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Analysis of efficiency and performance of global retail supply chains using integrated fuzzy SWARA and Fuzzy EATWOS methods

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Abstract

The current paper aims to fill the two severe and significant gaps in the literature related to global retail chains. First, it presents the criteria set identified by performing comprehensive fieldwork together with experts highly experienced and have extensive knowledge of the retailing industry and a detailed literature review. Secondly, it proposes a robust, applicable, and powerful novel integrated MCDM framework dealing with many complicated uncertainties. As one of the significant practical and managerial implications, the current paper highlights the significance of sustainable retailing operations to better global retail chains. After the proposed model was implemented, a comprehensive sensitivity analysis was performed to test the validation of the model and its obtained results. According to the validation test results, A12 Walmart&ASDA has remained the best option for all scenarios. It has been observed that there are slight changes that did not change the overall results in the ranking performance of some decision alternatives. As a result, the analysis results prove that the proposed integrated fuzzy approach can be applied to solve highly complex decision-making problems encountered in various fields and the retailing industry.

Keywords Fuzzy SWARA · Fuzzy EATWIOS · Performance analysis · Retail chains

1 Introduction

In recent years, the balance of power in supply chains has started to change in retailers' favor. In this process, while manufacturers, who were the determinative factors in supply chains until recently, have begun to lose their positions, retailers have become more powerful actors of the supply chains. Moreover, while they have only competed in the domestic market until recently, they have become the most important actors of the global supply chains now. Indeed, the global retail market has continued to grow in recent years (Oberlo 2021). Although there has been a slight dip in the growth rate in 2019 compared to growth recorded in previous years due to COVID 19 pandemic, reports published by global market evaluation institutions indicated that the global retail market continues to grow by 4.1% annually (Oberlo 2021). Of course, those are optimistic expectations, and it means a growth rate of 24.6% in total from 2021 to 2027. Even pessimistic reports expect that the global retail market will grow at 21.4% during the forecast period. Consequently, this market size will reach USD 17.84 billion by 2027 (Fortune Business 2021) from USD 4.3 billion by 2020 (Market and Market 2021), even considering the pessimistic evaluations.

The global retail industry is the most affected industry among other supply chain actors from the COVID 19 pandemic since this pandemic has caused dramatic changes in individuals' daily lives and business life. While many customers want almost all products (including even the most minor items) to be delivered at the door, they want to pay charges at the door for the delivered products. Few people

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continue to shop traditionally due to fear of contagious disease and death from COVID 19. As a result of these developments, retailers have encountered a more competitive business environment and more complicated conditions.

First of all, new generation retailers such as Getir, Bana Bi, Gorillas, Dija, and so on have appeared in conditions of the pandemic, and they are very competitive players as they don't need to hold inventory at a high level and can-do quicker delivery. In addition, they can give discounts at a higher level than traditional retailers. Moreover, they can use almost all instruments (i.e., using high technology, making deliveries with more advanced technological tools such as electric vehicles, drones, and so on) to gain competitive advantages. Also, they can make strategic alliances with many collaborators such as suppliers and manufacturers. As is seen, traditional retailers (i.e., retail chains, independent retailers, shopping centers, and super & hypermarkets) are in serious trouble at present.

Traditional retailers stay weak to compete with these new market players, which gain strength each passing day although they have entered the retail market. Thus, they need new and powerful strategies and approaches to survive in this highly competitive business environment. Therefore, making comparatively self-evaluations concerning their performances has become more critical and crucial for retailers during and post COVID 19 global pandemics.

1.1 Research gap analysis

The current paper's general findings evinced two significant gaps in the existing literature. First, there are no criteria set commonly accepted in the current industry to assess the performance of the global retail chains. Although some previous papers presented some evaluation criteria, it is unclear how these criteria were determined, and there is no sufficient information about the used methodological frame or techniques. Thus, the proposed criteria by previous works may not be sufficiently reliable to carry out an evaluation process in real life due to these kinds of lacks. The second critical gap is related to the methodological frame that can be implemented for evaluating the performance of the global retail chains. As given in Sect. 2 in detail, most of the previous papers existing in the literature preferred to examine efficiencies of the retailers by using Data Envelopment Analysis (DEA) technique. However, DEA has many drawbacks and structural problems, and due to its limitations, it cannot meet the decision-makers' requirements related to performance analysis and evaluation in the current industry. In addition, different techniques commonly used in the existing literature are the traditional and classical MCDM methods such as AHP, TOPSIS, and DEMATEL techniques. These approaches cannot meet the requirements of the retailing industry related to robust, practical, and applicable MCDM framework that can overcome uncertainties, as they also have some drawbacks and limitations. As is seen, there is a strong motivation in the current industry to use an applicable, powerful, and effective MCDM framework to obtain more reasonable and realistic results.

In addition, the proposed objective and subjective classical frameworks by previous papers existing in the literature cannot capture and process many uncertainties. However, there are many complicated situations and ambiguities in evaluation processes, and decision-makers in the retailing industry may have to decide with insufficient information and a lack of data in real life. Thus, these approaches do not meet the requirements and cannot give accurate, reliable, and reasonable results sufficiently due to their nature and limitations.

Also, we noticed severe and surprising gaps related to decision-makers' information level on the performance analysis for performing retail chains. According to the experts' opinion, decision-makers in the retail industry focus on their companies' profitability and mostly ignore the impacts of the other factors and criteria when evaluating their performances. Furthermore, most of them have no idea or have information on creating and operating a sustainable retail chain partly.

Contrary to the vital importance of the retail industry for supply chains and other stakeholders of the business life, the literature review performed by researchers shows that the number of previous papers dealing with the performances of the global retail chain is exceptionally scarce. Besides, decision-makers and practitioners in the current industry have not been aware of the opportunities provided by a proper performance analysis approach as a proper, robust and powerful tool to improve a sustainable retail chain. As discussed above, there are severe and surprising gaps for evaluating the overall performance of the global retail chains within the perspective of sustainability in the existing literature.

Besides, three mathematical tools such as DEA, OCRA, and EATWIOS, apply to make performance analysis in the existing literature. However, DEA has many drawbacks, limitations, and structural problems (these problems are presented in detail in Sect. 2). Similarly, the operational competitiveness rating analysis (OCRA) has many drawbacks and limitations. For instance, using a single measurement to categorize factors, i.e., input and output, can make the performance analysis difficult (Wang 2006). Also, the OCRA requires using a single measurement (i.e., currency unit) to evaluate all factors (Parkan and Wu 1999). Also, it does not present an objective evaluation, and it gives higher significance to the input (cost) factors than output factors. Hence, ratings identified by the OCRA technique may not reflect the actual performance (Wang and Wang 2005).

1.2 The motivation of the work

The current study has essentially two significant aims. First, by considering the main gaps in the literature and requirements of the retail industry, the current paper aims to develop a novel methodology based on the fuzzy sets (Zadeh 1965) to analyze the efficiency and performances of the global retail chains. For this purpose, the current paper proposes to use a novel integrated fuzzy approach consisting of the extended version of the traditional SWARA and EATWOS techniques with the help of the fuzzy set theory. The main reason for integrating these techniques is to combine the advantages given below of both approaches by taking benefits from fuzzy numbers to overcome ambiguities existing in an assessment process.

The SWARA technique introduced by Keršuliene et al. (2010) has a basic algorithm that is easily applicable, simple, and practical. It is also not time-consuming and can reach results with fewer computations. In addition, it is a weighting technique through which decision-makers can reflect their experiences and knowledge (Zolfani and Saparauskas 2013; Yazdani et al. 2021). This technique is a practical tool for transforming the experts' individual opinions to the common opinion of decision-makers by ultimately providing a complete consensus among experts. Its essential advantages can be summarized as follows: i) it can rank the selection criteria concerning their degree of significance; ii) it can eliminate the insignificant criteria with the procedure of voting; iii) it can help identify the criteria with a complete consensus among decision-makers; iv) it provides an opportunity to evaluate for the ranking determined by each decision-maker (Yazdani et al. 2021). From this perspective, the SWARA technique can be defined as an approach focusing on experts' opinions, including the individual assessment of decision-makers in the scope of the evaluation process.

Also, the EATWOS technique applied for determining the performances and efficiencies of the alternatives is an MCDM approach introduced by Peters and Zelewski (2006) (Doğan 2020). The main advantages of this technique can be summarized as follows: i) it provides an opportunity to evaluate many factors and variables with fewer computations; ii) it can be applied by decision-makers easily; iii) it does not require the use of software or programs (Görçün 2021). The classical EATWIOS technique is a robust and effective tool for evaluating the overall performance of companies compared to the other performance & efficiency analysis techniques. However, the retail industry has many complicated uncertainties, and decision-makers can decide with insufficient information and a lack of data in many conditions. By considering this requirement, we decided to expand the classical EATWIOS technique with the help of the fuzzy sets to capture and process the ambiguities existing in the current industry. According to the authors' information, the current paper is the first study implementing this hybrid combination that consists of the fuzzy SWARA and the fuzzy EATWIOS in the existing literature.

The fuzzy EATWIOS can help assess the companies' overall performance by considering the impacts of both input and output factors on the performance jointly and severally. Practitioners can determine the critical factors, which can help increase overall performance, i.e., both for reducing the impacts of the input factors and increasing the impacts of the output factors. Hence, the proposed model can help focus on the most critical factors, which can affect the performance and sustainability at a high level instead of other factors, which have limited impacts on the overall performance of the global retail chains.

The second aim of the paper is to propose criteria set that is updated and suitable for real-life decision-making problems to analyze the overall performance of the global retail chains. For this purpose, this paper presents the criteria set identified by carrying out comprehensive fieldwork with highly experienced experts. Hence, the determining criteria are entirely actual and suitable to real-life decision-making problems. In addition to a comprehensive literature review, we conducted a research process consisting of many phases as an empirical study to identify the criteria set. Therefore, the evaluation criteria are robust and applicable to real-life decision-making problems, as the paper has provided justifications, which are entirely transparent and reasonable related to selecting these criteria. Hence, the proposed input and output factors can be considered by practitioners when they carry out an evaluation process in real life, and they can serve to make more realistic and reasonable assessments for decision-makers. Also, it can be inspirational for authors who carry out on this issue in the future.

The proposed model attempts to develop a systematic implementation to identify the significances of the factors and provide consideration of them by decision-makers in an evaluation process to improve the overall performance and sustainability of the global retail chains. For this purpose, the proposed model applied the fuzzy SWARA technique, an efficient and practical weighting technique. Besides, it introduces a novel performance analysis technique that is a powerful and effective mathematical tool for comparatively evaluating the overall performance of the global retail chains.

The proposed fuzzy model can help assess the companies' overall performance by considering the impacts of both input and output factors on the performance jointly and severally. Practitioners can determine the critical factors, which can help increase overall performance, i.e., both for reducing the impacts of the input factors and increasing the impacts of the output factors. Hence, the proposed model can help focus on the most critical factors, which can affect the performance and sustainability at a high level instead of other factors, which have limited impacts on the overall performance of the global retail chains.

It also aims to demonstrate the applicability of the proposed model to improve and develop the performances of global retail companies. In this context, the current paper presents the implementation of the proposed model to analyze the performance of the 12 global retail chains comparatively by considering the set of factors identified by decision-makers, consisting of eight input and three output factors.

1.3 Research questions (Hypothesis)

The current paper aims to find reasonable and realistic answers to the research questions. from this perspective, researchers prepared a set of research questions as follows. (1) Is there any mathematical model or decision support systems used to evaluate their own and other competitors' performances in the retail industry? (2) How do decision-makers make performance analyses, and what is the frequency of performance analysis for decision-makers in the related industry? (3) What is the significance of well-structured performance analysis for system design and retail chain structuring? (4) What are the input and output factors affecting the overall performance of the global retail chains? (5) How input and output factors can affect the sustainability of the global retail chains? These research questions can help the researchers to identify an applicable, reliable, and realistic methodological frame for solving these kinds of decision-making problems encountered in the field of the retail industry, as these questions can clearly and highlight the gaps existing in the literature, in addition to the real problems encountered in the retail industry.

1.4 Structure of the article

The rest of the paper is organized as follows. In Sect. 2, we performed a comprehensive literature review. In Sect. 3, the novel integrated fuzzy MCDM model consisting of the fuzzy SWARA and the fuzzy EATWIOS techniques and its primary model's basic algorithm are presented. In Sect. 4, as a numerical example, the proposed model is applied to measure the performances of the global retail chains. Then, a comprehensive sensitivity analysis was performed to test the validation of the proposed model and its results. In Sect. 5, the obtained results of the current study are discussed, and the managerial implications of the paper are summarized. In Sect. 6, the work is concluded, and existing limitations and suggestions for future work are presented.

2 Literature review

This section provides a detailed literature review concerning three primary aspects of the decision-making problem. First, it reviews the studies performing general evaluation without using a mathematical tool or decision support system. Secondly, it examines the previous works applying the data envelopment analysis (DEA) technique that is an efficiency analysis approach. Thirdly, it overviews papers implementing MCDM frameworks for evaluating the global retail chains' performance.

2.1 General overviews for the retail industry

Recent research on the global retail chains and their productivity shows that researchers' interest in the retailing industry's sustainability, performance, efficiency, and productivity has continued to grow. For instance, Thangavelu (2019) examined Singapore's retail industry's value chain. He indicated that there are positive correlations between the productivity of the retail industry and countries' economic development and growth. Also, this paper highlighted the critical factors affecting the productivity of the current industry.

Migdadi and Abdel-Rahman (2020) evaluated the impact of retailers' location on the perceived service quality of the industry by performing a comprehensive survey with a sample of 1055 consumers to evaluate the overall performances of the retailers in Jordan. Swoboda et al. (2008) assessed the international retail chains concerning their productivities, and they make a judgment that there is a meaningful correlation between productivity and becoming internationalized for retail firms. Christopherson (2007) examined the failures in the global retail industry by considering Walmart's failure story in the German retail market. According to the main finding of the work, the international investment process in the retail industry is not static, inexorable, and linear; on the contrary, it has a dynamic characteristic, and it can be affected to the productivity of the global retail firms directly. Also, Wang et al. (2018) tried to show connections between the retailers' performances and incentives applied to increase customer satisfaction. In addition to these studies, there are many papers focused on the efficiency and performance of the retail industry.

However, these previous papers have some limitations. First, they (Thangavelu 2019; Migdadi and Abdel-Rahman 2020; Swoboda et al. 2008; Christopherson 2007; Wang et al. 2018) did not propose a mathematical tool or decision support system as a methodological frame to evaluate the performances of the retail industry. Besides, some of them dealt with the dynamics of the local retail market (Thangavelu 2019) instead of the global retail market.

Many previous papers deal with retailing management in the existing literature. However, a great majority of these papers are not related to the focal point of the current paper. For instance, Gao et al. (2017) dealt with the bullwhip effect in an online retail supply chain. Proposed technology road mapping for the retail industry. Also, many papers focus on different subjects related to the retail industry, such as outsourcing for the retail industry (Niu et al. 2021), retail supply chain risk management (Wu et al. 2013), competition between online and conventional retailers (Li et al. 2015), distribution strategies (Koster 2003). Although these papers are exciting and have many valuable contributions to the literature, they are not related to the current paper's primary subject and focal point. These papers did not attempt to develop a methodological frame for evaluating the performances of the global retail chains. Some limitations of other previous works are given in Table 2.

Siddiqui et al. (2021) introduced a novel forecasting model, and they indicated a strong correlation between accurate and reasonable forecasting and the performance of the supply chains. Also, forecasting accuracy can serve to improve supply chain operations. Also, Rusca et al. (2020) examined a different industry concerning productivity, and they proposed a simulation technique developed by them to evaluate container terminals' efficiency, productivity, and overall performance. Besides, Ahmed et al. (2021) carried out an interesting and exciting study to evaluate the impacts of the internet of things (IoT) on supply chain performance. For this purpose, they identified the set of criteria concerning the quality of services, and they highlighted that IoT technologies could help improve the productivity of the supply chains and make it easy to manage the performance of the SCs.

In addition, it has been observed that there is no sufficiently robust, applicable, and powerful mathematical model or computational tool that can overcome the complex uncertainties used to measure the performances of the players in the retail industry. In addition, although there are some well-meaning attempts to suggest a methodological frame in the literature, the contributions of these previous studies have remained limited. These limitations consist of the central gap of the literature. The main gaps related to the lack of papers and their theoretical contributions are presented in Table 1.

2.2 Efficiency analysis with the DEA approach for the retail industry

Data Envelopment Analysis (DEA) technique is the most commonly used technique by the earlier studies to measure efficiencies of retailers in the literature as given in Table 1. However, the contributions of these papers are limited, and the proposed technique cannot be used as a methodological frame for practitioners who are decision-makers in the field of retailing since the DEA technique has some limitations. Initially, this efficiency analysis technique is susceptible to the selection of criteria. If appropriate input and output factors are not selected carefully, many ambiguities and aberrations in the obtained results are likely to emerge. Also, the number of factors can affect the analysis results on the efficiency of firms, and each criterion added can cause dramatic changes in the results. More importantly, this technique does not consider ambiguities occurring in an evaluation process since it deals with only crisp values.

2.3 Evaluation of the retail industry with MCDM approaches

When we reviewed the previous studies applying MCDM frameworks to evaluate the retail chains' performance, it has been observed that the number of studies is exceptionally scarce. These previous papers collected from scientific databases such as Web of Science (WoS), SCOPUS, and Google Scholar are presented below. Tirkolaee et al. (2020) examined the best way to enhance the supply chains' sustainability and reliability by applying some MCDM fuzzy frameworks such as Fuzzy ANP, Fuzzy DEMATEL, Fuzzy TOPSIS, Weighted goal programming. They indicated that sustainable-reliable supplier selection could increase the performance of the supply chains. Guo et al. (2020) examined the business risk evaluation of retail electricity companies in China with the help of an extended version of the Best and Worst Method (BWM). Since the selected criteria are unique to the firm, it did not propose a generalized methodology that can be applied to solve similar decision-making problems and did not suggest a comparative analysis.

Furthermore, although the proposed method is an advantageous technique, it can only be implemented to calculate the weights of criteria. In addition, the BWM technique requires linear programming information; hence, it may stay insufficient concerning applicability depending on decision-makers' knowledge and information level on this issue. Comparatively analyzing a firm's performance is not possible by using this technique.

Also, some previous papers on the literature dealt with retail food chains concerning product safety (Sufiyan et al. 2019; Wang et al. 2014; Aramyan et al. 2007). These studies mainly used classical MCDM techniques such as AHP, DEMATEL, TOPSIS, and so on based on crisp values. However, collecting crisp values may not be possible, and many uncertainties may exist in an evaluation process performed to measure the retailer companies' performance. Also, some papers used the AHP technique for facility selection for an omnichannel retail chain (Jain et al. 2020). Although this paper is not related to the main subject of the current paper, it is an excellent example that applies an MCDM technique.

However, the decision framework proposed by this paper has many drawbacks and limitations. First, the AHP technique is the most criticized approach, as it suffers from the rank reversal problem. The ranking results may change dramatically if we add or remove a criterion or decision alternative. Because of that, the AHP technique is not a sufficiently reliable approach, and decision-makers cannot be sure of the accuracy of the obtained results. Also, this technique needs many pairwise comparisons and computations; it can increase the complexity of the basic algorithm of the technique. Moreover, it requires the use of additional techniques for calculating consistency. Similar drawbacks and structural problems exist for the TOPSIS and DEMATEL techniques.

In addition, the fuzzy AHP technique is an MCDM method applied to determine the retailers' performances in the literature (Haldar et al. 2018), but it has some limitations. For example, it requires time-consuming and complicated computational operations, and deterioration and deviations are widespread when the number of factors is changed; hence it is susceptible to the number of factors. Also, it requires extra computations to determine whether the calculations are consistent. Even though it tries to deal with uncertain situations, the current lack of this method restrains the opportunity from being a practical tool in the retailing industry. Even though the number of these papers is few, the fuzzy TOPSIS (Rouyendegh et al. 2018) and traditional TOPSIS techniques (Kabir and Hasin 2012) were also used for measuring retailers' performances in the existing literature. These techniques have many drawbacks because when changes are made, i.e., a criterion alternative is removed or added, the ranking performance of the alternatives is changed dramatically. Therefore, it is not easy to obtain consistent results by applying these techniques.

3 The proposed MCDM framework

This section presents the basic algorithm of the suggested integrated fuzzy approach. The algorithm and general structure of the model are given in Fig. 1.

3.1 Preliminaries

Zadeh (1965) introduced the fuzzy set theory, which is a valuable technique enabling us to deal with ambiguities for decision-makers. The fuzzy sets have degrees of membership, and the fuzzy set theory uses fuzzy triangular numbers (TFNs) to convert the linguistic evaluations.

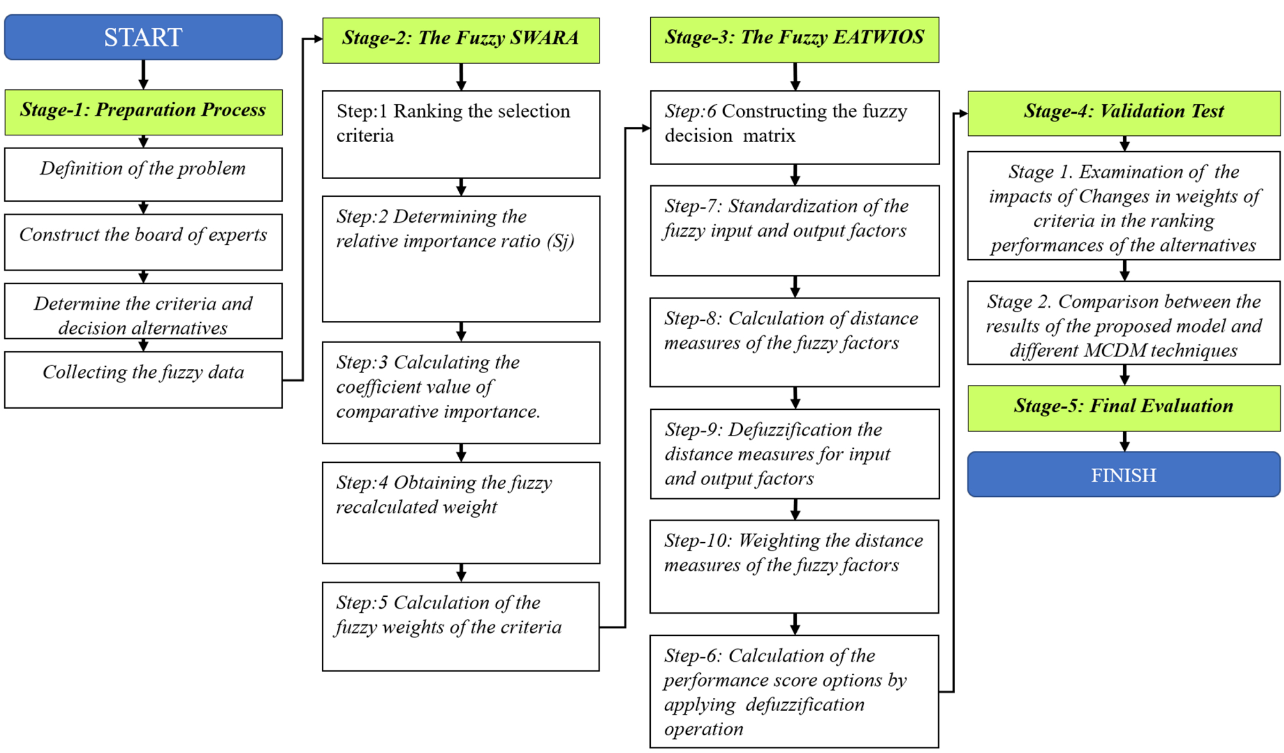

Fig. 1 The proposed integrated MCDM approach

Table 1 The main gaps related to efficiency & performance analysis techniques in the literature

Author(s)	Review Area	Techniques	Research Gap(s)
Gao et al. 2017	The bullwhip effect in an online retail supply chain	Statistical Analysis	There is no methodological framework
	Proposed technology road mapping	Foresight	It only consists of foresight for improving technology
Niu et al. 2021	Outsourcing for the retail industry	Benchmarking	It made benchmarking only without an MCDM model
Wu et al. 2013	Retail supply chain risk management	Agent-based simulation	It examined risk factors in retailing processes
Li et al. 2015	Competition between online and conventional retailers	Pareto Analysis	It is not related to performance analysis directly
Koster 2003	Distribution strategies	Statistical Analysis	It is limited to statistical analysis
Thangavelu 2019	The value chain of the retail industry in Singapore	Benchmarking	There is no MCDM tool
Migdadi and Rahman 2020	The impact of retailers' location on the perceived service quality	Survey	There is no MCDM tool
Swoboda et al. 2008	The overall performances of the retailers in Jordan	Survey	There is no MCDM tool
Christopherson 2007	Failures in the global retail industry	A case study	The findings of the paper cannot be generalized
Wang et al. 2018	Connections between the retailers' performances and incentives	A case study	The findings of the paper cannot be generalized
Guo et al. 2020	Business risk evaluation of retail electricity companies in China	Best and Worst Method	It only focused on identifying the criteria
Sufiyan et al. 2019	Retail food chains concerning product safety	Fuzzy DEMATEL	It dealt with an only food chain
Wang et al. 2014	Retail food chains concerning product safety	AHP & TOPSIS	It focused only food chain and rank reversal problem
	Retail food chains concerning product safety	TOPSIS	It focused only food chain and rank reversal problem
Aramyan et al. 2007	Retail food chains concerning product safety	A case study	The findings of the paper cannot be generalized
Jain et al. 2020	Facility selection for an omnichannel retail chain	AHP	The rank reversal problem & structural problems
Haldar et al. 2018	Measuring retailers' performances	Fuzzy AHP	The rank reversal problem & structural problems
Rouyendegh et al. 2018	Measuring retailers' performances	Fuzzy TOPSIS	The rank reversal problem & structural problems
Kabir and Hasin 2012	Measuring retailers' performances	TOPSIS	The rank reversal problem & structural problems
Siddiqui et al. (2021)	A novel forecasting model for the performance of the SCs	ARIMA & Holt Model	Different industry and there is no MCDM tool
Rusca et al. (2020)	Performance analysis for container terminals	Simulation Model	Different industry and there is no MCDM tool
Ahmed et al. (2021)	IoT technologies and impacts on the performance of the SCs	Time-Period Analysis	Different industry and there is no MCDM tool
Ko et al. 2017	Efficiencies of retailers	DEA	Limitations of the DEA technique
Barros 2006 [1]	Efficiencies of retailers	DEA	Limitations of the DEA technique
	Efficiencies of retailers	DEA	Limitations of the DEA technique
Donthu and Yoo 1998 [3]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Thomas et al. 1998 [11]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Keh and Chu 2003 [6]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Sellers-Rubio and Mas-Ruiz 2006 [9]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Mostafa 2009 [7]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Gupta and Mittal 2010 [5]	Efficiencies of retailers	DEA	Limitations of the DEA technique

Table 1 (continued)

Author(s)	Review Area	Techniques	Research Gap(s)
Sharma and Choudary [10]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Barros 2006; Gandhi and Shankar 2014 [4]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Perrigot and Barros 2008 [8]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Yu and Ramanathan 2008 [13]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Yu and Ramanathan 2009 [14]	Efficiencies of retailers	DEA	Limitations of the DEA technique
Uyar et al. 2013 [12]	Efficiencies of retailers	DEA	Limitations of the DEA technique

A fuzzy number $\tilde{A}$ on R to be an FTN if its membership function $\mu_{\tilde{A}}(x)$: R→[0,1] is equal to the following Eq. (1) (Zadeh 1965):

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-l}{m-l} & l \le x \le m \\ \frac{u-x}{u-m} & m \le x \le u \\ 0 & otherwise \end{cases} \tag{1}$$

As is seen from Eq. (1), the values of l, m, and u symbolize TFNs, and while l is the minimum value, u denotes the maximum value of the fuzzy number, and m represents the moderate value of the fuzzy number. The fuzzy set theory has been used by many studies (Petrovic et al. 2019; Deveci et al. 2020; Pamucar and Ecer 2020; Ecer and Pamucar 2020).

3.2 The fuzzy SWARA technique

The fuzzy Step-wise Weight Assessment Ratio Analysis (F-SWARA) technique is an extended version of the traditional SWARA method introduced. Besides being a novel technique (Perçin 2018), it is a useful weighting method since it can calculate weights of criteria with fewer computational operations than other traditional weighting techniques. According to Mardani et al. (2017), it can estimate decision makers' preferences considering the significances of the criteria. Because this technique is maximally consistent, it does not require an additional consistency analysis. The basic algorithm of the fuzzy SWARA technique consisting of five implementation steps is given below: (Mavi et al. 2017; Perçin 2018; Zolfani and Saparauskas 2013).

Step 1. Ranking the selection criteria: decision-makers rank the selection criteria in descending order of their significance. Then, the final significance score of each factor is calculated by applying the arithmetic mean of evaluations performed by experts for each criterion.

Step 2. Determining the relative importance ratio $\left(\widetilde{S}_j\right)$: The relative importance ratio denotes the significance of a factor compared to the previous one in terms of percentage. Experts make linguistic evaluations to determine the relative importance ratio for each criterion in each pairwise comparison. Next, these evaluations are converted to the corresponding triangular fuzzy numbers (TFNs) in the evaluation scale given in Table 6.

Step 3. Calculating the coefficient value of comparative importance: the coefficient value of comparative importance $\left(\widetilde{k}_j\right)$ value for each criterion is computed with the help of Eq. (2).

$$\widetilde{k}_j = \begin{cases} 1, j = 1 \\ \widetilde{S}_j + 1, j > 1 \end{cases} \tag{2}$$

Step 4: Obtaining the fuzzy recalculated weight: The fuzzy intermediate weights of the criteria $\left(\widetilde{q}_j\right)$ are computed by using Eq. (3).

$$\widetilde{q}_j = \begin{cases} 1, j = 1 \\ \frac{\widetilde{q}_{j-1}}{\widetilde{k}_j}, j > 1 \end{cases} \tag{3}$$

Table 2 Details of the Members of the Board of Experts

No	Graduation Degree	Duty	Experience	Institute
DM-1	Logistics & Supply Chain Man	Operation Manager	16	Metro Gross
DM-2	Business Management	General Manager	18	Metro Mall
DM-3	Logistics Management	Sales Manager	17	Polar XP
DM-4	Business Management	Sales Manager	17	Araz SM
DM-5	Electrical Engineering	Head of Sales Dept	21	Hepsiburada

$where; \widetilde{q}_j = \left(\widetilde{q}_j^l, \widetilde{q}_j^m, \widetilde{q}_j^u\right)$

Step 5: Calculation of the fuzzy weights of the criteria: In the step of the fuzzy SWARA method, weight values of criteria are calculated as follows:

$$\widetilde{w}_j = \frac{\widetilde{q}_j}{\sum_{k=1}^{n} \widetilde{q}_j} \tag{4}$$

where $\widetilde{w}_j$ symbolizes the relative fuzzy weight of the criterion j, $\widetilde{w}_j = \left(\widetilde{w}_j^l, \widetilde{w}_j^m, \widetilde{w}_j^u\right)$.

Step 6. Calculation of the weights of the criteria: In the final step of the fuzzy SWARA method, fuzzy weight values are converted to the final weight values for criteria by applying defuzzification operations as follows:

$$w_j = \frac{\left(w_j^u - w_j^l\right) + \left(w_j^m - w_j^l\right) + \left(w_j^l\right)}{3} \tag{5}$$

3.3 The fuzzy EATWIOS technique

Traditional EATWOS (Efficiency Analysis Technique With Output Satisficing) technique introduced by Peters and Zelewski (2006) is a performance analysis technique. It was extended by adding the satisfaction level approach developed by Simon (1979). Some relative advantages of this technique are compared to other performance & efficiency analysis techniques such as DEA and OCRA. Firstly, it can propose ways to improve the performance, giving a relatively more consistent result than others. In addition, the closeness of factors to the satisfaction level may be a helpful indicator for decision-makers to determine the practical way to improve performance.

More importantly, an optimal solution may not be reasonable for decision-makers at all times, and it may also not meet real-life requirements. Hence, Peters et al. (2012) indicated that the satisfaction level is more reasonable and significant than an optimal result concerning meeting the real-life requirements. Also, this technique can give more accurate and realistic results with fewer computational operations. In this paper, the traditional EATWOS technique is extended with the help of the fuzzy set theory developed by Zadeh (1965) to deal with uncertainties existing in real life. The basic algorithm of the fuzzy Efficiency Analysis Technique With Output Satisficing (F-EATWOS) approach is given as follows:

Step 1. Constructing the fuzzy decision matrix: In this step, k number of experts $\{k_1, k_2, ..., k_n\}$ perform linguistic evaluations for decision alternatives by considering the linguistic terms given in the linguistic evaluation scale. Experts evaluate options by considering i number of inputs $\{i_1, i_2, ..., i_n\}$ and o number of output factors $\{o_1, o_2, ..., o_n\}$ separately. Then, linguistic evaluations are converted to the corresponding TFNs in the linguistic evaluation scale given in Table 8, and the k number of fuzzy matrices are generated.

$$\widetilde{X}^1 = \begin{bmatrix} x_{11}^1 & x_{12}^1 & \dots & x_{1n}^1 \\ x_{21}^1 & x_{22}^1 & \dots & x_{2n}^1 \\ x_{31}^1 & x_{32}^1 & \dots & x_{3n}^1 \\ x_{m1}^1 & x_{m2}^1 & \dots & x_{mn}^1 \end{bmatrix}, \widetilde{X}^2 = \begin{bmatrix} x_{11}^2 & x_{12}^2 & \dots & x_{1n}^2 \\ x_{21}^2 & x_{22}^2 & \dots & x_{2n}^2 \\ x_{31}^2 & x_{32}^2 & \dots & x_{3n}^2 \\ x_{m1}^2 & x_{m2}^2 & \dots & x_{mn}^2 \end{bmatrix}, \dots, \widetilde{X}^k = \begin{bmatrix} x_{11}^k & x_{12}^k & \dots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \dots & x_{2n}^k \\ x_{31}^k & x_{32}^k & \dots & x_{3n}^k \\ x_{m1}^k & x_{m2}^k & \dots & x_{mn}^k \end{bmatrix} \tag{6}$$

$$\widetilde{Y}^1 = \begin{bmatrix} y_{11}^1 & y_{12}^1 & \dots & y_{1n}^1 \\ y_{21}^1 & y_{22}^1 & \dots & y_{2n}^1 \\ y_{31}^1 & y_{32}^1 & \dots & y_{3n}^1 \\ y_{m1}^1 & y_{m2}^1 & \dots & y_{mn}^1 \end{bmatrix}, \widetilde{Y}^2 = \begin{bmatrix} y_{11}^2 & y_{12}^2 & \dots & y_{1n}^2 \\ y_{21}^2 & y_{22}^2 & \dots & y_{2n}^2 \\ y_{31}^2 & y_{32}^2 & \dots & y_{3n}^2 \\ y_{m1}^2 & y_{m2}^2 & \dots & y_{mn}^2 \end{bmatrix}, \dots, \widetilde{Y}^k = \begin{bmatrix} y_{11}^k & y_{12}^k & \dots & y_{1n}^k \\ y_{21}^k & y_{22}^k & \dots & y_{2n}^k \\ y_{31}^k & y_{32}^k & \dots & y_{3n}^k \\ y_{m1}^k & y_{m2}^k & \dots & y_{mn}^k \end{bmatrix} \tag{7}$$

Next, these matrices are combined with the help of the geometric mean operation, and the aggregated initial fuzzy decision input matrix and the aggregated initial fuzzy decision output matrix are constructed. The fuzzy matrices are presented as follows:

$$\widetilde{X} = \begin{bmatrix} \widetilde{x}_{11} & \widetilde{x}_{12} & \dots & \widetilde{x}_{1n} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & \dots & \widetilde{x}_{2n} \\ \widetilde{x}_{31} & \widetilde{x}_{32} & \dots & \widetilde{x}_{3n} \\ \widetilde{x}_{m1} & \widetilde{x}_{m2} & \dots & \widetilde{x}_{mn} \end{bmatrix}; \widetilde{Y} = \begin{bmatrix} \widetilde{y}_{11} & \widetilde{y}_{12} & \dots & \widetilde{y}_{1n} \\ \widetilde{y}_{21} & \widetilde{y}_{22} & \dots & \widetilde{y}_{2n} \\ \widetilde{y}_{31} & \widetilde{y}_{32} & \dots & \widetilde{y}_{3n} \\ \widetilde{y}_{m1} & \widetilde{y}_{m2} & \dots & \widetilde{y}_{mn} \end{bmatrix} \tag{8}$$

where $\widetilde{x}_{ij} = \left(\widetilde{x}_{ij}^l, \widetilde{x}_{ij}^m, \widetilde{x}_{ij}^u\right)$ and $\widetilde{y}_{ij} = \left(\widetilde{y}_{ij}^l, \widetilde{y}_{ij}^m, \widetilde{y}_{ij}^u\right)$ are the aggregated TFNs, and these values are calculated with the help of Eqs. (9) and (10).

$$\widetilde{x}_{ij} = \left(\widetilde{x}_{ij}^l, \widetilde{x}_{ij}^m, \widetilde{x}_{ij}^u\right) = \left(\widetilde{x}_{ij}^l = \sqrt[k]{\prod_{i=1}^{k} \widetilde{x}_{ij}^k}\right), \left(\widetilde{x}_{ij}^m = \sqrt[k]{\prod_{i=1}^{k} \widetilde{x}_{ij}^k}\right), \left(\widetilde{x}_{ij}^u = \sqrt[k]{\prod_{i=1}^{k} \widetilde{x}_{ij}^k}\right) \tag{9}$$

$$\widetilde{y}_{ij} = \left(\widetilde{y}_{ij}^{l}, \widetilde{y}_{ij}^{m}, \widetilde{y}_{ij}^{u}\right) = \left(\widetilde{y}_{ij}^{l} = \sqrt[k]{\prod_{i=1}^{k} \widetilde{y}_{ij}^{k}}\right), \left(\widetilde{y}_{ij}^{m} = \sqrt[k]{\prod_{i=1}^{k} \widetilde{y}_{ij}^{k}}\right), \left(\widetilde{y}_{ij}^{u} = \sqrt[k]{\prod_{i=1}^{k} \widetilde{y}_{ij}^{k}}\right) \tag{10}$$

where $\widetilde{x}_{ij}^{k}$ and $\widetilde{y}_{ij}^{k}$ are the preferences of the k^{th} expert considering the input and output factors, k is the total number of experts.

Step 2. Standardization of the fuzzy input and output factors: the initial fuzzy input and output matrices are normalized with the help of Eqs. (11) and (12). Then, the standardized fuzzy input and output matrices are generated as follows:

$$\widetilde{s}_{ij} = \left[\left(\frac{\widetilde{x}_{ij}^{l}}{\sqrt{\sum_{i=1}^{m}\left(\widetilde{x}_{ij}^{l}\right)^{2}}}\right); \left(\frac{\widetilde{x}_{ij}^{m}}{\sqrt{\sum_{i=1}^{m}\left(\widetilde{x}_{ij}^{m}\right)^{2}}}\right); \left(\frac{\widetilde{x}_{ij}^{u}}{\sqrt{\sum_{i=1}^{m}\left(\widetilde{x}_{ij}^{u}\right)^{2}}}\right)\right] \tag{11}$$

$$\widetilde{r}_{ij} = \left[\left(\frac{\widetilde{y}_{ij}^{l}}{\sqrt{\sum_{i=1}^{m}\left(\widetilde{y}_{ij}^{l}\right)^{2}}}\right); \left(\frac{\widetilde{y}_{ij}^{m}}{\sqrt{\sum_{i=1}^{m}\left(\widetilde{y}_{ij}^{m}\right)^{2}}}\right); \left(\frac{\widetilde{y}_{ij}^{u}}{\sqrt{\sum_{i=1}^{m}\left(\widetilde{y}_{ij}^{u}\right)^{2}}}\right)\right] \tag{12}$$

$$\widetilde{S} = \begin{bmatrix} \widetilde{s}_{11} & \widetilde{s}_{12} & \dots & \widetilde{s}_{1n} \\ \widetilde{s}_{21} & \widetilde{s}_{22} & \dots & \widetilde{s}_{2n} \\ \widetilde{s}_{31} & \widetilde{s}_{32} & \dots & \widetilde{s}_{3n} \\ \widetilde{s}_{m1} & \widetilde{s}_{m2} & \dots & \widetilde{s}_{mn} \end{bmatrix}; \widetilde{R} = \begin{bmatrix} \widetilde{r}_{11} & \widetilde{r}_{12} & \dots & \widetilde{r}_{1n} \\ \widetilde{r}_{21} & \widetilde{r}_{22} & \dots & \widetilde{r}_{2n} \\ \widetilde{r}_{31} & \widetilde{r}_{32} & \dots & \widetilde{r}_{3n} \\ \widetilde{r}_{m1} & \widetilde{r}_{m2} & \dots & \widetilde{r}_{mn} \end{bmatrix} \tag{13}$$

Step 3. Calculation of distance measures of the fuzzy factors: While the distance measures of the input factors are computed by applying Eqs. (14) and (15), the distance measures for output factors are calculated with the help of Eqs. (16) and (17).

$$\widetilde{ip}_{ij} = 1 + \left(\widetilde{s}_{ij} - \widetilde{s}_{ij}^{*}\right) \tag{14}$$

where $\widetilde{s}_{ij}^{*}$ denotes the minimum values of each column, and it is defined as follows:

$$\widetilde{s}_{ij}^{*} = \min\left\{\overrightarrow{\widetilde{s}_{ij}^{l}}; \overrightarrow{\widetilde{s}_{ij}^{m}}; \overrightarrow{\widetilde{s}_{ij}^{u}}\right\} \tag{15}$$

Next, the distance measures for output factors are calculated as follows:

$$\widetilde{op}_{ij} = 1 - \left(\widetilde{r}_{ij}^{*} - \widetilde{r}_{ij}\right) \tag{16}$$

where $\widetilde{r}_{ij}^{*}$ denotes the maximum values of each column, and it is defined as follows:

$$\widetilde{r}_{ij}^{*} = \min\left\{\overrightarrow{\widetilde{r}_{ij}^{l}}; \overrightarrow{\widetilde{r}_{ij}^{m}}; \overrightarrow{\widetilde{r}_{ij}^{u}}\right\} \tag{17}$$

Step 4. Defuzzification of the distance measures for input and output factors: In this step, the values of the distance measures for output and input factors are converted to crisp values using the Best Nonfuzzy Performance Value—(BNP) technique in Eq. (18).

$$d_{cr} = \frac{(u - l) + (m - l)}{3} + l_{s} \tag{18}$$

Step 5. Weighting the distance measures: the defuzzied distance measures are weighted with the help of Eqs. (19) and (20).

$$ip_{ij}^{w} = \widetilde{ip}_{ij}.w_{ij}^{*} \tag{19}$$

$$op_{ij}^{w} = op_{ij}.w_{ij}^{-} \tag{20}$$

Step 6. Calculation of the fuzzy performance score of the decision options and ranking: each decision alternative's final input value is divided into each option's final input value by applying the following equation.

$$F_{i} = \frac{\sum_{j=1}^{J} ip_{ij}^{w}}{\sum_{k=1}^{K} op_{ij}^{w}} \tag{21}$$

F_i denotes the final performance score of each decision alternative.

Next, decision options are ranked by considering the final performance scores $\left(F_i\right)$ of the alternatives. While the option with the highest performance score is determined as the best option, the lowest performance score is accepted as the worst option.

4 Evaluation of performances of the global retail chains

Before implementing the basic algorithm of the proposed model, we designed a preparation process consisting of three phases. In the first phase, we constructed the board of experts with five highly experienced people with extensive retail industry knowledge to obtain more rational, realistic, and reasonable results. In the second phase, we identified the main problems and research questions. Finally, we determined the input and output factors and decision alternatives together with the members of the board of experts. Details of this process are presented in the following section.

4.1 Constructing the board of experts

Here, to demonstrate the implementation of the proposed fuzzy model, we applied it to measure the performances of the global retail chains comparatively. In the group decision-making process, five highly experienced and knowledgeable professionals in the retail industry were selected as the board of experts. Details of the selected members of the board of experts are presented in Table 2.

Researchers determined three conditions to be a member of the board of experts as follows: The first is to be an experienced professional in the field of the retail industry for at least 15 years; the second is to be a senior executive in a retail chain company; the third is to be a member of the board in a professional association.

4.2 Problem description

The global retail chains are essential actors managing the global supply chains and one of the most crucial parts of the supply chains. Thus, well-structuring these chains have a vital significance concerning engineering and managerial applications; a retail chain that is not well-designed or well-operated may cause extra costs and inefficiencies. When it is evaluated from this perspective, evaluating the overall performance of the retail chains by including the technical, operational, and financial performances of these chains can provide valuable contributions in restructuring the retail chains or improving the existing systems. Realistic and well-structured performance analysis can signal decision-makers which aspects (i.e., financial, operational, or technical) should be developed. Otherwise, a general improvement approach may cause a needless evaluation of the already well-operating processes and unnecessarily cause resource utilization. Whereas a retail chain has high financial performance, it may show operational or technical underperformance. Therefore, focusing on improving the operational or technical performance of the retail chain instead of financial performance can provide better and more accurate results.

Besides, developing an approach for continuous benchmarking between a retail chain and other competitors may also be an essential component of the continuous improvement approach, as retailing processes are highly dynamic systems. A well-structured performance analysis from both engineering and management perspectives can make it possible to manage the effective and productive retailing processes and the system design. Therefore, a realistic, robust and applicable performance analysis approach is the main requirement for system design, which is one of the main components of engineering and management processes. In addition to methodological advantages, a measurement system developed for performance analysis should be applied easily by decision-makers. Also, decision-makers may decide with insufficient information and lack of data in the retail industry since it may not be possible to get crisp and definite data in many situations. Therefore, the methodological frame that is used has to overcome uncertainties. As indicated in the previous sections, the number of studies dealing with the overall performances, including technical, financial, and operational performances of the retail chains using MCDM approaches, is extremely scarce.

Also, the large part of the previous papers dealt with operational or financial performances of the retail chains and cannot present a methodological frame that can evaluate all efficiencies of the global and local retail chains together. Moreover, in many studies using MCDM approaches, the proposed methodologies have many structural problems and drawbacks. As a result, we noticed severe and surprising gaps in the existing literature. The main reason for these gaps is the structural problems and disadvantages of the MCDM techniques proposed by these previous studies. Hence, no commonly-held methodological framework is used to measure the related industry's retail chains' performances. Therefore, applications and approaches related to system design are not sufficiently reliable, as there is no methodological frame for identifying the overall performances of the chains in the retail industry.

The research questions presented in the first section were directed to the decision-makers, and the obtained evaluations were recorded. According to the general opinions of the experts, there is not a generally accepted mathematical model or decision support system used for assessing the performances of the global retail chains in the retailing industry. Also, decision-makers in the related industry make performance analyses periodically, and they evaluate their companies' performances based on their experiences and individual judgments. Besides, a performance analysis focusing on technical, operational, and financial efficiencies is not a common approach; financial performance analysis is a frequently seen evaluation technique in the retail industry field. In addition, there are no commonly used input and output factors in the related industry. Lastly, preparing a list for criteria and decision alternatives was requested from decision-makers. After the lists were collected, researchers eliminated the repetitive criteria and options, and the final criteria and alternatives were determined by providing a complete consensus among experts. Details of this process are given in the following section.

Also, the current study has been derived from a real-life decision-making problem. one of the biggest dairy product supply chains in Turkey needed a powerful and practical performance analysis technique to evaluate existing and potential retail chains, as existing approaches could not meet their requirements. For this

Table 3 The selection criteria identified by experts

Code	Criteria	DM1	DM2	DM3	DM4	DM5	DM6
I-1	Shareholder's equity	✓			✓		✓
I-2	Number of Country		✓	✓	✓	✓	✓
I-3	The Number of Branches	✓			✓		
I-4	The Number of Employees (M)		✓				
I-5	Current Assets				✓		
I-6	Sales Costs	✓		✓		✓	✓
I-7	Operating Costs		✓		✓		
I-8	Size of Outlet	✓		✓			✓
O-1	Operating Profit/Loss EBIT		✓			✓	✓
O-2	Net Sales	✓			✓		✓
O-3	The ratio of Operating Margin/Net Sales	✓	✓		✓	✓	

purpose, they contacted the researchers and requested to develop a practical, robust, and reliable evaluation tool. After the first meetings with the company's senior executives, we noticed that they don't rely on the existing decision-making tools and doubt that they give good and accurate results because traditional performance analysis techniques require crisp and definite values. However, decision-makers in the retail industry decide with insufficient information and lack of data in most situations, as there are many complicated ambiguities in an assessment process. Thus, the traditional decision-making approaches may not be functional concerning evaluating the overall performances of the global retail chains.

By keeping these limitations and requirements in mind, since the traditional EATWIOS has many advantages and superiorities compared to the OCRA and the DEA approach, which are the other alternative performance & efficiency analysis techniques, we decided to develop an extended version of the traditional EATWIOS technique with the help of the fuzzy set theory. Then, we constructed and followed the basic algorithm of the proposed model presented in Fig. 1 with the company's executives. Besides, we generated a board of experts from outside to provide maximally objective unbiased evaluations. Hence, these top managers monitored the progress and all phases of the research process, but they did not intervene in the evaluation processes.

As a result, both engineers and managers need an applicable, robust, continuous, and powerful performance evaluation system to design a well-operating retailing system or develop continuous improvement applications in an existing system. Thus, the proposed methodological framework may be a valuable and applicable tool for engineers and managers. In addition, the model can respond to requirements of performance analysis and evaluation in various fields such as engineering, management, logistics, supply chain management.

4.3 Identifying the input & output factors and decision alternatives

The researcher held many meetings with these experts. In addition, they performed many face-to-face interviews with these professionals to determine the input and output factors in the first stage of the research process. In this process, preparing a list for input and output factors was requested from each expert at the end of the face-to-face interviews to determine the evaluation criteria (as mentioned above), in addition to a comprehensive literature review performed to determine the criteria used in the previous studies as presented in Appendix 1.

After the lists were collected, researchers removed the repetitive criterion; and the latest list was formed by adding some criteria used in the literature. At the end of this process, researchers requested experts to give a score between 1 and 9 for each criterion, and the final significance value of each factor was determined by calculating the geometric means of these scores given by experts for each factor. The final input and output factors taking scores over five on average were determined by providing a complete consensus among experts in the current paper. The determining input and output factors are given in Table 3.

Next, the decision alternatives were determined together with experts as follows (see Table 4):

Table 4 The decision alternatives for evaluating the global retail chains

Code	ALTERNATIVE	Code	ALTERNATIVE
A1	BİM	A7	METRO GM
A2	ŞOK	A8	SPAR
A3	KİPA	A9	TESCO
A4	MİGROS	A10	SAINSBURY'S
A5	CARREFOUR	A11	BİZİM
A6	MARKS&SPENCER	A12	WALMART&ASDA

Table 5 Linguistic weighting scale for criteria (Perçin 2018)

Linguistic terms	Abbr	Triangular Fuzzy Number (TFNs) for tangible criteria		
		l	*m*	*u*
Very Low	VL	0.00	0.00	0.30
Low	L	0.00	0.25	0.50
Medium	M	0.30	0.50	0.70
High	H	0.50	0.75	1.00
Very High	VH	0.70	1,00	1.00

(a) Implementation of the fuzzy SWARA technique

After determining factors and decision alternatives, experts performed linguistic evaluations for input & output factors by considering the linguistic evaluation scale given in Table 5.

In this step, each expert ranked the criteria, then by calculating the geometric mean of ranking scores of each criterion, the final ranks of the factors were determined presented in Appendix 2. Then, the relative importance ratios for each criterion are determined in Appendix 3. Next, the remaining steps of the fuzzy SWARA techniques weight values of the factors were computed.

When the results of the analysis shown in Table 6 are evaluated, the essential input factor is determined as "Operating Cost" (I7) with the relative importance score of 0.319, and the least important factor is also "Size of Outlet" (I8) with the relative importance score of 0.022. Also, the Ratio of Operating Margin/Net Sales is determined as the most significant output factor (O3).

(b) Implementation of the fuzzy EATWOS technique

Here, we demonstrate the implementation of the fuzzy EATWOS technique proposed in the current paper.

Step 1. Decision-makers performed linguistic evaluations by considering the linguistic evaluation scale given in Table 7. Then, collected evaluations were converted to the corresponding TFNs. At the end of the process, *k* number of decision matrices were generated.

Next, these fuzzy decision matrices were combined, and the initial fuzzy decision input and output matrices were constructed, as seen in Appendix 4.

Step 2. In the second step of the fuzzy EATWOS technique, fuzzy decision input and output matrices were normalized by applying Eqs. (10) and (11), and the normalized fuzzy input and output matrices were generated, as seen in Appendix 5.

Step 3. By applying expressions 13, 14, 15, and 16, respectively, distance measures for each element of standardized fuzzy input and output matrices were computed. The calculated distance measures are given in Appendix 6.

Step 4. After the distance measures were calculated, the obtained values were defuzzied with the help of Eq. (17) in Appendix 7.

Step 5. The defuzzied distance measures were weighted with the help of Eqs. (18) and (19), as seen in Appendix 8.

Step 6. In this step, the sum of the weighted defuzzied input values in each row was computed to determine the total input value of each decision alternative. Also, the sum of output values in each row denotes the final output score of each option. Then, the computed output score is divided into the final input score of the alternative. After the performance score of each option was determined,

Table 6 The results obtained by applying the fuzzy SWARA technique

s~j				***k~j***			***q~j***			***(w_j)~***			***Defuzzified***	***Normalized Weights***
Code	***l***	***m***	***u***	***l***	***m***	***u***	***l***	***m***	***u***	***l***	***m***	***u***		
I7				1.000	1.000	1.000	1.000	1.000	1.000	0.303	0.320	0.339	0.320	0.319
I1	0.280	0.500	0.720	1.280	1.500	1.720	0.581	0.667	0.781	0.176	0.213	0.264	0.218	0.217
I6	0.000	0.100	0.380	1.000	1.100	1.380	0.566	0.606	0.581	0.171	0.194	0.197	0.187	0.187
I4	0.620	0.900	1.000	1.620	1.900	2.000	0.291	0.319	0.349	0.088	0.102	0.118	0.103	0.102
I5	0.180	0.400	0.620	1.180	1.400	1.620	0.216	0.228	0.246	0.065	0.073	0.083	0.074	0.074
I3	0.320	0.550	0.720	1.320	1.550	1.720	0.143	0.147	0.163	0.043	0.047	0.055	0.049	0.048
I2	0.380	0.600	0.760	1.380	1.600	1.760	0.093	0.092	0.104	0.028	0.029	0.035	0.031	0.031
I8	0.180	0.400	0.620	1.180	1.400	1.620	0.064	0.066	0.079	0.019	0.021	0.027	0.022	0.022
O3				1.000	1.000	1.000	1.000	1.000	1.000	0.366	0.429	0.487	0.427	0.416
O1	0.120	0.350	0.580	1.120	1.350	1.580	0.633	0.741	0.893	0.231	0.317	0.435	0.328	0.319
O2	0.060	0.250	0.500	1.060	1.250	1.500	0.422	0.593	0.842	0.154	0.254	0.410	0.273	0.265

Table 7 Linguistic rating for alternatives (Zamri and Abdullah 2015)

Linguistic assessment scale	Abbr	Triangular Fuzzy Number		
		l	*m*	*u*
Extremely Low	EL	1	1	3
Very Low	VL	1	1	3
Low	L	1	3	3
Medium Low	ML	3	3	5
Medium	M	3	5	5
Medium High	MH	5	5	7
High	H	5	7	7
Very High	VH	7	7	9
Extremely High	EH	7	9	9

decision alternatives were ranked considering the performance scores. In Table 9, the sum of input and output score, the final performance score F_i, and the ranking positions of alternatives are given in Table 8.

According to the proposed fuzzy integrated model results, A12 Walmart & Asda is the best option with a performance score of 0.484. A9 TESCO is the second-best alternative with a score of 0.421. Also, Marks & Spencer is the option that has the worst performance score.

(c) Validation test

Here, a comprehensive sensitivity analysis consisting of two stages was performed to test the validation of the proposed integrated novel fuzzy model. First, the impacts of modifications of the input and output factor weights on the ranking results were examined. Secondly, the proposed model results were compared to the results of different fuzzy techniques.

4.3.1 Changing the weights of input and output factors

In the first stage of the sensitivity analysis, the impacts of each input and output factor on the ranking results were examined by forming 320 different scenarios. The weight of each factor was modified at the rate of 10% in each scenario to 100%. The weights of the remaining factors were corrected to meet the sum of weights, which should be equal to 1. New weight values of the factors were determined for each scenario with the help of Eqs. (22), (23), and (24), respectively.

$$w^1_{fv} = w^1_{pv} - \left(w^1_{pv}.m_v\right) \tag{22}$$

$$w^2_{nv} = \frac{\left(1 - w^1_{fv}\right)}{n-1} + w^2_{pv} \tag{23}$$

$$w^1_{fv} + \sum w^2_{nv} = 1 \tag{24}$$

Here, w^1_{fv} denotes a new value of the modified weight of j^{th} factor, w^1_{pv} is the previous values of the criterion, m_v is the modification degree in terms of percentage (i.e., 10%, 20%,…,100%). Also, w^2_{nv} it symbolizes new values of remaining factors, n is the number of factors, w^2_{pv} is the previous values of the remaining criteria.

After the scenarios were formed, new ranking performances of the decision alternatives were computed using the changed, new weight values of input and output factors. The obtained results are presented in Fig. 2.

When the results are obtained in the first phase of the sensitivity analysis, A12 Walmart & Asda, which is determined as the best option using the proposed integrated fuzzy technique, is also the best alternative for all 320 scenarios, and its ranking performance has not changed. In addition, A8 Spar, the second-best alternative, has remained the second-best option for 294 scenarios (i.e., At the rate of 92%). Also, While A5 Carrefour has been ranked at the same ranking position for 218 scenarios, A1 has remained in the same ranking position 244 times. As a result, the average

Table 8 The final performance scores of the alternatives and ranking

Code	**Options**	INPUT	OUTPUT	PEFORMANCE	RANK
A1	BİM	1.2039	0.3905	0.324	9
A2	ŞOK	1.2071	0.3865	0.320	11
A3	KİPA	1.2727	0.4785	0.376	4
A4	MİGROS	1.2062	0.3905	0.324	10
A5	CARREFOUR	1.1200	0.3676	0.328	8
A6	MARKS&SP	1.1711	0.3634	0.310	12
A7	METRO GM	1.1657	0.3942	0.338	7
A8	SPAR	1.1365	0.3979	0.350	6
A9	TESCO	1.1888	0.5007	0.421	2
A10	Sainsbury's	1.2052	0.4470	0.371	5
A11	BİZİM	1.2727	0.4825	0.379	3
A12	Walmart&ASDA	1.0024	0.4850	0.484	1

Table 9 Similarities between original and re-calculated ranking performances for 320 scenarios

Code	Option	1th	2th	3th	4th	5th	6th	7th	8th	9th	10th	11th	12 th	%
A1	BİM	0	0	0	0	0	4	26	242	18	26	4	0	76
A2	ŞOK	0	0	0	2	32	55	215	16	0	0	0	0	67
A3	KİPA	0	0	0	0	1	1	6	2	10	2	42	256	80
A4	MİGROS	0	0	0	63	180	46	7	14	10	0	0	0	56
A5	CARREFOUR	0	0	218	25	12	37	8	20	0	0	0	0	68
A6	MARKS&SP	0	1	16	44	33	139	38	5	3	7	12	22	43
A7	METRO GM	0	25	44	152	34	19	5	6	4	11	17	3	48
A8	SPAR	0	294	9	5	7	2	2	1	0	0	0	0	92
A9	TESCO	0	0	33	9	0	4	3	2	20	148	64	37	46
A10	Sainsbury's	0	0	0	17	11	4	7	5	240	28	8	0	75
A11	BİZİM	0	0	0	3	11	8	3	7	15	99	174	0	54
A12	Walmart&ASDA	320	0	0	0	0	0	0	0	0	0	0	0	100
														67.1%

similarity score between the results of the proposed fuzzy model and the obtained results for 320 scenarios is approximately 67.10%, as shown in Table 9.

4.3.2 Comparison with another approach

Here, the second stage of the validation test was performed. The proposed integrated fuzzy approach results are compared with the results obtained using a different fuzzy technique to measure companies' performance. For this purpose, the fuzzy OCRA technique, which is a performance analysis technique, was applied since the proposed fuzzy integrated approach is not a ranking technique, and it can only be used for measuring the performance; and the obtained results are presented as follows:

As seen in Table 10, although there have been observed deviations between the results of some alternatives, A12 is the best alternative with the highest performance score for both performance analysis techniques. Also, A9 is determined as the second-best alternative according to the results of both fuzzy methods. In addition, the ranking performances of some alternatives such as A3, A7, and A6 are almost the same. When the results of the OCRA technique are evaluated in general, even if there are deviations between the ranking performance of some options, they did not change the overall results. Also, the best and the second-best options have remained in the same ranking positions.

4.3.3 Investigation of the effect of alternative removal on ranking

This section examined deviations occurring in the ranking results by eliminating each alternative in each scenario. For this purpose, we formed 11 different scenarios. Actual ranking according to the first scenario is A12 > A8 > A5 > A7 > A4 > A6 > A2 > A1 > A10 > A9 > A11 > A3. The second scenario consists of eliminating the weakest alternative determined according to the results of the first scenarios. This approach was applied similarly for other scenarios, and the obtained results concerning all scenarios are given in Table 11.

When the results in Table 11 are evaluated, A12 determined that the best option has remained in the first rank for all scenarios. Hence, the overall results of the sensitivity analysis approve the robustness of the proposed model and its obtained results.

As a result, the validation test results prove that the proposed novel integrated fuzzy approach can be applied to develop a measurement for analyzing the performance of companies, public authorities, and institutes. According to the analysis outcomes, it is an advantageous and applicable performance analysis technique that provides a comparative perspective and can provide very accurate and realistic results.

Table 10 The final performance scores of the alternatives and ranking

Code	**Options**	F-EATWOS	F-OCRA
A1	BİM	9	11
A2	ŞOK	11	10
A3	KİPA	4	4
A4	MİGROS	10	7
A5	CARREFOUR	8	9
A6	MARKS&SP	12	12
A7	METRO GM	7	7
A8	SPAR	6	4
A9	TESCO	2	2
A10	Sainsbury's	5	6
A11	BİZİM	3	5
A12	Walmart&ASDA	1	1

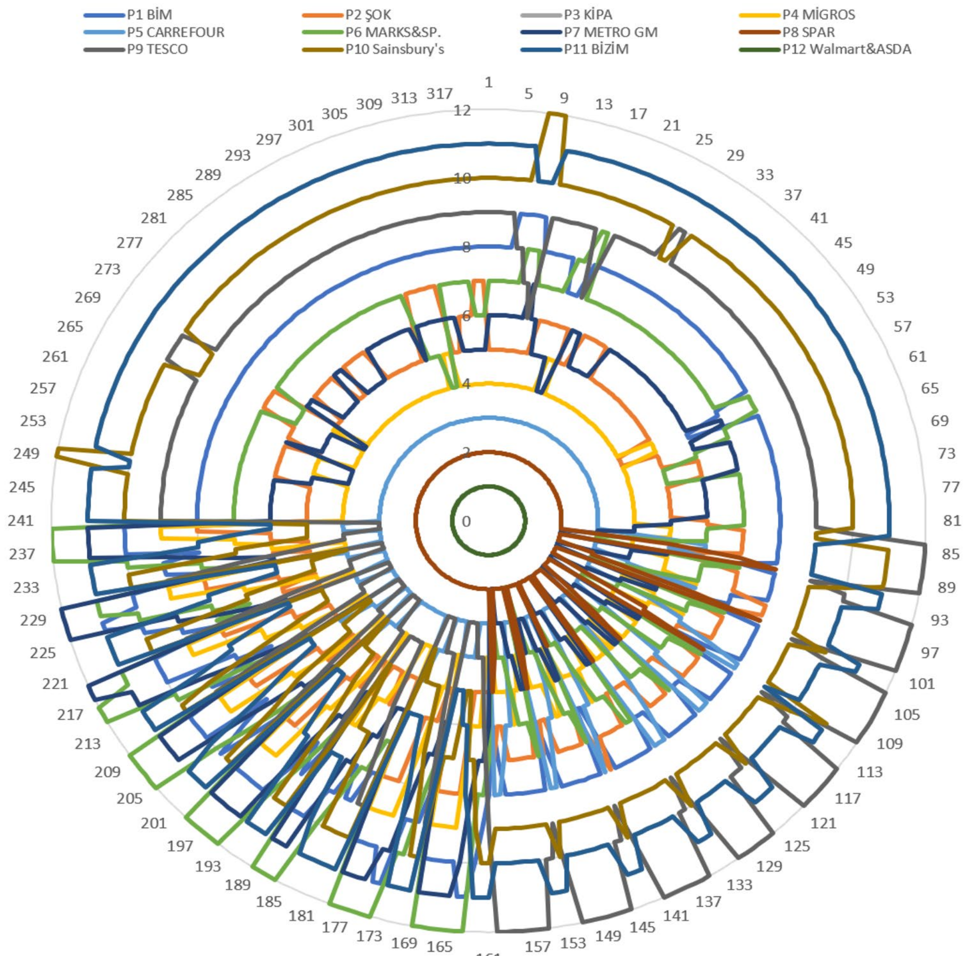

Fig. 2 The changes in the ranking performances of alternatives based on changing the criteria weights

5 Results and discussions

The overall results of the current paper are evaluated; it has been observed that this paper has many valuable theoretical contributions and managerial implications. The following sections can summarize its contributions, implications, and overall results.

5.1 Overall results of the study

When the practical results of the paper are evaluated, it has been observed that the most significant input factor is Operating Cost (I7). It highlights the level of cost that a retail company needs to make to generate revenues, which is the primary goal of a retail chain. Relatively higher opex as a percentage of sales indicates that a retail company shows activity with a low-efficiency level. Hence, reducing operating costs is one of the crucial requirements to construct a well-operating system for a retail chain. Thus, engineers, managers, and other practitioners should consider this factor when evaluating the overall performance of retail companies.

According to the analysis results, the second important input factor was determined as the I1 "shareholder's equity" criterion". This criterion is a determinative factor for growing companies, as it may be attractive for

Table 11 Ranking the decision alternatives with respect to the scenarios

Scenarios	*Ranking*
Original	*A12 > A8 > A5 > A7 > A4 > A6 > A2 > A1 > A10 > A9 > A11 > A3*
S1	*A12 > A9 > A11 > A3 > A10 > A8 > A7 > A5 > A1 > A4 > A2*
S2	*A12 > A9 > A11 > A3 > A10 > A8 > A7 > A5 > A1 > A4*
S3	*A12 > A9 > A11 > A3 > A10 > A8 > A7 > A5 > A1*
S4	*A12 > A9 > A11 > A3 > A10 > A8 > A7 > A5*
S5	*A12 > A9 > A11 > A3 > A10 > A8 > A7*
S6	*A12 > A9 > A11 > A3 > A10 > A8*
S7	*A12 > A9 > A11 > A3 > A10*
S8	*A12 > A9 > A11 > A3*
S9	*A12 > A9 > A11*
S10	*A12 > A9*
S11	*A12*

investors. Also, it makes it easy to fund transfers from external sources. Hence, shareholder's equity can be accepted as a good indicator to evaluate the global retail chains' financial and overall performances. Also, it should be minimized, as it refers to resource utilization for a company.

The third essential input criterion is the I6 "Cost of Sales". The cost of sales is an essential indicator of a global retail chain's performance, as it measures all operational activities such as supplying, manufacturing, and distributing. It is defined as total costs for responding to customer demands and expectations. Being low is an expectation because sales cost is a cost factor for companies. If a company gains profits with the lower cost of sales, its financial and overall performances can be accepted. This factor is significant for engineers and managers since it can help construct a retail chain's well-operating logistics, manufacturing, and supply systems. They can form and structure these systems successfully by considering sales costs.

I4 the number of employees is also a cost factor for retail companies. Because of that, it is accepted as an input factor. Companies try to construct a system based on balanced human resources. Therefore, low human resource utilization is crucial for system design, but it is not a single factor providing effectivity. Thus, retail chains try to balance the number of employees and qualified human resources; hence, while they want to reduce the number of employees, they also try to increase their human resource quality to form an efficient and productive system in a global retail chain. The remaining factors are ranked such as I5 current assets, I3 the number of branches, I2 number of countries, and I8 size of outlet. These results approve the outputs of some papers (Barros 2006; Yu and Ramanathan 2008; Gupta and Mittal 2010) in the literature. These previous papers indicated that some criteria, such as operating costs and sales, are the most crucial factors affecting the overall performance of a retail chain.

The O3 "ratio of operating margin to net sales" is the most influential output factor when evaluating the output factors. It is a meaningful and understandable result. It provides a measure to determine the net income per sold product or service. Also, it can help engineers, managers, investors, and other stakeholders to assess whether the company generates enough profit from its sales. It is one of the most significant indicators of a retail company's overall and financial performance. A system designer tries to increase the value of this output factor to construct a healthy system. Hence, it can help form well-operating systems for practitioners.

The second important output factor is O1 operating profit/loss EBIT. It is a crucial factor, as the higher the value of this factor is, the more effective and profitable a retailing company's core business is. It can also be accepted as a measure of managerial flexibility and competency, particularly during tough economic times. Also, O2 “net sales” is the third significant output factor. Although it is crucial, it is in the last rank, as computations for determining net sales are not always transparent. Thus, it is not entirely reliable for making performance analyses.

Nevertheless, it can be considered when the financial performance of a retail company is evaluated. As a result, we can note that cost and revenues are essential since hot sales and cash flow velocity are crucial factors for the retail industry. Hence, it has been seen clearly that financial factors are more significant than technical and operating factors. When the overall performance scores of the alternatives are evaluated in general, the performances of the global retail chains (multinational) are relatively higher than semi-global retail chains. When the overall performance scores of the alternatives are evaluated in general, the performances of the global retail chains (multinational) are relatively higher than semi-global retail chains. This result approves the main output of the study carried out by Chung et al. (2006). This study indicated that those retail companies who expanded overseas have higher sales volumes, longer histories of establishment, larger sales floor spaces at domestic stores, and more assets.

The results of a study carried out by Haque et al. (2017) also verify the results of the current paper. According to the results of this paper, efficiencies and performance of the global retail chains are higher than local retail chains. Therefore, within possibility, directing to the global market for a retail company may be a suitable way to reach higher efficiency and performance, as it can allow an opportunity to grow and obtain new opportunities. According to the overall results of the analysis, A12 Walmart & ASDA is the best alternative that has the highest performance score. Other options are ranked as follows: $A8 > A5 > A7 > A4 > A6 > A2 > A1 > A10 > A9 > A11 > A3$.

5.2 Practical and managerial implications

The most significant implications of the paper are to present a novel integrated fuzzy approach to evaluate the overall performance of the global retail chains. The proposed model can provide many valuable advantages. First, it enables us to assess both input and output factors together. Also, it resists the rank reversal problem. Because of that, it is a stable and consistent MCDM framework. Finally, it can reach accurate and reasonable results with fewer computations; hence, this advantage of the proposed model also validates its applicability. In addition, it has some managerial implications as follows. First, this paper highlights the relative significance of the identified input & output factors. Therefore, practitioners such as engineers and managers can consider the paper's outputs concerning the factors to solve evaluation and decision-making problems encountered in the real world. Besides, it remarked the importance of globalizing for retail chains for increasing efficiency and productivity. As a result, engineers and managers can consider the results and findings of the current paper when constructing a well-operating system for a global or local retail chain.

By keeping these advantages of the model, this paper proposes an integrated novel fuzzy approach to measure the performances of the global retail chains. In recent years, the average efficiency of the top 250 global retailers has shown a significant increase at 4.1% annually (Deloitte 2020). But it may not be appropriate to measure the performance of the retailers because only the annual revenues of these companies have been taken into consideration as the main factor to determine their efficiencies. However, many input and output factors that can affect the performances of retailer companies exist, and it is required to consider these factors in an assessment process. For this purpose, this paper determined a set of the input and output factors that can also be used in future works by performing a comprehensive literature review and fieldwork performed with highly experienced professionals in the retail industry.

The proposed novel integrated fuzzy model can help managers prove the companies' financial, operational, and technique performances because they have to show the company's positive performance results to the top management of the firm and investors who plan to make investments in the company. With this perspective, this paper's proposed model can help measure the performance of companies and institutions. In addition, it can provide a set of suggestions to develop a company's performance. Furthermore, it presents impacts of both input and output factors on the performance; hence it is possible to evaluate the effects of both criteria sets.

Secondly, there are many uncertainties in the evaluation process. It may not be possible to collect crisp values related to the alternatives at all times. These ambiguities should be considered to obtain realistic and accurate results. A novel integrated fuzzy model has been developed by extending the traditional EATWOS technique with the help of the fuzzy set theory. The proposed model is an integrated MCDM technique that can also deal with uncertainties to propose a more realistic and applicable methodological frame.

Since the productivity assessment of multiple outlets is a significant issue (Keh and Chu 2003), the proposed novel fuzzy model was applied to develop a measurement to analyze the performances of the global retail chains in the current paper especially. However, it can also be applied in various fields such as automotive, food processing, and tourism industries.

Also, the proposed integrated model has a set of advantages compared to other performance & efficiency analysis techniques such as DEA and OCRA methods. Foremost, the results obtained by implementing this technique are more detailed. It allows evaluating from a broader perspective than the DEA technique as the DEA can only give the result that a company is efficient or inefficient. In addition, the DEA technique is susceptible to selecting the input and output factors. Hence, some aberrations may occur in the results of the factors that are not determined carefully. Also, the DEA technique cannot provide a comparative analysis because it deals with only a single firm's efficiency. Still, the proposed model gives these requirements, making it possible to perform a comparative analysis. Therefore, it can be accepted as an advantageous technique for benchmarking for decision-makers. Also, the proposed fuzzy model is maximally consistent. It does not require an additional computation to determine the consistency of the obtained results; however, the OCRA technique is a method criticized in aspects of consistency (Wang and Wang 2005). Moreover, the fuzzy EATWOS technique is a more reliable approach than the OCRA technique, as the OCRA technique may give results that may not be reasonable.

5.3 Theoretical contributions of the work

The proposed integrated fuzzy model is a novel MCDM combination consisting of the fuzzy SWARA and the fuzzy EATWIOS. The suggested model has valuable theoretical contributions as follows.

- It is an extended version of the traditional EATWIOS technique with the help of the fuzzy set theory, and it combines the advantages of the EATWIOS technique and the fuzzy set theory. Thus, the traditional performance analysis approach has become more powerful and applicable, and it can overcome many complicated uncertainties, as the proposed model can capture and process the existing ambiguities.
- It provides a more flexible group decision-making environment to the decision-makers.
- Each stage of the sensitivity analysis shows that the proposed model is a maximally consistent and stable MCDM framework despite excessive changing of the conditions. Hence, it is a reliable decision-making tool for decision-makers, and it can be applied for solving highly complicated decision-making problems encountered in real life.
- The proposed model can be applied for solving decision-making problems and performance analysis encountered in various fields such as logistics, supply chain management, engineering, etc.
- It has an efficient and applicable basic algorithm, and decision-makers can easily implement it without advanced mathematical knowledge. It can reach reason-

able and realistic results with fewer computations than the other traditional MCDM frameworks.
- Since it provides maximally consistent results, it is not required to apply an additional approach to identify the consistency ratio.

6 Conclusions

The proposed integrated fuzzy model is a novel performance analysis technique. It can provide a very comprehensive evaluation methodology that can be used as a mathematical model to measure the performance of companies and institutions. It can help deal with highly complex evaluation processes and many uncertainties. In addition, it presents a novel computational tool that can be used to assess companies' performances. It has a basic algorithm consisting of a few easily applicable and followable implementation steps. Hence, a decision-maker can easily apply this technique and obtain more accurate, reliable, and realistic results than other efficiency analysis techniques. Moreover, it presents the reasons for efficiency or inefficiency and shows a set of ways to improve decision-makers' performance. There are many ambiguities in an evaluation process; the developed fuzzy EATWOS technique can deal with uncertainties since it includes uncertainties in the evaluation process.

As a result, the proposed integrated fuzzy technique can help future work on the performance analysis of companies and institutions and practitioners responsible for deciding on a firm's performance. Furthermore, it can be applied to measure financial, technical, and operational performance in various fields from almost all industries, even players or sports teams. Although it has many advantages, it has suffered some limitations. First of all, collecting reliable and real-time data is extremely difficult in the field of the retail industry; because of that, for collecting the financial data, figures and statistics published by the international stock exchange were collected since these data have been accepted as more reliable by researchers and the members of the board of experts. Secondly, the number of the previous papers is scarce, and it is unclear how the selected factors were determined. Hence, most of them mainly preferred financial criteria since data on these factors can be more accessible than others. The current paper suggests that different criteria can be added to the evaluation process's scope based on some developments in future work. Therefore, the scope of this study can be extended by adding new criteria, sub-criteria, and options. As a result, it is required to make more case studies to construct a user-friendly decision support system that generalizes the obtained results.

In addition, the fuzzy EATWOS technique can be extended with the help of different operators such as the normalized weighted and normalized weighted geometric Bonferroni aggregate functions (Ecer and Pamucar 2020), Heronian mean (HM) operators, hybrid weight Power Heronian operator (WPHAP, q) and hybrid weight geometric Power Heronian operator (WGPHA p, q). In addition, it can be examined comparatively with different approaches based on different IVIF sets such as fuzzy CODAS-SORT, interval-valued intuitionistic trapezoidal fuzzy, picture fuzzy, and Pythagorean fuzzy sets.

Appendix 1

The input and output factors determined by experts and used in the literature.

	Factors and previous studies														Experts' evaluations					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	DM1	DM2	DM3	DM4	DM5	Score
Shareholder's equity	✓					✓		✓	✓						7	9	9	8	8	8.165
Number of Country														✓	6	7	5	8	8	6.694
The Number of Branches	✓								✓						7	5	7	7	9	6.882
The Number of Employee (M)	✓	✓			✓	✓	✓		✓		✓	✓	✓	✓	9	6	7	7	8	7.331
Current Assets															8	9	6	6	8	7.300
Sales Costs											✓				8	9	7	8	7	7.765
Operating Costs		✓		✓	✓			✓				✓			9	9	8	7	9	8.360
Size of Outlet		✓	✓		✓							✓	✓	✓	7	5	6	6	8	6.320
Age of the outlet		✓			✓							✓			4	8	3	4	5	4.536

	Factors and previous studies														Experts' evaluations					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	DM1	DM2	DM3	DM4	DM5	Score
Education of manager												✓			2	3	6	4	4	3.565
Inventory	✓										✓	✓			3	4	6	3	4	3.866
Manager 's experience										✓					4	3	3	5	4	3.728
Ownership	✓			✓									✓		2	2	3	5	2	2.605
Salaries											✓	✓			4	3	2	3	5	3.245
Operating Profit/ Loss EBIT				✓		✓		✓	✓			✓	✓	✓	7	6	9	8	7	7.331
Net Sales	✓	✓		✓	✓	✓			✓	✓		✓		✓	9	7	6	6	8	7.108
The ratio of Operating Margin/ Net Sales							✓								9	6	8	8	7	7.529
Accessibility											✓				4	3	3	4	6	3.866
Assortment											✓				4	3	4	2	2	2.862
Customer satisfaction			✓		✓					✓					3	3	5	4	4	3.728
Earn share							✓								2	2	3	5	4	2.993
Market value							✓								3	7	4	5	5	4.618
Operational results	✓	✓													4	5	2	3	3	3.245
Product information											✓				3	4	3	5	3	3.519

Appendix 2

Experts' evaluations and ranking of the factors.

Code	Input Factors	DM1	DM2	DM3	DM4	DM5	Rank Score
I7	Operating Costs	1	1	2	1	1	1.14870
I1	Shareholder's equity	2	2	3	2	2	2.16894
I6	Sales Costs	3	3	1	3	3	2.40822
I4	The Number of Employee (M)	5	4	4	4	4	4.18256
I5	Current Assets	4	5	5	6	5	4.95934
I3	The Number of Branches	6	7	6	5	6	5.96629
I2	Number of Country	7	6	7	7	8	6.97119
I8	Size of Outlet	8	8	8	8	7	7.78918
Code	Output Factors	DM1	DM2	DM3	DM4	DM5	
O3	The ratio of Operating Margin to Net Sales	1	2	1	1	2	1.31951
O1	Operating Profit/Loss EBIT	2	3	2	2	1	1.88818
O2	Net Sales	3	1	3	3	3	2.40823

Appendix 3

Linguistic evaluations for the relative importance ratios

Code	Input Factors	DM1	DM2	DM3	DM4	DM5
I7	Operating Costs	-	-	-	-	-
I1	Shareholder's equity	H	M	M	M	L
I6	Sales Costs	L	VL	VL	L	VL
I4	The Number of Employee (M)	VH	VH	VH	H	H
I5	Current Assets	M	M	L	M	L
I3	The Number of Branches	VH	M	M	M	L
I2	Number of Country	VH	M	M	M	M
I8	Size of Outlet	M	L	M	M	L
Code	Output Factors	DM1	DM2	DM3	DM4	DM5
O3	Ratio of Operating Margin to Net Sales	-	-	-	-	-
O1	Operating Profit/Loss EBIT	M	L	M	L	L
O2	Net Sales	M	L	L	L	VL

Appendix 4

The aggregated fuzzy decision input & output matrices.

	Input Factors																
	I1			**I2**			**I3**			**I4**			**I5**			**I6**	
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*
A1	6.54	8.56	8.56	7.00	9.00	9.00	4.08	4.66	6.12	7.00	9.00	9.00	7.00	9.00	9.00	3.00	3.00
A2	7.00	9.00	9.00	7.00	9.00	9.00	3.32	5.35	5.35	7.00	9.00	9.00	7.00	9.00	9.00	3.00	3.00
A3	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00
A4	7.00	9.00	9.00	5.00	5.00	7.00	5.00	7.00	7.00	7.00	9.00	9.00	7.00	9.00	9.00	3.00	3.00
A5	4.51	5.00	6.54	5.00	7.00	7.00	1.25	3.00	3.32	5.00	6.54	7.00	6.54	7.00	8.56	1.00	3.00
A6	7.00	7.00	9.00	1.00	3.00	3.00	5.35	7.00	7.36	7.00	7.36	9.00	7.00	7.36	9.00	1.00	3.00
A7	7.00	7.00	9.00	3.00	5.00	5.00	7.00	7.00	9.00	5.00	7.00	7.00	5.00	7.00	7.00	1.00	3.00
A8	5.35	7.00	7.36	1.00	3.00	3.00	1.00	3.00	3.00	5.00	7.00	7.00	3.32	5.00	5.35	1.25	3.00
A9	5.00	7.00	7.00	5.00	5.00	7.00	3.00	5.00	5.00	5.00	5.35	7.00	5.00	5.00	7.00	7.00	7.00
A10	5.00	7.00	7.00	5.00	5.00	7.00	3.00	3.00	5.00	7.00	7.00	9.00	5.00	7.00	7.00	5.00	7.00
A11	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00
A12	1.00	3.00	3.00	3.00	5.00	5.00	1.00	3.00	3.00	1.00	3.00	3.00	1.00	3.00	3.00	1.00	1.25

	Input Factors							Output Factors								
	I7			**I8**				**O1**			**O2**			**O3**		
	u	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
A1	5.00	7.00	9.00	9.00	3.00	3.00	5.00	**A1**	1.00	3.00	3.00	1.00	3.00	3.00	3.62	5.16	5.91
A2	5.00	7.00	9.00	9.00	3.00	3.00	5.00	**A2**	1.00	2.41	3.00	1.00	3.00	3.00	2.41	2.41	4.51
A3	9.00	7.00	9.00	9.00	7.00	9.00	9.00	**A3**	1.00	2.41	3.00	1.00	3.00	3.00	1.00	1.00	3.00
A4	5.00	7.00	9.00	9.00	3.00	3.00	5.00	**A4**	1.00	3.00	3.00	1.00	3.00	3.00	5.00	5.00	7.00
A5	3.00	5.00	7.00	7.00	1.00	3.00	3.00	**A5**	1.25	3.00	3.32	3.00	3.32	5.00	3.32	5.00	5.35
A6	3.00	7.00	7.00	9.00	1.00	3.00	3.00	**A6**	1.00	3.00	3.00	1.00	3.00	3.00	5.00	5.00	7.00
A7	3.00	7.00	7.00	9.00	1.00	3.00	3.00	**A7**	3.00	3.00	5.00	3.00	3.00	5.00	5.00	7.00	7.00

	Input Factors								Output Factors								
A8	3.32	7.00	7.00	9.00	1.25	3.00	3.32	**A8**	3.00	3.00	5.00	3.00	3.32	5.00	5.00	7.00	7.00
A9	9.00	5.00	7.00	7.00	7.00	7.00	9.00	**A9**	3.00	3.00	5.00	3.00	3.00	5.00	5.00	7.00	7.00
A10	7.00	7.00	9.00	9.00	5.00	7.00	7.00	**A10**	1.25	3.00	3.32	3.00	3.00	5.00	5.00	5.00	7.00
A11	9.00	7.00	9.00	9.00	7.00	9.00	9.00	**A11**	1.00	3.00	3.00	1.00	3.00	3.00	1.25	3.00	3.32
A12	3.00	1.00	3.00	3.00	1.00	1.25	3.00	**A12**	7.00	9.00	9.00	7.00	9.00	9.00	7.00	9.00	9.00

Appendix 5

The standardized fuzzy input & output matrix.

	Input Factors																
	I1			**I2**			**I3**			**I4**			**I5**		**I6**		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*
A1	0.31	0.33	0.31	0.39	0.40	0.37	0.26	0.23	0.28	0.33	0.34	0.32	0.34	0.35	0.33	0.21	0.17
A2	0.33	0.35	0.33	0.39	0.40	0.37	0.21	0.26	0.24	0.33	0.34	0.32	0.34	0.35	0.33	0.21	0.17
A3	0.33	0.35	0.33	0.39	0.40	0.37	0.44	0.44	0.41	0.33	0.34	0.32	0.34	0.35	0.33	0.49	0.50
A4	0.33	0.35	0.33	0.28	0.22	0.29	0.32	0.34	0.32	0.33	0.34	0.32	0.34	0.35	0.33	0.21	0.17
A5	0.22	0.19	0.24	0.28	0.31	0.29	0.08	0.15	0.15	0.24	0.25	0.25	0.32	0.27	0.31	0.07	0.17
A6	0.33	0.27	0.33	0.06	0.13	0.12	0.34	0.34	0.33	0.33	0.28	0.32	0.34	0.29	0.33	0.07	0.17
A7	0.33	0.27	0.33	0.17	0.22	0.21	0.44	0.34	0.41	0.24	0.27	0.25	0.24	0.27	0.26	0.07	0.17
A8	0.26	0.27	0.27	0.06	0.13	0.12	0.06	0.15	0.14	0.24	0.27	0.25	0.16	0.19	0.20	0.09	0.17
A9	0.24	0.27	0.25	0.28	0.22	0.29	0.19	0.24	0.23	0.24	0.20	0.25	0.24	0.19	0.26	0.49	0.39
A10	0.24	0.27	0.25	0.28	0.22	0.29	0.19	0.15	0.23	0.33	0.27	0.32	0.24	0.27	0.26	0.35	0.39
A11	0.33	0.35	0.33	0.39	0.40	0.37	0.44	0.44	0.41	0.33	0.34	0.32	0.34	0.35	0.33	0.49	0.50
A12	0.05	0.12	0.11	0.17	0.22	0.21	0.06	0.15	0.14	0.05	0.11	0.11	0.05	0.12	0.11	0.07	0.07
	Input Factors								**Output Factors**								
	I7			**I8**					**O1**			**O2**			**O3**		
	u	*l*	*m*	*u*	*l*	*m*	*u*		*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
A1	0.25	0.32	0.33	0.31	0.21	0.17	0.25	**A1**	0.21	0.17	0.25	0.11	0.23	0.20	0.10	0.22	0.19
A2	0.25	0.32	0.33	0.31	0.21	0.17	0.25	**A2**	0.21	0.17	0.25	0.11	0.18	0.20	0.10	0.22	0.19
A3	0.44	0.32	0.33	0.31	0.49	0.50	0.44	**A3**	0.49	0.50	0.44	0.11	0.18	0.20	0.10	0.22	0.19
A4	0.25	0.32	0.33	0.31	0.21	0.17	0.25	**A4**	0.21	0.17	0.25	0.11	0.23	0.20	0.10	0.22	0.19
A5	0.15	0.23	0.26	0.24	0.07	0.17	0.15	**A5**	0.07	0.17	0.15	0.14	0.23	0.22	0.30	0.24	0.31
A6	0.15	0.32	0.26	0.31	0.07	0.17	0.15	**A6**	0.07	0.17	0.15	0.11	0.23	0.20	0.10	0.22	0.19
A7	0.15	0.32	0.26	0.31	0.07	0.17	0.15	**A7**	0.07	0.17	0.15	0.33	0.23	0.33	0.30	0.22	0.31
A8	0.16	0.32	0.26	0.31	0.09	0.17	0.16	**A8**	0.09	0.17	0.16	0.33	0.23	0.33	0.30	0.24	0.31
A9	0.44	0.23	0.26	0.24	0.49	0.39	0.44	**A9**	0.49	0.39	0.44	0.33	0.23	0.33	0.30	0.22	0.31
A10	0.34	0.32	0.33	0.31	0.35	0.39	0.34	**A10**	0.35	0.39	0.34	0.14	0.23	0.22	0.30	0.22	0.31
A11	0.44	0.32	0.33	0.31	0.49	0.50	0.44	**A11**	0.49	0.50	0.44	0.11	0.23	0.20	0.10	0.22	0.19
A12	0.15	0.05	0.11	0.10	0.07	0.07	0.15	**A12**	0.07	0.07	0.15	0.76	0.68	0.59	0.70	0.66	0.56

Appendix 6

The distance measures of the fuzzy input & output factors.

	Input Factors																
	I1			**I2**			**I3**			**I4**			**I5**		**I6**		
	l	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*
A1	1.265	1.214	1.201	1.338	1.264	1.247	1.195	1.081	1.141	1.285	1.229	1.216	1.291	1.233	1.220	1.140	1.097
A2	1.287	1.231	1.217	1.338	1.264	1.247	1.147	1.115	1.106	1.285	1.229	1.216	1.291	1.233	1.220	1.140	1.097
A3	1.287	1.231	1.217	1.338	1.264	1.247	1.380	1.293	1.271	1.285	1.229	1.216	1.291	1.233	1.220	1.420	1.430
A4	1.287	1.231	1.217	1.225	1.088	1.165	1.253	1.195	1.180	1.285	1.229	1.216	1.291	1.233	1.220	1.140	1.097
A5	1.168	1.077	1.128	1.225	1.176	1.165	1.016	1.000	1.015	1.190	1.135	1.144	1.269	1.155	1.204	1.000	1.097
A6	1.287	1.154	1.217	1.000	1.000	1.000	1.275	1.195	1.197	1.285	1.166	1.216	1.291	1.169	1.220	1.000	1.097
A7	1.287	1.154	1.217	1.113	1.088	1.082	1.380	1.195	1.271	1.190	1.153	1.144	1.194	1.155	1.147	1.000	1.097
A8	1.208	1.154	1.158	1.000	1.000	1.000	1.000	1.000	1.000	1.190	1.153	1.144	1.113	1.078	1.086	1.017	1.097
A9	1.191	1.154	1.145	1.225	1.088	1.165	1.127	1.098	1.090	1.190	1.090	1.144	1.194	1.078	1.147	1.420	1.319
A10	1.191	1.154	1.145	1.225	1.088	1.165	1.127	1.000	1.090	1.285	1.153	1.216	1.194	1.155	1.147	1.280	1.319
A11	1.287	1.231	1.217	1.338	1.264	1.247	1.380	1.293	1.271	1.285	1.229	1.216	1.291	1.233	1.220	1.420	1.430
A12	1.000	1.000	1.000	1.113	1.088	1.082	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

	Input Factors								**Output Factors**								
	I7			**I8**					**O1**			**O2**			**O3**		
	u	*l*	*m*	*u*	*l*	*m*	*u*		*l*	*m*	*u*	*l*	*m*	*u*	*l*	*m*	*u*
A1	1.098	1.271	1.221	1.208	1.140	1.097	1.098	**A1**	0.720	0.667	0.803	0.350	0.545	0.606	0.400	0.558	0.628
A2	1.098	1.271	1.221	1.208	1.140	1.097	1.098	**A2**	0.720	0.667	0.803	0.350	0.500	0.606	0.400	0.558	0.628
A3	1.295	1.271	1.221	1.208	1.420	1.430	1.295	**A3**	1.000	1.000	1.000	0.350	0.500	0.606	0.400	0.558	0.628
A4	1.098	1.271	1.221	1.208	1.140	1.097	1.098	**A4**	0.720	0.667	0.803	0.350	0.545	0.606	0.400	0.558	0.628
A5	1.000	1.180	1.147	1.138	1.000	1.097	1.000	**A5**	0.580	0.667	0.705	0.376	0.545	0.627	0.600	0.582	0.752
A6	1.000	1.271	1.147	1.208	1.000	1.097	1.000	**A6**	0.580	0.667	0.705	0.350	0.545	0.606	0.400	0.558	0.628
A7	1.000	1.271	1.147	1.208	1.000	1.097	1.000	**A7**	0.580	0.667	0.705	0.566	0.545	0.737	0.600	0.558	0.752
A8	1.016	1.271	1.147	1.208	1.017	1.097	1.016	**A8**	0.598	0.667	0.721	0.566	0.545	0.737	0.600	0.582	0.752
A9	1.295	1.180	1.147	1.138	1.420	1.319	1.295	**A9**	1.000	0.889	1.000	0.566	0.545	0.737	0.600	0.558	0.752
A10	1.197	1.271	1.221	1.208	1.280	1.319	1.197	**A10**	0.860	0.889	0.902	0.376	0.545	0.627	0.600	0.558	0.752
A11	1.295	1.271	1.221	1.208	1.420	1.430	1.295	**A11**	1.000	1.000	1.000	0.350	0.545	0.606	0.400	0.558	0.628
A12	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**A12**	0.580	0.570	0.705	1.000	1.000	1.000	1.000	1.000	1.000

Appendix 7

Defuzzied values of input and output factors.

Code	**Options**	I10	I11	I13	I14	I15	I16	I17	I18	O1	O2	O3
A1	BİM	1.227	1.234	1.139	1.243	1.248	1.112	1.233	1.112	0.730	0.500	0.529
A2	ŞOK	1.245	1.234	1.122	1.243	1.248	1.112	1.233	1.112	0.730	0.485	0.529
A3	KİPA	1.245	1.234	1.314	1.243	1.248	1.382	1.233	1.382	1.000	0.485	0.529
A4	MİGROS	1.245	1.068	1.210	1.243	1.248	1.112	1.233	1.112	0.730	0.500	0.529
A5	CARREFOUR	1.124	1.156	1.010	1.156	1.209	1.032	1.155	1.032	0.651	0.516	0.644
A6	MARKS&SP	1.219	1.000	1.222	1.222	1.227	1.032	1.208	1.032	0.651	0.500	0.529
A7	METRO GM	1.219	1.078	1.282	1.162	1.165	1.032	1.208	1.032	0.651	0.616	0.637
A8	SPAR	1.173	1.000	1.000	1.162	1.092	1.043	1.208	1.043	0.662	0.616	0.644
A9	TESCO	1.163	1.068	1.105	1.141	1.139	1.345	1.155	1.345	0.963	0.616	0.637

Code	**Options**	I10	I11	I13	I14	I15	I16	I17	I18	O1	O2	O3
A10	Sainsbury's	1.163	1.068	1.072	1.218	1.165	1.265	1.233	1.265	0.884	0.516	0.637
A11	BİZİM	1.245	1.234	1.314	1.243	1.248	1.382	1.233	1.382	1.000	0.500	0.529
A12	Walmart&ASDA	1.000	1.078	1.000	1.000	1.000	1.000	1.000	1.000	0.618	1.000	1.000

Appendix 8

Weighted defuzzied values of input and output factors.

Code	**Options**	I10	I11	I13	I14	I15	I16	I17	I18	O1	O2	O3
A1	BİM	0.266	0.038	0.055	0.127	0.092	0.207	0.393	0.025	0.025	0.233	0.133
A2	ŞOK	0.270	0.038	0.054	0.127	0.092	0.207	0.393	0.025	0.025	0.233	0.129
A3	KİPA	0.270	0.038	0.064	0.127	0.092	0.258	0.393	0.031	0.031	0.319	0.129
A4	MİGROS	0.270	0.033	0.059	0.127	0.092	0.207	0.393	0.025	0.025	0.233	0.133
A5	CARREFOUR	0.244	0.036	0.049	0.118	0.089	0.193	0.369	0.023	0.023	0.208	0.137
A6	MARKS&SP	0.265	0.031	0.059	0.125	0.090	0.193	0.386	0.023	0.023	0.208	0.133
A7	METRO GM	0.265	0.033	0.062	0.119	0.086	0.193	0.386	0.023	0.023	0.208	0.164
A8	SPAR	0.255	0.031	0.048	0.119	0.080	0.195	0.386	0.023	0.023	0.211	0.164
A9	TESCO	0.252	0.033	0.053	0.117	0.084	0.251	0.369	0.030	0.030	0.307	0.164
A10	Sainsbury's	0.252	0.033	0.052	0.125	0.086	0.236	0.393	0.028	0.028	0.282	0.137
A11	BİZİM	0.270	0.038	0.064	0.127	0.092	0.258	0.393	0.031	0.031	0.319	0.133
A12	Walmart&ASDA	0.217	0.033	0.048	0.102	0.074	0.187	0.319	0.022	0.022	0.197	0.265

Declarations

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