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SUSTAINABLE RESILIENT SUPPLIER SELECTION FOR IOT IMPLEMENTATION BASED ON THE INTEGRATED BWM AND TRUST UNDER SPHERICAL FUZZY SETS

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Abstract: *Supplier selection process plays a vital role in supply chain management and is the most important variable in its success. With increasing environmental considerations, organizations must consider sustainability considerations and economic goals to protect the environment. Furthermore, the destructive effects of disruptions on the supply chain performance of companies have prompted organizational experts to pay special attention to the concept of resilience. This study developed an integrated approach based on the extended version of Multi-Criteria Decision-Making (MCDM) methods in a spherical fuzzy (SFS) environment to address sustainable and resilient IoT supplier selection. In the proposed approach, the main criteria (i.e., resilience, and sustainability) have been used in the supplier selection process. Then, these criteria are weighted using the developed SFS-Best-Worst Method (BWM), which reduces uncertainty in pairwise comparisons. In the next step, the 14 selected IoT suppliers are evaluated and prioritized by applying SFS-mulTi-noRmalization mUlti-Distance aSsessmenT (TRUST) that considers a multi-normalization algorithm to reduce subjectivity in normalized data. The results of this study shows that the pollution control and risk-taking sub-criteria are placed in the first and second priorities, respectively. The comparison of the results of the SFS-TRUST with other MCDM methods and sensitivity analysis demonstrates the performance of the proposed approach and its ranking stability in various scenarios.*

Key words: *Supplier Selection, Sustainability, IoT, Spherical fuzzy sets, Best-Worst Method, TRUST.*

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1. Introduction

Due to the increase in consumption and production rate, supply chains have faced severe environmental challenges. Therefore, the need for sustainable solutions to protect the environment is strongly felt (Rajabzade et al., 2022a, Mondal & Giri, 2020). Supply chain management is one of the crucial factors in improving the income and efficiency of different organizations, hence it has become one of the attractive and important topics among experts (Sharma et al., 2022). Nowadays, due to the competitiveness of the production market, companies have a special look at supply chain management to improve their competitiveness. The key issue in this field is choosing the right supplier. Due to the expansion of activities in various fields, supplier selection has become a general process that affects legal, cultural, and political issues (Hoseini et al., 2021a). Also, the right choice of suppliers significantly impacts the relationship between customers and organizations (Nourmohamadi Shalke et al., 2018). Therefore, the wrong choice of supplier can have destructive economic, environmental, and social effects on lower levels of the supply chain.

Nimsai et al., (2020) stated that sustainability is a vital factor in the promotion and evolution of supply chain management. In recent years, environmental sustainability has gained potential importance due to the emission of greenhouse gases and the increase in global warming and other adverse effects of human activities on the environment (Schramm et al., 2020; Deveci et al., 2022a). Also, at the same time, the social approach of the manufacturing industries has attracted the attention of the customers, investors and beneficiaries of the manufacturing industries. Therefore, considering sustainability and implementing sustainability in supply chain management means considering environmental, economic and social requirements at the same time (Afrasiabi et al., 2022). Sustainability is a helpful strategy to solve supply chain management challenges and increases financial performance and competitiveness (Muhammad et al., 2020; Alcaraz et al., 2022). Indeed, choosing a sustainable supplier means realizing the environmental, social, and economic goals of companies and is very vital for the success of the organization (Song et al., 2017). In Figure 1, the goals obtained based on supply chain management and implementation of sustainability in the supply chain are presented.

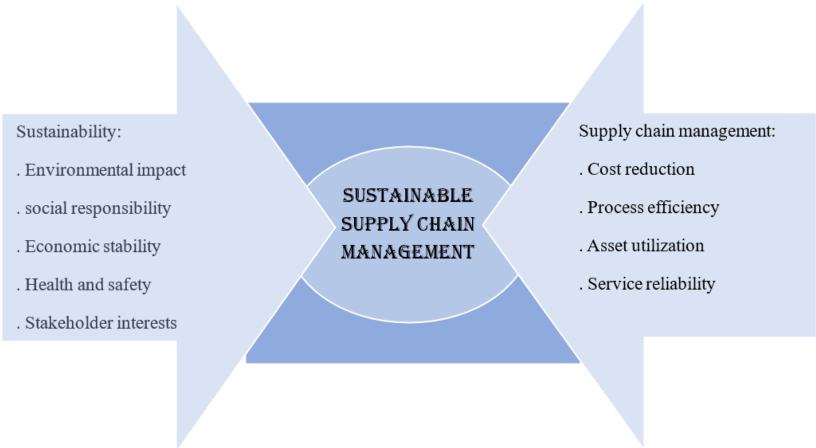

Figure 1. Objectives considered in sustainable supply chain management

There may be disruptions in the supply chain in cultural, social, and economic aspects, and these disruptions will negatively impact the supply chain's income, efficiency, and quality (Rajabzadeh & Babazadeh, 2022, Fallahpour et al., 2021). Resilience is a concept that is used to return the system to its initial state after disturbances (Davoudabadi et al., 2019). Therefore, considering resilience when choosing a supplier increases the ability to control the supply chain when disruptions occur. Also, the resilient supply chain can protect various industries from disruptions and facilitate the return to the original state (Hoseini et al., 2021b). The concept of resilience should be developed in the supply chain to overcome potential disruptions. Hamel and Valikangas (2004) defined resilience as an effective factor for sustainable supplier competition.

Since organizations are trying to implement sustainability in supply chains, they should improve their capabilities and use the Internet of Things (IoT) to innovate and improve sustainability performance (Salehi-Amiri et al., 2022a; Najafi et al., 2023). The IoT is one of the new technologies that can significantly impact the supply chain due to its capabilities and applications (Salehi-Amiri et al., 2022b). Also, one of the most essential and fundamental parts of supply chain management is dealing with crises and disruptions that may occur. Therefore, it is necessary to develop and invest in key technology parameters such as IOT (Najafi et al., 2022). With the mentioned challenges, evaluating IoT supplier companies is a critical issue that should be based on multiple criteria. Evaluation of multiple criteria to make an optimal decision is called multi-criteria decision-making (MCDM) (Haseli et al., 2020; Torkayesh et al., 2022a; Ma et al., 2022). The aim of decision making is to select and evaluate the best option based on different criteria (Haseli et al., 2022; Deveci et al., 2022b).

In addition, according to the definitions of the concepts of sustainability and resilience as well as organizational goals, choosing the right supplier is very important. When choosing a supplier, decision-makers (DMs) in different areas, such as production, procurement, etc. process the decision-making process from different perspectives. Therefore, selecting a sustainable and resilient supplier should be considered a complex MCDM method according to the many existing factors. In the field of supplier selection, the preferences and opinions of DMs are usually accompanied by uncertainty, and DMs express their preferences based on the linguistic variables (Cheraghalipour et al ., 2018). The uncertainty is a very important factor that increases the complexity of the supplier selection problem (Pamucar et al., 2022; Ecer & Torkayesh, 2022; Rajabzadeh et al., 2022b). According to the limitations of classical MCDM, MCDM methods with a fuzzy approach use experts who evaluate and describe their opinions using fuzzy linguistic terms (Deveci et al., 2022c; Rahnamay Bonab & Osgooei, 2022). Therefore, the fuzzy concept is very suitable for overcoming and covering uncertainty.

The fuzzy set was introduced by Zadeh (1995) to control incomplete information and uncertainty. But these fuzzy sets cannot deal with uncertainty and unclear information in actual problems (Deveci et al., 2022d; Haseli & Jafarzadeh Ghoushchi, 2022). Therefore, many fuzzy sets have been developed, recently, the Spherical fuzzy set (SFS) was established by Gündoğdu & Kahraman (2019), which is the extended form of Neutrosophic sets (NS), Pythagorean fuzzy sets (PFS). By giving DMs more space to express their opinions, more reliable decisions can be made and uncertainty and doubts are overcome as much as possible (Ghoushchi et al., 2021; Bonab et al., 2023). The degree of membership function of SFS can ultimately state people's decision-making awareness and adjust the range of decision-making data with the flexibility parameter and accurately describe it (Ghoushchi et al., 2022; Jafarzadeh Ghoushchi et al., 2022).

However, the MulTi-noRmalization mUlti-distance aSsessmenT (TRUST) technique (Torkayesh & Deveci, 2021) has not been integrated with the Best-Worst Method (BWM) (Rezaei, 2015) within the context of SFS, though SFS are proven jointly of the special tools to control the uncertainty and overcome vagueness that happen in real-life issues. Accordingly, the present study focuses on SFS. Choosing the suitable supplier is very serious issue for the success of the organization and the supply chain. Choosing the wrong supplier can be the source of many issues and problems. A supplier defect may cause irreparable damages and costs to the buying organization. One of the key issues in choosing a supplier is the need to consider many selection criteria. Therefore, this paper aims to provide an approach to prioritize suppliers and identify the best supplier according to the main criteria of sustainability and resilience. By considering the concepts of sustainability and resilience, not only are the organization's environmental, economic and social goals considered, but the organization has a high ability to deal with disturbances.

Therefore, to solve the problem raised, a strong systematic approach is needed to evaluate suppliers. An integrated BWM–TRUST approach in the SFS environment is developed to solve this issue. The developed approach gives DMs the power to determine the membership, non-membership, and hesitant functions in a spherical region independently. Therefore, implementing the proposed approach using the advantages of SFS leads to reliable, real, and accurate results. Also, the uncertainty in the experts' opinions is properly controlled and the ambiguity of the data is overcome.

In summary, this research attempts to answer the following research questions in the sustainable resilience supplier selection decision problem.

- What are the effective criteria for sustainable resilience supplier selection for IoT implementation?
- Which criteria have the most impact on sustainable resilience supplier selection for IoT implementation?
- What is the prioritization of sustainable resilience suppliers?
- What is the weight of each of the identified criteria using the SF-BWM?
- What is the sustainable resilience suppliers' ranking using the SF-TRUST?

The rest of this study is as follows: Section 2 is devoted to the literature review and research gap. Next section introduces the concept of SFS and SFS-BWM weighting method and SFS-TRUST ranking method. In section 4, a case study and the proposed approach's results are implemented in detail, and the analysis resulting from the implementation of the proposed approach are explained, then sensitivity analysis, and comparative analysis comparison are performed. Eventually, in Section 5, conclusions, limitations, and suggestions for the development of this study are presented.

2. Literature Review

Intense competition in today's markets and the rapid change of customer preferences prompts organizations to cooperate as supply chain members along with the development of technology and globalization. Due to the increase in environmental considerations and resilience in organizations, choosing a supplier is a critical and challenging issue. So far, various types of research have been conducted in supplier selection, which usually examines the criteria affecting supplier selection. Some of the research conducted by researchers are reviewed in this section.

2.1. Sustainable and resilient supply chain

Nasrollahi et al., (2021) investigated the choice of resilient supplier in the desalination supply chain. Therefore, to prioritize the suppliers, they identified criteria and used ISM and DEMATEL methods in the fuzzy environment to check the most effective criteria. Hoseini et al., (2021b) defined resilient supplier selection as a challenging problem for the supply chain management. They defined sub-criteria for the main criterion of resilience and used BWM and TOPSIS methods to prioritize suppliers. Also, they implemented the proposed approach in type 2 fuzzy environment to deal with the uncertainty in experts' opinions. A lot of attention has been drawn from organizations to the environment and sustainability, so there is a need to impose green strategies on the supply chain. Gupta & Barua, (2017) proposed green innovation criteria and prioritized suppliers based on BWM and TOPSIS methods.

Today, choosing a green supplier has become a competitive strategy for companies. Haeri & Rezaei, (2019) developed an integrated BMW and TOPSIS approach in a fuzzy environment to prioritize green suppliers. Gupta et al., (2019) declared that organizations need to adopt green supply chain management practices to improve their supply chain and make positive changes. They developed an integrated approach of AHP, MABAC and TOPSIS to weigh green supplier selection criteria and rank green suppliers. Stević et al., (2020) studied sustainable supplier selection in the healthcare industry. They defined 21 criteria for evaluation and ranked 8 suppliers using the MARCOS method.

Abdullah et al. (2019) examined 7 environmental and economic criteria to evaluate 4 green suppliers. They used PROMETHEE method to rank the suppliers. Rahman et al. (2022) investigated the selection of sustainable suppliers in the textile dyeing supply chain. They identified the social, economic, and environmental criteria by reviewing the literature and experts' opinions and weighted them using the SWARA method. Then they used the WASPAS method for the final ranking of suppliers. In order to implement sustainability in supply chain management, Tushar et al., (2022) suggested a circular supply chain. They introduced 3 circular criteria including green packaging, pollution control, and environmental standards, and based on AHP and PROMETHEE methods, weighting the criteria and ranking suppliers was done. They also compared the obtained results with the WASPAS method.

Shang et al. (2022) announced that due to the increase in social responsibility and environmental protection awareness, choosing a sustainable supplier is a main requirement for every supply chain. Therefore, they developed the MULTIMOORA method in a fuzzy environment to select a sustainable forklift supplier. Tajmiri & Farhadi, (2022) focused on the issue of resilience in the iron ore supply chain. They identified the criteria influencing the choice of resilient supplier and ranked three supplier companies using the MARCOS method. Also, to validate the results, the ranking was compared with VIKOR, TOPSIS and COPRAS methods. Leong et al. (2022) studied the concept of resilience to deal with unexpected disruptions that may occur in any supply chain. They introduced the decision-making approach of BWM-TOPSIS for resilient supplier selection. They utilized the BWM method to weight seven resilience criteria and the TOPSIS method to evaluate suppliers.

Table 1. Research related to supplier selection based on MCDM methods

Author(s)	methods	Fuzzy	Description
Nasrollahi et al., (2021)	DEMATEL	✓	Identification of resilient supplier selection criteria in the desalination supply chain.
Hoseini et al., (2021)	BWM & TOPSIS	✓	Creating a decision framework for choosing the best supplier.
Gupta & Barua, (2017)	BWM & TOPSIS	✓	Supplier selection among small and medium companies based on green innovations.
Haeri & Rezaei, (2019)	BWM	✓	Choosing a green supplier based on economic and environmental criteria to protect the environment.
Gupta et al., (2019)	AHP, TOPSIS MABAC, and WAPAS	✓	Evaluation of a set of green suppliers is primarily based on both conventional and environmental criteria.
Stević et al., (2020)	MARCOS		Sustainable supplier selection in private healthcare industry.
Abdullah et al., (2019)	PROMETHEE		Examining environmental and economic criteria to evaluate green suppliers.
Rahman et al., (2022)	SWARA & WASPAS		Develops a framework for sustainable supplier selection for the textile dyeing industries.
Tushar et al., (2022)	AHP & PROMETHEE	✓	Explores sustainable supplier selection in the construction industry of an emerging economy.
Shang et al., (2022)	Shannon, BWM, MULTIMOORA	✓	An integrated model for sustainable supplier selection.
Tajmiri & Farhadi, (2022)	MARCOS, COPRAS, VIKOR, TOPSIS		Identifying the criteria influencing the choice of resilient supplier.
Leong et al., (2022)	BWM & TOPSIS		Evaluation of resilient suppliers based on 7 resilience criteria and using MCDM methods.

According to the review of previous researches in Table 1, it can be seen that until now the researchers have not evaluated the suppliers in the SFS. Considering the importance of the subject, it is felt that using the SFS set makes it possible to overcome the ambiguity and uncertainty in the experts' opinions. Therefore, an attempt has been made to provide a decision-making framework based on BWM and TRUST methods in the SFS, considering the main sustainability and resilience criteria to assess IoT suppliers.

2.2. Research gap and contributions of the present study

Considering the fact that people are engaged in business throughout their lives, the importance and necessity of choosing a supplier, which is one of the critical needs of all people and producers, is determined. Choosing the right supplier that meets the conditions and constraints of the organization is one of the most critical activities in supply chain management. Selecting a few suppliers from a large number of suppliers has a significant impact on supply chain management and is very important for the success of organizations. One of the key issues in choosing a supplier is the need to consider many selection criteria. Usually, no unique supplier can best estimate all the considered selection criteria. Considering the importance of supplier selection, it is that researchers have addressed several issues related to supply chain management. However, by reviewing the literature, it can be seen that no research has been done to evaluate sustainable and flexible IoT supplier companies.

Sustainability and resilience are the most vital and fundamental criteria to consider when choosing a supplier to protect the environment and deal with disruptions and crises. Therefore, in this paper, 2 main criteria of sustainability and resilience have been considered and experts have identified several sub-criteria for each of them. Often, experts express their preferences based on linguistic variables in such matters, so definite numbers cannot solve such problems. For this reason, if the evaluation of suppliers is based on fuzzy sets, more accurate and reliable results will be obtained. In this paper, an attempt has been made to present an integrated BMW-TRUST approach in SFS environment to evaluate IoT suppliers.

According to the literature review, an article has not examined the evaluation of IoT suppliers in the SFS based on BWM and TRUST methods. In this paper, the TRUST method, which has 4 normalization techniques and has different steps compared to other MCDM methods, has been developed in the SFS for the first time. The SFS is a very strong three-dimensional set with a high ability to deal with the uncertainty in experts' opinions, leading to reliable and accurate results. The main aim of this paper is to evaluate 14 IoT supplier companies based on two main criteria of sustainability and resilience and nine sub-criteria identified to protect the environment and deal with crises and possible disruptions in the supply chain. Therefore, based on the literature review, the main contributions of this paper are as follows.

- Providing a new approach based on MCDM methods to evaluate IoT suppliers based on sustainability and resilience criteria.
- The proposed new approach based on MCDM methods in the SFS environment provides conditions for dealing with uncertainty and processing ambiguous information.
- Develop the TRUST ranking method in SFS for the first time to evaluate suppliers.
- Investigating the evaluation of IoT suppliers in the two categories of sustainability and resilience to protect the environment and deal with possible crises and disruptions.
- Combining BWM and TRUST methods with SFS to create a stronger and more stable framework, assign more degrees of freedom to DMs to express preferences on a spherical level based on membership functions, and achieve more accurate results.

3. Methodology

3.1. Prelamination of SFS

One of the latest fuzzy sets is the SFS, introduced by Kutlu Gündoğdu and Kahraman (2019). SFS are extensions of the PFS and NS, and provide a larger domain to experts. In SFS, the squared sum of membership, non-membership, and hesitance degrees can be between 0 and 1, each of which can be defined independently between 0 and 1 (Memarpour Ghiaci et al., 2022). Some of the principles of SFSs and their operation are presented in this section.

Definition 1: Let c be a universe of discourse. Eq. (1) is called SFS over the domain c (Kutlu Gündoğdu & Kahraman, 2019).

$$\mathrm{l} = \left[\left(\mathrm{c}\,.\left(\mu_{\mathrm{l}}(\mathrm{c}).\,\mathrm{v}_{\mathrm{l}}(\mathrm{c}).\,\pi_{\mathrm{l}}(\mathrm{c})\right)\right) \mid \mathrm{c}\epsilon\mathrm{C}\right] \tag{1}$$

In Eq. (1), μ_l: C→[0.1]. v_l: C→[0.1]. π_l: C→[0.1] respectively present the membership, non-membership, and hesitance degrees for every cϵC in the SFS, and the Eq. (2). holds:

$$0 \le \left(\mu_{\mathrm{l}}(\mathrm{c})\right)^2 + \left(\mathrm{v}_{\mathrm{l}}(\mathrm{c})\right)^2 + \left(\pi_{\mathrm{l}}(\mathrm{c})\right)^2 \le 1 \tag{2}$$

Definition 2: Let $l_1 = [\mu_{l1}.\ v_{l1}.\ \pi_{l1}]$ and $l_2 = [\mu_{l2}.\ v_{l2}.\ \pi_{l2}]$ be two SFS numbers and K>0. So, the mathematical operations of these two SFS numbers are applied via Eqs. (3-6).

$$\mathrm{l1} \oplus \mathrm{l2} = \left[\sqrt{\mu_{\mathrm{l1}}^2 + \mu_{\mathrm{l2}}^2 - \mu_{\mathrm{l1}}^2\mu_{\mathrm{l2}}^2}\,.\,\mathrm{v}_{\mathrm{l1}}\mathrm{v}_{\mathrm{l2}}\,.\sqrt{(1-\mu_{\mathrm{l2}}^2)\pi_{\mathrm{l1}} + (1-\mu_{\mathrm{l1}}^2)\pi_{\mathrm{l2}} - \pi_{\mathrm{l1}}\pi_{\mathrm{l2}}}\right] \tag{3}$$

$$\mathrm{l1} \otimes \mathrm{l2} = \left[\mu_{\mathrm{l1}}\mu_{\mathrm{l2}}.\sqrt{\mathrm{v}_{\mathrm{l1}}^2 + \mathrm{v}_{\mathrm{l2}}^2 - \mathrm{v}_{\mathrm{l1}}^2\mathrm{v}_{\mathrm{l2}}^2}\,.\sqrt{(1-\mathrm{v}_{\mathrm{l2}}^2)\pi_{\mathrm{l1}}^2 + (1-\mathrm{v}_{\mathrm{l1}}^2)\pi_{\mathrm{l2}}^2 - \pi_{\mathrm{l1}}^2\pi_{\mathrm{l2}}^2}\right] \tag{4}$$

$$\mathcal{K}\mathrm{l} = \left[\sqrt{1-(1-\mu_{\mathrm{l}}^2)^{\mathcal{K}}}\,.\,\mathrm{v}_{\mathrm{l}}^2.\sqrt{(1-\mu_{\mathrm{l}}^2)^{\mathcal{K}} - (1-\mu_{\mathrm{l}}^2-\pi_{\mathrm{l}}^2)^{\mathcal{K}}}\right] \tag{5}$$

$$\mathrm{l}^{\mathcal{K}} = \mu_{\mathrm{l}}^{\mathrm{k}}.\sqrt{1-(1-\mathrm{v}_{\mathrm{l}}^2)^{\mathcal{K}}}\,.\sqrt{(1-\mathrm{v}_{\mathrm{l}}^2)^{\mathcal{K}} - (1-\mathrm{v}_{\mathrm{l}}^2-\pi_{\mathrm{l}}^2)^{\mathcal{K}}} \tag{6}$$

Definition 3: The distance between two SFS numbers M and N is calculated as Eq. (7).

$$\mathrm{dis}\ (\mathrm{M},\mathrm{N}) = \arccos\left\{1-\frac{1}{2}((\mu_{\mathrm{M}}-\mu_{\mathrm{N}})^2 + (\mathrm{v}_{\mathrm{M}}-\mathrm{v}_{\mathrm{N}})^2 + (\pi_{\mathrm{M}}-\pi_{\mathrm{N}})^2)\right\} \tag{7}$$

Eq. (7) Can be rewritten as Eq. (8).

$$\mathrm{dis}(\mathrm{M},\mathrm{N}) = \frac{2}{\pi}\sum_{\mathrm{i}=1}^{\mathrm{n}}\arccos\left\{1-\frac{1}{2}((\mu_{\mathrm{M}}-\mu_{\mathrm{N}})^2 + (\mathrm{v}_{\mathrm{M}}-\mathrm{v}_{\mathrm{N}})^2 + (\pi_{\mathrm{M}}-\pi_{\mathrm{N}})^2)\right\} \tag{8}$$

The normalized SFS distance between M and N is calculated as Eq. (9).

$$\mathrm{dis}^{\mathrm{n}}(\mathrm{M},\mathrm{N}) = \frac{2}{\mathrm{n}\pi}\sum_{\mathrm{i}=1}^{\mathrm{n}}\arccos\left\{1-\frac{1}{2}((\mu_{\mathrm{M}}-\mu_{\mathrm{N}})^2 + (\mathrm{v}_{\mathrm{M}}-\mathrm{v}_{\mathrm{N}})^2 + (\pi_{\mathrm{M}}-\pi_{\mathrm{N}})^2)\right\} \tag{9}$$

Definition 3: Let $M = [\mu_M, v_M, \pi_M]$ and $N = [\mu_N, v_N, \pi_N]$ be two SFS numbers. Eqs. (10-15) with the condition $K_1, K_2 > 0$, $K > 0$ hold for SFS numbers.

$$\mathrm{M} \oplus \mathrm{N} = \mathrm{N} \oplus \mathrm{M} \tag{10}$$

$$\mathrm{M} \otimes \mathrm{N} = \mathrm{N} \otimes \mathrm{M} \tag{11}$$

$$k(M \oplus N) = kM \oplus kN \tag{12}$$

$$\mathcal{K}_1 M + \mathcal{K}_2 N = (\mathcal{K}_1 + \mathcal{K}_2) N \tag{13}$$

$$(M \otimes N)^{\mathcal{K}} = \mathcal{A}^{\mathcal{K}} \otimes N^{\mathcal{K}} \tag{14}$$

$$M^{\mathcal{K}1} \otimes M^{\mathcal{K}2} = M^{\mathcal{K}1+\mathcal{K}2} \tag{15}$$

Definition 4: Let M1 = $\{\mu_{M1}, \nu_{M1}, \pi_{M1}\}$ and M2= $\{\mu_{M2}, \nu_{M2}, \pi_{M2}\}$ represents the SFS number. The score value and accuracy function of the number M are computed as Eqs. (16-19).

$$\text{Score}(M1) = (\mu_{M1} - \pi_{M1})^2 - (v_{M1} - \pi_{M1})^2 \tag{16}$$

$$\text{Accuracy } (M1) = \mu_{M1}^2 + v_{M1}^2 + \pi_{M1}^2 \tag{17}$$

Note that: M1<M2 if and only if

$$\text{score}(M1) < \text{score}(M2) \text{ or} \tag{18}$$

$$\text{score}(M1) = \text{score}(M2) \text{ and Accuracy}(M1) < \text{Accuracy}(M2) \tag{19}$$

Sometimes the values obtained through Eqs. (16-17) are negative or zero, and even sometimes, the SFS values are obtained equally. As a result, the prioritization function (PF) function has been introduced as Eq. (20) for prioritizing SFS numbers.

$$\mathcal{PF}(M1) = \mu_{M1} * (1 - v_{M1}) * (1 - \pi_{M1}) \tag{20}$$

3.2. SFS best-worst method

Rezaei (2015) introduced BWM to obtain weight coefficients of criteria using an optimization model. The BWM is a vector-based MCDM method. The BWM uses the pairwise comparisons approach to collect DM preferences (Moslem et al., 2020a; Haseli & Sheikh, 2022). Hafezalkotob and Hafezalkotob (2017) introduced group fuzzy BWM to improve the BWM for group decision-making. Also, Haseli et al. (2021) proposed a novel approach for group BWM requiring fewer mathematical modeling. The BWM method is extended using various approaches such as, fuzzy BWM (Moslem et al., 2020b; Yazdani et al., 2022), stratified BWM (Torkayesh et al., 2022b), gray BWM (Torkayesh et al., 2021), interval rough BWM (Deveci et al., 2021). This section aims to explain BWM for obtaining the criteria weight based on linguistic variables of the SFS.

Step 1: Identify a set of affecting criteria on the decision problem. In this step, the set of affecting criteria {C1, C2, C3, …, Cn} should be defined.

Step 2: Find the best (foremost importance) and the worst (least importance) criteria. The involved DMs does that.

Step 3: Form a best criterion relative importance vector over all other criteria by applying the linguistic variables of Table 2.

Table 2. The linguistic variables of SFS values (Kutlu Gündoğdu & Kahraman, 2019)

Linguistic terms	(μ, ν, π)
Absolutely More Importance (AMI)	(0.1, 0.9, 0.1)
Very High Importance (VHI)	(0.2, 0.8, 0.2)
High Importance (HI)	(0.3, 0.7, 0.3)
Slightly More Importance (SMI)	(0.4, 0.6, 0.4)
Equally Importance (EI)	(0.5, 0.5, 0.5)
Slightly Low Importance (SLI)	(0.6, 0.4, 0.4)
Low Importance (LI)	(0.7, 0.3, 0.3)
Very Low Importance (VLI)	(0.8, 0.2, 0.2)
Absolutely Low Importance (ALI)	(0.9, 0.1, 0.1)

The relative importance vector of the best criterion to the other criteria based on the SFSs would be as follows:

$$A_{Bj} = ((\mu_{B1}, v_{B1}, \dots, \pi_{B1}), (\mu_{B2}, v_{B2}, \dots, \pi_{B2}), \dots, (\mu_{Bn}, v_{Bn}, \dots, \pi_{Bn})) \quad (21)$$

Step 4: Form the relative importance vector of all criteria over the worst criterion by applying the linguistic variables of Table 2. The vector of worst criterion to the other criteria based on the SFSs would be as follows:

$$A_{jw} = ((\mu_{1w}, v_{1w}, \dots, \pi_{1w}), (\mu_{2w}, v_{2w}, \dots, \pi_{2w}), \dots, (\mu_{nw}, v_{nw}, \dots, \pi_{nw})) \quad (22)$$

Step 5: Using Eq. (20), calculate the prioritization function of the SF values of the vectors obtained in steps 3 and 4. At this point, the values of the vectors will be crisp numbers, as follows;

$$A_{Bj} = (a_{B1}, a_{B2}, \dots, a_{Bm}) \quad (23)$$

$$A_{jw} = (a_{1W}, a_{2w}, \dots, a_{mW}) \quad (24)$$

Step 6: Calculate the optimal criteria weight using the Eq. (25).

Min ξ
subject to

$$\begin{cases} \left|\dfrac{w_B}{w_j} - a_{Bj}\right| \le \xi\,, \\ \left|\dfrac{w_j}{w_W} - a_{jw}\right| \le \xi\,, \\ \sum_{j=1}^{n}(w_j) = 1, \\ w_j \ge 0 \text{ for all } j. \end{cases} \quad (25)$$

Finally, the consistency ratio should be calculated as follows:

$$\text{Consistency ratio} = \frac{\xi}{\text{Consistency Index}} \quad (26)$$

The consistency index in Eq. (26) for different values of the a_{bw} is shown in Table 3.

Table 3. Consistency Index (Rezaei, 2015)

a_{BW}	1	2	3	4	5	6	7	8	9
Consistency Index	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

3.3. SFS TRUST method

The TRUST method was introduced as a MCDM method for ranking alternatives by Torkayesh and Deveci (2021). Different procedures and 4 types of normalization techniques somewhat distinguish this method from other methods. This method uses priorities, types of criteria and standards to normalize based on constraint and increase reliability. Also, to aggregate four normalization techniques and reduce subjectivity and bias, a combined technique is used. Linear sum-based normalization, linear ratio-based, logarithmic normalization, and linear max-min normalization, are four used normalization techniques.

The SFS-TRUST method is defined as the following steps:

Step 1: Formation of SFS decision matrix

Assume A = {A_1, A_2, ..., A_i, ..., A_m} is a set alternatives 'm' and x = {x_1, x_2, ..., x_j, ..., x_n} is a set of criteria 'n'. Suppose $i = 1(1)m \,.\, j = 1(1)n$, $Z = \left(z_{ij}{}^{(L)}\right)$ is the evaluation decision matrix. Therefore, $a_{ij}{}^{(L)}$ is the evaluation of the Ai choice on the X_j criterion. Therefore, the decision matrix based on SFS linguistic variables is formed as an Eq. (27).

$$Z = \left(\mathrm{x_j(a_i)}\right)_{\mathrm{m*n}} = \begin{bmatrix} \{\mu_{11}.\,\mathrm{v}_{11}.\,\pi_{11}\} & \cdots & \{\mu_{1\mathrm{n}}.\,\mathrm{v}_{1\mathrm{n}}.\,\pi_{1\mathrm{n}}\} \\ \vdots & \ddots & \vdots \\ \{\mu_{\mathrm{m}1}.\,\mathrm{v}_{\mathrm{m}1}.\,\pi_{\mathrm{m}1}\} & \cdots & \{\mu_{\mathrm{mn}}.\,\mathrm{v}_{\mathrm{mn}}.\,\pi_{\mathrm{mn}}\} \end{bmatrix} \tag{27}$$

Step 2: Transformation of linguistic variables to SFS numbers

To make a decision matrix based on SFS numbers, the SFS linguistic variables of the initial matrix are converted to SFS numbers using Table 2. The decision matrix based on SFS numbers is formed as an Eq. (28).

$$Z = \left[z_{ij}\right]_{n*m} = \begin{bmatrix} z_{11} & \cdots & z_{1m} \\ \vdots & \ddots & \vdots \\ z_{n1} & \cdots & z_{nm} \end{bmatrix} \tag{28}$$

Step 3: Computing the prioritization function

Using Eq. (20), the prioritization value of each SFS number is calculated and the matrix $F = \left[f_{ij}\right]_{n*m}$ is formed.

Step4: Decision matrix normalization:

Normalization occurs in almost all MCDM methods, and usually, one technique is used, but TRUST uses four normalization techniques for normalization of the decision matrix.

Step 4.1: In type 1 normalization, normalization is done based on linear ratio using Eqs. (29-30).

$$f_{ij}^{a}=\frac{f_{ij}}{\max_{i} s_{ij}} \quad if\ j\epsilon B \tag{29}$$

$$f_{ij}^{a}=\frac{\min_{i} f_{ij}}{s_{ij}} \quad if\ j\epsilon C \tag{30}$$

B indicates benefit criteria and C denotes the cost criteria.

Step 4.2: In type 2 normalization, normalization of decision matrix numbers is done based on linear-sum and using Eqs. (31-32).

$$f_{ij}^{b}=\frac{f_{ij}}{\sum_{i=1}^{m} f_{ij}} \quad if\ j\epsilon B \tag{31}$$

$$f_{ij}^{b}=\frac{\frac{1}{f_{ij}}}{\sum_{i=1}^{m}\frac{1}{f_{ij}}} \quad if\ j\epsilon C \tag{32}$$

Step 4.3: In type 3 normalization, the linear maximum-minimum technique and Eqs. (33-34) are used to form the normalized decision matrix.

$$f_{ij}^{c}=\frac{\left(f_{ij}-\min_{i} f_{ij}\right)}{(\max_{i} f_{ij}-\min_{i} f_{ij})} \quad if\ j\epsilon B \tag{33}$$

$$f_{ij}^{c}=\frac{(\max_{i} f_{ij}-f_{ij})}{(\max_{i} f_{ij}-\min_{i} f_{ij})} \quad if\ j\epsilon C \tag{34}$$

Step 4.4: In the last step of normalization, the logarithmic technique based on Eqs. (35). is used to form the normalized matrix.

$$f_{ij}^{d}=\frac{\log\left(f_{ij}\right)}{\log\left(\prod_{i=1}^{m} f_{ij}\right)} \tag{35}$$

Step 4.5: Finally, Eq. (36). is used to integrate 4 normalized matrices.

$$\mathfrak{h}_{ij}=\alpha_1 f_{ij}^{a}+\alpha_2 f_{ij}^{b}+\alpha_3 f_{ij}^{c}+\alpha_4 f_{ij}^{d} \tag{36}$$

The Eq. (37) must be met:

$$\alpha_1+\alpha_2+\alpha_3+\alpha_4=1 \tag{37}$$

Step 5: Satisfaction degree matrix:

The primary decision matrix and the limit values determined for the criteria are used to form the degree of satisfaction. The normalization steps based on the constraints are as follows.

In the matrix F, f_j^{min}= $Min(f_{ij})$ and f_j^{max}= $Max\left(f_{ij}\right)$ represents the minimum and maximum values.

Step 5.1: The limit values of the criteria are determined based on the experience and expertise of the DMs. The limit values are determined as [LB_J, UB_J] which LB_J and UB_J respectively indicate the lower and upper limits of criterion j. The Constraint values must be inside the values f_j^{min} and f_j^{max} values as Eq. (38).

$$Co_j = [LB_j, UB_j] \subseteq [f_j^{min}, f_j^{max}] \tag{38}$$

Step 5.2: The satisfaction degree matrix is computed based on the initial matrix and constraint values. Another matrix is formed as matrix D. In matrix D, d_{ij} indicates the degree of constraint satisfaction of alternative i concerning the constrained value of criterion j. Elements of matrix D can be calculated as Eqs. (39-44).

For a benefit criterion:

$$d_{ij} = 1, if\, s_{ij} \epsilon [LB_j, UB_j] \tag{39}$$

$$d_{ij} = 1 - \frac{LB_j - f_{ij}}{max(LB_j - f_j^{min}, f_j^{max} - UB_j) + 1}, if\ f_{ij} \epsilon [s_j^{min}, LB_j] \tag{40}$$

$$d_{ij} = 1 - \frac{1 - UB_j + f_{ij}}{\max(LB_j - f_j^{min}, f_j^{max} - UB_j) + 1}, if\ f_{ij} \epsilon [UB_j, f_j^{max}] \tag{41}$$

For a cost criterion:

$$d_{ij} = \frac{1}{\max(LB_j - f_j^{min}, f_j^{max} - UB_j) + 1}, if\ f_{ij} \epsilon [LB_j, UB_j] \tag{42}$$

$$d_{ij} = \frac{LB_j - f_{ij}}{\max(LB_j - f_j^{min}, f_j^{max} - UB_j)}, if\ f_{ij} \epsilon [f_j^{min}, LB_j] \tag{43}$$

$$d_{ij} = \frac{f_{ij} - UB_j}{\max(LB_j - f_j^{min}, f_j^{max} - UB_j)}, if\ f_{ij} \epsilon [UB_j, f_j^{max}] \tag{44}$$

Step 6: Constrained aggregated normalized decision matrix:

To form constrained aggregated normalized decision matrix, Eq. (45) is used.

$$\mathcal{Y}_{ij} = d_{ij} \mathfrak{h}_{ij} \tag{45}$$

Step 7: The matrix formed in step 6, is multiplied by weight of criteria to produce a weight-constrained aggregated normalized matrix, $P = [p_{ij}]_{m*n}$, as Eq. (46).

$$p_{ij} = \mathcal{Y}_{ij} w_j \tag{46}$$

Step 8: Negative-ideal solution of weighted matrix P:

Eq. (47) is used to specify Negative-ideal solution.

$$\eta_j = \min_i p_{ij} \tag{47}$$

where η_j represents a negative-ideal solution of criterion j.

Step 9: In the TRUST method, a two-step technique is used to calculate the distance of the options from the negative ideal.

Step 9.1: In phase 1, Euclidean and Manhattan distance measures are utilized as Eqs. (48) to (49).

$$\mathbb{E}_i = \sqrt{\sum_{i=1}^{m} \left(p_{ij} - \eta_j\right)^2} \tag{48}$$

$$\mathbb{T}_i = \sum_{i=1}^{m} \left|p_{ij} - \eta_j\right| \tag{49}$$

Step 9.2: In phase 2, Lorentzian distance measure, and Pearson distance measure are utilized to as Eqs. (50-51).

$$\mathbb{L}_i = \sum_{i=1}^{m} log\left(1 + \left|p_{ij} - \eta_j\right|\right) \tag{50}$$

$$\mathbb{p}_i = \sum_{i=1}^{m} \frac{\left(p_{ij} - \eta_j\right)^2}{\eta_j} \tag{51}$$

Step 10: Based on the calculation of distances, relative evaluation matrices are calculated based on Eqs. (52-53).

$$ⓠ_{ik} = (\mathbb{E}_i - \mathbb{E}_k) + ((\mathbb{E}_i - \mathbb{E}_k) * (\mathbb{T}_i - \mathbb{T}_k)) \tag{52}$$

$$\varphi_{ik} = (\mathbb{L}_i - \mathbb{L}_k) + ((\mathbb{L}_i - \mathbb{L}_k) * (\mathbb{P}_i - \mathbb{P}_k)) \tag{53}$$

Step 11: Finally, a score for each alternative, σ_i, is computed as Eq. (54).

$$\sigma_i = \beta \sum_{k=1}^{n} ⓠ_{ik} + (1 - \beta) \sum_{k=1}^{n} \varphi_{ik} \tag{54}$$

β represents the parameter that is used to calculate the final score. It is a non-negative parameter that can have a value below one, and usually DMs choose a value of 0.5 for it. Then, based on the final value σ_i, the options are sorted in descending order. The integrated approach is presented graphically in Figure 2.

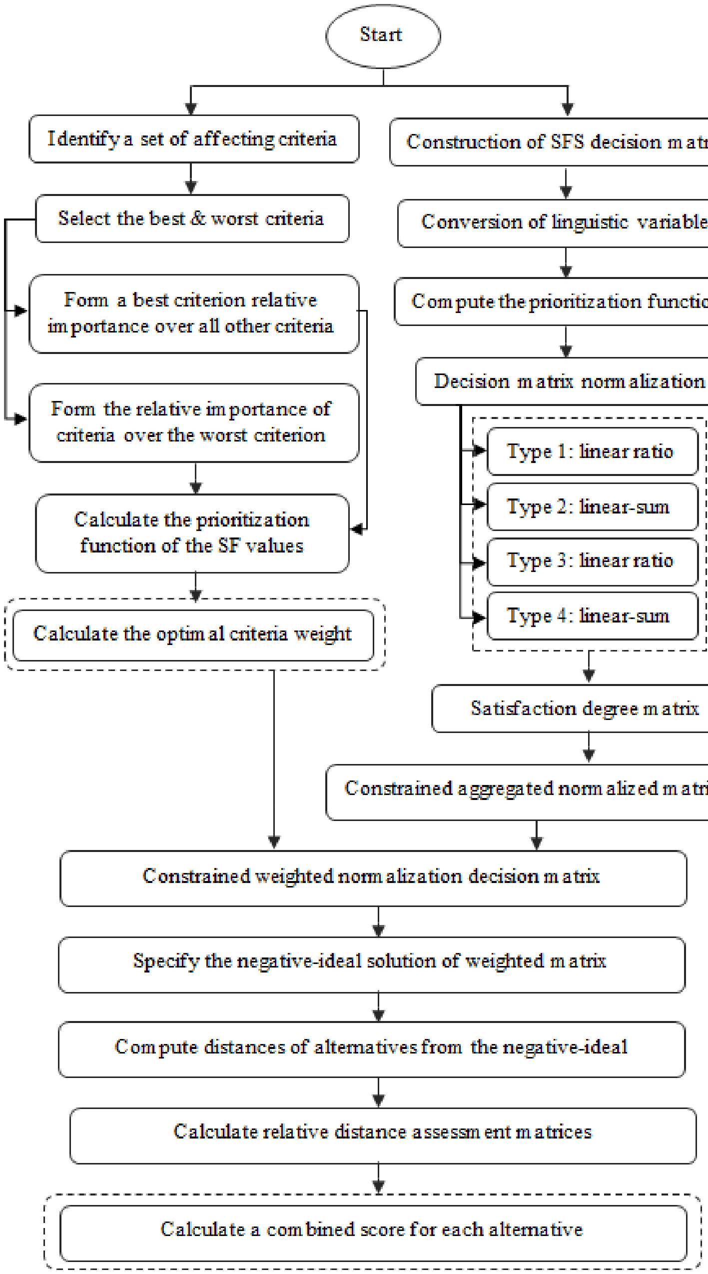

Figure 2. The integrated proposed approach model

4. Experimental results

Here, the integrated BWM-TRUST framework is implemented to select the sustainable and resilient IoT supplier company in the SFS framework, demonstrating the proposed approach's performance and applicability.

4.1. SFS TRUST method

Reviewing the literature shows that no research has been done to evaluate IoT suppliers with the SFS-BWM-TRUST approach to ensure sustainability and resilience in the supply chain. Since organizations want to choose suppliers who have strong characteristics, in this section, we have identified two main and essential criteria of sustainability and resilience to evaluate 14 IoT supplier companies. The sub-criteria explanations and their types are presented in Table 4.

Table 4. Criteria, sub-criteria, and explanations related to them

Criteria & Sub criteria		Description	References	Type *
Sustainability	Environmental management system (C_1)	Activities, methods and policies of environmental protection by suppliers in all sectors (Implementation of ISO 14001 standards).	Stević et al., (2020), Afrasiabi et al., (2022), Tong et al., (2022)	B
	Green products (C_2)	Production of products that cause the least damage to the environment in their life cycle and are environmentally friendly.	Yu et al., (2019), Rahman et al., (2022)	B
	Green finance (C_3)	Investing in a variety of green business operations that prevent carbon emissions, such as switching companies to renewable energy sources and adopting a variety of emission reduction technologies.	Afrasiabi et al., (2022), Stević et al., (2020)	C
	Pollution control (C_4)	A set of rules to reduce the emission of greenhouse gases during the production of products.	Afrasiabi et al., (2022), Yu et al., (2019), Tong et al., (2022)	B
	Reuse and recycle (C_5)	Greening all production processes, reusing products and recycling waste.	Yu et al., (2019), Stević et al., (2020)	B
Resilient	Vulnerability and reaction (C_6)	The capacity of the supplier to deal with threats and have structured and flexible planning.	Parkouhi & Ghadikolaei (2017), Afrasiabi et al., (2022)	B
	Risk taking (C_7)	The extent of the supplier's awareness and recognition of potential risks and dealing with them in emergency situations.	Amindoust (2018), Sonar et al., (2022), Stević et al., (2020)	B
	The capacity to return to the initial state (C_8)	The extent of the supplier's ability to implement restoration protocols to return to original conditions.	Afrasiabi et al., (2022), Stević et al., (2020), Yu et al., (2019)	B

Criteria & Sub criteria	Description	References	Type *
Adaptation (system flexibility) (C_9)	The supplier's ability to face innovations, accept and adapt to new technologies.	Stević et al., (2020), Yu et al., (2019), Davoudabadi et al., (2020)	B

* B means benefit and C means cost.

4.2. Results

This section provides detailed results of the weight of criteria and the ranking of the alternatives using the novel proposed approach. The surveys were evaluated in three interview sessions. Performing pairwise comparisons and evaluation was done in the first session for 90 minutes. Also, the duration of evaluating the value of each alternative about each criterion lasted for two sessions of 60 and 70 minutes. The determining weight of the identified criteria is done using the steps mentioned in section 3.2. First, affecting criteria were identified for the prioritization of the IoT suppliers. Then, the best and worst criteria for each category were determined. The C4 and C2 in the sustainability sub-criteria were chosen as the best and worst criteria, respectively. Also, C7 and C9 in resilient sub-criteria were chosen as the best and worst criteria, respectively. It can be seen in Table 5, the results of pairwise comparisons of the best criterion over the other criteria as well as the other criteria over the worst criterion using the linguistic variables mentioned in Table 2.

Table 5. The decision matrix in the form of SFS linguistic variables

Criteria	Best & Worst		Sub-criteria								
			C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Sustainability	Best	C_4	SLI	ALI	SLI	EI	VLI	-	-	-	-
	Worst	C_2	VLI	EI	VLI	ALI	SLI	-	-	-	-
Resilient	Best	C_7	-	-	-	-	-	LI	EI	SLI	LI
	Worst	C_9	-	-	-	-	-	SLI	LI	SLI	EI

By transforming the corresponding SFS values of the linguistic variables of the pairwise comparisons to the crisp values using Eq. (20), a nonlinear programming model based on Eq. (25) is written for the problem. The results of the criteria weight are calculated by solving the nonlinear programming model, which can be seen in Table 6.

Table 6. Final weight of the criteria

Category	weight	Sub criteria	local weight	Global weight	Priority
Sustainability	0.6	(C_1)	0.235	0.141	3
		(C_2)	0.050	0.030	9
		(C_3)	0.235	0.141	3
		(C_4)	0.394	0.236	1
		(C_5)	0.080	0.051	4
Resilient	0.4	(C_6)	0.184	0.074	5
		(C_7)	0.508	0.203	2
		(C_8)	0.184	0.074	5
		(C_9)	0.124	0.050	8

As can see in Table 6, the pollution control (C4) and risk-taking (C7) sub-criteria obtained high weight values as the sustainability and resilient sub-criteria, respectively. Also, the green products (C2) and adaptation (system flexibility) (C9) sub-criteria obtained the least weight values as the sustainability and resilient sub-criteria, respectively. The important point is the difference in the weight and importance of sustainability and resilience criteria. Allocating higher weight to the sustainability criterion compared to resilience has been mentioned in the results. While if the weight of these two criteria were considered equal, the risk-taking (C7) sub-criteria would get the highest value of the final weight.

After weighting the criteria using SFS-BWM method, to rank the alternatives, the initial matrix is formed based on SFS linguistic variables mentioned in Table 2 (see Table 7).

Then, using Table 2, linguistic variables are transformed to SFS numbers. Based on step 3, the decision matrix is constructed based on the PF to perform normalization techniques. In this step, it is essential to specify the type of criteria to determine the minimum and maximum criteria. Normalized decision matrices based on Eqs. (29-35) are provided in the Table 8.

Table 7. The decision matrix in the form of SFS linguistic variables

Alt.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	SLI	LI	SMI	SLI	EI	HI	VHI	VHI	VHI
A_2	SLI	LI	VLI	EI	SMI	HI	VHI	SMI	HI
A_3	SLI	ALI	HI	SLI	SMI	SMI	VHI	VHI	AMI
A_4	SLI	LI	EI	LI	SLI	HI	VHI	HI	SMI
A_5	VHI	HI	SLI	EI	SLI	HI	HI	HI	AMI
A_6	SLI	LI	EI	VLI	VHI	VHI	VHI	VHI	AMI
A_7	SMI	SLI	VHI	LI	SMI	HI	HI	EI	VHI
A_8	SLI	SLI	LI	HI	SMI	VHI	VHI	VHI	VHI
A_9	EI	SMI	EI	EI	LI	HI	HI	SMI	VHI
A_{10}	SLI	VLI	EI	LI	VLI	VHI	VHI	VHI	VHI
A_{11}	SLI	ALI	LI	SLI	EI	AMI	VHI	VHI	VHI
A_{12}	EI	VLI	SMI	EI	SLI	VHI	VHI	HI	AMI
A_{13}	LI	EI	HI	SLI	VLI	VHI	VHI	AMI	AMI
A_{14}	EI	EI	HI	LI	SMI	HI	VHI	HI	AMI

Table 8. Normalized decision matrix: (f_{ij}^{a}, f_{ij}^{b} , f_{ij}^{c} and f_{ij}^{d} values)

Alt.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	
A_1	0.19	0.14	0.15	0.28	0.24	0.47	1.00	0.70	0.70	**Type 1**
A_2	0.19	0.14	1.00	0.36	0.42	0.47	1.00	0.30	0.47	
A_3	0.19	1.00	0.09	0.28	0.42	0.30	1.00	0.70	1.00	
A_4	0.19	0.14	0.26	0.18	0.19	0.47	1.00	0.47	0.30	
A_5	1.00	0.03	0.33	0.36	0.19	0.47	0.67	0.47	1.00	
A_6	0.19	0.14	0.26	0.09	1.00	0.70	1.00	0.70	1.00	
A_7	0.42	0.09	0.06	0.18	0.42	0.47	0.67	0.17	0.70	
A_8	0.19	0.09	0.51	1.00	0.42	0.70	1.00	0.70	0.70	
A_9	0.24	0.04	0.26	0.36	0.12	0.47	0.67	0.30	0.70	

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	
A10	0.19	0.28	0.26	0.18	0.06	0.70	1.00	0.70	0.70	
A11	0.19	1.00	0.51	0.28	0.24	1.00	1.00	0.70	0.70	
A12	0.24	0.28	0.15	0.36	0.19	0.70	1.00	0.47	1.00	
A13	0.12	0.07	0.09	0.28	0.06	0.70	1.00	1.00	1.00	
A14	0.24	0.07	0.09	0.18	0.42	0.47	1.00	0.47	1.00	
Alt.	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	
A1	0.05	0.04	0.04	0.06	0.11	0.06	0.08	0.09	0.06	Type 2
A2	0.05	0.04	0.25	0.08	0.20	0.06	0.08	0.04	0.04	
A3	0.05	0.28	0.02	0.06	0.22	0.04	0.08	0.09	0.09	
A4	0.05	0.04	0.06	0.04	0.11	0.06	0.08	0.06	0.03	
A5	0.26	0.01	0.08	0.08	0.12	0.06	0.05	0.06	0.09	
A6	0.05	0.04	0.06	0.02	0.66	0.09	0.08	0.09	0.09	
A7	0.11	0.03	0.02	0.04	0.42	0.06	0.05	0.02	0.06	
A8	0.05	0.03	0.13	0.23	0.41	0.09	0.08	0.09	0.06	
A9	0.06	0.01	0.06	0.08	0.10	0.06	0.05	0.04	0.06	
A10	0.05	0.08	0.06	0.04	0.04	0.09	0.08	0.09	0.06	
A11	0.05	0.28	0.13	0.06	0.14	0.12	0.08	0.09	0.06	
A12	0.06	0.08	0.04	0.08	0.10	0.09	0.08	0.06	0.09	
A13	0.03	0.02	0.02	0.06	0.02	0.09	0.08	0.13	0.09	
A14	0.06	0.02	0.02	0.04	0.14	0.06	0.08	0.06	0.09	
Alt.	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	
A1	0.07	0.84	0.62	0.21	0.19	0.25	1.00	0.64	0.58	Type 3
A2	0.07	0.84	1.00	0.30	0.38	0.25	1.00	0.15	0.25	
A3	0.07	1.00	0.35	0.21	0.38	0.00	1.00	0.64	1.00	
A4	0.07	0.84	0.81	0.10	0.13	0.25	1.00	0.36	0.00	
A5	1.00	0.00	0.87	0.30	0.13	0.25	0.00	0.36	1.00	
A6	0.07	0.84	0.81	0.00	1.00	0.58	1.00	0.64	1.00	
A7	0.34	0.74	0.00	0.10	0.38	0.25	0.00	0.00	0.58	
A8	0.07	0.74	0.94	1.00	0.38	0.58	1.00	0.64	0.58	
A9	0.14	0.38	0.81	0.30	0.06	0.25	0.00	0.15	0.58	
A10	0.07	0.93	0.81	0.10	0.00	0.58	1.00	0.64	0.58	
A11	0.07	1.00	0.94	0.21	0.19	1.00	1.00	0.64	0.58	
A12	0.14	0.93	0.62	0.30	0.13	0.58	1.00	0.36	1.00	
A13	0.00	0.65	0.35	0.21	0.00	0.58	1.00	1.00	1.00	
A14	0.14	0.65	0.35	0.10	0.38	0.25	1.00	0.36	1.00	
Alt.	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	
A1	0.08	0.07	0.06	0.07	0.07	0.08	0.06	0.05	0.08	Type 4
A2	0.08	0.07	0.13	0.06	0.05	0.08	0.06	0.11	0.13	
A3	0.08	0.12	0.04	0.07	0.05	0.12	0.06	0.05	0.04	
A4	0.08	0.07	0.08	0.08	0.08	0.08	0.06	0.08	0.18	
A5	0.02	0.03	0.09	0.06	0.08	0.08	0.10	0.08	0.04	
A6	0.08	0.07	0.08	0.10	0.02	0.05	0.06	0.05	0.04	
A7	0.05	0.06	0.03	0.08	0.05	0.08	0.10	0.15	0.08	

Alt.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_8	0.08	0.06	0.10	0.03	0.05	0.05	0.06	0.05	0.08
A_9	0.07	0.04	0.08	0.06	0.09	0.08	0.10	0.11	0.08
A_{10}	0.08	0.09	0.08	0.08	0.12	0.05	0.06	0.05	0.08
A_{11}	0.08	0.12	0.10	0.07	0.07	0.02	0.06	0.05	0.08
A_{12}	0.07	0.09	0.06	0.06	0.08	0.05	0.06	0.08	0.04
A_{13}	0.09	0.05	0.04	0.07	0.12	0.05	0.06	0.02	0.04
A_{14}	0.07	0.05	0.04	0.08	0.05	0.08	0.06	0.08	0.04

Then, to merge the matrices and form the $\mathfrak{h}_i$ matrix, Eq. (36) is used, in which the equal value of 0.25 is considered for all four α. The $\mathfrak{h}_i$ matrix is in the form of Table 9.

Table 9. Aggregated normalized decision matrix ($\mathfrak{h}_{ij}$values)

Alt.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	0.10	0.27	0.21	0.15	0.15	0.22	0.54	0.37	0.36
A_2	0.10	0.27	0.59	0.20	0.26	0.22	0.54	0.15	0.22
A_3	0.10	0.60	0.13	0.15	0.27	0.11	0.54	0.37	0.53
A_4	0.10	0.27	0.30	0.10	0.13	0.22	0.54	0.24	0.13
A_5	0.57	0.02	0.34	0.20	0.13	0.22	0.21	0.24	0.53
A_6	0.10	0.27	0.30	0.05	0.67	0.35	0.54	0.37	0.53
A_7	0.23	0.23	0.03	0.10	0.32	0.22	0.21	0.09	0.36
A_8	0.10	0.23	0.42	0.56	0.32	0.35	0.54	0.37	0.36
A_9	0.13	0.12	0.30	0.20	0.10	0.22	0.21	0.15	0.36
A_{10}	0.10	0.35	0.30	0.10	0.05	0.35	0.54	0.37	0.36
A_{11}	0.10	0.60	0.42	0.15	0.16	0.54	0.54	0.37	0.36
A_{12}	0.13	0.35	0.21	0.20	0.13	0.35	0.54	0.24	0.53
A_{13}	0.06	0.20	0.13	0.15	0.05	0.35	0.54	0.54	0.53
A_{14}	0.13	0.20	0.13	0.10	0.25	0.22	0.54	0.24	0.53

Eq. (36) uses the assigned α values to determine the h_{ij} values, for example:

$$\mathfrak{h}_{21} = (0.046) + (0.012) + (0.018) + (0.019) = 0.10$$

In the next step, the constraint-based normalization process begins. Initially, experts determine the LB_J and UB_J values of each criterion based on experience, expertise, and actual standards. (See Table 10). Baesd on the constraints' values and the criteria type, the Satisfaction degree matrix is determined using Eqs. (39-44). The Satisfaction degree matrix is presented in Table 11.

Table 10. Constraint values of the criteria

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
LB	MIN	0.063	0.096	0.096	0.216	MIN	0.425	0.343	MIN
UB	MAX	0.125	0.343	MAX	0.512	MAX	MAX	0.512	max

The Constrained aggregated normalized decision matrix is then formed based on Eq. (45) (see Table12).

Table 11. Satisfaction degree values decision matrix (F_{ij} values)

Alt.	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
A_1	1.00	0.82	0.86	1.00	0.92	1.00	1.00	1.00	1.00
A_2	1.00	0.82	0.38	1.00	1.00	1.00	1.00	0.90	1.00
A_3	1.00	0.25	0.86	1.00	1.00	1.00	1.00	1.00	1.00
A_4	1.00	0.82	0.86	0.97	0.90	1.00	1.00	1.00	1.00
A_5	1.00	1.00	0.86	1.00	0.90	1.00	0.92	1.00	1.00
A_6	1.00	0.82	0.86	0.94	1.00	1.00	1.00	1.00	1.00
A_7	1.00	0.82	1.00	0.97	1.00	1.00	0.92	0.82	1.00
A_8	1.00	0.28	0.20	1.00	1.00	1.00	1.00	1.00	1.00
A_9	1.00	0.42	0.86	1.00	0.87	1.00	0.92	0.90	1.00
A_{10}	1.00	0.14	0.86	0.97	0.84	1.00	1.00	1.00	1.00
A_{11}	1.00	0.25	0.20	1.00	0.92	1.00	1.00	1.00	1.00
A_{12}	1.00	0.14	0.86	1.00	0.90	1.00	1.00	1.00	1.00
A_{13}	1.00	0.82	0.86	1.00	0.84	1.00	1.00	0.08	1.00
A_{14}	1.00	0.82	0.86	0.97	1.00	1.00	1.00	1.00	1.00

The satisfaction degree is also calculated as follows:

$$\mathcal{F}_{22} = \frac{1}{\max(0{,}063 - 0{,}063.0{,}283 - 0{,}125) + 1} = 0.82$$

Then Eq (46) is used to form the weighted normalized decision matrix. After that, the values of the negative ideal solution of each criterion are specified using Eq. (47), which is given in Table 13. Table 13 shows the weighted constrained aggregated normalized decision matrix.

Table 12. Constrained aggregated normalized decision matrix (y_{ij} values)

	y_{ij}								
Alt.	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
A1	0.10	0.22	0.18	0.15	0.14	0.22	0.54	0.37	0.36
A2	0.10	0.22	0.23	0.20	0.26	0.22	0.54	0.13	0.22
A3	0.10	0.15	0.11	0.15	0.27	0.11	0.54	0.37	0.53
A4	0.10	0.22	0.26	0.10	0.11	0.22	0.54	0.24	0.13
A5	0.57	0.02	0.29	0.20	0.12	0.22	0.19	0.24	0.53
A6	0.10	0.22	0.26	0.05	0.67	0.35	0.54	0.37	0.53
A7	0.23	0.19	0.03	0.10	0.32	0.22	0.19	0.07	0.36
A8	0.10	0.07	0.08	0.56	0.32	0.35	0.54	0.37	0.36
A9	0.13	0.05	0.26	0.20	0.08	0.22	0.19	0.13	0.36
A10	0.10	0.05	0.26	0.10	0.05	0.35	0.54	0.37	0.36
A11	0.10	0.15	0.08	0.15	0.15	0.54	0.54	0.37	0.36
A12	0.13	0.05	0.18	0.20	0.11	0.35	0.54	0.24	0.53
A13	0.06	0.16	0.11	0.15	0.04	0.35	0.54	0.04	0.53
A14	0.13	0.16	0.11	0.10	0.25	0.22	0.54	0.24	0.53

Table 13. Weighted constrained aggregated normalized decision matrix (P_{ij} values)

	p_{ij}								
Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9
A1	0.01	0.01	0.03	0.04	0.01	0.02	0.11	0.03	0.02
A2	0.01	0.01	0.03	0.05	0.01	0.02	0.11	0.01	0.01
A3	0.01	0.00	0.02	0.04	0.01	0.01	0.11	0.03	0.03
A4	0.01	0.01	0.04	0.02	0.01	0.02	0.11	0.02	0.01
A5	0.08	0.00	0.04	0.05	0.01	0.02	0.04	0.02	0.03
A6	0.01	0.01	0.04	0.01	0.03	0.03	0.11	0.03	0.03
A7	0.03	0.01	0.00	0.02	0.02	0.02	0.04	0.01	0.02
A8	0.01	0.00	0.01	0.13	0.02	0.03	0.11	0.03	0.02
A9	0.02	0.00	0.04	0.05	0.00	0.02	0.04	0.01	0.02
A10	0.01	0.00	0.04	0.02	0.00	0.03	0.11	0.03	0.02
A11	0.01	0.00	0.01	0.04	0.01	0.04	0.11	0.03	0.02
A12	0.02	0.00	0.03	0.05	0.01	0.03	0.11	0.02	0.03
A13	0.01	0.00	0.02	0.04	0.00	0.03	0.11	0.00	0.03
A14	0.02	0.00	0.02	0.02	0.01	0.02	0.11	0.02	0.03
η_j	0.01	0.00	0.00	0.01	0.00	0.01	0.04	0.00	0.01

To calculate the evaluation of distances in step 7, Eqs. (48-49) are utilized to compute the value of q_{ik} in Eq. (52). Eqs. (50-51) are also used to determine the value of φ_{ik} in Eq. (53). The matrix formed in this step is presented in Table 14. Using the q_{ik} and φ_{ik} values, the final score o_i of the alternatives is obtained by considering β=0.5. By examining Table 14, it can be seen that alternative A2 is chosen as the most appropriate IoT supplier.

Table 14. Ranking results based on TRUST method

Alt.	$\mathbb{E}_i$	$\mathbb{T}_i$	$\mathbb{L}_i$	$\mathbb{p}_i$	$\mathbb{q}_{ik}$	φ_{ik}	σ_i	**Rank**
A1	0.08	0.18	0.08	0.62	0.01	0.11	0.064	8
A2	0.09	0.18	0.07	0.62	0.05	0.11	0.078	6
A3	0.08	0.17	0.07	0.55	0.01	0.09	0.047	9
A4	0.08	0.15	0.06	0.60	-0.02	-0.02	-0.022	12
A5	0.09	0.19	0.08	1.23	0.15	0.27	0.210	3
A6	0.09	0.21	0.09	1.26	0.14	0.43	0.286	2
A7	0.03	0.08	0.03	0.25	-0.61	-0.23	-0.420	14
A8	0.14	0.27	0.11	1.69	0.97	1.24	1.106	1
A9	0.05	0.11	0.05	0.45	-0.40	-0.20	-0.298	13
A10	0.08	0.17	0.07	0.67	0.04	0.10	0.069	7
A11	0.09	0.18	0.08	0.56	0.05	0.15	0.101	5
A12	0.09	0.19	0.08	0.56	0.09	0.21	0.146	4
A13	0.08	0.15	0.06	0.36	-0.03	0.00	-0.015	11
A14	0.08	0.16	0.07	0.42	-0.06	0.04	-0.009	10

4.3. Sensitivity Analysis

In this section, a set of tests is done on the parameters of the TRUST method. Validation tests examine the effect of parameters in prioritizing alternatives.

In this way, various tests are done on α and β. α is the most important parameter in the normalization section, which uses it to merge the normalized values obtained from the four techniques. Several scenarios have been defined to observe changes in the impact of α on alternative ranking. Table 15 shows the different α values. Based on Figure 3, we find that different α values do not have a significant effect on the ranking order. Because A2 has been chosen as the most appropriate in all scenarios. Nonetheless, slight changes are seen in the prioritization. If ranking is important, experts or DMs should make serious decisions about α values based on the type of the data and problem, and their expertise and preferences.

β is a positive parameter that has a value between zero and one and helps determine the final score of the alternatives. The β determines how much of the final score should be of the criteria q and φ. Typically, the β is set to 0.5 to maintain balance. However, experts may consider different β values depending on the type of the issue. Eleven scenarios with violating β values (between zero and one) are considered to observe changes in ranking results. Figure 4 shows that by changing the β value, there is no significant change in the final score of the alternatives and A8 remains the best.

Table 15. Scenarios with different α values

Scenarios	SC0	SC1	SC2	SC3	SC4
α	$\alpha_1 = 0.25$ $\alpha_2 = 0.25$ $\alpha_3 = 0.25$ $\alpha_4 = 0.25$	$\alpha_1 = 1$ $\alpha_2 = 0$ $\alpha_3 = 0$ $\alpha_4 = 0$	$\alpha_1 = 0.5$ $\alpha_2 = 0.3$ $\alpha_3 = 0.2$ $\alpha_4 = 0$	$\alpha_1 = 0.5$ $\alpha_2 = 0.1$ $\alpha_3 = 0.3$ $\alpha_4 = 0.1$	$\alpha_1 = 0.7$ $\alpha_2 = 0.1$ $\alpha_3 = 0.1$ $\alpha_4 = 0.1$

Scenarios	SC5	SC6	SC7	SC8	SC9
α	$\alpha_1 = 0.33$ $\alpha_2 = 0.33$ $\alpha_3 = 0.34$ $\alpha_4 = 0$	$\alpha_1 = 0.2$ $\alpha_2 = 0.1$ $\alpha_3 = 0.1$ $\alpha_4 = 0.6$	$\alpha_1 = 0.5$ $\alpha_2 = 0.5$ $\alpha_3 = 0$ $\alpha_4 = 0$	$\alpha_1 = 0.5$ $\alpha_2 = 0$ $\alpha_3 = 0.5$ $\alpha_4 = 0$	$\alpha_1 = 0.5$ $\alpha_2 = 0$ $\alpha_3 = 0$ $\alpha_4 = 0.5$

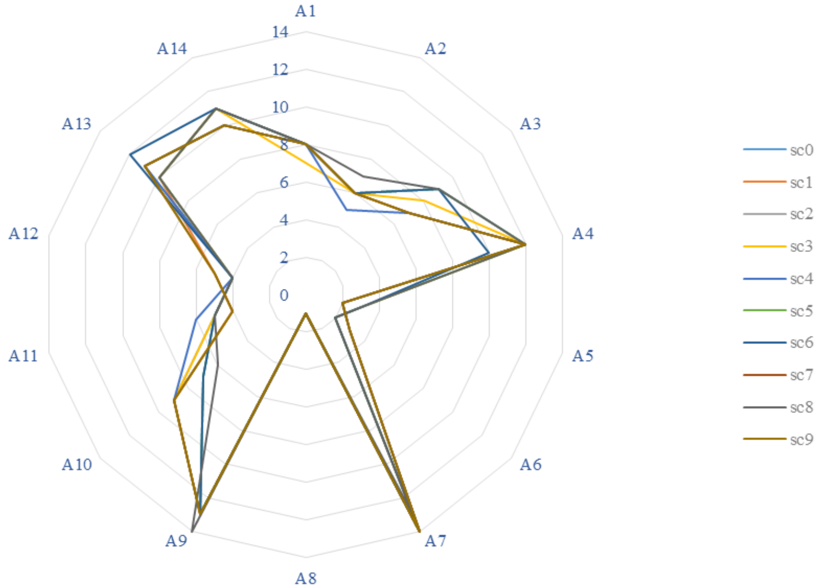

Figure 3. The impact of α on rankings

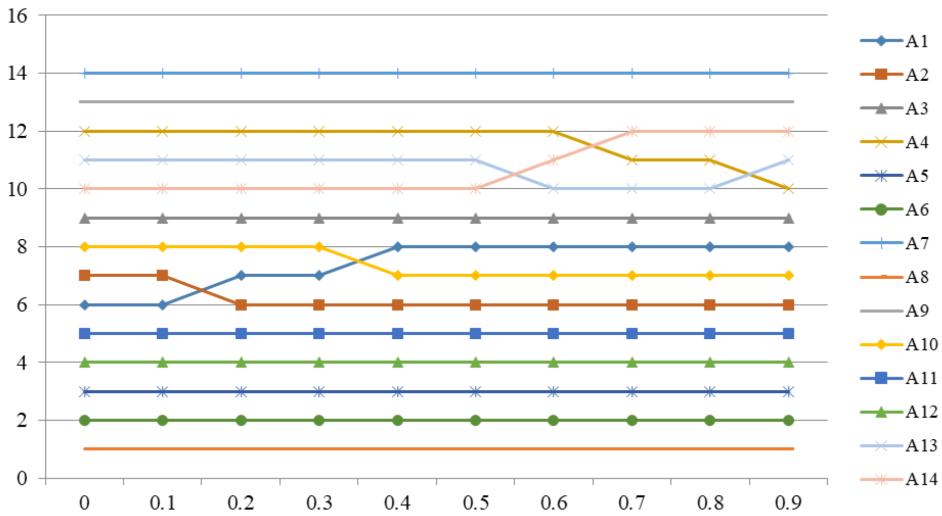

Figure4. The impact of β on rankings

4.4. Comparative Analysis

TRUST is one of the new and special methods of MCDM methods that are used for ranking. Different procedures and 4 types of normalization techniques somewhat distinguish this method from other methods. This section's purpose is to compare companies' ranking in different methods of MCDM.

In this section, the ranking is done using the complex proportional assessment (COPRAS) (Zavadskas et al., 1994), Multi-Objective Optimization based on the Ratio Analysis (MOORA) (Brauers & Zavadskas, 2006), and combined compromise solution (CoCoSo) (Yazdani et al. 2018) methods for comparative analysis. Table 16 shows the obtained prioritization of the TRUST method and other mentioned MCDM methods to choose the best supplier. According to the results of the TRUST, in terms of choosing the best alternative, it is completely correlated with other methods. In all methods, A8 has been selected as the superior alternative. However, the TRUST method is only wholly correlated with the other methods in choosing the superior alternative. According to the ranking, A6 is only second in the TRUST. In the COPRAS and MOORA method, A5 was selected as the second and A11 as the second in CoCoSo. Other priorities have also changed. This difference can be due to the different procedures of the TRUST method, the main reason for these differences in ranking can be related to normalization techniques. Unlike other methods, 4 normalizations of linear ratio, linear-sum, the linear maximum minute technique, and the logarithmic technique have been used. In addition, other MCDM methods do not discuss limitations and matrix satisfaction, so business standards and guidelines may not be considered when making decisions. This feature can also be another reason for differences because constraints and satisfaction matrices directly impact rankings.

Table 16. Comparing the proposed approach's results with other MCDM methods in SFS environment

Alt.	TRUST		COPRAS		MOORA		COCOSO	
	SCORE	RANK	SCORE	RANK	SCORE	RANK	SCORE	RANK
A_1	0.063	8	%54.0	8	0.042	8	2.162	8
A_2	0.075	6	%76.7	3	0.053	4	2.278	5
A_3	0.051	9	%53.5	9	0.038	10	2.093	9
A_4	-0.027	12	%49.6	13	0.037	11	1.986	11
A_5	0.205	3	%78.3	2	0.070	2	2.192	7
A_6	0.282	2	%60.0	6	0.049	6	2.391	4
A_7	-0.410	14	%46.2	14	0.021	14	1.215	14
A_8	1.113	1	%100.0	1	0.092	1	3.122	1
A_9	-0.311	13	%51.5	11	0.039	9	1.529	13
A_{10}	0.064	7	%54.7	7	0.042	7	2.229	6
A_{11}	0.108	5	%76.2	4	0.056	3	2.537	2
A_{12}	0.146	4	%60.7	5	0.050	5	2.416	3
A_{13}	-0.011	11	%52.8	10	0.036	12	1.537	12
A_{14}	-0.005	10	%49.8	12	0.032	13	2.049	10

5. Conclusions, limitations, and future suggestions

Today, due to the competitiveness of the production market, organizations attach special importance to supply chain management. Due to the expansion of activities in different fields, choosing a supplier in supply chain management is a challenging and important issue. In recent years, environmental sustainability has gained potential importance due to the increase in air pollution, greenhouse gas emissions and global warming. From this point of view, considering the concept of sustainability in supply chain management means protecting the environment. In addition, the destructive effects of disruptions on the supply chain performance of companies have led organizations to pay special attention to the concept of risk and how to deal with it. One of the ways to deal with this challenge is to consider the concept of resilience while choosing a supplier. Choosing a resilient supplier is an important and new issue that is placed next to choosing a sustainable supplier. Various companies have been trying to choose sustainable and resilient suppliers to compete with their competitors in recent years. Supplier evaluation and determination based on multiple criteria is an important strategy that can be considered as a complex MCDM problem.

Therefore, the ability of DMs to protect the environment and deal with disturbances that may occur increases. This paper aims to present a new MCDM approach based on BWM and TRUST methods to assess and choose a sustainable and resilient IoT supplier company. In the proposed approach, 2 main criteria of sustainability and resilience and 9 related sub-criteria have been identified by experts to evaluate 14 IoT supplier companies. With the development of BWM in the SFS, this model has tried dealing with the uncertainty in experts' opinions and obtaining accurate weights for the criteria. Also, to evaluate suppliers, the TRUST method, which unlike other MCDM methods has 4 normalization techniques, has been developed for the first time in the SFS. According to the obtained results, it was observed that the pollution control and risk-taking sub-criteria have potential importance compared to other sub-criteria. Also, by comparing the results of SFS-TRUST with other MCDM methods, the validity of the obtained results was proved. Also, the sensitivity analysis on the input parameters showed that the results have high reliability and efficiency.

The stability and flexibility of the obtained prioritization showed that the proposed approach could be applied to other management fields. TRUST method is different from other MCDM methods by having 4 normalization techniques and different evaluation steps. Developing such a different and powerful method in the SFS increases the power of information processing by overcoming uncertainty to a relatively high level. The SFS gives the freedom and power to the DMs to express their opinions based on membership, non-membership and hesitant degrees with greater freedom at the spherical level.

However, the limitations of this paper should also be considered the SFS variables used in this research are in the form of a 9-point scale, in future research to increase the degree of freedom of DMs in expressing their opinions and increasing the accuracy of evaluation, the scale of the linguistic variables can be developed. On the other hand, in this article, the experience and expertise of an expert has been used to collect data and information to evaluate suppliers. It is possible that by using the opinions of other experts or increasing the number of experts, the results of supplier evaluation will change to some extent. In addition, in this paper, it has been considered that the criteria are independent and that there is no direct or indirect relationship between them. While usually, the criteria considered for evaluation have interactions with each other. Hence, in future research, Choquet Integral or fuzzy cognitive map can consider the relationships between the criteria to obtain ranking results based on relationships between the criteria. Also, future research can be implemented in other industrial cases, such as pharmaceuticals, manufacturing, automobile, to show the application of the proposed approach to select a sustainable and resilient supplier. In addition, other critical criteria such as economic, social can be considered to evaluate the suppliers more accurately. It is also suggested that experts with more experience in this field be used in future research to obtain more reliable results and more accurate evaluation of suppliers. In addition, two fuzzy numbers can be used to increase confidence in experts' opinions. Therefore, the proposed approach can be developed with Z-number and D-number theories to reduce uncertainty in experts' opinions.

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