity of those segmentation studies. Here, those factors are related to the core of the segmentation process (either in clustering or classification form) employed in these studies. Hence, the concern is here not the reliability and validity of those articles as a whole piece but the focus is only on the segmentation part takes place. The existence of reliability was looked for as a binary manner (yes or no). However, for internal and external validities different categories were created based on the author's experience and information available in the social science literature. This categorisation includes different ways of measuring internal and external validities and as well as the option for the cases where there is no internal/external validity. As similar to other factors/variables in which the categorisation made by the numbers, there were cases where the joint coding procedure was necessary.

4.3. Coding reliability

All of the selected studies were coded independently by the two evaluators. In order to ensure consistency, initially a random sample of eight articles was coded and then the results were compared to measure the preliminary inter-rater reliability. The consistency between the two evaluators was measured as 78%. In order to improve this rate a meeting was held to discuss the current discrepancies. The rest of the articles, 30 studies, were then coded with a 92% inter-rater reliability that can be considered as a quite acceptable rate compared to the studies conducted to accomplish somehow similar objective as this study has. The discrepancies were resolved by the evaluators through reviewing the differences again and consequently a joint decision was obtained by recoding the relevant items.

5. Results

This section highlights major important points regarding the descriptive results of the examination of each factor/variable used in the study. The results were presented in a structural way by the author.

5.1. Distribution of studies by year, journal name and industry

Fig. 2 represents the distribution of the selected articles. The time period covers more than 25 years starting from 1986 to 2012. Almost one fourth of the studies ($n = 10$, 23.8% of the total

Table 4
The coding scheme for each factor or variable.

Critical factors or variables	Coding scheme (categorisation)
Year	None
Journal name	None
Objective	Exploitation of new customers potentials Development of existing customer potentials Increasing customer profitability Improving targeting of marketing measures Identification of new sub-markets
Unit of analysis	Not Available Anonymous sub-markets Anonymous groups or typologies of customers Personalised existing customers Personalised potential customers
Segmentation variable	General observable Product specific observable General unobservable Product specific unobservable
Segmentation model	Single-stage models Two-stage models Multi-stage models
SC technology	Fuzzy computing Neural computing Evolutionary computing Rough computing
SC technique	None
Purpose of the usage of SC technique	Clustering Classification Both clustering and classification Contributory to clustering Both clustering and contributory to clustering
Data type	Survey/Secondary data/Simulation data
Sample size	None
Industry	None
Segmentability criteria satisfied	None Homogeneity Substantiality Identifiability Actionability Measurability Differentiability
Normalisation	Yes/No/Not Available
Determining the number of segments	Not Applicable Two-stage method Special techniques Agglomeration coefficient Dendogram Arbitrary
Reliability	Yes/No
Internal validity	Clustering efficiency Statistical tests on non-clustering variables None
External validity	Hold-out samples Applying in another data None

studies located) were published in year 2004. Before 1999 there is an even distribution and at average one article was published each year. However, following that period we can talk about an increase on the average number of publications. After 1998, if the extreme case was excluded (year 2004) the average number of publication per year would have become three.

If we look at the distribution of the articles in terms of the journals in which they were published (see Table 5), it could easily be seen that more than 40% of the publications belong to one particular journal, namely, Expert Systems with Applications. Also, an interesting point is that the cumulative number of publications in marketing related journals is not even more than 20% of the total publications.

Table 6 indicates that the studies were implemented in several industries covering different types of sectors. Tourism industry has the biggest number of applications by 19% of total studies and retail and e-business follow tourism industry as second most implemented areas.

5.2. Distribution of studies by SC technology, technique and the purpose of usage the techniques

With regard to the deployment of soft computing technologies across the studies Table 7 shows that around 65% of the studies used neuro computing as soft computing technology. There is only one recorded study, which made use of rough computing. The usage of evolutionary and fuzzy computing is substantially less compared to neuro computing. Also, three studies utilised both neural and evolutionary computing in a collaborative way in the form of hybrid soft computing.

Should one looks at the distribution of the soft computing technologies across the industries as it is shown in Table 8, it can be noticed that neuro computing technologies had applications in all industries. Also, Rough computing technology applied only in e-business area while the application of fuzzy and evolutionary computing technologies can be seen in half of the industries. Moreover, it is possible to see that three different soft computing technologies were utilised in e-business, logistics and transportation, and manufacturing-automotive-food industries.

Pertaining to the above soft computing technologies variety of techniques were utilised as it can be seen from Table 9. This variety in fact mainly belongs to neuro computing consisting of techniques including self-organising maps, back propagation, vector quantisation, and Hopfield–Kagmar algorithms. Self-organising maps method is the most utilised technique across studies by 45% of total publications including the complementary usage with evolutionary algorithms. Also, the studies that do not specify the technique made use of neuro computing as well. Regarding fuzzy computing, only fuzzy clustering technique was utilised and while for evolutionary computing genetic algorithm and particle swarm optimization were used.

As far as the purpose of the usage of these techniques is concerned, Fig. 3 indicates that those techniques are used to perform clustering task in more than 80% of the studies. It should be noted that this percentage also includes the usage of the techniques as contributory to clustering task. The contribution of the used clustering technique stems from either for the purpose of determining the number of clusters or increasing clustering efficiency.

5.3. Segmentation objective and unit of analysis

In terms of the pre-specified segmentation objectives, Table 10 shows that the studies which have objectives of increasing customer profitability and developing existing customers potentials are the two highest categories. This is followed by the objective of improving targeting marketing measures. The objective related to new markets or customers did only appear in three studies.

Basically, this result is linked with the unit of analysis being used across studies as it can be observed from Table 11. If we look at the frequencies and percentages, more than 80% of the studies used personalised existing customers as unit of analysis. Among the pre-specified categories for unit of analysis, anonymous sub-markets option was not used in a single study. We could say the anonymity of the customers or customer groups is a key factor for soft computing techniques to perform segmentation. Because, almost all of the soft computing techniques need an information table consisting of individual-level attributes in order to perform clustering or classification task. Similar to the traditional clustering analysis the data should be presented to these techniques in matrix format (cases as rows and attributes as columns).

As far as the distribution of the objective of those studies across industries is concerned, the objectives related to existing customers were aimed in the majority of the industries while studies aim at exploitation of new customers or identification of new markets applied only in banking-insurance-stock markets and e-business sectors, respectively as shown in Table 12.

5.4. Segmentation variables and models and segmentability criteria

The results indicated that all types of segmentation variables were used in the studies as shown in Table 13. However, general unobservable variables were only used in two studies in which one of them is combined with general and product specific observable variables. General observable category was used alone in two studies and occurred in 12 studies in different combinatorial categories. The highest percentages belong to product specific observable and unobservable categories with the alone usage rate of 28.6% for both of them. They also involved into combinatorial categories with different usage rates.

With regards to the segmentation model used in those studies it can be concluded that there is no application of multi-stage model as it can be seen from Fig. 4. This is partly, because of the fact that almost all studies were conducted within the context of customer segmentation rather than in the scope of industrial or global market segmentation. More than 90% of the studies can fall into the category of single-stage model. However, it is noticeable that there are three studies that were utilised the two-stage segmentation model.

The results associated with the segmentability criteria is the most important aspect of this study. It could be argued that there is a real gap between applied science and social science research in terms of taking this issue as a priority. As it was mentioned before, the majority of those studies were written from the perspective of applied science. The analysis results as shown in Table 14 indicated that segmentability criteria were not taken into consideration from the social science perspective. Almost 12% of the studies did not consider any of the criteria as a proof of segmentation effectiveness. Homogeneity was calculated in around 17% of these studies. Identifiability stands out as the highest percentages among the criteria. Also, the results showed that there are combinatorial categories (double and triple) with respect to the usage of those criteria. The combination of homogeneity, identifiability and actionability were measured in only five studies. In fact, for a segmentation study to be considered as an effective study depends on the measurement of those criteria. Furthermore, the measurement should not be only based on one of them but if possible it should cover all criteria to prove the effectiveness.

5.5. Factors related to the analysis stage of the studies

Table 15 provides the results of the examination of the articles with respect to the issues related to data analysis. The examination of the articles indicated that almost half of the studies clearly mentioned that they performed a normalisation process before conducting the data analysis. However, for almost the other half it was impossible to extract this information from the corresponding manuscripts. In six studies it was clear to conclude that they do not possess any course of action regarding normalisation.

The data were used in those studies usually either in the form of questionnaire or secondary data that procured from an external party. Although the results show that simulation (hypothetical) data was used in only one study, we could absolutely ensure that some of the studies that used secondary data also possess hypothetical data. However, during the coding process if there were two different data sets in a particular study, one from secondary source and the other is hypothetical, the secondary data source was accepted as the main data type. In such cases that the simulation data was considered as another sample, it was accepted that an analysis concerning external validation was carried out.

With regard to the actions taken in order to determine the number of clusters during the analysis stage, the results illustrated that sixteen studies did not utilise any of the specified methods. When there was a method for determining the number of clusters in a particular study either a special technique from clustering literature or the two-stage method was utilised. For the classification

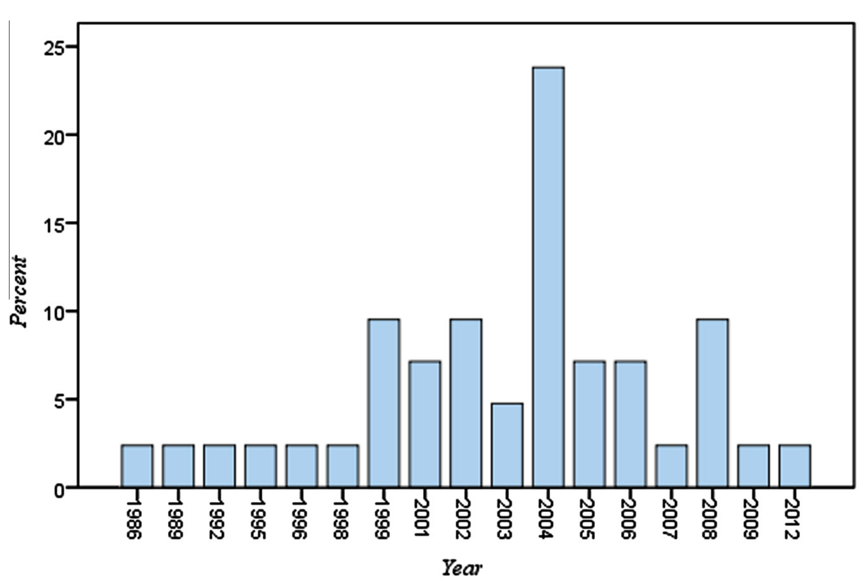

Fig. 2. Publications by year.

Table 5
Publications by journal name.

Journal name	Frequency	Percentage
Advanced engineering informatics	1	2.4
Annals of tourism research	1	2.4
Asian journal of management and humanity sciences	1	
Australasian marketing journal	1	2.4
Computers and industrial engineering	1	2.4
Computers and operations research	1	2.4
Decision support systems	1	2.4
European journal of marketing	1	2.4
European journal of operational research	2	4.8
Expert systems with applications	18	42.9
Fuzzy sets and systems	2	4.8
Industrial marketing management	1	2.4
International journal of research in marketing	2	4.8
Journal of operational research society	1	2.4
Journal of organisational computing and electronic	1	2.4
Journal of research in marketing	1	2.4
Journal of retailing and consumer services	1	2.4
Journal of travel and tourism marketing	1	2.4
Journal of travel research	1	2.4
Omega	1	2.4
Tourism management	2	4.8
Total	42	100.0

Table 6
Publications by industry.

Industry	Frequency	Percentage
Banking & insurance & stock markets	4	9.5
Charity & social club	2	4.8
E-business	7	16.7
Household & universal products	4	9.5
Logistics and transportation	3	7.1
Manufacturing & automotive & food	4	9.5
Retail	6	14.3
Telecommunication	3	7.1
Tourism	8	19.0
Not available	1	2.4

Table 7
Publications by soft computing technology.

SC technology	Frequency	Percentage
Evolutionary computing	5	11.6
Fuzzy computing	6	13.9
Hybrid computing	3	7.0
Neuro computing	28	65.1
Rough computing	1	2.0

techniques, this option was not applicable since the issue in those studies was in the form of binary classification.

An interesting result occurred when reliability factor was explored. Approximately 65% of the studies did not include a reliability measure regarding the consistency of the clustering and/or classification methodology they employed. Among the remaining studies, 13 articles were considered to possess reliability since they either provided a reliability measure or they conducted the analysis in at least two data sets and obtained consistent results. In fact, in the latter cases the reliability was ensured through obtaining stable results as a result of replication of the analysis.

In connection with reliability, 14 studies carried out some analyses regarding external validity as it can be seen in Table 16. They assured the external validity either by having a different data set or allocating a hold-out sample. However, in general, external validity did not exist in 28 studies. In comparison with external validity, better results were emerged with respect to internal validity of the examined studies. In total, 31 studies have at least one measurement associated with internal validity. Yet, no method or technique was carried out in 11 studies to ensure internal validity.

6. Discussions for the future of SC in segmentation research

A large volume of data about customers has created opportunities for businesses and enables them to gain competitive advantage (Shaw et al., 2001). However, because of the lack of appropriate tools and techniques to analyse customer databases, a wide variety of customer information and buying patterns are hidden in these databases (Shaw et al., 2001). Soft computing techniques have been getting attention in this context by the interdisciplinary researchers. The application areas of soft computing are mainly human-related fields ranging from manufacturing, automation and robotics to transportation and communication systems that involve uncertainty and vagueness to some extent (Bonissone, Chen, Goebel, & Khedkar, 1999; Dote & Ovaska, 2001; Martinez et al., 2005). Those applications have stimulated other applications related to business and finance. In fact, Kordon (2006) pointed out eight future industrial needs that are associated business and finance for which SC technologies can be very much useful. The article lists four problem domains; predictive marketing, accelerated new product diffusion, manufacturing at economic optimum, and predictive optimal supply chain.

However, compared to other disciplines it is difficult to see a growing number of soft computing technologies applications to business and management problems particularly for customer segmentation. There may be four main reasons that SC has not been taken enough attention by the academics and practitioners. The first reason can be linked to human factors in the context of "politics" as it has been discussed in Kordon (2006). According to the author although there are people advocate the benefits of SC and ready to take risk to implement them, there are however a lot of scepticism regarding the value of SC as some people see the implementation efforts as a "research toy exercise". The second reason is

Table 8
Publications by industry and SC technology.

Industry	Evolutionary computing	Fuzzy computing	Hybrid soft computing	Neuro computing	Rough computing
Banking & insurance & stock markets	0	2	0	2	0
Charity & social club	1	0	0	1	0
E-business	1	1	0	4	1
Household & universal products	0	1	0	3	0
Logistics and transportation	0	1	1	1	0
Manufacturing & automotive & food	1	1	0	2	0
Retail	2	0	0	5	0
Telecommunication	0	0	1	2	0
Tourism	0	0	1	7	0
Not available	0	0	0	1	0

Table 9
Usage of SC technique across the studies.

SC technique	Frequency	Percentage
Back propagation	5	11.9
FSCL	1	2.4
Fuzzy clustering	6	14.3
Genetic algorithm	4	9.5
Hopfield–Kagmar	1	2.4
Self-organising maps	15	35.7
Self-organising maps and genetic algorithm	2	4.8
Self-organising maps and particle swarm optimisation	2	4.8
Vector quantisation	3	7.1
Rough set theory	1	2.4
Not available	2	4.8

Table 10
Segmentation objective across studies.

Objective	Frequency	Percentage
Exploitation of new customers potentials	2	4.8
Development of existing customer potentials	14	33.3
Increasing customer profitability	13	31.0
Improving targeting of marketing measures	10	23.8
Identification of new sub-markets	3	7.1

Table 11
Unit of analysis across studies.

Unit of analysis	Frequency	Percentage
Not available	1	2.4
Anonymous groups or typologies of customers	4	9.5
Personalised existing customers	35	83.3
Personalised potential customers	2	4.8

associated with the technical and methodological requirements (including data requirement) of these technologies as additional analytical reasoning skills or training may be needed before implementing them. The third reason is that both the researchers in social science and the practitioners see those technologies quite complex and hard to implement to perform a segmentation study. Although, those technologies have some sort of technical aspects, the majority of them are included in some of the latest data mining software and they are easy to use likewise its counter data analysis tools. The last reason stems from the gap between applied science researchers and social scientists. This is due to the fact that either the researchers in both parties may not be completely aware of each other's studies or it is partly because of the reality that both research orientations follow different scientific paradigms. A systematic solution to the credibility of SC in general (but can be applied to social science research and practice) is provided by Kordon (2006) to which the more interested readers can refer.

Although business and finance applications may not be as sophisticated as science and engineering applications so that SC can play a role in business-related problems, the applicability of SC in social science problems represents a significant paradigm shift (breakthrough) that reflects the human mind possesses a remarkable ability to store and process information in the aim of computing (Dote & Ovaska, 2001). Within the scope of customer segmentation it can be said that although the techniques based on statistical approaches to classify customers to form segments have met with various degrees of success, it is noteworthy to mention that those approaches are not capable of executing large number of data and do not provide a flexible segmentation structure as soft computing technologies are capable of to do so.

The soft computing technologies can be used individually, integrated or in combination as hybridizations like neuro-fuzzy, fuzzy-neuro, fuzzy-genetic, genetic-fuzzy, neuro-genetic, rough-neuro, rough-fuzzy, rough-neuro-fuzzy, rough-neuro-genetic or rough-neuro-fuzzy-genetic (Bonissone et al., 1999; Komorowski et al., 1999; Mitra & Hayashi, 2000; Mitra et al., 2002; Pal et al., 2002). The main difference between the usages of these techniques, either in an integrated or combinatorial manner, is that combination consists of merging two or more techniques in a unitary structure, while integration refers to a dividable series of continua. In customer segmentation literature most of them were used individually rather than integrated or hybridised. In another words, appropriate combination of those techniques has not been accomplished yet. The appropriateness is with regards to obtaining efficient clusters both from the clustering and marketing points of views. Therefore, one needs to look at the methodological frameworks that give us the idea of how to combine different clustering or classification techniques in an appropriate manner and more importantly in a simplified way. This simplicity is partly due to the fact that the majority of researchers in business and management area may have been facing difficulty to understand the technical background of the methods developed by information technologists and computers scientists.

When the issue comes to the application of soft computing technologies, there are however some critical issues regarding the usage of them in a specific problem domain (Mitra et al., 2002). These are (1) scalability problem, (2) feature evaluation and dimensionality reduction, (3) choice of metrics and evaluation

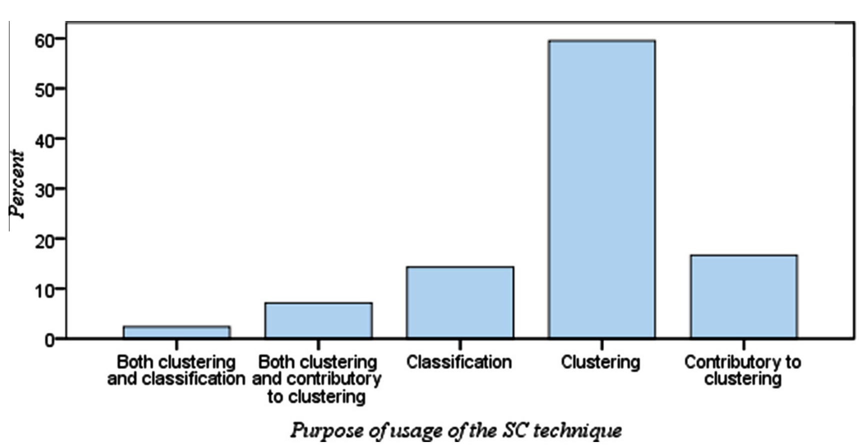

Fig. 3. Purpose of the usage of SC technique in publications.

Table 12
Publications by industry and segmentation objective.

Industry	Exploitation of new customers potentials	Development of existing customer potentials	Increasing customer profitability	Improving targeting of marketing measures	Identification of new sub-markets
Banking & insurance & stock markets	1	0	3	0	0
Charity & social club	0	0	2	0	0
E-business	0	3	0	2	2
Household & universal products	1	1	0	2	0
Logistics and transportation	0	1	1	1	0
Manufacturing & automotive & food	0	1	1	2	0
Retail	0	2	4	0	0
Telecommunication	0	2	1	0	0
Tourism	0	4	1	2	1
Not available	0	0	0	1	0

Table 13
The usage of segmentation variables across studies.

Segmentation variables	Frequency	Percentage
General observable	2	4.8
General unobservable	1	2.4
Product specific observable	12	28.6
Product specific unobservable	12	28.6
General observable & product specific observable	6	14.3
General observable & product specific unobservable	2	4.8
Product specific observable & product specific unobservable	1	2.4
General unobservable & product specific unobservable	2	4.8
General observable & product specific observable & general unobservable	1	2.4
General observable & product specific observable & product specific unobservable	3	7.1

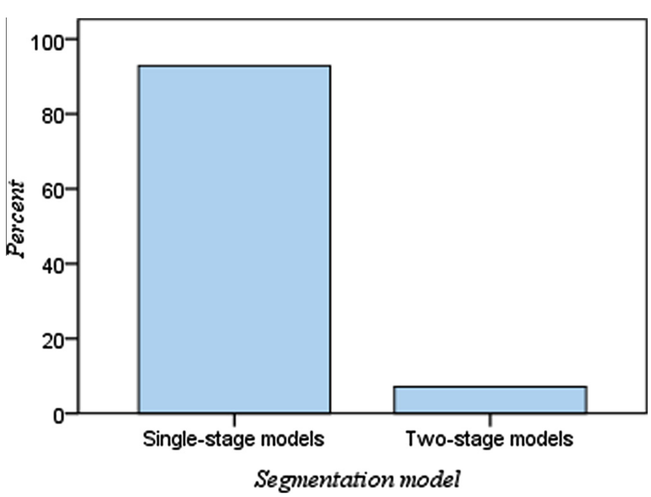

Fig. 4. Segmentation model across studies.

Table 14
The deployment of segmentability criteria across studies.

Segmentability criteria satisfied	Frequency	Percentage
None	5	11.9
Homogeneity	7	16.7
Identifiability	8	19.0
Actionability	1	2.4
Homogeneity & substantiality	1	2.4
Homogeneity & identifiability	11	26.2
Homogeneity & actionability	1	2.4
Identifiability & actionability	2	4.8
Homogeneity & identifiability & actionability	5	11.9
Substantiality & identifiability & differentiability	1	2.4

Table 15
Publications by factors related to the analysis (normalisation, data type, determination of the number of clusters).

Normalisation	Frequency	Data type	Frequency	Det. no of cluster	Frequency
Not available	17	Survey	20	Not applicable	5
No	6	Secondary data	21	Two-stage method	8
Yes	19	Simulation data	1	Special techniques	9
				Dendogram	2
				Arbitrary	16
				Two-stage method & special techniques	2

Table 16
Internal and external validity status of the studies.

Internal validity	Frequency	External validity	Frequency
Clustering efficiency	25	Hold-out sample	3
Statistical tests on non-clustering variables	1	Different data	10
Clustering efficiency & statistical tests on non-clustering variables	5	Hold-out sample & different data	1
None	11	None	28

techniques for dynamic changes in data, (4) incorporation of domain knowledge and user interaction, (5) efficient integration of soft computing tools. The majority of the those issues stem from the contemporary challenges of data mining itself. What is more important to point out that integration or hybridisation of these technologies in different data mining application domains has become an important future research area. Should one considers the fact that the data mining researchers highlight especially the necessity of dealing with web data, there is still much to research on the application of those technologies either in single or integrated/combinatorial way within the context of web mining (Pal et al., 2002). In particular, within the web mining domain performing different segmentation studies by making use of soft computing technologies could be of great importance for further studies.

Although soft computing is a major area of academic research, the concept is still in its evolving stage, and new methodologies, e.g., chaos computing and immune networks are nowadays considered to be belong to SC (Dote & Ovaska, 2001). In conclusion, the advances in fuzzy systems such as investigations on computing with words, cognitive and reactive distributed artificial intelligence applications including intelligent agents, the emerging applications of evolutionary computing including meta-heuristics, probabilistic models, and rough computing, and will lead us to the construction of more advanced intelligent systems, which can also be applicable for business problems (Kordon, 2006; Verdegay, Yager, & Bonissone, 2008).

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