Using the Fuzzy Multicriteria Decision Making Approach to Evaluate Brand Equity: A Study of Privatized Firms

Abstract

Purpose: The objective of this paper is to present a multidimensional evaluation of brand equity performance incorporating dimensions adopted from the balance scorecard (BSC) approach to business performance.

Design/methodology/approach: In this study, text mining is employed for automatic extraction of valuable information from textual data such as the financial reports of firms. Instead of expert opinions, linguistic scales built upon outcomes of text mining are utilized as inputs for decision-making. The proposed model combines fuzzy DEMATEL (FDEMATEL), fuzzy ANP (FANP), fuzzy TOPSIS (FTOPSIS), and fuzzy VIKOR (FVIKOR) methods for weighting criteria and ranking alternatives.

Findings: Using data from 5 privatized firms in Turkey, the study's findings demonstrate that the customer is the most important dimension of brand equity performance evaluation. Cash flow and brand loyalty are identified as the most important criteria in the measurement of brand equity performance.

Managerial Implications: Findings highlight the importance of firms taking action to increase consumer perceptions, attitudes and behaviors in the privatization processes. For this purpose, privatized firms need to understand the expectations of customers to increase customer satisfaction and loyalty and therefore improve brand equity.

Originality/value: The paper contributes to literature in several important ways. First, by adopting the BSC approach, it proposes a holistic and a multidimensional model for measuring brand equity performance. Second, the study offers a novel methodology using a hybrid multi-criteria decision-making model designed for the fuzzy environment. Third, the study utilizes the knowledge extraction tool of text mining in the fuzzy decision-making process. Finally, the study evaluates the brand equity performance of privatized firms in an emerging country context.

Keywords: Branding; Brand Equity; Brand Name; Corporate Branding; Brand Performance; Brand Management; Knowledge Extraction; Text Mining; Fuzzy Logic

1. Introduction

Over the past twenty years, the topic of brand equity has received considerable attention in the marketing literature (Yoo et al., 2000; Tong and Hawley, 2009; Washburn and Plank, 2002). Rapid technological innovation, the globalization of markets, and the growth of retail power have all highlighted the importance of understanding and measuring brand equity. Despite many definitions, there is general consensus in the literature that brand equity represents the incremental value of a product or firm due to the brand name (Srivastava and Shocker, 1991). Positive brand equity is important to customers, firms and investors alike. Consumers trust firms that demonstrate positive brand equity (Augusto and Torres, 2018; Phung et al., 2019). Brand equity also provides value to the firm by enhancing efficiency and effectiveness of marketing programs, prices and profits, brand extensions and competitive advantage relative to rivals (Yoo and Donthu, 2001; Schivinski et al., 2019). Understanding brand equity and how to measure it is also important to investors of privatized firms. Investors expect shareholder value and profitability to increase because of privatization and thus analyze assets and liabilities before they decide to invest in a given firm (Pappu, Quester and Cooksey, 2005). Given that the privatization process seeks to make firms more profitable and productive, investors also need to understand and measure the brand equity of firms post privatization (Ahn et al., 2018; Kodua and Mensah, 2017).

Not surprisingly, brand equity is a strategic resource to be analyzed, measured and managed over time. Building and maintaining the continuity and success of a brand is therefore important and selecting an appropriate methodology to evaluate brand equity effectively is a major task confronting managers (Reinders and Bartels, 2017). However, the process of building and maintaining positive brand equity involves a high degree of uncertainty and ambiguity (Farquhar, 1989; Ghosh and Chakraborty, 2004). Indeed, marketing decisions in general are subject to multiple sources of uncertainties that are affected by fuzziness and imprecise issues (Levy and Yoon, 1995). Despite these complexities however, the study of marketing problems has traditionally relied on a linear model (Mela and Lehmann 1995), which is rooted in the binary choice of classical set theory where elements possessing a set of critical features are included as members of specific category, and elements lacking those attributes are excluded (Cohen and Basu 1987). Binary thought is a way of simplifying a complex world. In real-world marketing, decision-makers face problems involving significant imperfect knowledge and vague factors in situations where ‘approximate reasoning’ is the dominant way to make marketing decisions. Known as fuzzy logic or fuzzy thinking (Zadeh,

1965 2008), this approach acknowledges that binary thought as a way of simplifying a complex world distorts reality, and categories of objects encountered in the real world cannot easily be classified with crispness (Viswanathan and Childers 1999; Zadeh 1965).

Our review of the extant literature suggests that multiple factors may affect the brand equity of a firm. A widely cited strategic decision-making tool that considers both financial and non-financial aspects of performance evaluation is the balanced scorecard (BSC) (Kaplan and Norton, 1991). Acknowledging that traditional performance approaches only consider financial data, and ignore non-monetary aspects of performance evaluation, the BSC considers four perspectives: a) financial, which measures the financial performance of firm, b) customer, which measures the satisfaction of the firm's customers, c) internal business process, which measures internal business results against measures from financial and customer perspectives, and d) innovation and learning, which measures the ability of the firm to adapt to changes (Kaplan and Norton, 2001). In the brand equity literature, measurement has largely focused on either financial performance indicators (e.g. Ailawadi et al., 2003; Simon and Sullivan, 1993), consumer-based equity measures (Aaker, 1991; Christodoulides et al., 2006; de Chernatony et al., 2004; Sinha, Ashill and Gazley, 2008) or employee-based measures (King and Grace, 2010). However, these studies have largely been undertaken in isolation. Although the BSC approach provides a broad and more holistic view of indicators for evaluating brand equity with its range of four different perspectives, its application in the strategic management literature has traditionally assigned numerical values to variables i.e binary thought. The few notable exceptions can be found in the work of Dinçer et al. (2019), Hamamura (2019) and Lu et al. (2018) who applied fuzzy logic to examine the relative weights of different BSC dimensions, the relationships between them and their causes and effects.

Against this backdrop, the objective of the current study is to apply a practical multidimensional analysis approach to measuring the brand equity of firms privatized through public offerings in Turkey. We ground our study in the BSC to provide marketing managers with a hybrid set of interdependent brand equity evaluation indicators. Acknowledging that marketing managers deal with uncertain and complex situations, our study applies a fuzzy rule-based approach to the evaluation of brand equity of privatized firms. We seek to demonstrate that brand equity, because of its complexity and the high degree of fuzziness of dimensions, can be evaluated effectively by integrating the BSC and multi-criteria decision-making techniques (MCDM) combining DEMATEL, ANP, VIKOR and TOPSIS. These techniques have received very little attention in the marketing literature.

Specifically, we first identify and discuss key dimensions of brand equity grounded in the strategy-related BSC perspective. In the first phase of the analysis process, we employ text mining for automatic extraction of valuable information from textual data, such as the financial reports of privatized firms. We then apply the fuzzy Decision-Making Trial and Evaluation Laboratory (fuzzy DEMATEL) approach to determine the interrelationships among these dimensions. Then, Analytic Network Process (ANP) is used to obtain the criterion weights (Bentes et al., 2012; Saaty, 1996). Finally, we examine the brand equity performance of privatized firms using VIKOR and TOPSIS, which represent powerful decision-making tools for ranking and prioritizing the privatized firms (Keramati and Shapouri, 2016).

Our study contributes to the brand management literature in a number of important ways. First, we extend the application of MCDM with fuzzy logic such as DEMATEL and ANP into the domain of brand equity evaluation. Although the application of MCDM can be found in a few marketing studies such as marketing strategy (Altuntas and Yilmaz, 2016), marketing databases (Casillas and Martínez-López, 2009) and segmentation (e.g. Dat et al., 2015; Rezaei and Ortt, 2013), its utility has largely remained unexplored in the marketing domain. Second, grounded in the BSC approach, we identify a hybrid set (financial and non-financial) of brand equity measures that recognize the multidimensional nature of the brand equity concept. Third, our study combines the use of text mining with MCDM. Specifically, we apply quantitative text mining for extracting data from the financial reports of privatized firms. As a quantitative method, text mining, which refers to the extraction of information from relatively large amounts of electronically stored textual data by means of computer applications (Witten and Frank, 2005), ensured an objective evaluation of brand equity performance measures. Finally, our use of different MCDM techniques allows for comparative analysis highlighting both similarities and differences in brand equity performance.

This article is organised as follows. Firstly, we provide a review of the extant literature in the area of brand equity measurement. This is followed by an explanation of our research methodology to evaluate the brand equity of privatized firms. The third section explains our conceptual framework using fuzzy-based MCDM. This is followed by the presentation of results using the FDEMATEL, FANP, FTOPSIS and FVIKOR methods. Finally, we discuss these findings alongside existing literature on brand equity and provide suggestions for future research.

2. Overview of Relevant Literature

The study of brand equity has attracted the attention of many researchers over the past 20 years. Evaluations of the concept have been wide ranging with the objective of identifying those factors, which increase the value of a brand. Numerous studies have examined consumer perceptions, attitudes and behaviors. For example, Algharabat et al. (2019) and Machado et al. (2019) concluded that customer satisfaction contributes positively to the financial performance of firms. Other scholars have identified customer commitment, brand involvement, brand knowledge and attachment to the brand as important facets or drivers of high brand equity (Duman et al., 2018; Hepola et al., 2017; Guzmán and Davis, 2017; Iglesias et al., 2019; Thakshak, 2018).

In contrast, financial measures of brand equity such as future earnings (Aaker, 1991) help investors determine the value of a brand or a company (Simon and Sullivan, 1993). Wang and Sengupta (2016) examined the relationship between brand equity and financial performance using Interbrand brand valuation data for 81 multinational firms and reported a significant and positive relationship. Rahman et al. (2019) also reported a positive and significant relationship between brand equity and financial performance using Interbrand data in a study of 62 US firms. de Oliveira et al. (2018) and Raithel et al. (2016) found a positive and significant relationship between brand equity and stock price. Other studies have shown a positive relationship between brand equity and market capitalization (Crass et al., 2019), sales performance (Wang and Sengupta, 2016) and cash flow (Narteh, 2018).

Other studies have focused on internal-based factors and how they enhance brand equity. For instance, Poulis and Wisker (2016) examined the impact of employee-based brand equity on firm performance and concluded that employee attachment to the brand is a key contributor to financial performance. Boukis et al. (2017), Erkmen (2018), King and Grace (2015) and Piehler et al. (2016) report similar conclusions using a variety of research methodologies. Other studies have examined the role of corporate culture and its affects on brand equity. For example, Graham and Cascio (2018), Keller and Richey (2017) and Roll (2015) concluded that building a healthy corporate culture has a positive influence on the brand equity of the firm. Other internal-based studies include an examination of the effects of effective organizational communication on brand equity (Beukeboom et al., 2015, Chang et al., 2015) and the role of IT infrastructure in facilitating positive brand equity. Albertini and Berger-Remy (2017), Olson (2017) and Yao et al. (2019) for example, concluded that effective technological infrastructure of firms has a positive impact on brand equity.

A fourth group of researchers has focused on the capability of the firm in creating a competitive advantage in the market. Specifically, studies have examined relationships between positioning and promotional strategies and the long-term health of the brand (Ahn et al., 2018; Skalický, 2016), relationships between research and development expenditures and brand equity (Crass et al., 2019; Sharma et al., 2016), and the role that innovation capacity (Davcik et al., 2017; Nørskov et al., 2015) and strategic orientation (Ponnam and Balaji, 2015) play in facilitating positive brand equity. A summary of this literature is shown in Table 1. These identified areas of investigation are broadly consistent with the four perspectives of the BSC approach.

Table 1. Brand Equity research

Dimensions	Definitions	Subdimensions	Definitions	Supporting Literature
Financial-based	Monetary value of the brand	Cash flow	current and future cash flow generated by the brand	Narteh (2018), Wen et al. (2017)
		Market capitalization	market reaction to the brand	Mizik and Pavlov (2018), Crass et al. (2019)
		Market returns	earnings from net brand related profits and stocks	Rahman et al. (2019), Anees-ur-Rehman et al. (2018), Raithel et al. (2016), de Oliveira et al. (2018)
		Sales Performance	brand sales, sales growth and brand revenue	Wang and Sengupta (2016)
Consumer-based	Consumer perceptions, attitudes, behaviors	Brand loyalty	consumers' preference and attachment to the brand	Duman et al. (2018), Iglesias et al. (2019), Yu et al. (2018)
		Consumer satisfaction	consumers' judgement of brand quality and fulfillment of consumer expectations	Machado et al. (2019), Algharabat et al. (2019)
		Brand knowledge	consumer recognition in terms of brand name, brand associations and brand image	Thakshak (2018), Dedeoğlu et al. (2019), Guzmán and Davis (2017)
		Consumer behaviors	consumer activities including purchasing, word-of mouth or active involvement in brand related activities	Hunt (2019), Chatzipanagiotou et al. (2019), Hepola et al. (2017), Baalbaki and Guzmán (2016)
Internal-based	Organizational attributes enhancing brand equity	Organizational structure	consumer-centered and less-structured organizational design for efficient use of resource and coordinated activity	Chang et al. (2015), Beukeboom et al. (2015)
		Organizational culture	organizationally shared set of values, beliefs, and norms for brand consistent actions	Graham and Cascio (2018), Roll (2015), Keller and Richey (2017)
		Employee attitude	employee-consumer relations (ex. after sales service) and employee- brand dynamics or employee attachment to the brand)	Boukis et al. (2017), Erkmen (2018), King and Grace (2015), Piehler et al. (2016), Poulis and Wisker (2016)
		IT infrastructure	sophisticated use of IT for qualified stakeholder relations and innovative branding activities	Albertini and Berger-Remy (2017), Yao et al. (2019), Olson (2017)
Learning and Growth	Capability in creating a competitive advantage in the market	Innovation competency	developing and delivering new services and products that can influence the competition in the market	Nørskov et al. (2015), Davcik et al. (2017)
		Strategic orientation	corporate strategies designed for brand growth and extensions	Ponnam and Balaji (2015)
		Marketing strategy	marketing strategies developed for current and future brand positioning, pricing, distribution, and placing	Ahn et al. (2018), Skalický (2016)

		Brand expenditures	Research & development and marketing expenditures for brand strength and growth	Sharma et al. (2016), Crass et al. (2019)

The marketing literature has spawned various methodologies for measuring the brand equity. These methodologies include the use of complex statistical models to measure consumers' preference and utilities (Leuthesser et al., 1995; Kamakura and Russell, 1993; Park and Srinivasan, 1994; Swait et al., 1993), survey-based methods that focus on measuring brand equity through its manifest dimensions (Aaker 1991; Christodoulides et al., 2006; Koçak et al., 2007; Lassar et al., 1995; Pappu et al., 2005; Vázquez et al., 2002; Yoo and Donthu, 2001) and outcome variables i.e., price premium, that calculate the additional income or profit generated as a result of the differential selling price between a branded and non-branded product (Ailawadi et al., 2003). Brand equity has also been studied using qualitative research methodology. For example, Zavattaro et al. (2015) conducted semi-structured interviews with 12 marketing managers and concluded that managers do not directly use consumer-based brand equity scales but instead use proxy measures that parallel with brand equity's components. These proxies were labelled revenue, web and social media analytics, benchmarking, and visibility. Naidoo and Abratt (2018) and Raji et al. (2018) have undertaken similar qualitative investigations.

In summary, the branding literature suggests that multiple factors may affect the brand equity of a firm. Accordingly, we introduce criteria and dimensions adapted from the 4 BSC perspectives based on our literature review. We now detail our research methodology explaining how the dimensions and criteria for brand equity performance were constructed and evaluated.

3. Methodology

Our research methodology followed a hybrid approach to evaluate the brand equity of privatized firms. In the first phase of analysis, the balanced scorecard-based brand equity dimensions were analysed using fuzzy DEMATEL to establish interrelationship among them. In the second phase of the hybrid approach, the relative importance of each dimension was established with fuzzy ANP. This second phase identified which brand equity factors were most important when measuring brand equity performance. We then generated a dataset using the text mining. For that, the annual reports of privatized firms were used to identify the frequencies of the selected criteria in the text. These frequencies were then converted into the

linguistic and fuzzy scales to measure the brand equity performance of the sample firms with fuzzy TOPSIS and fuzzy VIKOR comparatively.

3.1. Text Mining

A sensor (for example a thermometer) measures a real-world situation (heat) and reports the results as numerical data. Likewise, humans express their perceptions about real-world situations in textual data format. Textual contents to be analyzed can be in the form of reports, messages, comments, warranty or insurance claims, survey responses, documents, emails, web pages, or social media posts. The main purpose of text mining is turning textual data into novel, useful, and actionable knowledge for supporting optimal decision making. Text mining provides semi-automated methods for mining available facts. Some of the applications of text mining include topic modelling (Nolasco and Oliveira 2018; Li et al. 2018), sentiment analysis (Ankit and Saleena 2018; Xiaomei et al. 2018), text categorization (Sboev et al. 2016; Park and Kremer 2017), and document summarization (Chaix et al. 2018; Eskici and Koçak 2018).

Non-textual (structured) data files that include numerical, categorical, or a combination of these data types can be analyzed using standard data mining techniques. In general, this kind of data is hosted as tables in relational databases, worksheets, or specially formatted files (such as csv or dat). However textual (non-structured) data needs some additional pre-processing steps to transform textual data into a more explicit format for further analysis. These steps include information retrieval, which is the collecting of textual data to be analyzed and the creation of a collection of these documents called corpus. Data may also be retrieved from different sources such as web, email, and documents, so suitable tools need to be employed such as crawlers or tokenization (splitting sentences into words that are called tokens or terms). It is necessary, though, to be able to identify sentence boundaries or stemming (removing suffixes to obtain the root of the term): connections', 'connecting', and 'connective' are reduced to 'connect'. Additional tools for filtering are multiple: stopwords (filtering terms that can be ignored from the text safely such as "because", "an", "the", "me", "what", "of" etc.) and vector representation of terms (calculating frequency of each tokens in each document). From the use of these tools, a matrix representing terms and frequencies of each term is constructed, and this matrix (called term-document matrix) is a base for quantitative analysis on the textual data. Regarding the type of application, various normalization and weighting schemes can be applied on frequencies and dimension reduction, which (if needed) are terms that have values below a predefined threshold value that can be omitted to have a more understandable model.

3.2. Fuzzy DEMATEL

DEMATEL (*Decision Making Trial and Evaluation Laboratory*) was developed at the Geneva Research Center by Gabus and Fontella (1973). The main purpose of the method is to uncover the direct and indirect causal relationships, such as dependencies among system variables, by using subjective perceptions of group members on complex problems (Gölcük and Baykasoğlu, 2016). Being highly dependent on experts' inaccurate and ambiguous subjective results and using numerical values for scoring expert opinions makes decision making more challenging. For this reason, this method is specifically used for decision making under uncertain conditions (Sayyadi et. al., 2017). The steps of this approach are given within the appendix.

3.3. Fuzzy ANP

ANP *(Analytic Network Process)* is a decision-making method that is a generalization of the *Analytic Hierarchy Process* (AHP). ANP was first proposed by Saaty (1996), who also developed AHP (Saaty, 1980). This approach can model complex decision problems by allowing feedbacks and loops where a hierarchical model as used in AHP is not capable. AHP is a top-down structure from the objective to criteria and from criteria to sub-criteria down to alternatives. In ANP, criteria, sub-criteria and alternatives are treated equally as nodes in a network. Each of these nodes might be compared to any other node, as long as there is a relation between them. Additionally, nodes might be grouped in clusters. All these properties allow ANP to manage multidimensional relationships (Zhou, 2012). The steps of this method are presented in the appendix.

3.4. Fuzzy TOPSIS

TOPSIS (*Technique for Order Preference by Similarity to Ideal Solution*) is one of the multicriteria decision-making (MCDM) techniques developed by Hwang and Yoon (1981). Alternatives are ranked by their similarity to the ideal solution. The main assumption of the method is that the best alternative is the one that has the shortest distance from the positive ideal solution and the furthest distance from the negative ideal solution (Aydoğan, 2011). In this study, we used this model with fuzzy logic to model real-life problems that have uncertainty and inherent imprecision. FTOPSIS steps are summarized in the appendix (Chen, 2000).

3.5. Fuzzy VIKOR

VIKOR (*VIseKriterijumsa Optimizacija I Kompromisno Resenje*) was developed by Opricovic (1998) as one of the most applicable multi-criteria decision-making methods for complex systems. The method provides a compromise solution by using maximum group utility for the majority and a minimum individual regret for the opponent. It ranks and selects from a set of alternatives in the presence of conflicting criteria and achieves the multi-criteria ranking by using a measure of closeness to the ideal solution (Opricovic and Tzeng, 2004). This method can be utilized for solving multicriteria decision problems with conflicting and incommensurable (different units) criteria. The steps of this approach are outlined in the appendix (Opricovic, 2011).

4. The integrated model

The proposed model consisted of three phases including the FDEMATEL, the FANP, the FTOPSIS and the FVIKOR respectively. The comparative fuzzy-based MCDM is detailed in Figure 1.



Figure 1. The flowchart of the proposed model

Comparative analysis begins by defining the multi-criteria decision-making problem. For this purpose, a set of dimensions and criteria were constructed for measuring the brand equity of privatized companies. The BSC perspective was adapted to the dimensions and sub-dimensions defined both by the criteria and supporting literature. In the next step, a set of alternatives were determined for ranking the brand equity performance of the privatized firms. Accordingly, privatized firms with the highest public offering shares - those with English annual reports listed in the Istanbul Stock Exchange (BIST), were selected, and five firms were found to meet these criteria. Details of the selected firms are provided in Table 2.

Table 2. The details of the privatized firms by public offerings listed in BIST

Firms	Index Traded	Rate of Public Offering	Date of Initial Public Offering	Value of Public Offering (million $)
A1	Transportation	49.90%	1990	403
A2	Financials	48.90%	2007	4,357
A3	Chem. Petrol Plastic	42.30%	1990	424
A4	Wholesale and Retail Trade	36.40%	1991	5.6
A5	Chem. Petrol Plastic	32%	1991	1,110

Source: Doğan (2016)

Table 2 illustrates the rate of public offering, date of initial public offering, and value of public offering for the selected privatized firms. The public offering shares in the privatized firms ranged between 32% and 49.90%. The first date of initial public offering occurred in 1990; the last date occurred in 2007.

The text mining method was employed to uncover keywords that defined the criteria as well as the frequencies of the criteria that were used for the weights and alternatives. First, the relevant keywords associated with each sub-dimension were researched using the Science direct database to scan titles, abstracts, and keywords of articles published in the journals of Business, Management, Accounting, Decision Science, Economics, Finance, and Social Science between 1999 and 2007. After scanning keywords, the first fifty words with the highest occurrence percentage and the highest representation ability within the related dimensions were chosen for the dataset. The dataset formed the main guide for analyzing the privatized firm's brand equity performance. The annual reports of five privatized firms, those publicly traded in BIST with the highest public offering shares, were then scanned using the text mining methodology to identify the frequency of fifty key terms. Then, through the knowledge extraction method, the weights of the sub-dimensions (criteria) were calculated by converting the linguistic scales into fuzzy numbers. The interaction between the dimensions were analyzed through FDEMATEL and the relative weights calculated by FANP. Finally, through FVIKOR and FTOPSIS methods, the brand equity performances of the selected firms were ranked.

The knowledge extraction-based hybrid MCDM method was adopted in three unique phases. This comparative knowledge extraction-based decision-making analysis offers a hybrid-integrated method under the fuzzy environment and aims to prevent subjective evaluations from the decision makers by converting the text mining results. We now present the results of the computed brand equity performances of the five privatized firms.

5. Results

Phase 1: The FDEMATEL method was employed to analyze the interaction of dimensions between each other, and the dimensions of brand equity were defined by adapting the BSC perspectives. Specifically, four dimensions were appointed to measure the influence degrees of brand equity. Pairwise comparisons of brand equity dimensions were constructed by considering the frequencies of the key terms obtained from text mining for each criterion and dimensions. Accordingly, the frequencies were transformed into the five-point linguistic scales and triangular fuzzy numbers of influence degrees. The linguistic scales were defined as "No influence", "Low influence", "Medium influence", "High influence", and "Very high influence" and the fuzzy numbers were (0,0,0.25), (0,0.25,0.5), (0.25,0.5,0.75), (0.5,0.75,1), (0.75,1,1). An initial direct relation fuzzy matrix was then computed. During the following steps, the initial direct-relation fuzzy matrix was normalized, and three crisp matrices were defined to construct the total influence matrix. The details of these tables (Table A1 and A2) are given on the appendix. Moreover, converting fuzzy data into crisp scores (CFCS method) was used for the defuzzification of dimensions, and thus, the causes or effects of each dimension could be understood as seen in Table 3.

Table 3. Deffuzzified values and cause-effect degrees of dimensions

Dimensions	**D1**	**D2**	**D3**	**D4**	$\widetilde{D}_i^{def}$	$\widetilde{R}_i^{def}$	$\widetilde{D}_i^{def} + \widetilde{R}_i^{def}$	$\widetilde{D}_i^{def} - \widetilde{R}_i^{def}$
D1	0,31	0,44	0,41	0,44	1,60	1,79	3,40	-0,19
D2	0,59	0,41	0,56	0,59	2,15	1,79	3,94	0,35
D3	0,44	0,44	0,28	0,44	1,60	1,62	3,22	-0,02
D4	0,45	0,51	0,37	0,32	1,65	1,79	3,44	-0,14

Table 3 illustrates the cause-effect and the importance degrees of the dimensions. D2 (consumer-based) was the most influential dimension, while D1 (financial-based) was the most influenced dimension. Additionally, D2 demonstrated the highest importance in the dimensions, and D3 (internal-based) demonstrated the weakest importance. The defuzzified total-relation matrix was averaged to define the threshold, and it was possible to find out the interrelation of dimensions. Figure 2 illustrates the impact-relationship degrees of brand equity dimensions and demonstrates that consumer and internal-based dimensions affect all other BSC perspectives. The financial-based dimension demonstrated an impact on the learning and growth, and the consumer-based and internal-based dimensions directly influenced the financial and learning and growth-based dimensions.

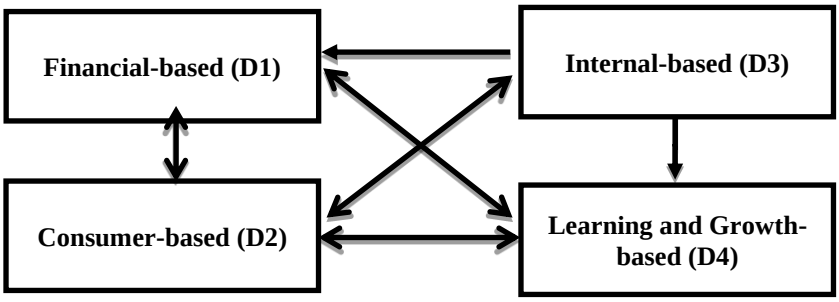


Figure 2. Impact-relationship map of brand equity dimensions

Phase 2: The FANP was used for weighting the criteria (sub-dimensions) of brand equity. Linguistic scales and triangular fuzzy numbers were respectively defined as "Equally important" (0.5,1,1.5), "Weakly more important" (1,1.5,2), "Strongly more important" (1.5,2,2.5), "Very strongly more important" (2,2.5,3), "Absolutely more important" (2.5,3,3.5) (Chang, 1996). Chang's extent analysis was applied to calculate the weights of criteria. For this purpose, the impact-relation map of dimensions was considered to construct the inner dependency of the FANP method. The results were computed local weights were utilized to employ the unweighted supermatrix, and the matrix was normalized to attain the weighted results. Final scores were then derived by constructing the limit supermatrix. The results are seen in the Appendix (Table A3, A4, A5, A6 and A7).

The limit supermatrix (see Table A7) was derived by multiplying within itself until each column was equal and stabilized. In the table, each line defines the weight of the criteria, and the results show that cash flow (C1) is the most important criteria in the performance measurement of brand equity; whereas, IT infrastructure (C12) demonstrated the weakest importance among the criteria. Specifically. Criterion 12 (IT infrastructure) (Sub-dimension 12 in the internal-based dimension) had the lowest importance with a value of 0,01 whereas criteria 1 (cash flow) (sub-dimension 1 in the financial-based dimension) demonstrated the highest importance among the criteria with a value of 0.14.

Phase 3: Integrated models were identified by using the FVIKOR and FTOPSIS methods for comparatively ranking alternatives. Similarly, the knowledge extraction-based MCDM analysis under the fuzzy environment was constructed using the text mining approach, and the dataset for alternatives was collected by considering the annual reports of the selected firms. At that point, the data was changed to linguistic variables with five-point scales and triangular fuzzy numbers equal scales were appointed to evaluate the alternatives. Linguistic scales and

their fuzzy numbers were listed as “Worst” (0,0,2.5), “Poor” (0,2.5,5), “Fair” (2.5,5,7.5), “Good” (5,7.5,10), “Best” (7.5,10,10) (Chen and Wang, 2009).

The integrated model with FVIKOR was initiated by the weighted normalized fuzzy decision matrix using the weights of criteria obtained from the FANP. The fuzzy best and worst values were then calculated, and the final ranking of alternatives computed with S*i*, R*i*, and Q*i* values. The results are shown in Table 4.

Table 4: The values of $S_i, R_i \; and \; Q_i$ and ranking the alternatives with the FVIKOR

Alternatives	S_i	R_i	Q_i	**Ranking**
A1	0,000	0,000	0,000	1
A2	0,791	0,136	0,895	3
A3	1,000	0,136	1,000	4
A4	1,000	0,136	1,000	4
A5	0,719	0,136	0,859	2

In Table 4, the values of Q*i* were ranked in ascending order for the alternatives and the results complied with the confirmatory conditions. The table demonstrates that A1 is the highest ranked company in brand equity performance while A3 and A4 are the worst ranked companies. The model with FTOPSIS considered the same dataset, but the normalization of the fuzzy decision matrix was differentiated. The distances of each alternative from the positive and negative ideal solution as well as the closeness coefficient was computed for ranking alternatives. The results can be seen in Table 5.

Table 5. The values of D_i^*, D_i^- and CC_i and ranking the alternatives with the FTOPSIS

Alternatives	D_i^*	D_i^-	CC_i	Ranking
A1	15,811	0,333	0,021	3
A2	15,775	0,359	0,022	2
A3	15,811	0,333	0,021	3
A4	15,811	0,333	0,021	3
A5	15,734	0,388	0,024	1

In Table 5, A5 had the highest rank followed by A2 for brand equity performance; whereas, A1, A3, and A4 were the worst performing privatized companies.

The comparative analysis results demonstrate that the integrated model with FVIKOR gives more sensitive ranking results than the FTOPSIS-based model for measuring the brand equity performance of the privatized companies listed in BIST. FVIKOR provided 4 different

ranking results whereas FTOPSIS provided 3 ranking results. However, both methods generated similar results for the lowest rankings.

6. Discussion, managerial implications and future research

The objective of this study is to provide a practical tool to evaluate the brand equity performance of five privatized firms in Turkey. To this end, we evaluated a hybrid set of brand equity measures using the BSC approach with fuzzy-based decision-making techniques. We suggest that brand equity, because of its complexity and the high degree of fuzziness of its dimensions, can be evaluated more effectively using these techniques. To date the application of MCDM with fuzzy logic has received very little attention in the marketing literature. Fuzzy logic theory assumes uncertainty and uses a linguistic variable instead of traditional quantitative expressions (Zadeh, 1965). Our study makes a novel contribution to existing literature by proposing a multidimensional performance measurement of brand equity and integrating this approach with multi-criteria decision-making techniques under fuzzy logic. To the best of our knowledge we are not aware of any research that has studied privatized firms using a multidimensional performance measurement of brand equity.

The brand equity performance of the five privatized firms was evaluated in terms of consumer, financial, internal, and learning and growth-based dimensions. First, the relevant keywords associated with each sub-dimension were searched on the ScienceDirect database. For this purpose, titles, abstracts, and keywords of the articles were scanned from the journals of Business, Management, Accounting, Decision Science, Economics, Finance, and Social Science between 1999 and 2007. After scanning keywords, the first fifty words with the highest occurrence percentage and the highest representation ability of the related dimension were chosen for the dataset. The dataset formed the main guide for analyzing the privatized firms' brand equity performances. The annual reports of the five privatized firms that publicly traded in BIST with the highest public offering shares were scanned through text mining methodology to establish the frequency of the fifty key terms. Then, through knowledge extraction methodology, linguistic scales were developed, and the sub-dimensions were translated into fuzzy numbers. The interaction between sub-dimensions were analyzed through FDEMATEL, and their relative weights were calculated by FANP. Finally, through FVIKOR and FTOPSIS methods, the brand equity performance of the selected firms were ranked.

Results of the FEMATEL analysis showed that consumers were the most influential dimension; in contrast, finance was the most influenced dimension. Similarly, the dimension weights (the values of Di and Ri) in Table 3 showed that consumers demonstrated the highest importance whereas the internal-based dimension was the least important. These findings are consistent with existing literature that identifies consumers as being the most important factor in brand equity performance evaluation (Casidy et al., 2018; Chatzipanagiotou et al., 2018; Haase et al., 2018; Iyer et al., 2018). These findings highlight the need for firms to take actions that generate positive consumer perceptions, attitudes and behaviors in order to improve brand equity performance. Findings also demonstrated that the internal-based dimension influenced all other dimensions in the model, similar to the customer dimension.

On the other hand, analysis results of the FANP method demonstrated that cash flow and brand loyalty were the most important criteria in the measurement of brand equity performance, while IT infrastructure demonstrated the weakest importance. The importance of brand loyalty is underlined in different studies within the literature (Duman et al., 2018; Iglesias et al., 2019). Similarly, the importance is brand equity's financial value in the form of some estimated future cash is highlighted in the work of Burmann, Jost-Benz and Riley (2009) and Leone et al. (2006), In addition, A1 was ranked best firm in terms of brand equity performance using the FVIKOR method. In contrast, A5 was ranked highest and A1 was ranked lowest using the FTOPSIS method. The FVIKOR method provides more sensitive results because the values for the companies using FTOPSIS are very similar.

The proposed dimensions and criteria in this study, which are grounded in the 4 BSC perspectives, provide a set of practical guidelines for marketing and brand managers to increase brand equity performance. First, our findings highlight the need for brand managers to identify and understand consumer perceptions, attitudes, and behaviors. Brand equity monitor systems should therefore consist of perceptual and attitudinal data that measure brand awareness, brand associations, perceived quality, and brand loyalty, which can be modeled against consequential behavioral (e.g. purchase frequency) measures. Second, given the importance of cash flow in brand equity performance measurement, brand managers need to effectively manage current and future cash flow generated by the brand. In this regard, managers should have an understanding of the net cash flow of the firm to avoid the onset of possible liquidity problems early on in the privatization process.

We acknowledge several limitations of our study. First, our data collection and analysis was specific to five privatized companies in Turkey. In future studies, the research sample

should be enlarged, new methodologies used, and comparative studies conducted. For example, an analysis could be performed for other countries. The implementation of hesitant fuzzy sets or interval type-2 fuzzy logic also has the potential to generate new insights. We further suggest that our integrated model can be extended to the evaluation of other marketing projects and decision-making problems. The study provides an alternative way of strategic thinking for marketing managers by using the multi-criteria decision making approach using fuzzy logic. We encourage future research to use linguistic evaluations for weighting the performance of other marketing topics. Finally, the effects of the privatization process on brand equity performance can be extended across multiple industries so that different industry sectors can be ranked.

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APPENDIX

Appendix A- The Steps of FDEMATEL

Step 1: The initial direct-relation fuzzy matrix is established.

Each expert or decision maker in the group makes pair-wise comparisons in terms of influences and directions between criteria. Then average fuzzy matrix A which is a $n \times n$ matrix whose elements are triangular fuzzy numbers $a_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is obtained using equation (1)

$$a_{ij} = (1/K)\sum_{k=1}^{K} x_{ij}^{k} \quad (1)$$

where x_{ij}^{k} denotes the score determined by the kth expert indicating the degree to which the criterion i affects the criterion j. K is used for the number of experts in the group.

Step 2: The normalized direct-relation fuzzy matrix is calculated.
Normalizing A matrix is managed by using equation (2) then normalized direct-relation matrix (N) is calculated by using equation (3).

$$s = min\left(\frac{1}{\max\limits_{1\le i\le n}\sum_{j=1}^{n} a_{ij}}, \frac{1}{\max\limits_{1\le j\le n}\sum_{i=1}^{n} a_{ij}}\right) \quad (2)$$

$$N = s \times A \quad (3)$$

Elements of N are denoted as $n_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

Step 3: Total relation fuzzy matrix is acquired.
Total relation fuzzy matrix (T) is calculated as in equation (4).

$$T = N(I - N)^{-1} \quad (4)$$

Moreover, it can be acquired as follow: Normalized direct-relation fuzzy matrix N is partitioned into three three matrices N_1, N_2 and N_3 respectively.

$$N_1 = \begin{pmatrix} 0 & l_{12} & \dots & l_{1n} \\ l_{21} & 0 & \dots & l_{2n} \\ \vdots & \ddots & \dots & \vdots \\ l_{n1} & l_{n2} & \dots & 0 \end{pmatrix}; \quad N_2 = \begin{pmatrix} 0 & m_{12} & \dots & m_{1n} \\ m_{21} & 0 & \dots & m_{2n} \\ \vdots & \ddots & \dots & \vdots \\ m_{n1} & m_{n2} & \dots & 0 \end{pmatrix}; \quad N_3 = \begin{pmatrix} 0 & u_{12} & \dots & u_{1n} \\ u_{21} & 0 & \dots & u_{2n} \\ \vdots & \ddots & \dots & \vdots \\ u_{n1} & u_{n2} & \dots & 0 \end{pmatrix}$$

Then, each element of total relation fuzzy matrix T is denoted by $t_{ij} = (l_{ij}, m_{ij}, u_{ij})$ and can be computed as in equation (5) where I indicates the identity matrix.

$$l_{ij} = N_1(I - N_1)^{-1}; \quad m_{ij} = N_2(I - N_2)^{-1}; \quad u_{ij} = N_3(I - N_3)^{-1} \quad (5)$$

In this study, CFCS (Converting Fuzzy data into Crisp Scores) defuzzification method (Opricovic and Tzeng, 2003) is employed for converting fuzzy elements of matrix T into crisp values. Implementation details of CFCS are given between Step 3.1 and 3.4.

Step 3.1 Normalization step.
In a group of K experts, the fuzzy weight of the ith criteria that affects the jth criteria scored by the kth expert of the group is represented by $w_{ij}^{k} = (l_{ij}^{k}, m_{ij}^{k}, u_{ij}^{k})$. Normalization is done by equations (6)-(9).

$$\Delta_{min}^{max} = \max u_{ij}^{k} - \min l_{ij}^{k} \quad (6)$$

$$xl_{ij}^{k} = \left(l_{ij}^{k} - \min l_{ij}^{k}\right)/\Delta_{min}^{max} \quad (7)$$

$$xm_{ij}^{k} = \left(m_{ij}^{k} - \min l_{ij}^{k}\right)/\Delta_{min}^{max} \quad (8)$$

$$xu_{ij}^{k} = \left(u_{ij}^{k} - \min l_{ij}^{k}\right)/\Delta_{min}^{max} \quad (9)$$

Step 3.2 Left side *(ls)* and right side *(rs)* normalized values are computed with the help of the equations (10) and (11).

$$xls_{ij}^{k} = xm_{ij}^{k}/\left(1 + xm_{ij}^{k} - xl_{ij}^{k}\right) \quad (10)$$

$$xrs_{ij}^{k} = xu_{ij}^{k}/\left(1 + xu_{ij}^{k} - xm_{ij}^{k}\right) \quad (11)$$

Step 3.3: Total normalized crisp values are computed, and this process is detailed on the equation (12).

$$x_{ij}^{k} = \left[xls_{ij}^{k}\left(1 - xls_{ij}^{k}\right) + xrs_{ij}^{k} xls_{ij}^{k}\right]/\left[1 - xls_{ij}^{k} + xrs_{ij}^{k}\right] \quad (12)$$

Step 3.4: Crisp values are computed by considering the equation (13).

$$x_{ij}^{k} = \min l_{ij}^{k} + x_{ij}^{k}\,\Delta_{min}^{max} \quad (13)$$

Step 4: A causal diagram is mapped.

A causal diagram is used to presents the complicated causal relationships among various factors. For plotting the causal diagram, the sum of rows and the sum of columns are denoted as D and R within matrix T and computed through the equations (14) and (15).

$$D_i = \sum_{j=1}^{n} t_{ij}, \quad \forall i \quad (14)$$

$$R_j = \sum_{i=1}^{n} t_{ij}, \quad \forall j \quad (15)$$

Then, P_i *(prominence value)* indicating each factor's degree of importance and E_i *(net effect value)* are calculated as in the equations (16) and (17).

$$P_i = \left\{D_i + R_j \,\middle|\, i = j\right\} \quad (16)$$

$$E_i = \left\{D_i - R_j \,\middle|\, i = j\right\} \quad (17)$$

On the causal diagram, P_i values are represented as a horizontal axis indicating how much importance the factor has, whereas E_i values are represented as a vertical axis defining the cause group and effect group. Generally, when E_i is positive, it is an indication of factor relates to the cause group and effects on the other criteria. Otherwise, if it is negative, the factor relates to the effect group and receives effects from the other criteria. By visually inspecting causal diagrams, complicated causal relationships of factors can be analyzed. It is possible to make proper decisions by recognizing the difference between cause and effect factors on the causal diagram (Wu and Lee, 2007).

Appendix B- The Steps of FANP

Step 1: Problem defining and model construction.

For the decision-making problem, all relations (interdependencies, inner dependencies, and feedbacks) among alternatives, criteria, sub-criteria, and objectives are defined clearly and a network model is constructed. For this purpose, a detailed literature review and (or) a brainstorming including domain experts and decision makers may be needed.

Step 2: Establishing pairwise comparison matrices.

To estimate the relative importance of elements pairwise comparisons are performed. For all pairwise comparisons, triangular fuzzy numbers are used. A fuzzy number M on R to be triangular fuzzy number if its membership function $\mu_M(x): R \to [0,1]$ is equal to

$$\mu_M(x) = \begin{cases} \frac{x}{m-l} - \frac{l}{m-l}, & x \in [l, m] \\ \frac{x}{m-u} - \frac{u}{m-u}, & x \in [m, u] \\ 0, & otherwise \end{cases} \quad (18)$$

The parameters of the membership function are l (smallest possible value), m (the most promising value) and u (the largest possible value). The fuzzy pairwise comparison matrix is denoted as $A = (a_{ij})_{nxm}$ where $a_{ij} = (l_{ij}, m_{ij}, u_{ij})$ which are satisfied with $l_{ij} = 1/l_{ji}$, $m_{ij} = 1/m_{ji}$ and $u_{ij} = 1/u_{ji}$. Linguistic scales shown in Table 2 are used for representing for relative importance of elements.

Table A1: Linguistic variables for relative importance

Linguistic scale for importance	Triangular fuzzy scale (l, m, u)
Equally important	(0.5,1,1.5)
Weakly more important	(1,1.5,2)
Strongly more important	(1.5,2,2.5)
Very strongly important	(2,2.5,3)
Absolutely more important	(2.5,3,3.5)

Source: Chang (1996)

Step 3. Calculating the local weights.
In this study, we used one of the most known of these methods called fuzzy extend analysis proposed by Chang (1996). Details of the method are given below.

Let $X = \{x_1, x_2, \dots x_n\}$ be object set, and $U = \{u_1, u_2, \dots u_m\}$ be a goal set. m extent analysis values for each object, with the following signs:
$M_{g_i}^1, M_{g_i}^2, \dots, M_{g_i}^m, \ i = 1,2, \dots, n,$
where all the $M_{g_i}^j, \ (j = 1,2, \dots, m)$ are triangular fuzzy numbers.

Step 3.1. The value of fuzzy synthetic extent with respect to the ith object (S_i) is defined as:

$$S_i = \sum_{j=1}^{m} M_{g_i}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1} \quad (19)$$

For the triangular fuzzy numbers $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ fuzzy addition, multiplication and inverse operators are defined as follows:

$$M_1 \oplus M_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (20)$$
$$M_1 \otimes M_2 = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \quad (21)$$
$$(M_1)^{-1} \approx (1/u_1, 1/m_1, 1/l_1) \quad (22)$$

By using these properties S_i can be decomposed as

$$\sum_{j=1}^{m} M_{g_i}^j = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \quad (23)$$

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \quad (24)$$

Thus, it is possible to express S_i as

$$S_i \approx \left(\sum_{j=1}^{m} l_j \times \frac{1}{\sum_{i=1}^{n} u_i}, \sum_{j=1}^{m} m_j \times \frac{1}{\sum_{i=1}^{n} m_i}, \sum_{j=1}^{m} u_j \times \frac{1}{\sum_{i=1}^{n} l_i} \right) \quad (25)$$

Step 3.2. The degree of possibility of $M_1 \geq M_2$ is defined as

$$V(M_1 \geq M_2) = \sup_{x \geq y} \left[min \left(\mu_{M_1}(x), \mu_{M_2}(y) \right) \right] \quad (26)$$

Since M_1 and M_2 are convex fuzzy numbers we have that $V(M_1 \geq M_2) = 1 \ \ iff \ m_1 \geq m_2$. The degree of possibility of $M_2 \geq M_1$ is defined as $V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_1}(d)$ where d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} (Figure x) and can be computed as $\frac{\boldsymbol{l_1 - u_2}}{\boldsymbol{(m_2 - u_2) - (m_1 - l_1)}}$

These explanations can be shortly expressed as in the equation (27)

$$V(M_2 \geq M_1) = \begin{cases} 1, & m_2 \geq m_1 \\ 0, & l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases} \quad (27)$$

To compare M_1 and M_2, both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ is employed.

Step 3.3. The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $M_i \ (i = 1,2, \dots, k)$ can be defined by

$$V(M \geq M_1, M_2, \dots, M_k) = V[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and } \dots \text{ and } (M \geq M_k)\,] = \min V\,(M \geq M_i), \ \ i = 1,2, \dots, k. \quad (28)$$

Assuming that $d'(A_i) = \min V(S_i \geq S_k)$ for $k = 1,2, \dots, n; k \neq i$. Then the weight vector is given by

$$W' = \left(d'(A_1), d'(A_2), \dots, d'(A_n) \right)^T \quad (29)$$

Step 3.4. Via normalization, the normalized weight vectors are obtained.

$$W = \left(d(A_1), d(A_2), \dots, d(A_n) \right)^T \text{where } \ d(A_i) = \frac{d'(A_i)}{\sum_{i=1}^{n} d'(A_i)} \quad (30)$$

In the equation (30) W is a nonfuzzy number.

Step 4. Forming the unweighted supermatrix.

A supermatrix (partitioned matrix) contains the submatrices where each submatrix represents relationships between two elements. By locating the local priority vectors in the convenient columns, the supermatrix is constructed (Büyüközkan and Çifçi, 2011). So supermatrix is directly related to the network structure defined at Step 1.

Step 5. Calculating the weighted supermatrix.

Supermatrix must be of a stochastic nature. Therefore, it must be normalized (weighted) in a way that values in every column sum to one. By doing so, it is possible to apply the properties of Markov chains to ANP computations (Akbaş and Bilgen, 2017).

Step 6. Acquiring the limit supermatrix.

To obtain all long-term direct and indirect relationships among elements weighted supermatrix is raised to limiting powers (Equation (31)). Due to supermatrix is in stochastic nature it converges to limit supermatrix. The columns become stabilized and identical in each block of submatrices (Büyüközkan and Çifçi, 2011).

$$\bar{W} = \lim_{t\to\infty} W^t \tag{31}$$

Step 7. Selecting the best alternative.

A priority weight is obtained from limit supermatrix for each alternative. Then, alternative with the highest priority weight is selected as the best alternative.

Appendix C – The Steps of FTOPSIS

The linguistic scales that are used for ranking of alternatives are given in the appendix.

Table A2: Linguistic scales for the rating of alternatives

Linguistic variable	Fuzzy Triangular Number
Worst	(0,0,2.5)
Poor	(0,2.5,5)
Fair	2.5,5,7.5)
Good	(5,7.5,10)
Best	(7.5,10,10)

Source: Dinçer et. al. (2016)

Step 1. Construct fuzzy decision matrix.

$\tilde{x}_{ij}^k$ denotes the fuzzy weight of ith alternative for the jth criterion of kth expert. $\tilde{x}_{ij}$ is a linguistic variable that is represented by triangular fuzzy numbers in the form of (l_{ij}, m_{ij}, u_{ij}). For a group of K experts fuzzy weight of ith alternative for the jth criterion is computed as:

$$\tilde{x}_{ij} = \frac{1}{K}\left[\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + \cdots + \tilde{x}_{ij}^K\right] \tag{32}$$

For m alternatives $(A_1, A_2, \ldots A_m)$ and n criteria $(C_1, C_2, \ldots C_n)$ fuzzy decision matrix $\left(\tilde{D}\right)$ is shown as:

$$\tilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & C_3 & \ldots & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & \ldots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & \ldots & \tilde{x}_{2n} \\ \tilde{x}_{31} & \tilde{x}_{32} & \tilde{x}_{33} & \ldots & \tilde{x}_{3n} \\ \vdots & \vdots & \ddots & \ldots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \tilde{x}_{m3} & \ldots & \tilde{x}_{mn} \end{bmatrix} \end{array}$$

Step 2. Obtain the weights of criteria.

Let $\tilde{w}_j^k$ denotes the fuzzy weight of jth criterion according to kth expert. For a group of K expert fuzzy weight of jth criterion is calculated as:

$$\tilde{w}_j = \frac{1}{K}\left[\tilde{w}_j^1 + \tilde{w}_j^2 + \cdots . + \tilde{w}_j^K\right] \tag{33}$$

Step 3. Compute the normalized fuzzy decision matrix.

$\tilde{R} = \left[\tilde{r}_{ij}\right]_{mxn}$ represents the normalized fuzzy decision matrix formed from fuzzy decision matrix by using:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}\right), \text{ where } u_j^* = \max_i u_{ij} \ (For\ Utility\ Criteria) \tag{34}$$

or

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right), \text{where } l_j^- = \min_i l_{ij} \quad (For\ Cost\ Criteria) \tag{35}$$

Step 4. Construct the weighted normalized fuzzy decision matrix.

The weighted normalized fuzzy decision matrix is represented as $\tilde{V} = \left[\tilde{V}_{ij}\right]_{mxn}$ and computed as

$$\tilde{V}_{ij} = \tilde{r}_{ij} \times \tilde{w}_j \tag{36}$$

All the elements of $\tilde{V}_{ij}$ are normalized and weighted triangular fuzzy numbers that are in [0,1] interval.

Step 5: Compute distances from fuzzy positive ideal and fuzzy negative ideal solutions.

Fuzzy positive ideal solution and fuzzy negative ideal solution are represented by $A^* = (\tilde{V}_1^*, \tilde{V}_2^*, \dots, \tilde{V}_n^*)$ and $A^- = \tilde{V}_1^-, \tilde{V}_2^-, \dots, \tilde{V}_n^-)$ respectively where $\tilde{v}_j^* = (1,\ 1,\ 1)$ and $\tilde{v}_j^- = (0,0,0)$. For each alternative distance from fuzzy positive ideal solution (d_i^*) and fuzzy negative ideal solution (d_i^-) are computed respectively as follows:

$$d_i^* = \sum_{j=1}^n d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right), \qquad i = 1,2,\dots,m \tag{37}$$

$$d_i^- = \sum_{j=1}^n d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), \qquad i = 1,2,\dots,m \tag{38}$$

In equations (37) and (38), d stands for the distance between two triangular fuzzy numbers and is computed by using Vertex method. Let $\tilde{a} = (l_1, m_1, u_1)$ and $\tilde{b} = (l_2, m_2, u_2)$ are two fuzzy triangular fuzzy numbers. Then, Vertex method gives the distance as:

$$d\left(\tilde{a}, \tilde{b}\right) = \sqrt{\frac{1}{3}\left[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right]} \tag{39}$$

Step 6. Compute closeness coefficient.

For the ith alternative closeness coefficient (CC_i) is computed as:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-} \qquad i = 1,2,\dots,m \tag{40}$$

CC_i takes values between 0 and 1 and used for ranking alternatives. The alternative having the maximum closeness coefficient is selected by the optimum alternative.

Appendix D- The Steps of Fuzzy VIKOR

Step 1. Identify alternatives, evaluation criteria and form a group of decision makers.

Step 2. Determine linguistic variables and their corresponding triangular fuzzy numbers to evaluate the relative importance of criteria and the ratings of alternatives with respect to various criteria.

Step 3. Construct fuzzy decision matrix.

Step 4. Compute the best fuzzy value (f_i^*) and the worst fuzzy value (f_i^-) for every evaluation criterion using the equation (41).

$$f_i^* = \max_j f_{ij}, \quad f_i^- = \min_j f_{ij} \tag{41}$$

Step 5. Compute ($\tilde{S}_j$) and ($\tilde{R}_j$) values for each alternative.

For the jth alternative (A_j), $\tilde{S}_j$ and $\tilde{R}_j$ denotes sum of distance for the best fuzzy value and maximum distance to the worst fuzzy value respectively. $\tilde{S}_j$ and $\tilde{R}_j$ are calculated as:

$$\tilde{S}_j = \sum_{i=1}^{m} \widetilde{w}_i (f_i^* - \tilde{x}_{ij}) / (f_i^* - f_i^-) \tag{42}$$

$$\tilde{R}_j = \max_j \left[\widetilde{w}_i \left(f_i^* - \tilde{x}_{ij} \right) / (f_i^* - f_i^-) \right] \tag{43}$$

where $\widetilde{w}_i$ is the fuzzy weight of ith criterion.

Step 6. Calculate $\tilde{S}^*, \tilde{S}^-, \tilde{R}^*, \tilde{R}^-$ and $\tilde{Q}_j$ values.

$\tilde{\boldsymbol{S}}^*$ is the maximum majority rule or maximum group utility which is the minimum value of $\tilde{S}_j$ and $\tilde{R}^*$ is the minimum individual regret of the opponent which is obtained from the minimum value of R_j. These values are computed as follow:

$$\tilde{S}^* = \min_j \tilde{S}_j, \qquad \widetilde{S}^- = \max_j \tilde{S}_j \tag{44}$$

$$\tilde{R}^* = \min_j R_j, \qquad \tilde{R}^- = \max_j \tilde{R}_j \tag{45}$$

$\tilde{Q}_j$ index is based on both the group utility and individual regret of the opponent and is shown in the equation (46) where q is the weight of the strategy of the maximum group utility and $(1-q)$ is the weight of the strategy of the minimum individual regret of the opponent. The decision tends toward the maximum majority rule in case of $v > 0.5$ and tends toward the individual regret of the opponent for $v = 0.5$ (Chen and Wang, 2009). In this study, *v* has the value of 0.5.

$$\tilde{Q}_j = q \frac{(S_j - S^*)}{S^- - S^*} + (1-q) \frac{\left(R_j - R^*\right)}{R^- - R^*} \tag{46}$$

Step 7. Defuzzifying triangular fuzzy number $\tilde{Q}_j$ and rank the alternatives by their $\tilde{Q}_j$ values.

There are numerous methods for converting a fuzzy number into a crisp value. In this study, for defuzzification step maximizing set and minimizing set method (Chen, 1985) is employed. Then for the alternatives Q_j values are ranked in descending order. Additionaly, for checking the final rankings two following conditions must be satisfied (Dincer and Hacioglu, 2013).

Condition 1: Acceptable advantage case is defined by

$$Q\left(A^{(\prime\prime)}\right) - Q\left(A^{(\prime)}\right) \geq \frac{1}{(j-1)} \tag{47}$$

where $A^{(\prime\prime)}$ refers the alternative with the second position in the ranking list by Q.

Condition 2: Acceptable stability in decision making when the alternative $A^{(\prime)}$ has the best rank by *S* or/and *R*. This compromised solution is stable within a decision making process, which could be: voting by majority rule (when $v > 0.5$ is needed) or by consensus (when $v \approx 0.5$), or with a vote when ($v < 0.5$).

If Condition 1 or Condition 2 is not satisfied a set of compromised solutions are recommended including (Mokhtarian et. al., 2014):

a) Alternative $A^{(\prime)}$ and $A^{(\prime\prime)}$ if only Condition 2 is not satisfited or

b) Alternative $A^{(\prime)}, A^{(\prime\prime)}, \ldots, A^{(k)}$ if Condition 1 is not satisfied and $A^{(k)}$ is determined by the relation $Q\left(A^{(\prime\prime)}\right) - Q\left(A^{(\prime)}\right) \prec \frac{1}{(j-1)}$ for maximum k (the positions of these alternatives are in closeness).

Appendix E – The Initial Direct Relation and the Total Influence Fuzzy Matrixes

Table A3: The initial direct-relation fuzzy matrix

Dimensions	D1			D2			D3			D4		
D1	0,000	0,000	0,000	0,250	0,500	0,750	0,250	0,500	0,750	0,250	0,500	0,750
D2	0,500	0,750	1,000	0,000	0,000	0,000	0,500	0,750	1,000	0,500	0,750	1,000
D3	0,250	0,500	0,750	0,250	0,500	0,750	0,000	0,000	0,000	0,250	0,500	0,750
D4	0,250	0,500	0,750	0,500	0,750	1,000	0,000	0,250	0,500	0,000	0,000	0,000

The results have been illustrated in Table 6.

Table A4: The total influence fuzzy matrix

Dimensions	D1			D2			D3			D4		
D1	0,037	0,190	0,891	0,114	0,333	1,091	0,105	0,310	1,018	0,114	0,333	1,091
D2	0,212	0,467	1,364	0,069	0,267	1,114	0,196	0,433	1,273	0,212	0,467	1,364
D3	0,114	0,333	1,091	0,114	0,333	1,091	0,029	0,167	0,818	0,114	0,333	1,091
D4	0,122	0,343	1,109	0,188	0,400	1,159	0,041	0,257	0,982	0,045	0,200	0,909

Appendix F – Unweighted, Weighted and Limit Supermatrixes

Table A5: Unweighted supermatrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
C1	0	0	0	0	0,44	0,62	0,52	0,52	0,53	0,38	0,39	0,43	0,38	0,62	0,38	0,32
C2	0	0	0	0	0,31	0,37	0,32	0,36	0,33	0,29	0,40	0,43	0,32	0,37	0,29	0,25
C3	0	0	0	0	0,20	0,01	0,16	0,11	0,12	0,22	0,20	0,13	0,19	0,01	0,22	0,22
C4	0	0	0	0	0,06	0,01	0,01	0,01	0,02	0,11	0,01	0,00	0,10	0,01	0,11	0,20
C5	0,27	0,51	0,29	0,25	0	0	0	0	0,35	0,29	0,55	0,46	0,29	0,54	0,29	0,25
C6	0,23	0,30	0,25	0,25	0	0	0	0	0,23	0,25	0,38	0,32	0,25	0,31	0,25	0,25
C7	0,25	0,17	0,25	0,25	0	0	0	0	0,22	0,25	0,05	0,14	0,25	0,03	0,25	0,25
C8	0,25	0,01	0,21	0,25	0	0	0	0	0,20	0,21	0,02	0,09	0,21	0,12	0,21	0,25
C9					0,52	0,39	0,23	0,68	0	0	0	0	0	0	0	0
C10					0,36	0,34	0,24	0,32	0	0	0	0	0	0	0	0
C11					0,11	0,17	0,33	0,00	0	0	0	0	0	0	0	0
C12					0,01	0,09	0,20	0,00	0	0	0	0	0	0	0	0
C13	0,33	0,63	0,44	0,27	0,43	0,43	0,56	0,68	0,44	0,45	0,67	0,61	0	0	0	0
C14	0,28	0,37	0,36	0,25	0,38	0,38	0,18	0,32	0,36	0,34	0,10	0,16	0	0	0	0
C15	0,23	0,00	0,19	0,27	0,16	0,16	0,17	0,00	0,19	0,20	0,10	0,02	0	0	0	0
C16	0,15	0,00	0,01	0,22	0,03	0,03	0,09	0,00	0,01	0,02	0,14	0,21	0	0	0	0

Table A6: Weighted supermatrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
C1	0,00	0,00	0,00	0,00	0,15	0,21	0,17	0,17	0,18	0,13	0,13	0,14	0,19	0,31	0,19	0,16
C2	0,00	0,00	0,00	0,00	0,10	0,12	0,11	0,12	0,11	0,10	0,13	0,14	0,16	0,18	0,15	0,12
C3	0,00	0,00	0,00	0,00	0,07	0,00	0,05	0,04	0,04	0,07	0,07	0,04	0,10	0,00	0,11	0,11
C4	0,00	0,00	0,00	0,00	0,02	0,00	0,00	0,00	0,01	0,04	0,00	0,00	0,05	0,00	0,05	0,10
C5	0,13	0,26	0,14	0,13	0,00	0,00	0,00	0,00	0,12	0,10	0,18	0,15	0,14	0,27	0,14	0,13
C6	0,12	0,15	0,12	0,13	0,00	0,00	0,00	0,00	0,08	0,08	0,13	0,11	0,12	0,16	0,12	0,13
C7	0,13	0,09	0,13	0,13	0,00	0,00	0,00	0,00	0,07	0,08	0,02	0,05	0,13	0,01	0,13	0,13
C8	0,13	0,01	0,11	0,13	0,00	0,00	0,00	0,00	0,07	0,07	0,01	0,03	0,11	0,06	0,11	0,13
C9	0,00	0,00	0,00	0,00	0,17	0,13	0,08	0,23	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
C10	0,00	0,00	0,00	0,00	0,12	0,11	0,08	0,11	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
C11	0,00	0,00	0,00	0,00	0,04	0,06	0,11	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
C12	0,00	0,00	0,00	0,00	0,00	0,03	0,07	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
C13	0,17	0,32	0,22	0,13	0,14	0,14	0,19	0,23	0,15	0,15	0,22	0,20	0,00	0,00	0,00	0,00
C14	0,14	0,18	0,18	0,12	0,13	0,13	0,06	0,11	0,12	0,11	0,03	0,05	0,00	0,00	0,00	0,00
C15	0,11	0,00	0,10	0,13	0,05	0,05	0,06	0,00	0,06	0,07	0,03	0,01	0,00	0,00	0,00	0,00
C16	0,08	0,00	0,00	0,11	0,01	0,01	0,03	0,00	0,00	0,01	0,05	0,07	0,00	0,00	0,00	0,00

Table A7: Limit supermatrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
C1	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14	0,14
C2	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10	0,10
C3	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04
C4	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02
C5	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12	0,12
C6	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08	0,08
C7	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06
C8	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06	0,06
C9	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05
C10	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03	0,03
C11	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02
C12	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01	0,01
C13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13	0,13
C14	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09	0,09
C15	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04	0,04
C16	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02