ANALYSIS OF SERVICE INNOVATION PERFORMANCE IN TURKISH BANKING SECTOR USING A COMBINING METHOD OF FUZZY MCDM AND TEXT MINING*

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Abstract

The purpose of the study is to examine the effecting factors for new service development capabilities in Turkish banking sector and to evaluate the performance of the banks in listed BIST based on the service innovation performance. The novelty of the study is to employ a two-step analysis considering the data mining and the hybrid MCDM respectively. The method is applied by using the data mining for extracting the literature based-criteria of service innovation. Accordingly, the fuzzy AHP is computed for weighting the criteria and the fuzzy TOPSIS is considered to rank the banks based on the service innovation performance. The results demonstrate that the service conditions for the customers are the most important factor in the service innovation performance while the employees are weakly considered to evaluate the new service development. In addition, it is seen that no bank type has a clear advantage over others. In other words, there are banks with both good and bad performance outcomes within each type of banking group. However, it is determined that foreign banks and private banks took place in the worst order. In this context, in order to achieve a competitive advantage, these low performing banks should focus on new services that take into account the customer expectations.

Keywords: Banking Sector, Service Innovation, Text Mining, Fuzzy AHP, Fuzzy TOPSIS

TÜRK BANKACILIK SEKTÖRÜNDEKİ HİZMET YENİLİĞİ PERFORMANSININ METİN MADENCİLİĞİ VE BULANIK ÇOK KRİTERLİ KARAR VERME YÖNTEMLERİ İLE ANALİZİ

Özet

Bu çalışmanın amacı, Türk bankacılık sektöründeki yeni hizmet geliştirme kabiliyetlerine etki eden faktörleri incelemek ve BIST'de işlem gören bankaların performansını, hizmet yeniliğine göre değerlendirmektir. Çalışmanın yeniliği, veri madenciliği ve hibrit çok kriterli karar verme yöntemlerini birlikte dikkate alan iki aşamalı bir analiz kullanmasıdır. Literatür tabanlı hizmet geliştirme kriterleri için veri madenciliği yöntemi uygulanmıştır. Buna göre, ölçütlerin ağırlıklandırılması için bulanık AHP, bankaların hizmet yeniliği performansına göre sıralanması için ise bulanık TOPSIS yöntemlerinden faydalanılmıştır. Elde edilen sonuçlara göre,

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müşterilerin en önemli boyut olduğu belirlenmiştir. Buna karşın, çalışanların ise daha düşük önem ağırlığına sahip olduğu sonucuna ulaşılmıştır. Ek olarak, herhangi bir banka türünün diğerlerine kıyasla bariz bir üstünlüğü bulunmadığı görülmüştür. Diğer bir ifadeyle, her banka türü içerisinde hem iyi hem de kötü performans sonuçlarına sahip olan bankalar bulunmaktadır. Bununla birlikte, en son sıralarda yabancı ve özel bankaların yer aldığı belirlenmiştir. Bu bağlamda, rekabetçi avantaj elde edebilmek için performansı düşük olan bu bankaların müşteri beklentilerini dikkate alan yeni hizmetler geliştirmeleri yerinde olacaktır.

Anahtar Kelimeler: Bankacılık Sektörü, Hizmet Yeniliği, Metin Madenciliği, Bulanık AHP, Bulanık TOPSIS

1. Introduction

Especially after the globalization, competition has increased almost all over the world. The main reason is that companies took the opportunity to enter new markets because of disappearing economic borders among the countries (Tunay and Yüksel, 2017:1628). Although this situation has many benefits for the consumers, it makes very hard for the companies to increase their profitability. Therefore, it becomes necessary for the companies to take some actions so as to survive in such a competitive environment (Yüksel, 2016:42).

Innovation and new service development are some example actions for these companies to reach this objective (Yüksel, 2017:2). With the help of innovative thinking, companies can have a chance to increase their efficiency. Within this framework, the concept of new service development plays a significant role to have a competitive power. In other words, companies should develop new services to become different in comparison with their rivals (Eti and İnel, 2016:470; Yüksel et al., 2016:1059).

Banking sector is also a market in which there is an important increase in the competition. Since foreign trade has an increasing trend after globalization, the significance of the banking sector went up considerably (Dinçer et al., 2018:203; Mukhtarov et al., 2018:65). Hence, many international banks entered into different countries. This situation has an increasing effect on the competition in this sector. Therefore, it is obvious that banks should develop new services to attract the attention of the consumers. Owing to this aspect, it can be much easier for them to survive in the market (Kartal, 2017:85; Ersin and Duran, 2017:110; Yüksel and Zengin, 2016:495).

Similar to the issues emphasized above, the aim of this study is to evaluate the performance of Turkish banks in listed BIST based on the service innovation performance. By using data mining methodology to the similar studies in the literature, the criteria for service innovation are identified. Additionally, the weights of the criteria are determined with the help of fuzzy AHP method. Moreover, fuzzy TOPSIS approach is taken into the consideration to rank the performance of the banks.

This study consists of 5 different sections. After the introduction part, the second section gives information about the text mining approach to multi criteria decision making. For this purpose, some similar studies in the literature are shared. Moreover, the third section explains fuzzy AHP and fuzzy TOPSIS methodologies. Furthermore, the fourth section focuses on the application on Turkish banking sector. Also, in the final part, the results and the recommendations are given.

2. Text Mining Approach to Multi Criteria Decision Making

2.1. Text Mining

Text mining is an approach for mining useful and novel patterns in textual data. Extracting these patterns is not an easy task because in contrast to numerical data, textual data is not structured. Hence, it must be organized in a way that is suitable for analytical methods. For this purpose, several preprocessing steps such as tokenizing, stemming, filtering stopword are implemented to represent textual data quantitatively.

Information retrieval includes collecting data from the data source which can be text files, reports, sheets, blogs, web pages, or social media and store collected data in the corpus. In preprocessing textual data transformed into numerical values. Tokenizing (breaking sentences into words), stemming (removing suffixes such as -ing or -er and obtaining the root), filtering stopwords (removing words that have no meaning such as “the”, “is” etc.) operations are executed (Karatzoglou & Feinerer, 2010:290). After this step, besides methods that are commonly used for text related tasks such as topic identification, sentiment analysis etc., standard data mining methods that are used for classification, clustering, and prediction can also be implemented on transformed data. Thanks to text mining that it is now possible to analyze voluminous textual data which is both online and offline data even if they are in very different file formats. In data model phase suitable algorithms are run for the intended task for example topic modeling or clustering. The result can be presented visually in visualization phase by using word clouds, histograms or correlation maps. At the final stage, interpretation of the results is performed.

Recent years number of studies that apply text mining methods has been increased. İt is commonly used in diverse fields especially in biochemical research, computational biology, information science, engineering, business, and finance. Table 1 presents some of the studies on the main application areas of text mining especially in finance and business domain.

Table 1. Selected studies on text mining

Subject	Study
Topic identification	(Correia & Goncalves, 2017), (Yao et al., 2017), (Schneider et al., 2017), (Clifton & Cooley, 1999)
Sentiment analysis, opinion mining	(Delmonte & Pallotta, 2011), (Hu et al., 2017), (Mostafa, 2013), (Khan et al., 2014), (Nagar & Hahsler, 2012)
Prediction	(Fung et al., 2003), (Wang et al., 2012), (Wong et al., 2014), (Ghose & Ipeirotis, 2011), (Kroha et al., 2006), (Ming et al., 2014), (Smalheiser, 2001)
Trend mining	(Baek & Hong, 2017), (Hung & Zhang, 2012), (Thorleuchter, 2008), (Li et al., 2017), (Park et al., 2017)

Text mining is also commonly used for bibliometric research namely analyzing the literature of a specified domain and finding patterns, trends, clusters or forming a specified dictionary for the field. For example, Delen & Crossland (2008) employed text mining to identify clusters and trends of related research topics from three major journals in the management information systems field. Garten & Altman (2009) developed a tool to assist in extracting pharmacogenomic concepts from the literature (using full-text articles) automatically. Scherf et al. (2005) used results from literature analysis in combination with evidence from experiments and genome analysis to improve the accuracy of results. Natarajan et al. (2006) reported that mining biological literature promises to play an increasingly important role in biological knowledge discovery. Yu et al. (2017) inspected 7721 publications in Information Sciences from 1968 to 2016. They used text mining to find the key contributors articles that have made a profound impact and illustrated salient patterns and emerging trends. Moro et al. (2017) performed text mining on articles published between 1996- 2016 related to the tourism research to uncover trends and gaps in the literature. Westergaard et al. (2018) presented the analysis results of 15 million English scientific full-text articles published during the period 1823–2016. They described the development in article length and publication sub-topics. They also extracted published protein-protein, disease–gene, and protein subcellular associations.

2.2. Multi-Criteria Decision Making (MCDM)

A classical Multi-Criteria Decision Making (MCDM) approach is applied for ranking decision alternatives based on predefined criteria. Criteria can be in conflict with each other. The scores for each criterion and decision alternatives are obtained from domain experts based on scales that are developed for selected MCDM method. In literature, there are numerous different MCDM methods that have differences in their theoretical bases, areas that they are particularly applied and the result that they produce. Some of these methods and references are listed in Table 2.

Table 2. Selected methods on the MCDM

MCDM Method	Reference
AHP	(Saaty, 1986), (Saaty & Vargas, 1987), (Saaty, 1990), (Saaty, 1994), (Saaty et al., 2007), (Saaty, 2008), (Dong et al., 2010; Kaya & Kahraman, 2010; Macharis et al., 2004; Tam & Tummala, 2001; Wei et al., 2005)
ANP	(Saaty, 1999), (Saaty, 2004), (Saaty, 2005), (Agarwal et al., 2006; Jharkharia & Shankar, 2007; Ravi et al., 2005; Wu, 2008; Yuksel & Dagdeviren, 2007)
ARAS	(Zavadskas et al., 2010), (Zavadskas & Turskis, 2010), (Dadelo et al., 2012), (Karabasevic et al., 2016)
COPRAS	(Zavadskas et al., 2007), (Podvezko, 2011), (Ecer, 2014), (Hashemkhani et al., 2014), (Stefano et al., 2015)
DEMATEL	(Wu & Lee, 2007), (Tzeng et al., 2007), (Wu, 2008), (Tseng, 2009), (Tsai & Chou, 2009), (Shieh et al., 2010), (Buyukozkan & Cifci, 2012)
ELECTRE	(Roy, 1991), (Mousseau & Slowinski, 1998), (Beccali et al., 2003), (de Almeida, 2007), (Wang & Triantaphyllou, 2008), (Sevkli, 2010), (Hatami-Marbini & Tavana, 2011)
MOORA	(Brauers & Zavadskas, 2006), (Brauers et al., 2008), (Kalibatas & Turskis, 2008), (Brauers & Zavadskas, 2009), (Chakraborty, 2011), (Karande & Chakraborty, 2012), (Stanujkic et al., 2012)
OWA	(Herrera et al., 1996), (Torra, 1997), (Xu, 2005), (Yager, 1992), (Yager, 1996)
PROMETHEE	(Albadvi et al., 2007), (Behzadian et al., 2010), (Brans & Vincke, 1985), (Brans et al., 1986), (Briggs et al., 1990), (Dagdeviren, 2008), (Macharis et al., 2004)
SAW	(Jibao et al., 2006), (Kaliszewski & Podkopaev, 2016), (Kavaliauskas et al., 2011), (Salih et al., 2015), (Shakouri et al., 2014), (Van Wijk et al., 2006)
SWARA	(Aghdaie et al., 2013), (Alimardani et al., 2013), (Hashemkhani Zolfani & Bahrami, 2014), (Hashemkhani Zolfani & Saparauskas, 2013), (Hashemkhani Zolfani et al., 2013), (Kersuliene et al., 2010), (Ruzgys et al., 2014)
TOPSIS	(Behzadian et al., 2012), (Chen & Tzeng, 2004), (Ertugrul & Karakasoglu, 2009), (Gumus, 2009), (Lai et al., 1994), (Lin et al., 2008), (Opricovic & Tzeng, 2004)
VIKOR	(Kaya & Kahraman, 2010), (Opricovic & Tzeng, 2004a, 2004b), (Serafim Opricovic & Tzeng, 2007), (San Cristobal, 2011)
WASPAS	(Chakraborty & Zavadskas, 2014), (Chakraborty et al., 2015), (Urosevic et al., 2017), (Zavadskas et al., 2016; (Zavadskas et al., 2013)

In this study, we applied text mining on the balanced scorecard literature to find out the potential of text mining to extract sub-dimensions of the four dimensions of the balanced scorecard. For this purpose, a total of 3756 scientific research abstracts were analyzed. By inspecting automated text mining results, a group of three keywords was identified for each dimension. These subdimensions were used to form criteria for solving the decision-making problem. Frequencies of each subdimensions are interpreted as scores to be used for the further steps of the analysis. Shortly, as a novel approach, criteria and scores were formed by text mining backed literature analysis automatically instead of a classical way of utilizing expert opinion or reviewing literature manually. In addition, results of the text mining combined with fuzzy AHP and fuzzy TOPSIS methods to weight criteria and ranking alternatives respectively in a fuzzy setting. In this manner, a hybrid decision making model is developed.

3. Methodology

In classical MCDM methods, experts use natural language expressions (linguistic variables) such as “Good” or “Very Important” or “Extremely preferred” in order to convey their subjective evaluations. Corresponding numerical values of these linguistic variables are used for evaluation of criteria directly. However, due to the inherent uncertainty in natural languages in addition to lack of enough information boundaries of these expressions are not so well defined. This is a common problem in MCDM methods. For expressing linguistic variables more appropriately, MCDM methods are occupied in fuzzy environments. Almost for every MCDM method, there is a fuzzy variant to overcome this difficulty.

The fuzzy set theory developed by Zadeh (1965, 1976) gives the opportunity to express linguistic variables to describe experts' subjective judgment in a quantitative way by using fuzzy numbers. Close interaction between fuzzy set theory and MCDM has resulted in a new decision theory called fuzzy multi-criteria decision-making (F-MCDM) (Nădăban et al., 2016:823). Considering benefits, F-MCDM is becoming more commonly used in literature in spite of their computational complexities.

A usual fuzzy MCDM process flow consists of three main parts. These are judgmental, analytical and evaluation parts. The judgmental part includes identifying objectives, criteria or topic related to the subject of decision-making, identifying and selecting experts, identifying and developing alternatives, weighting fuzzy criteria, defining the hierarchy of objectives. The analytical part contains reviewing the quality of data and information available for applying fuzzy weighting and hierarchy, selecting fuzzy mathematical algorithms and procedures, collecting data and applying the fuzzy algorithm. In the evaluation part reviewing data quality and criteria weighting, running several iterations, interpreting fuzzy decision-making calculations and results, and finalizing recommendations steps are carried out (Mardani et al., 2015:4126).

3.1. Fuzzy AHP

Saaty (1990, 1994) developed the analytic hierarchy process (AHP) to solve complex decision-making problems. AHP uses a hierarchical structure of elements to incorporate expert's knowledge for the decision-making problem. Priorities for each criterion in terms of their importance with respect to achieving objective are determined based on a scale. Similarly, priorities form the alternatives on each criterion are derived. By using pairwise comparison of criteria and alternatives a decision matrix is formed. To calculate the overall priorities for each alternative based on how they help to achieve the objectives, a weighting process is employed. In standard AHP all scores for comparisons are based on Saaty's rating scale. However, in Fuzzy AHP, all crisp scale values are transformed into triangular fuzzy numbers (fuzzification) so all operations are based on these triangular fuzzy numbers. Ranking of alternatives is performed after the defuzzification step (Özdağoğlu & Özdağoğlu, 2007:65)

Fuzzy AHP is applied in diverse fields such management, business, medicine, engineering, logistics, technology, tourism, and agriculture. Table 3 shows some of the most recent studies that employed fuzzy AHP method as a tool for designing a decision-making system.

Table 3. Selected studies on fuzzy AHP

Study	Application
(Nazari et al., 2018)	Developing a clinical decision support system for diagnosis of heart diseases
(Fadafan et al., 2018)	Identifying suitable zones for intensive tourism in an environmentally sensitive landscape
(Yadegaridehkordi et al., 2018)	Predicting the adoption of cloud-based technology
(Sirisawat & Kiatcharoenpol, 2018)	Prioritizing solutions for reverse logistics barriers
(Ilbahar et al., 2018)	Assessing risk for occupational health and safety
(Dožić et al., 2018)	Passenger aircraft type selection
(Seyedmohammadi et al., 2018)	Cultivation priority planning crops
(Rufuss et al., 2018)	Techno-economic analysis of solar stills
(Jayawickrama et al., 2017)	Plant sustainability evaluation
(Awasthi et al., 2018)	Global supplier selection
(Tyagi et al., 2017)	Ranking the influences of factors on product development phase.
(Asakereh et al., 2017)	Evaluation of solar farms locations
(Modak et al., 2017)	Performance evaluation of outsourcing decision
(Anand et al., 2017)	Evaluation of sustainability indicators in smart cities
(Kanuganti et al., 2017)	Analyzing road safety
(Neokosmidis et al., 2017)	Assessing of socio-techno-economic factors affecting the market adoption and evolution of 5G networks

The flow of Fuzzy AHP steps are summarized as follows:

Step 1. Identifying the decision-making problem exactly and determining objectives, criteria, and alternatives clearly.

Step 2. Transforming the complex decision-making problem into a hierarchical structure with criteria and alternatives.

Step 3. Constructing pairwise comparisons between decision elements and so form comparison matrices with fuzzy numbers.

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 $\mathcal{R}$ to be a triangular fuzzy number if its membership function $\mu_M(x): \mathcal{R} \rightarrow [0,1]$ is

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

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 $u_{ij} = 1/u_{ji}$.

Triangular fuzzy numbers are helpful for capturing vagueness inherently exists in linguistic scales that appraised by decision makers. Linguistic scales and their corresponding Triangular Fuzzy Numbers (TFN), which are used for representing the relative importance of criteria, are shown in Table 4.

Table 4. Linguistic variables for relative importance

Linguistic Scales	Corresponding TFN (l, m, u)
Equally important (EI)	(1/2, 1, 3/2)
Moderately more important (MI)	(1, 3/2, 2)
Strongly more important (SI)	(3/2, 2, 5/2)
Very strong more important (VSI)	(2, 5/2, 3)
Extremely more important (EMI)	(5/2, 3, 7/2)

Source: Chang, 1996:649; Lee, 2010:4941; Bozbura et. al., 2007:1100

Step 4. Using a fuzzy mathematical algorithm to build the relative weights of the decision elements.

In literature, there exist different methods for relative weights of the decision elements. These methods are listed in Table 5.

Table 5. Methods for computing local weights.

Method	Reference
Fuzzy logarithmic least squares	(Van Laarhoven and Pedrycz, 1983)
Geometric mean	(Buckley, 1985)
Fuzzy extend analysis	(Chang, 1996)
Fuzzy least squares priority	(Xu, 2000)
Lambda-Max	(Csutora and Buckley, 2001)
Fuzzy preference programming	(Mikhailov, 2003)

In this study, Chang's fuzzy extend analysis (Chang, 1996:649) which is the most widely used of these methods is preferred. 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:

$$M_{g_i}^j : M_{g_i}^1, M_{g_i}^2, \dots, M_{g_i}^m, \quad i = 1,2, \dots, n, \qquad j = 1,2, \dots, m$$

where all the $M_{g_i}^j$, $(i = 1,2, \dots, n, \quad j = 1,2, \dots, m)$ are triangular fuzzy numbers.

Step 4.1. The value of fuzzy synthetic extent with respect to the ith object (S_i) is defined as:

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

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

$$M_1 \oplus M_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$$

$$M_1 \otimes M_2 = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2)$$

$$(M_1)^{-1} \approx (1/u_1, 1/m_1, 1/l_1)$$

Considering these operations S_i can be decomposed by following

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

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^j = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i\right)$$

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

Finally, S_i can be expressed as

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

Step 4.2. The degree of possibility of $M_1 \geq M_2$ is defined as

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

Since M_1 and M_2 are convex fuzzy numbers we have $V(M_1 \geq M_2) = 1 \;\; iff \; m_1 \geq m_2$. 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} and can be computed as $\frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}$. These explanations can be shortly expressed as

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

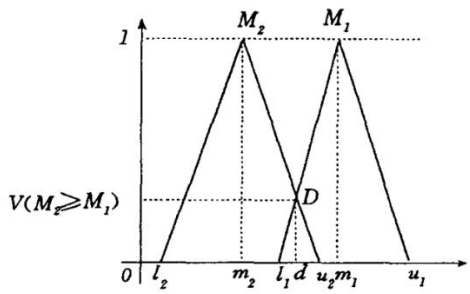

Figure 2: The degree of possibility $V(M_2 \geq M_1)$ (Chang, 1996:649)

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 4.3. 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

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

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

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

Step 4.4. Via normalization, the normalized weight vectors are obtained.

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

W is a nonfuzzy number.

Step 5. Consistency checking to be certain of the judgments of the decision makers are consistent.

Step 6. Ranking the alternatives by aggregating the relative weights of decision elements.

3.2. Fuzzy TOPSIS

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is one of multi-criteria decision-making 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, 2011:3992). In this paper, we used fuzzy TOPSIS instead of traditional TOPSIS to be able to model real-life problems that have uncertainty and imprecision inherently. Table 6 presents some of the most cited studies that employ Fuzzy TOPSIS as a decision-making tool.

Table 6: Literature Review of Fuzzy TOPSIS

Study	Application
(Amiri, 2010)	Project selection for oil-fields development
(Buyukozkan and Cifci, 2012a)	Strategic analysis of electronic service quality in the healthcare industry
(Buyukozkan and Cifci, 2012b)	Evaluating green suppliers
(Chu, 2002)	Facility location selection
(Chu & Lin, 2003)	Robot selection
(Dagdeviren et al., 2009)	Weapon selection
(Ertugrul & Karakasoglu, 2009)	Performance evaluation of cement firms
(Kannan et al., 2014)	Green suppliers selection
(Kannan et al., 2009)	Selection of reverse logistics provider
(Kaya & Kahraman, 2011)	Energy planning
(Kutlu & Ekmekcioglu, 2012)	Failure mode and effects analysis
(Liao & Kao, 2011)	Supplier selection in supply chain management
(Oenuet & Soner, 2008)	Transshipment site selection
(Secme et al., 2009)	Performance evaluation in the banking sector
(Sun, 2010)	Performance evaluation
(Taylan et al., 2014)	Construction projects selection and risk assessment
(Wang et al., 2009	Supplier selection
(Yong, 2006)	Plant location selection

Fuzzy TOPSIS steps are summarized below (Chen, 2000:2; Paksoy et. al., 2013:15):

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:

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

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

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

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:

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

Step 3. Compute the normalized fuzzy decision matrix.

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

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

or

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

Step 4. Construct the weighted normalized fuzzy decision matrix.

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

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

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

$$d_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^*), i = 1,2, \ldots, m$$

and

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), i = 1,2, \ldots, m$$

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

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

Step 6. Compute closeness coefficient.

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

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

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.

4. Analysis of Banking Sector

For identifying the three most important sub-dimensions for each dimension text mining technique that is based on literature analysis is applied. For collecting data to achieve domain analysis, search queries were executed on ScienceDirect portal. Only research articles published after 2007 in (Business, Management and Accounting), (Decision Sciences), and (Economics, Econometrics and Finance) subsections of ScienceDirect were taken into consideration. Search keywords used for dimensions were "competition", "customer", "organizational" and "financial". Abstracts of studies that resulted from each search were ordered in relevance. Following these lists, for each dimension, a corpus that containing 939 abstracts were constructed. A total of 3756 research article abstracts were included in the analysis. By following standard text mining steps such as transforming cases, tokenization, filtering stopwords, stemming, generating n-grams, filtering token by the length the most frequent keywords were determined for each dimension. Since there was the same number of abstract for each dimension, no normalization procedure was applied on frequency results. Resulting keywords were accepted as sub-dimensions (criteria for decision making problem). Table 7 shows final dimensions and sub-dimensions.

Table 7. The most frequent keywords for each dimension resulting from domain analysis.

competition			customer			organizational			financial		
market	price	product	service	satisfaction	value	management	innovation	employee	risk	crisis	growth
1145	579	484	1282	873	776	863	597	590	479	470	419

Annual reports of deposit banks that are listed in BIST-100 were collected from their websites to analyze by text mining technique for identifying the frequency of each sub-dimension keyword on these reports. Some of these banks had not on 2017 annual reports of their websites so 2016 annual reports were used in the analysis. A normalization procedure is applied because of the different sizes of annual reports. For a bank, the frequency of each sub-dimension was divided by the frequency of most frequent sub-dimension for this bank. Thus, for each bank, the most frequent sub-dimension has the value of 1 and the others less than 1. Resulting frequencies of sub-dimensions results are given and for gaining more understandable scores that lie in [0, 1000] interval each score is multiplied by 1000 and rounded to the nearest upper integer. Details of these operations are given in Table 8 and 9.

Table 8. Results of the normalized frequencies obtained from 2016 annual reports for each bank

	competition			customer			organizational			financial		
	market	price	product	service	satisfaction	value	management	innovation	employee	risk	crisis	growth
S1	0,5895	0,0738	0,1940	0,3217	0,0125	0,5457	0,8811	0,0188	0,1414	1,0000	0,0038	0,0551
S2	0,3853	0,1068	0,1829	0,2591	0,0223	0,4234	0,6825	0,0102	0,1337	1,0000	0,0084	0,1031
P1	0,4624	0,1686	0,7494	0,1663	0,0501	0,4123	1,0000	0,0433	0,2483	0,6401	0,0046	0,0524
P2	0,4635	0,0527	0,1358	0,2099	0,0034	0,4961	0,5477	0,0123	0,1358	1,0000	0,0011	0,0606
P3	0,3264	0,0803	0,0903	0,1913	0,0060	0,3492	0,3946	0,0187	0,1110	1,0000	0,0033	0,0455
P4	0,4752	0,1031	0,1739	0,2912	0,0243	0,5399	0,7199	0,0374	0,1476	1,0000	0,0051	0,0708
F1	0,4327	0,0926	0,2670	0,6383	0,0258	0,3628	0,5404	0,1432	0,1421	1,0000	0,0000	0,0280
F2	0,3699	0,0881	0,1096	0,1977	0,0222	0,4885	0,4555	0,0107	0,0988	1,0000	0,0132	0,0280
F3	0,3282	0,0305	0,1145	0,2672	0,0267	0,0802	1,0000	0,0229	0,2061	0,5496	0,0000	0,0649
F4	0,3680	0,0596	0,2107	0,3021	0,0360	0,4532	0,5752	0,0554	0,1601	1,0000	0,0028	0,0603

Table 9. Results of the frequencies in [0, 1000] interval

	competition			customer			organizational			financial		
	market	price	product	service	satisfaction	value	management	innovation	employee	Risk	crisis	growth
S1	590	74	194	322	13	546	882	19	142	1000	4	56
S2	386	107	183	260	23	424	683	11	134	1000	9	104
P1	463	169	750	167	51	413	1000	44	249	641	5	53
P2	464	53	136	210	4	497	548	13	136	1000	2	61
P3	327	81	91	192	7	350	395	19	112	1000	4	46
P4	476	104	174	292	25	540	720	38	148	1000	6	71
F1	433	93	267	639	26	363	541	144	143	1000	0	28
F2	370	89	110	198	23	489	456	11	99	1000	14	29
F3	329	31	115	268	27	81	1000	23	207	550	0	65
F4	368	60	211	303	37	454	576	56	161	1000	3	61

For weighting the criteria using Fuzzy AHP. Initially, weights of dimensions have been computed with the frequencies of each dimension in the data mining process and then, linguistic evaluations have been obtained from the expert team to construct the pairwise comparison matrices. Data mining results demonstrate that customer dimension is the most importance factor in the balanced-scorecard perspectives while the finance is the relatively weakest as seen in Table 10. The weights of dimensions have been considered to compute the global weights of the criteria.

Table 10. Frequencies and weights of dimensions with data mining

Dimensions	Defined Keywords	Count	Dimension Frequencies	Weights
Finance (D1)	Risk	479	1368	0.16
	Crisis	470		
	Growth	419		
Customer (D2)	Service	1282	2931	0.34
	Satisfaction	873		
	Value	776		
Organization (D3)	Management	863	2050	0.24
	Innovation	597		
	Employee	590		
Competition (D4)	Market	1145	2208	0.26
	Price	579		
	Product	484		

The fuzzy pair-wise comparison matrices of the criteria have been constructed in table 11.

Table 11. Fuzzy pair-wise comparison matrix for the criteria and weights

		C1			C2			C3		Weights
Risk (C1)	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	0.43
Crisis (C2)	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.27
Growth (C3)	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.30
		C4			**C5**			**C6**		
Service (C4)	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	0.43
Satisfaction (C5)	0.50	0.67	1.00	1.00	1.00	1.00	0.50	1.00	1.50	0.27
Value (C6)	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.30
		C7			**C8**			**C9**		
Management (C7)	1.00	1.00	1.00	1.00	1.50	2.00	1.00	1.50	2.00	0.45
Innovation (C8)	0.50	0.67	1.00	1.00	1.00	1.00	1.00	1.50	2.00	0.34
Employee (C9)	0.50	0.67	1.00	0.50	0.67	1.00	1.00	1.00	1.00	0.21
		C10			**C11**			**C12**		
Market (C10)	1.00	1.00	1.00	0.50	1.00	1.50	1.00	1.50	2.00	0.37
Price (C11)	0.67	1.00	2.00	1.00	1.00	1.00	0.50	1.00	1.50	0.33
Product (C12)	0.50	0.67	1.00	0.67	1.00	2.00	1.00	1.00	1.00	0.30

After the pairwise comparison matrices of the criteria, the local weights of the criteria have been computed as seen in Table 12.

Table 12. Local and Global weights of new service development factors

Dimensions	Dimension Weights	Criteria	Local Weights	Global Weights
Finance (D1)	0.16	Risk (C1)	0.43	0.069
		Crisis (C2)	0.27	0.044
		Growth (C3)	0.30	0.047
Customer (D2)	0.34	Service (C4)	0.43	0.147
		Satisfaction (C5)	0.27	0.094
		Value (C6)	0.30	0.102
Organization (D3)	0.24	Management (C7)	0.45	0.108
		Innovation (C8)	0.34	0.082
		Employee (C9)	0.21	0.050
Competition (D4)	0.26	Market (C10)	0.37	0.095
		Price (C11)	0.33	0.085
		Product (C12)	0.30	0.077

The weights of the new service development factors are shown in Table 12 and the global weights illustrate that the service is the most important criteria in the balanced scorecard-based factors of new service development. This result is also underlined in many different studies in the literature (Lin et al., 2008; Cui and Wu, 2017; Romano et al., 2017). On the other side, employee factor has the weakest importance in comparison with the others.

Table 13. Weighted normalized fuzzy decision matrix

		C1			**C2**			**C3**			**C4**			**C5**			**C6**	
S1	0.00	0.02	0.04	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.01	0.02	0.03	0.04
S2	0.00	0.00	0.02	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.01	0.03	0.01	0.02	0.03
P1	0.00	0.00	0.02	0.01	0.02	0.03	0.02	0.03	0.04	0.00	0.00	0.03	0.04	0.05	0.05	0.01	0.02	0.03
P2	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.01	0.02	0.03	0.04
P3	0.00	0.00	0.02	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.01	0.01	0.02	0.03
P4	0.00	0.00	0.02	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.01	0.03	0.02	0.03	0.04
F1	0.00	0.00	0.02	0.00	0.01	0.01	0.00	0.01	0.02	0.03	0.07	0.10	0.00	0.01	0.03	0.01	0.02	0.03
F2	0.00	0.00	0.02	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.01	0.03	0.02	0.03	0.04
F3	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.01	0.03	0.04	0.00	0.00	0.01
F4	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.03	0.01	0.03	0.04	0.01	0.02	0.03
	C7			C8			C9			C10			C11			C12		
S1	0.00	0.02	0.04	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.03	0.00	0.01	0.02	0.00	0.01	0.03
S2	0.00	0.02	0.04	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.03	0.02	0.03	0.04	0.01	0.03	0.04
P1	0.02	0.04	0.05	0.00	0.01	0.03	0.01	0.02	0.03	0.00	0.00	0.02	0.00	0.01	0.02	0.00	0.00	0.01
P2	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.03	0.00	0.00	0.01	0.00	0.01	0.03
P3	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.03	0.00	0.01	0.02	0.00	0.00	0.01
P4	0.00	0.02	0.04	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.03	0.01	0.02	0.03	0.00	0.01	0.03
F1	0.00	0.00	0.02	0.04	0.06	0.06	0.00	0.00	0.01	0.00	0.02	0.03	0.00	0.00	0.01	0.00	0.00	0.01
F2	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.02	0.03	0.03	0.04	0.04	0.00	0.00	0.01
F3	0.02	0.04	0.05	0.00	0.00	0.01	0.00	0.01	0.02	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.01	0.03
F4	0.00	0.00	0.02	0.00	0.01	0.03	0.00	0.00	0.01	0.00	0.02	0.03	0.00	0.01	0.02	0.00	0.01	0.03

Table 13 represents the weighted values of normalized decision matrix using the results of the fuzzy AHP. Table 14 shows the distances of each alternative from the positive and negative ideal solution as well as the values of the closeness coefficient.

Table 14. Ranking Results with Fuzzy TOPSIS

	D+	**D-**	**Cci**	**Ranking**
S1	11.859	0.187	0.0155	5
S2	11.838	0.205	0.0170	3
P1	11.775	0.261	0.0217	1
P2	11.896	0.148	0.0123	9
P3	11.903	0.142	0.0118	10
P4	11.853	0.192	0.0160	4
F1	11.789	0.250	0.0208	2
F2	11.855	0.186	0.0155	6
F3	11.874	0.168	0.0140	8
F4	11.867	0.177	0.0147	7

Ranking results demonstrate that P1 is the best bank in the balanced scorecard-based new service development evaluations while P3 has the worst rank in the list. However, state owned banks are listed in the third and fifth seats and foreign banks are in the second, sixth, seventh, and eighth ranks. These results show that the best and worst performed banks are owned by the private sector.

Moreover, it can be seen that no bank type has a clear advantage over others. In other words, there are banks with both good and bad performance outcomes within each type of banking group. However, it is determined that foreign banks and private banks took place in the worst order. In this context, in order to achieve a competitive advantage, these low performing banks should focus on new services that take into account the customer expectations. Yüksel et al. (2017) also underlined the importance of the same issue in their study.

5. Discussions and Conclusions

With the effect of globalization, the competition in banking sector increased significantly. Because banks play a significant role in foreign trade, a lot of international banks entered to many different countries to increase their profitability (Oktar and Yüksel, 2016:31; Yüksel and Özsarı, 2017:16). Therefore, it can be said that banks must take necessary actions to increase their competitive power. Otherwise, it may be impossible for these countries to survive in this environment (Kartal et al., 2018:209). Generating new services is a way of increasing competitive advantage because with the help of innovative services, banks can attract the attention of the consumers (Terzioğlu, 2018:155; Girgin, 2018:621).

The aim of this study is to evaluate the performance of Turkish deposit banks with respect to the service innovation performance. Within this context, by using content data mining approach, similar studies in the literature are searched and the criteria for service innovation are identified. In addition to this situation, by using fuzzy AHP method, the weights of the criteria are determined. Furthermore, fuzzy TOPSIS approach is used to rank the performance of these deposit banks.

As a result, it is defined that customer is the most important dimension whereas finance has the least significance in comparison with the others. Additionally, service is defined as the most important criterion, but crisis and growth have the lowest weights. Moreover, it is determined that a private bank has the highest performance. Also, a foreign bank is on the second rank and a state bank has the third highest performance. Furthermore, two different private banks have the lowest performance.

While considering the results of this study, it is understood that no bank type has a clear advantage over others. That is to say, there are banks with both good and bad performance outcomes within each type of banking group. Nevertheless, it is defined that the banks, which have the lowest performance, are the foreign banks and private banks. Within this framework, with respect to the strategic policy, it is recommended that the low performing banks should focus on new services that consider the customer expectations to have a competitive advantage. By focusing on this important topic for banking sector, it is aimed to make contribution to the literature. However, it is also believed that a new study considering banking sectors in different countries at the same time will also very beneficial.

References

Agarwal, A., Shankar, R., & Tiwari, M. K. (2006). Modeling the metrics of lean, leagile and agile supply chain: An ANP-based approach. European Journal of Operational Research, 173(1), 211–225. https://doi.org/10.1016/j.ejor.2004.12.005

Aghdaie, M. H., Hashemkhani Zolfani, S., & Zavadskas, E. K. (2013). Decision Making in Machine Tool Selection: An Integrated Approach with SWARA and COPRAS-G Methods. Inzinerine Ekonomika-Engineering Economics, 24(1), 5–17. https://doi.org/10.5755/j01.ee.24.1.2822

Albadvi, A., Chaharsooghi, S. K., & Esfahanipour, A. (2007). Decision making in stock trading: An application of PROMETHEE. European Journal of Operational Research, 177(2), 673–683. https://doi.org/10.1016/j.ejor.2005.11.022

Alimardani, M., Hashemkhani Zolfani, S., Aghdaie, M. H., & Tamosaitiene, J. (2013). A Novel Hybrid Swara and Vikor Methodology for Supplier Selection in an Agile Environment. Technological and Economic Development of Economy, 19(3), 533–548. https://doi.org/10.3846/20294913.2013.814606

Amiri, M. P. (2010). Project selection for oil-fields development by using the AHP and fuzzy TOPSIS methods. Expert Systems with Applications, 37(9), 6218–6224. https://doi.org/10.1016/j.eswa.2010.02.103

Anand, A., Rufuss, D. D. W., Rajkumar, V., & Suganthi, L. (2017). Evaluation of Sustainability Indicators in Smart Cities for India Using MCDM Approach. Energy Procedia, 141, 211–215. https://doi.org/10.1016/j.egypro.2017.11.094

Asakereh, A., Soleymani, M., & Sheikhdavoodi, M. J. (2017). A GIS-based Fuzzy-AHP method for the evaluation of solar farms locations: Case study in Khuzestan province, Iran. Solar Energy, 155, 342–353. https://doi.org/10.1016/j.solener.2017.05.075

Awasthi, A., Govindan, K., & Gold, S. (2018). Multi-tier sustainable global supplier selection using a fuzzy AHP-VIKOR based approach. International Journal of Production Economics, 195, 106–117. https://doi.org/10.1016/j.ijpe.2017.10.013

Aydogan, E. K. (2011). Performance measurement model for Turkish aviation firms using the rough-AHP and TOPSIS methods under fuzzy environment. Expert Systems with Applications, 38(4), 3992–3998. https://doi.org/10.1016/j.eswa.2010.09.060

Baek, S.-C., & Hong, W.-H. (2017). Exploring convergence research trends of spatial information based on UAV using text mining technique. Spatial Information Research, 25(2), 315–322. https://doi.org/10.1007/s41324-017-0095-5

Beccali, M., Cellura, M., & Mistretta, M. (2003). Decision-making in energy planning. Application of the Electre method at regional level for the diffusion of renewable energy technology. Renewable Energy, 28(13), 2063–2087. https://doi.org/10.1016/S0960-1481(03)00102-2

Behzadian, M., Kazemadeh, R. B., Albadvi, A., & Aghdasi, M. (2010). PROMETHEE: A comprehensive literature review on methodologies and applications. European Journal of Operational Research, 200(1), 198–215. https://doi.org/10.1016/j.ejor.2009.01.021

Behzadian, M., Otaghsara, S. K., Yazdani, M., & Ignatius, J. (2012). A state-of the-art survey of TOPSIS applications. Expert Systems with Applications, 39(17), 13051–13069. https://doi.org/10.1016/j.eswa.2012.05.056

Bozbura, F. Tunc, B., & Kahraman, C. (2007). Prioritization of human capital measurement indicators using fuzzy AHP. Expert Systems with Applications, 32, 1100–1112. http://dx.doi.org/10.1016/j.eswa.2006.02.006

Brans, J., & Vincke, P. (1985). A Preference Ranking Organization Method - (the Promethee Method for Multiple Criteria Decision-Making). Management Science, 31(6), 647–656. https://doi.org/10.1287/mnsc.31.6.647

Brans, J., Vincke, P., & Mareschal, B. (1986). How to Select and How to Rank Projects - the Promethee Method. European Journal of Operational Research, 24(2), 228–238. https://doi.org/10.1016/0377-2217(86)90044-5

Brauers, W. K. M., & Zavadskas, E. K. (2006). The MOORA method and its application to privatization in a transition economy. Control and Cybernetics, 35(2), 445–469.

Brauers, W. K. M., Zavadskas, E. K., Turskis, Z., & Vilutiene, T. (2008). Multi-Objective Contractor's Ranking by Applying the Moora Method. Journal of Business Economics and Management, 9(4), 245–255. https://doi.org/10.3846/1611-1699.2008.9.245-255

Brauers, W. K., & Zavadskas, E. K. (2009). Robustness of the Multi-Objective Moora Method with a Test for the Facilities Sector. Technological and Economic Development of Economy, 15(2), 352–375. https://doi.org/10.3846/1392-8619.2009.15.352-375

Briggs, T., Kunsch, P., & Mareschal, B. (1990). Nuclear Waste Management - an Application of the Multicriteria Promethee Methods. European Journal of Operational Research, 44(1), 1–10. https://doi.org/10.1016/0377-2217(90)90308-X

Buckley, J. J. (1985). Fuzzy hierarchical analysis. Fuzzy Sets and Systems, vol. 17, pp. 233-247

Buyukozkan, G., & Cifci, G. (2012). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. Expert Systems with Applications, 39(3), 3000–3011. https://doi.org/10.1016/j.eswa.2011.08.162

Buyukozkan, G., & Cifci, G. (2012a). A combined fuzzy AHP and fuzzy TOPSIS based strategic analysis of electronic service quality in healthcare industry. Expert Systems with Applications, 39(3), 2341–2354. https://doi.org/10.1016/j.eswa.2011.08.061

Buyukozkan, G., & Cifci, G. (2012b). A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. Expert Systems with Applications, 39(3), 3000–3011. https://doi.org/10.1016/j.eswa.2011.08.162

Chakraborty, S. (2011). Applications of the MOORA method for decision making in manufacturing environment. International Journal of Advanced Manufacturing Technology, 54(9–12), 1155–1166. https://doi.org/10.1007/s00170-010-2972-0

Chakraborty, S., & Zavadskas, E. K. (2014). Applications of WASPAS Method in Manufacturing Decision Making. Informatica, 25(1), 1–20. https://doi.org/10.15388/Informatica.2014.01

Chakraborty, S., Zavadskas, E. K., & Antucheviciene, J. (2015). Applications of Waspas Method as a Multi-Criteria Decision-Making Tool. Economic Computation and Economic Cybernetics Studies and Research, 49(1), 5–22.

Chang, D.-Y. (1996). Applications of the extent analysis method on fuzzy AHP. European Journal of Operational Research, 95(3), 649–655.

Chen, C.T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets and Systems, 114(1), 1–9. http://dx.doi.org/10.1016/S0165-0114(97)00377-1.

Chen, M. F., & Tzeng, G. H. (2004). Combining grey relation and TOPSIS concepts for selecting an expatriate host country. Mathematical and Computer Modelling, 40(13), 1473–1490. https://doi.org/10.1016/j.mcm.2005.01.006

Chu, T. C. (2002a). Facility location selection using fuzzy TOPSIS under group decisions. International Journal of Uncertainty Fuzziness and Knowledge-Based Systems, 10(6), 687–701. https://doi.org/10.1142/S0218488502001739

Chu, T. C., & Lin, Y. C. (2003). A fuzzy TOPSIS method for robot selection. International Journal of Advanced Manufacturing Technology, 21(4), 284–290. https://doi.org/10.1007/s001700300033

Clifton, C., & Cooley, R. (1999). TopCat: Data mining for topic identification in a text corpus. In J. M. Zytkow & J. Rauch (Eds.), Principles of Data Mining and Knowledge Discovery (Vol. 1704, pp. 174–183). Berlin: Springer-Verlag Berlin.

Correia, A., & Goncalves, A. (2017). Topics Discovery in Text Mining. In A. Rocha, A. M. Correia, H. Adeli, L. P. Reis, & S. Costanzo (Eds.), Recent Advances in Information Systems and Technologies, Vol 1 (Vol. 569, pp. 251–256). Berlin: Springer-Verlag Berlin.

Csutora, R. & Buckley, J. J. (2001). Fuzzy hierarchical analysis: The Lambda-Max method. Fuzzy Sets and Systems, vol. 120, pp. 181-195

Cui, A. S., & Wu, F. (2017). The impact of customer involvement on new product development: Contingent and substitutive effects. Journal of Product Innovation Management, 34(1), 60-80.

Dadelo, S., Turskis, Z., Zavadskas, E. K., & Dadeliene, R. (2012). Multiple Criteria Assessment of Elite Security Personal on the Basis of Aras and Expert Methods. Economic Computation and Economic Cybernetics Studies and Research, 46(4), 65–87.

Dagdeviren, M. (2008). Decision making in equipment selection: an integrated approach with AHP and PROMETHEE. Journal of Intelligent Manufacturing, 19(4), 397–406. https://doi.org/10.1007/s10845-008-0091-7

Dagdeviren, M., Yavuz, S., & Kilinc, N. (2009). Weapon selection using the AHP and TOPSIS methods under fuzzy environment. Expert Systems with Applications, 36(4), 8143–8151. https://doi.org/10.1016/j.eswa.2008.10.016

de Almeida, A. T. (2007). Multicriteria decision model for outsourcing contracts selection based on utility function and ELECTRE method. Computers & Operations Research, 34(12), 3569–3574. https://doi.org/10.1016/j.cor.2006.01.003

Delen, D., & Crossland, M. D. (2008). Seeding the survey and analysis of research literature with text mining. Expert Systems with Applications, 34(3), 1707–1720. https://doi.org/10.1016/j.eswa.2007.01.035

Delmonte, R., & Pallotta, V. (2011). Opinion Mining and Sentiment Analysis Need Text Understanding. In V. Pallotta, A. Soro, & E. Vargiu (Eds.), Advances in Distributed Agent-Based Retrieval Tools (Vol. 361, pp. 81-+). Berlin: Springer-Verlag Berlin.

Dinçer, H., Yuksel, S., & Adalı, Z. (2018). Relationship Between Non-Performing Loans, Industry, and Economic Growth of the African Economies and Policy Recommendations for Global Growth. *In Globalization and Trade Integration in Developing Countries* (pp. 203-228). IGI Global.

Dong, Y., Zhang, G., Hong, W.-C., & Xu, Y. (2010). Consensus models for AHP group decision making under row geometric mean prioritization method. Decision Support Systems, 49(3), 281–289. https://doi.org/10.1016/j.dss.2010.03.003

Dožić, S., Lutovac, T., & Kalić, M. (2018). Fuzzy AHP approach to passenger aircraft type selection. Journal of Air Transport Management, 68, 165–175. https://doi.org/10.1016/j.jairtraman.2017.08.003

Ecer, F. (2014). A hybrid banking websites quality evaluation model using AHP and COPRAS-G: a Turkey case. Technological and Economic Development of Economy, 20(4), 758–782. https://doi.org/10.3846/20294913.2014.915596

Ersin, İ., & Duran, S. (2017). Faizsiz Finans Döngüsünü Oluşturma Açısından Adil Ekonomik Düzen Söyleminin Kredileşme İlkeleri ve Uygulanabilirliğinin Değerlendirilmesi. *Electronic Turkish Studies*, 12(8), 109-132.

Ertugrul, I., & Karakasoglu, N. (2009). Performance evaluation of Turkish cement firms with fuzzy analytic hierarchy process and TOPSIS methods. Expert Systems with Applications, 36(1), 702–715. https://doi.org/10.1016/j.eswa.2007.10.014

Ertugrul, I., & Karakasoglu, N. (2009). Performance evaluation of Turkish cement firms with fuzzy analytic hierarchy process and TOPSIS methods. Expert Systems with Applications, 36(1), 702–715. https://doi.org/10.1016/j.eswa.2007.10.014

Eti, S., & İnel, M. N. (2016). A Research on Comparison of Regression Models Explaining the Profitability Base on Financial Data. *International Journal of Business and Management*, 4(10), 470-475.

Fadafan, F. K., Danehkar, A., & Pourebrahim, S. (2018). Developing a non-compensatory approach to identify suitable zones for intensive tourism in an environmentally sensitive landscape. Ecological Indicators, 87, 152–166. https://doi.org/10.1016/j.ecolind.2017.11.066

Fung, G. P. C., Yu, J. X., & Lam, W. (2003). Stock prediction: Integrating text mining approach using real-time news. New York: Ieee.

Garten, Y., & Altman, R. B. (2009). Pharmspresso: a text mining tool for extraction of pharmacogenomic concepts and relationships from full text. Bmc Bioinformatics, 10, S6. https://doi.org/10.1186/1471-2105-10-S2-S6

Ghose, A., & Ipeirotis, P. G. (2011). Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics. Ieee Transactions on Knowledge and Data Engineering, 23(10), 1498–1512. https://doi.org/10.1109/TKDE.2010.188

Girgin, G. K. (2018). Tüketicilerin Ramazan Ayinda Televizyonlardaki Yiyecek-İçecek Reklamlarina Yönelik Görüşlerinin Belirlenmesi. *Kırgızistan-Türkiye Manas Üniversitesi*, 7(2), 621-635.

Gumus, A. T. (2009). Evaluation of hazardous waste transportation firms by using a two step fuzzy-AHP and TOPSIS methodology. Expert Systems with Applications, 36(2), 4067–4074. https://doi.org/10.1016/j.eswa.2008.03.013

Hashemkhani Zolfani, S., & Bahrami, M. (2014). Investment prioritizing in high tech industries based on SWARA-COPRAS approach. Technological and Economic Development of Economy, 20(3), 534–553. https://doi.org/10.3846/20294913.2014.881435

Hashemkhani Zolfani, S., & Bahrami, M. (2014). Investment prioritizing in high tech industries based on SWARA-COPRAS approach. Technological and Economic Development of Economy, 20(3), 534–553. https://doi.org/10.3846/20294913.2014.881435

Hashemkhani Zolfani, S., & Saparauskas, J. (2013). New Application of SWARA Method in Prioritizing Sustainability Assessment Indicators of Energy System. Inzinerine Ekonomika-Engineering Economics, 24(5), 408–414. https://doi.org/10.5755/j01.ee.24.5.4526

Hashemkhani Zolfani, S., Zavadskas, E. K., & Turskis, Z. (2013). Design of Products with Both International and Local Perspectives Based. Ekonomska Istrazivanja-Economic Research, 26(2), 153–166.

Hatami-Marbini, A., & Tavana, M. (2011). An extension of the Electre I method for group decision-making under a fuzzy environment. Omega-International Journal of Management Science, 39(4), 373–386. https://doi.org/10.1016/j.omega.2010.09.001

Herrera, F., Herrera-Viedma, E., & Verdegay, J. L. (1996). Direct approach processes in group decision making using linguistic OWA operators. Fuzzy Sets and Systems, 79(2), 175–190. https://doi.org/10.1016/0165-0114(95)00162-X

Hu, Y.-H., Chen, Y.-L., & Chou, H.-L. (2017). Opinion mining from online hotel reviews - A text summarization approach. Information Processing & Management, 53(2), 436–449. https://doi.org/10.1016/j.ipm.2016.12.002

Hung, J.-L., & Zhang, K. (2012). Examining mobile learning trends 2003-2008: a categorical meta-trend analysis using text mining techniques. Journal of Computing in Higher Education, 24(1), 1–17. https://doi.org/10.1007/s12528-011-9044-9

Hwang, C. L., & Yoon, K. (1981). Multiple attribute decision making. Berlin: Springer-Verlag.

Ilbahar, E., Karaşan, A., Cebi, S., & Kahraman, C. (2018). A novel approach to risk assessment for occupational health and safety using Pythagorean fuzzy AHP & fuzzy inference system. Safety Science, 103, 124–136. https://doi.org/10.1016/j.ssci.2017.10.025

Jayawickrama, H. M. M. M., Kulatunga, A. K., & Mathavan, S. (2017). Fuzzy AHP based Plant Sustainability Evaluation Method. Procedia Manufacturing, 8, 571–578. https://doi.org/10.1016/j.promfg.2017.02.073

Jharkharia, S., & Shankar, R. (2007). Selection of logistics service provider: An analytic network process (ANP) approach. Omega-International Journal of Management Science, 35(3), 274–289. https://doi.org/10.1016/j.omega.2005.06.005

Jibao, L., Huiqiang, W., & Liang, Z. (2006). Study of network security situation awareness model based on simple additive weight and grey theory. (Y. M. Cheung, Y. Wang, & H. Lium, Eds.). New York: Ieee.

Kalibatas, D., & Turskis, Z. (2008). Multicriteria evaluation of inner climate by using MOORA method. Information Technology and Control, 37(1), 79–83.

Kaliszewski, I., & Podkopaev, D. (2016). Simple additive weighting-A metamodel for multiple criteria decision analysis methods. Expert Systems with Applications, 54, 155–161. https://doi.org/10.1016/j.eswa.2016.01.042

Kannan, D., Lopes de Sousa Jabbour, A. B., & Chiappetta Jabbour, C. J. (2014). Selecting green suppliers based on GSCM practices: Using fuzzy TOPSIS applied to a Brazilian electronics company. European Journal of Operational Research, 233(2), 432–447. https://doi.org/10.1016/j.ejor.2013.07.023

Kannan, G., Pokharel, S., & Kumar, P. S. (2009). A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider. Resources Conservation and Recycling, 54(1), 28–36. https://doi.org/10.1016/j.resconrec.2009.06.004

Kanuganti, S., Agarwala, R., Dutta, B., Bhanegaonkar, P. N., Singh, A. P., & Sarkar, A. K. (2017). Road safety analysis using multi criteria approach: A case study in India. Transportation Research Procedia, 25, 4649–4661. https://doi.org/10.1016/j.trpro.2017.05.299

Karabasevic, D., Zavadskas, E. K., Turskis, Z., & Stanujkic, D. (2016). The Framework for the Selection of Personnel Based on the SWARA and ARAS Methods Under Uncertainties. Informatica, 27(1), 49–65. https://doi.org/10.15388/Informatica.2016.76

Karande, P., & Chakraborty, S. (2012). Application of multi-objective optimization on the basis of ratio analysis (MOORA) method for materials selection. Materials & Design, 37, 317–324. https://doi.org/10.1016/j.matdes.2012.01.013

Karatzoglou, A., & Feinerer, I. (2010). Kernel-based machine learning for fast text mining in R. Computational Statistics & Data Analysis, 54(2), 290–297. https://doi.org/10.1016/j.csda.2009.09.023

Kartal, M. T. (2017). Türk Bankacılık Sektöründe Müşteri Şikâyetleri Yönetimi Üzerine Bir Değerlendirme. *İstanbul Üniversitesi İşletme İktisadı Enstitüsü Dergisi*, 28(83), 85-108.

Kartal, M. T., Depren, S. K., & Depren, Ö. (2018). Türkiye'de Döviz Kurlarini Etkileyen Makroekonomik Göstergelerin Belirlenmesi: Mars Yöntemi İle Bir İnceleme. *Kırgızistan-Türkiye Manas Üniversitesi*, 7(1), 209-229.

Kavaliauskas, M., Deltuvas, R., & Cinga, G. (2011). Simple Additive Weighting Approach to Score the State Forest Enterprises in Lithuania. In Rural Development in Global Changes, Vol 5, Book 2 (Vol. 5, pp. 34–40). Akademija: Aleksandras Stulginskis University.

Kaya, T., & Kahraman, C. (2010). Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul. Energy, 35(6), 2517–2527. https://doi.org/10.1016/j.energy.2010.02.051

Kaya, T., & Kahraman, C. (2010). Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul. Energy, 35(6), 2517–2527. https://doi.org/10.1016/j.energy.2010.02.051

Kaya, T., & Kahraman, C. (2011). Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. Expert Systems with Applications, 38(6), 6577–6585. https://doi.org/10.1016/j.eswa.2010.11.081

Kersuliene, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of Rational Dispute Resolution Method by Applying New Step-Wise Weight Assessment Ratio Analysis (swara). Journal of Business Economics and Management, 11(2), 243–258. https://doi.org/10.3846/jbem.2010.12

Khan, K., Baharudin, B., Khan, A., & Ullah, A. (2014). Mining opinion components from unstructured reviews: A review. Journal of King Saud University - Computer and Information Sciences, 26(3), 258–275. https://doi.org/10.1016/j.jksuci.2014.03.009

Kroha, P., Baeza-Yates, R., & Krellner, B. (2006). Text mining of business news for forecasting. In Seventeenth International Conference on Database and Expert Systems Applications, Proceedings (pp. 171-+). Los Alamitos: Ieee Computer Soc.

Kutlu, A. C., & Ekmekcioglu, M. (2012). Fuzzy failure modes and effects analysis by using fuzzy TOPSIS-based fuzzy AHP. Expert Systems with Applications, 39(1), 61–67. https://doi.org/10.1016/j.eswa.2011.06.044

Lai, Y., Liu, T., & Hwang, C. (1994). Topsis for Modm. European Journal of Operational Research, 76(3), 486–500. https://doi.org/10.1016/0377-2217(94)90282-8

Lee, S. (2010). Using fuzzy AHP to develop intellectual capital evaluation model for assessing their performance contribution in a university. Expert Systems with Applications, 37, 4941–4947. http://dx.doi.org/10.1016/j.eswa.2009.12.020

Li, G., Dai, J. S., Park, E.-M., & Park, S.-T. (2017). A study on the service and trend of Fintech security based on text-mining: focused on the data of Korean online news. Journal of Computer Virology and Hacking Techniques, 13(4), 249–255. https://doi.org/10.1007/s11416-016-0288-9

Liao, C.-N., & Kao, H.-P. (2011). An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management. Expert Systems with Applications, 38(9), 10803–10811. https://doi.org/10.1016/j.eswa.2011.02.031

Lin, M.-C., Wang, C.-C., Chen, M.-S., & Chang, C. A. (2008). Using AHP and TOPSIS approaches in customer-driven product design process. Computers in Industry, 59(1), 17–31. https://doi.org/10.1016/j.compind.2007.05.013

Macharis, C., Springael, J., De Brucker, K., & Verbeke, A. (2004). PROMETHEE and AHP: The design of operational synergies in multicriteria analysis. Strengthening PROMETHEE with ideas of AHP. European Journal of Operational Research, 153(2), 307–317. https://doi.org/10.1016/S0377-2217(03)00153-X

Macharis, C., Springael, J., De Brucker, K., & Verbeke, A. (2004). PROMETHEE and AHP: The design of operational synergies in multicriteria analysis. Strengthening PROMETHEE with ideas of AHP. European Journal of Operational Research, 153(2), 307–317. https://doi.org/10.1016/S0377-2217(03)00153-X

Mardani, A., Jusoh, A., & Zavadskas, E. K. (2015). Fuzzy multiple criteria decision-making techniques and applications – Two decades review from 1994 to 2014. Expert Systems with Applications, 42(8), 4126–4148. https://doi.org/10.1016/j.eswa.2015.01.003

Mikhailov, L. (2003). Deriving priorities from fuzzy pairwise comparison judgments. Fuzzy Sets and Systems, vol. 134, pp. 365-385

Ming, F., Wong, F., Liu, Z., & Chiang, M. (2014). Stock Market Prediction from WSJ: Text Mining via Sparse Matrix Factorization (pp. 430–439). IEEE. https://doi.org/10.1109/ICDM.2014.116

Modak, M., Pathak, K., & Ghosh, K. K. (2017). Performance evaluation of outsourcing decision using a BSC and Fuzzy AHP approach: A case of the Indian coal mining organization. Resources Policy, 52, 181–191. https://doi.org/10.1016/j.resourpol.2017.03.002

Moro, S., Rita, P., & Cortez, P. (2017). A text mining approach to analyzing Annals literature. Annals of Tourism Research, 66, 208–210.

Mostafa, M. M. (2013). More than words: Social networks' text mining for consumer brand sentiments. Expert Systems with Applications, 40(10), 4241–4251. https://doi.org/10.1016/j.eswa.2013.01.019

Mousseau, V., & Slowinski, R. (1998). Inferring an ELECTRE TRI model from assignment examples. Journal of Global Optimization, 12(2), 157–174. https://doi.org/10.1023/A:1008210427517

Mukhtarov, S., Yüksel, S., & Mammadov, E. (2018). Factors that increase credit risks of Azerbaijani banks. Journal of International Studies Vol, 11(2), 63-75.

Nădăban, S., Dzitac, S., & Dzitac, I. (2016). Fuzzy TOPSIS: A General View. Procedia Computer Science, 91, 823–831. https://doi.org/10.1016/j.procs.2016.07.088

Nagar, A., & Hahsler, M. (2012). Using Text and Data Mining Techniques to extract Stock Market Sentiment from Live News Streams. In 2012 International Conference on Computer Technology and Science (Vol. 47, pp. 91–95).

Nassirtoussi, A. K., Aghabozorgi, S., Teh, Y. W., & Ngo, D. C. L. (2015). Text mining of news-headlines for FOREX market prediction: A Multi-layer Dimension Reduction Algorithm with semantics and sentiment. Expert Systems with Applications, 42(1), 306–324. https://doi.org/10.1016/j.eswa.2014.08.004

Natarajan, J., Berrar, D., Dubitzky, W., Hack, C., Zhang, Y., DeSesa, C., … Bremer, E. G. (2006). Text mining of full-text journal articles combined with gene expression analysis reveals a relationship between sphingosine-I-phosphate and invasiveness of a glioblastoma cell line. Bmc Bioinformatics, 7, 373. https://doi.org/10.1186/1471-2105-7-373

Nazari, S., Fallah, M., Kazemipoor, H., & Salehipour, A. (2018). A fuzzy inference- fuzzy analytic hierarchy process-based clinical decision support system for diagnosis of heart diseases. Expert Systems with Applications, 95, 261–271. https://doi.org/10.1016/j.eswa.2017.11.001

Neokosmidis, I., Rokkas, T., Parker, M. C., Koczian, G., Walker, S. D., Siddiqui, M. S., & Escalona, E. (2017). Assessment of socio-techno-economic factors affecting the market adoption and evolution of 5G networks: Evidence from the 5G-PPP CHARISMA project. Telematics and Informatics, 34(5), 572–589. https://doi.org/10.1016/j.tele.2016.11.007

Oenuet, S., & Soner, S. (2008). Transshipment site selection using the AHP and TOPSIS approaches under fuzzy environment. Waste Management, 28(9), 1552–1559. https://doi.org/10.1016/j.wasman.2007.05.019

Oktar, S., & Yüksel, S. (2016). Bankalarin Türev Ürün Kullanimini Etkileyen Faktörler: Mars Yöntemi ile Bir Inceleme/Determinants of the Use Derivatives in Banking: An Analysis with MARS Model. *Finans Politik & Ekonomik Yorumlar*, 53(620), 31-46.

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445–455. https://doi.org/10.1016/s0377-2217(03)00020-1

Opricovic, S., & Tzeng, G. H. (2004a). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445–455. https://doi.org/10.1016/s0377-2217(03)00020-1

Opricovic, S., & Tzeng, G. H. (2004b). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445–455. https://doi.org/10.1016/s0377-2217(03)00020-1

Opricovic, Serafim, & Tzeng, G.-H. (2007). Extended VIKOR method in comparison with outranking methods. European Journal of Operational Research, 178(2), 514–529. https://doi.org/10.1016/j.ejor.2006.01.020

Özdağoğlu, A., & Özdağoğlu, G. (2007). Comparison of AHP And Fuzzy AHP For The Multi-Criteria Decision Making Processes With Linguistic Evaluations. İstanbul Ticaret Üniversitesi Fen Bilimleri Dergisi, (11), 65–85.

Paksoy, T., Pehlivan, N. Y., & Özceylan, E. (2013). Bulanık Küme Teorisi / Bulanık Matematiksel Programlamaya Giriş. Ankara: Nobel Akademik Yayıncılık

Park, B., Oh, K.-Y., Lee, J.-H., Yoon, J.-H., Kuk, L. S., & Lee, M.-J. (2017). A Study on Environmental research Trends by Information and Communications Technologies using Text-mining Technology. Korean Journal of Remote Sensing, 33(2), 189–199. https://doi.org/10.7780/kjrs.2017.33.2.7

Podvezko, V. (2011). The Comparative Analysis of MCDA Methods SAW and COPRAS. Inzinerine Ekonomika-Engineering Economics, 22(2), 134–146.

Ravi, V., Shankar, R., & Tiwari, M. K. (2005). Analyzing alternatives in reverse logistics for end-of-life computers: ANP and balanced scorecard approach. Computers & Industrial Engineering, 48(2), 327–356. https://doi.org/10.1016/j.cie.2005.01.017

Romano, M., Del Giudice, M., & Bresciani, S. (2017). Open innovation and customer-based development of new products. Mercati e competitività, 3(3), 15-20.

Roy, B. (1991). The Outranking Approach and the Foundations of Electre Methods. Theory and Decision, 31(1), 49–73. https://doi.org/10.1007/BF00134132

Rufuss, D. D. W., Kumar, V. R., Suganthi, L., Iniyan, S., & Davies, P. A. (2018). Techno-economic analysis of solar stills using integrated fuzzy analytical hierarchy process and data envelopment analysis. Solar Energy, 159, 820–833. https://doi.org/10.1016/j.solener.2017.11.050

Ruzgys, A., Volvaciovas, R., Ignatavicius, C., & Turskis, Z. (2014). Integrated Evaluation of External Wall Insulation in Residential Buildings Using Swara-Todim Mcdm Method. Journal of Civil Engineering and Management, 20(1), 103–110. https://doi.org/10.3846/13923730.2013.843585

Saaty, T. (1990). How to Make a Decision - the Analytic Hierarchy Process. European Journal of Operational Research, 48(1), 9–26. https://doi.org/10.1016/0377-2217(90)90057-I

Saaty, T. L. (1986). Axiomatic foundation of the analytic hierarchy process. Management Science, 32(7), 841–855.

Saaty, T. L. (1994). How to make a decision: the analytic hierarchy process. Interfaces, 24(6), 19–43.

Saaty, T. L. (1999). Fundamentals of the analytic network process. In Proceedings of the 5th international symposium on the analytic hierarchy process (pp. 12–14).

Saaty, T. L. (2004). Fundamentals of the analytic network process—Dependence and feedback in decision-making with a single network. Journal of Systems Science and Systems Engineering, 13(2), 129–157.

Saaty, T. L. (2005). Making and validating complex decisions with the AHP/ANP. Journal of Systems Science and Systems Engineering, 14(1), 1–36.

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. International Journal of Services Sciences, 1(1), 83–98.

Saaty, T. L., Peniwati, K., & Shang, J. S. (2007). The analytic hierarchy process and human resource allocation: Half the story. Mathematical and Computer Modelling, 46(7–8), 1041–1053. https://doi.org/10.1016/j.mcm.2007.03.010

Saaty, T., & Vargas, L. (1987). Uncertainty and Rank Order in the Analytic Hierarchy Process. European Journal of Operational Research, 32(1), 107–117. https://doi.org/10.1016/0377-2217(87)90275-X

Salih, Y. K., See, O. H., Ibrahim, R. W., Yussof, S., & Iqbal, A. (2015). A novel noncooperative game competing model using generalized simple additive weighting method to perform network selection in heterogeneous wireless networks. International Journal of Communication Systems, 28(6), 1112–1125. https://doi.org/10.1002/dac.2747

San Cristobal, J. R. (2011). Multi-criteria decision-making in the selection of a renewable energy project in Spain: The Vikor method. Renewable Energy, 36(2), 498–502. https://doi.org/10.1016/j.renene.2010.07.031

Scherf, M., Epple, A., & Werner, T. (2005). The next generation of literature analysis: Integration of genomic analysis into text mining. Briefings in Bioinformatics, 6(3), 287–297. https://doi.org/10.1093/bib/6.3.287

Schneider, N., Fechner, N., Landrum, G. A., & Stiefl, N. (2017). Chemical Topic Modeling: Exploring Molecular Data Sets Using a Common Text-Mining Approach. Journal of Chemical Information and Modeling, 57(8), 1816–1831. https://doi.org/10.1021/acs.jcim.7b00249

Secme, N. Y., Bayrakdaroglu, A., & Kahraman, C. (2009). Fuzzy performance evaluation in Turkish Banking Sector using Analytic Hierarchy Process and TOPSIS. Expert Systems with Applications, 36(9), 11699–11709. https://doi.org/10.1016/j.eswa.2009.03.013

Sevkli, M. (2010). An application of the fuzzy ELECTRE method for supplier selection. International Journal of Production Research, 48(12), 3393–3405. https://doi.org/10.1080/00207540902814355

Seyedmohammadi, J., Sarmadian, F., Jafarzadeh, A. A., Ghorbani, M. A., & Shahbazi, F. (2018). Application of SAW, TOPSIS and fuzzy TOPSIS models in cultivation priority planning for maize, rapeseed and soybean crops. Geoderma, 310, 178–190. https://doi.org/10.1016/j.geoderma.2017.09.012

Shakouri, H. G., Nabaee, M., & Aliakbarisani, S. (2014). A quantitative discussion on the assessment of power supply technologies: DEA (data envelopment analysis) and SAW (simple additive weighting) as complementary methods for the “Grammar.” Energy, 64, 640–647. https://doi.org/10.1016/j.energy.2013.10.022

Shieh, J.-I., Wu, H.-H., & Huang, K.-K. (2010). A DEMATEL method in identifying key success factors of hospital service quality. Knowledge-Based Systems, 23(3), 277–282. https://doi.org/10.1016/j.knosys.2010.01.013

Sirisawat, P., & Kiatcharoenpol, T. (2018). Fuzzy AHP-TOPSIS approaches to prioritizing solutions for reverse logistics barriers. Computers & Industrial Engineering, 117, 303–318. https://doi.org/10.1016/j.cie.2018.01.015

Smalheiser, N. R. (2001). Predicting emerging technologies with the aid of text-based data mining: the micro approach. Technovation, 21(10), 689–693. https://doi.org/10.1016/S0166-4972(01)00048-7

Stanujkic, D., Magdalinovic, N., Jovanovic, R., & Stojanovic, S. (2012). An Objective Multi-Criteria Approach to Optimization Using Moora Method and Interval Grey Numbers. Technological and Economic Development of Economy, 18(2), 331–363. https://doi.org/10.3846/20294913.2012.676996

Stefano, N. M., Casarotto Filho, N., Vergara, L. G. L., & Rocha, R. U. G. (2015). COPRAS (Complex Proportional Assessment): State of the Art Research and its Applications. Ieee Latin America Transactions, 13(12), 3899–3906.

Sun, C.-C. (2010). A performance evaluation model by integrating fuzzy AHP and fuzzy TOPSIS methods. Expert Systems with Applications, 37(12), 7745–7754. https://doi.org/10.1016/j.eswa.2010.04.066

Tam, M. C. Y., & Tummala, V. M. R. (2001). An application of the AHP in vendor selection of a telecommunications system. Omega-International Journal of Management Science, 29(2), 171–182. https://doi.org/10.1016/S0305-0483(00)00039-6

Taylan, O., Bafail, A. O., Abdulaal, R. M. S., & Kabli, M. R. (2014). Construction projects selection and risk assessment by fuzzy AHP and fuzzy TOPSIS methodologies. Applied Soft Computing, 17, 105–116. https://doi.org/10.1016/j.asoc.2014.01.003

Terzioğlu, M. K. (2018). The Nexus Among Fiscal Policies, Fiscal Decentralization, And Economic Performance: Joint Effect Of Globalization And Institutional Quality. *Kırgızistan-Türkiye Manas Üniversitesi*, 7(2), 155-172.

Thorleuchter, D. (2008). Finding new technological ideas and inventions with text mining and technique philosophy. In C. Preisach, H. Burkhardt, L. SchmidtThieme, & R. Decker (Eds.), Data Analysis, Machine Learning and Applications (pp. 413–420). Berlin: Springer-Verlag Berlin.

Torra, V. (1997). The weighted OWA operator. International Journal of Intelligent Systems, 12(2), 153–166. https://doi.org/10.1002/(SICI)1098-111X(199702)12:2<153::AID-INT3>3.0.CO;2-P

Tsai, W.-H., & Chou, W.-C. (2009). Selecting management systems for sustainable development in SMEs: A novel hybrid model based on DEMATEL, ANP, and ZOGP. Expert Systems with Applications, 36(2), 1444–1458. https://doi.org/10.1016/j.eswa.2007.11.058

Tseng, M.-L. (2009). A causal and effect decision making model of service quality expectation using grey-fuzzy DEMATEL approach. Expert Systems with Applications, 36(4), 7738–7748. https://doi.org/10.1016/j.eswa.2008.09.011

Tunay, K. B., & Yüksel, S. (2017). The relationship between corporate governance and foreign ownership of the banks in developing countries. *Contaduría y Administración*, 62(5), 1627-1642.

Tyagi, S., Agrawal, S., Yang, K., & Ying, H. (2017). An extended Fuzzy-AHP approach to rank the influences of socialization-externalization-combination-internalization modes on the development phase. Applied Soft Computing, 52, 505–518. https://doi.org/10.1016/j.asoc.2016.10.017

Tzeng, G.-H., Chiang, C.-H., & Li, C.-W. (2007). Evaluating intertwined effects in e-learning programs: A novel hybrid MCDM model based on factor analysis and DEMATEL. Expert Systems with Applications, 32(4), 1028–1044. https://doi.org/10.1016/j.eswa.2006.02.004

Urosevic, S., Karabasevic, D., Stanujkic, D., & Maksimovic, M. (2017). An Approach to Personnel Selection in the Tourism Industry Based on the Swara and the Waspas Methods. Economic Computation and Economic Cybernetics Studies and Research, 51(1), 75–88.

Van Laarhoven, P. J. M. & Pedrycz, W. (1983). A fuzzy extension of Saaty's priority theory. Fuzzy Sets and Systems, vol. 11, pp. 229-241

Van Wijk, B. L. G., Klungel, O. H., Heerdink, E. R., & De Boer, A. (2006). A comparison of two multiple characteristics decision making techniques for the comparison of antihypertensive drugs: Simple additive weighting and technique for order preference by similarity to an ideal solution. Pharmacoepidemiology and Drug Safety, 15, S224–S224.

Wang, B., Huang, H., & Wang, X. (2012). A novel text mining approach to financial time series forecasting. Neurocomputing, 83, 136–145. https://doi.org/10.1016/j.neucom.2011.12.013

Wang, J.-W., Cheng, C.-H., & Kun-Cheng, H. (2009). Fuzzy hierarchical TOPSIS for supplier selection. Applied Soft Computing, 9(1), 377–386. https://doi.org/10.1016/j.asoc.2008.04.014

Wang, X., & Triantaphyllou, E. (2008). Ranking irregularities when evaluating alternatives by using some ELECTRE methods. Omega-International Journal of Management Science, 36(1), 45–63. https://doi.org/10.1016/j.omega.2005.12.003

Wei, C. C., Chien, C. F., & Wang, M. J. J. (2005). An AHP-based approach to ERP system selection. International Journal of Production Economics, 96(1), 47–62. https://doi.org/10.1016/j.ijpe.2004.03.004

Westergaard, D., Stærfeldt, H.-H., Tønsberg, C., Jensen, L. J., & Brunak, S. (2018). A comprehensive and quantitative comparison of text-mining in 15 million full-text articles versus their corresponding abstracts. PLOS Computational Biology, 14(2), e1005962. https://doi.org/10.1371/journal.pcbi.1005962

Wong, F. M. F., Liu, Z., & Chiang, M. (2014). Stock Market Prediction from WSJ: Text Mining via Sparse Matrix Factorization. In R. Kumar, H. Toivonen, J. Pei, J. Z. Huang, & X. Wu (Eds.), 2014 Ieee International Conference on Data Mining (icdm) (pp. 430–439). New York: Ieee.

Wu, W.-W. (2008). Choosing knowledge management strategies by using a combined ANP and DEMATEL approach. Expert Systems with Applications, 35(3), 828–835. https://doi.org/10.1016/j.eswa.2007.07.025

Wu, W.-W. (2008). Choosing knowledge management strategies by using a combined ANP and DEMATEL approach. Expert Systems with Applications, 35(3), 828–835. https://doi.org/10.1016/j.eswa.2007.07.025

Wu, W.-W., & Lee, Y.-T. (2007). Developing global managers' competencies using the fuzzy DEMATEL method. Expert Systems with Applications, 32(2), 499–507. https://doi.org/10.1016/j.eswa.2005.12.005

Xu, R. (2000). Fuzzy least-squares priority method in the analytic hierarchy process. Fuzzy Sets and Systems, vol. 112, pp. 359-404

Xu, Z. S. (2005). An overview of methods for determining OWA weights. International Journal of Intelligent Systems, 20(8), 843–865. https://doi.org/10.1002/int.20097

Yadegaridehkordi, E., Nasir, M. H. N. B. M., Noor, N. F. B. M., Shuib, L., & Badie, N. (2018). Predicting the adoption of cloud-based technology using fuzzy analytic hierarchy process and structural equation modelling approaches. Applied Soft Computing, 66, 77–89. https://doi.org/10.1016/j.asoc.2017.12.051

Yager, R. (1992). Applications and Extensions of Owa Aggregations. International Journal of Man-Machine Studies, 37(1), 103–132. https://doi.org/10.1016/0020-7373(92)90093-Z

Yager, R. (1993). Families of Owa Operators. Fuzzy Sets and Systems, 59(2), 125–148. https://doi.org/10.1016/0165-0114(93)90194-M

Yager, R. R. (1996). Quantifier guided aggregation using OWA operators. International Journal of Intelligent Systems, 11(1), 49–73. https://doi.org/10.1002/(SICI)1098-111X(199601)11:1<49::AID-INT3>3.3.CO;2-L

Yao, L., Zhang, Y., Chen, Q., Qian, H., Wei, B., & Hu, Z. (2017). Mining coherent topics in documents using word embeddings and large-scale text data. Engineering Applications of Artificial Intelligence, 64, 432–439. https://doi.org/10.1016/j.engappai.2017.06.024

Yong, D. (2006). Plant location selection based on fuzzy TOPSIS. International Journal of Advanced Manufacturing Technology, 28(7–8), 839–844. https://doi.org/10.1007/s00170-004-2436-5

Yu, D., Xu, Z., Pedrycz, W., & Wang, W. (2017). Information sciences 1968-2016: A retrospective analysis with text mining and bibliometric. Information Sciences, 418, 619–634. https://doi.org/10.1016/j.ins.2017.08.031

Yuksel, I., & Dagdeviren, M. (2007). Using the analytic network process (ANP) in a SWOT analysis - A case study for a textile firm. Information Sciences, 177(16), 3364–3382. https://doi.org/10.1016/j.ins.2007.01.001

Yüksel, S. (2017). The impacts of research and development expenses on export and economic growth. *International Business and Accounting Research Journal*, 1(1), 1-8.

Yüksel, S. (2016). Bankaların Takipteki Krediler Oranını Belirleyen Faktörler: Türkiye İçin Bir Model Önerisi. *Bankacılar Dergisi*, 98, 41-56.

Yüksel, S., & Özsarı, M. (2017). Türkiye'nin Kredi Notunu Etkileyen Faktörlerin MARS Yöntemi İle Belirlenmesi. *Politik Ekonomik Kuram*, 1(2), 16-31.

Yüksel, S., Mukhtarov, S., & Mammadov, E. (2016). Comparing the efficiency of Turkish and Azerbaijani banks: An application with data envelopment analysis. *International Journal of Economics and Financial Issues*, 6(3), 1059-1067.

Yüksel, S., & Zengin, S. (2016). Leading Indicators of 2008 Global Crisis: An Analysis with Logit and Mars Methods. *Finansal Araştırmalar ve Çalışmalar Dergisi*, 8(15), 495-518.

Yüksel, S., Dinçer, H., & Emir, Ş. (2017). Comparing the performance of Turkish deposit banks by using DEMATEL, Grey Relational Analysis (GRA) and MOORA approaches. World Journal of Applied Economics, 3(2), 26-47.

Zadeh, L., A fuzzy-algorithmic approach to the definition of complex or imprecise concepts. International Journal of Man–Machine Studies, 1976, 8, 249–291

Zadeh, L., Information and Control, 1965, 8, 338–358.

Zavadskas, E. K., & Turskis, Z. (2010). A New Additive Ratio Assessment (aras) Method in Multicriteria Decision-Making. Technological and Economic Development of Economy, 16(2), 159–172. https://doi.org/10.3846/tede.2010.10

Zavadskas, E. K., Kaklauskas, A., Peldschus, F., & Turskis, Z. (2007). Multi-attribute assessment of road design solutions by using the COPRAS method. Baltic Journal of Road and Bridge Engineering, 2(4), 195–203.

Zavadskas, E. K., Kalibatas, D., & Kalibatiene, D. (2016). A multi-attribute assessment using WASPAS for choosing an optimal indoor environment. Archives of Civil and Mechanical Engineering, 16(1), 76–85. https://doi.org/10.1016/j.acme.2015.10.002

Zavadskas, E. K., Turskis, Z., & Vilutiene, T. (2010). Multiple criteria analysis of foundation instalment alternatives by applying Additive Ratio Assessment (ARAS) method. Archives of Civil and Mechanical Engineering, 10(3), 123–141. https://doi.org/10.1016/S1644-9665(12)60141-1

Zavadskas, Edmundas Kazimieras, Antucheviciene, J., Saparauskas, J., & Turskis, Z. (2013). Mcdm Methods Waspas and Multimoora: Verification of Robustness of Methods When Assessing Alternative Solutions. Economic Computation and Economic Cybernetics Studies and Research, 47(2), 5–20.