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MULTIPLE NORMALIZATION RATING ANALYSIS (MUNRA) AND ITS APPLICATION TO DIGITAL SUPPLIER SELECTION IN THE TEXTILE INDUSTRY

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Abstract. The rapid development of digital technologies – such as IoT, AI, blockchain, and digital twins – has transformed supply chains into interconnected ecosystems, making digital supplier selection both critical and complex. For the first time, this study proposes a novel multi-criteria decision-making (MCDM) method, Multiple Normalization Rating Analysis (MUNRA), for ranking alternatives. It integrates linear, vector, and non-linear normalization to improve robustness, reduce rank reversal, and enhance decision accuracy. A case study of digital supplier selection in the textile industry is considered for a real-life application of the method. Results highlight technology integration, flexibility, and technological capability as the most influential criteria for selecting digital suppliers. Moreover, the final ranking of the six digital suppliers is as follows: DS5, DS4, DS2, DS6, DS1, and DS3. Validation through comparative MCDM methods, Spearman correlation, and sensitivity analyses confirms the credibility of the method. It is also shown that it is free from the rank reversal phenomenon. The research presents a computationally efficient and rigorous method for evaluating digital suppliers, offering strategic insights for digital supply chain management. The application of MUNRA to a larger decision-making problem further illustrates its scalability and cross-domain applicability.

Keywords: digital supply chain, digital supplier selection, supply chain management, supplier selection, MUNRA, MCDM.

JEL Classification: C02, C44, E17.

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1. Introduction

Digital Supply Chain (DSC) integrates digital technologies, such as blockchain, Internet of Things (IoT), digital twins, big data, Artificial Intelligence (AI), machine learning, cloud computing, digital twin, etc., into supply chain management processes to enhance efficiency, visibility, and responsiveness (Sarkis et al., 2021; Turskis & Šniokienė, 2024). Such a transformation leverages these advanced technologies to improve the traditional supply chain, making it more dynamic, interconnected, and intelligent (Latan et al., 2024). IoT tools yield real-time data about the location, condition, and status of goods and assets throughout the supply chain (Kumar et al., 2024). Through big data analytics, large volumes of data produced by diverse supply chain operations are analyzed to uncover patterns, trends, and insights (Lee et al., 2024). AI and machine learning algorithms help automate and optimize complex supply chain processes. They can be utilized for demand prediction, route optimization, anomaly detection, and decision-making (Wang et al., 2024). Blockchain ensures transparency, traceability, and security in the supply chain (Han & Fang, 2024). Cloud-based platforms provide innovative solutions for managing supply chain operations, spanning from procurement to delivery (Gammelgaard & Nowicka, 2023). Robotics and automation technologies facilitate warehousing, manufacturing, and distribution processes, reducing human errors (Brintrup et al., 2024). Digital twins, which are imaginary duplicates of assets, processes, or systems, enable the real-time monitoring, simulation, and optimization of supply chain operations, helping to predict and mitigate potential problems (Lim et al., 2024b). Recent technologies, including augmented reality, virtual reality, and extended reality, support training, maintenance, and visualization of supply chain processes. They can also improve warehouse operations and remote collaboration (Tsang et al., 2022). In this context, DSC offers companies numerous advantages, including real-time tracking and monitoring, reduced manual efforts, lower operational costs, and the ability to adapt to changes in demand, supply disruptions, and market conditions. It also enhances collaboration among supply chain partners and identifies and mitigates potential risks (Schilling & Seuring, 2024).

Supplier selection is a multifaceted process requiring careful consideration of numerous factors to ensure the chosen suppliers can meet the company's needs effectively and efficiently (Ecer et al., 2024). The process is essential for ensuring the quality, reliability, and cost-effectiveness of the goods and services a company requires (Pamucar et al., 2024). The evaluation process by highly qualified project managers of suppliers and their proposed products has resulted in a newly created product that best meets the customers' requirements (Turskis & Keršulienė, 2024). Supplier selection highly depends on the availability of technologies and equipment (Sivilevičius et al., 2008). Moreover, supplier selection depends on the project location (Peldschus et al., 2010) and the project implementation environment (Zavadskas et al., 2009). The project's performance depends on management strategy (Zavadskas et al., 2017). Sustainable supplier selection (Ecer & Pamucar, 2020; Ecer et al., 2025), green supplier selection (Chen et al., 2023; Ecer, 2022; Zulqarnain et al., 2024), resilient supplier selection (Sun et al., 2024), agile supplier selection (Sheykhzadeh et al., 2024), green and resilient supplier selection (Ulutaş et al., 2025a), circular supplier selection (Ecer & Torkayesh, 2022), and digital supplier selection (Sharma & Joshi, 2023) have been realized successfully by researchers.

In this research, however, we focus only on digital supplier selection. Digital supplier selection transforms traditional supplier selection by leveraging advanced technologies, such as AI, big data analytics, IoT, blockchain, cloud computing, etc. (Tavana et al., 2021). This approach enhances efficiency, accuracy, transparency, and risk management, ultimately leading to improved supplier relationships and enhanced supply chain performance (Büyüközkan & Göçer, 2018a).

In Multi-Criteria Decision-Making (MCDM) techniques, alternative rankings are obtained by analyzing alternatives according to specific criteria. TOPSIS (Hwang & Yoon, 1981), MARCOS (Stević et al., 2020), COPRAS (Zavadskas et al., 1994), ARAS (Zavadskas & Turskis, 2010), and WASPAS (Zavadskas et al., 2012) are among the most well-known and widely used MCDM methods. Since no technique is impeccable and each has various disadvantages, the investigation for more effective MCDM methods has accelerated in recent years. To this end, researchers have recently developed new MCDM methods to aid in making more accurate decisions across various fields, including engineering, energy, business administration, healthcare, and agriculture. Alternative Ranking using two-step LOgarithmic Normalization (ARLON) (Kara et al., 2024), Alternative Prioritization and Assessment System (ALPAS) (Ulutaş et al., 2025b), Total Differential of Alternative (TODIFFA) (Gligorić et al., 2024), and Ranking of Alternatives with Weights of Criterion (RAWEC) (Puška et al., 2024) are among the newest ranking-based MCDM methods.

Since selecting the suppliers who best meet the overall criteria simultaneously is an MCDM problem, the Multiple Normalization Rating Analysis (MUNRA) method is developed in this research for the first time. In other words, the study introduces the MUNRA method for alternative ranking, comprising three distinct normalization techniques. The first is a linear normalization technique, the second is a vector normalization technique, and the third is a nonlinear normalization technique. It is hypothesized that applying these three normalization techniques will yield more robust results. MUNRA is a candidate method to overcome the disadvantages of most MCDM methods, offering ease of calculation, a short analysis time, and easy understanding. Furthermore, the Defining Interrelationships Between the Rank (DIBR) method, proposed by Pamucar et al. (2021), are utilized to weight the criteria. DIBR, a new weighting method, enables the consistent attainment of results by considering the relationships between neighboring criteria through pairwise comparison. Unlike AHP and BWM, DIBR is an advantageous choice since it is not affected by many criteria in real-world problems. In sum, this research handles a DIBR-MUNRA methodology for digital supplier selection. DIBR is employed for criteria weighting, whereas MUNRA is utilized for alternative ranking.

The research aims to address some crucial research questions. (i) What factors are involved in the digital supplier selection process? (ii) What factors influence the digital supplier selection process more? (iii) How can one choose the best alternative in the digital supplier selection process? To address these research questions, the following practical and methodological aims are outlined. The work's primary objective is to identify the most suitable digital supplier, thereby contributing to the field of digital supply chain management and meeting the needs of managers, authorities, and researchers. Moreover, the work's methodological aim is to develop a cutting-edge MCDM method for ranking alternatives, as outlined in the relevant literature. To achieve this, the MUNRA method has been developed for the first time in the literature. The study explains how digital supplier selection is carried out through a case study in a textile company, thereby demonstrating the applicability of MUNRA. Further, sensitivity and comparison controls are performed to highlight its robustness and effectiveness.

This work bridges two significant gaps in the relevant literature. First, it presents a new MCDM ranking method, MUNRA, to the operations research literature, enabling scientists, consultants, and research personnel to apply it to solve real-world problems. Second, it meets the needs of the digital supply chain literature by performing digital supplier evaluation and selection. Consequently, the practical and theoretical contributions of the research are summarized below.

- Digital supplier selection is still in its infancy and needs further development. Reliable decision tools are essential in evaluating suppliers equipped with advanced technologies. This study introduces the MUNRA method, a robust and helpful tool.

- The criteria for digital supplier selection are not fully clear in the literature. The work clarifies the evaluation criteria following a comprehensive review of the current literature and in line with the opinions of textile industry experts.
- Digital supplier selection has been realized in a limited number of sectors. The work contributes to the literature by conducting a case study in the textile sector.
- The methods used for digital supplier selection have various disadvantages, such as rank reversal problems, and thus, the results could be unsatisfactory. The proposed MUNRA method produces reliable results thanks to its unique three-step normalization stage and utility function.
- The MUNRA technique is assisted using sensitivity and comparison checks, allowing insights into its solidity.

The second section examines studies on digital supplier selection, clarifies the criteria and methods used, and highlights research gaps. The third section introduces the MUNRA method. Since the study employs the DIBR method for weight determination, a subsection is also included on that method. The following section provides a comprehensive explanation of the application and presents the results. It further highlights the results of the sensitivity analysis. The fifth section is devoted to discussion and conclusions. Consequently, the last section concludes the study.

2. Literature review

2.1. Survey on digital supplier selection

Organizations worldwide have begun to adopt digitalization due to its significant benefits for their businesses (Lee et al., 2024). Digitalization has profoundly impacted how companies and individuals interact and communicate (Rashid et al., 2024). Thus, in this digital era, companies employ various processes, strategies, and mechanisms to transition to a digital supply chain and leverage digital technology in business (Brintrup et al., 2024). The digital supply chain is a family of interlinked activities included in supply chain operations between suppliers and customers, managed using new technologies (Lim et al., 2024a). Digital supply chains offer greater access to information, enhanced interaction, communication, and collaboration, thereby increasing confidence, agility, and productivity (Li et al., 2025). They require an integrated set of advanced technologies, strategies, and practices that enable customers, suppliers, and the workforce to interact with each other (Iftikhar et al., 2024). Recognizing the benefits of the digital supply chain necessitates new approaches that incorporate technology-driven digital transformation (Kim et al., 2024).

Research on supplier selection and evaluation continues to grow daily. After examining the Scopus database, which contains extensive scientific literature, data, and analytical tools with over 94 million records (Elsevier, n.d.), we identified 4,229 articles and 103 reviews in English on supplier selection and evaluation as of June 2024. It is worth noting that conference proceedings, books, and book series were excluded from the search. The most preferred keywords in these works were supplier selection, decision-making, supply chain management, supply chains, and fuzzy sets. China, Iran, the United States, India, and Taiwan were the most prolific countries. AHP, DEA (Charnes et al., 1978; Farrell, 1957), TOPSIS, ANP (Saaty, 1996), Entropy

(Shannon, 1948), VIKOR (Opricovic, 1998), DEMATEL (Gabus & Fontela, 1972; 1973), and Grey Relational Analysis (GRA) (Ju-Long, 1982) were the most used MCDM methods with 647, 287, 213, 101, 69, 47, 46, and 34 papers, respectively. These methods are frequently preferred due to their reliability, ease of understanding, and familiarity, a preference that has persisted for over three decades. According to Scopus records, the first study on supplier selection was conducted by Wieters and Ostrom (1979), and the most cited study was prepared by Weber et al. (1991). Once we aligned more closely with our research objectives, we noticed that there are only a few studies regarding digital supplier selection. Büyüközkan and Göçer (2018a) proposed an IVIF framework that combines AHP and ARAS for digital supplier selection. To demonstrate the applicability of the proposed approach, a real case study was conducted with a freight company in Turkey. They concluded that "customization and personalization" is the foremost factor for digital supplier selection, followed by real-time visibility. Büyüközkan and Göçer (2018b) provided a comprehensive overview of current research in digital supply chains, identified vital gaps, and proposed a framework to guide future research. Liao et al. (2019) introduced a sophisticated and realistic approach to financial supplier selection in the context of digital supply chains. By leveraging hesitant linguistic terms and integrating BWM and ARAS, they offered a robust framework that addresses the complexities and uncertainties inherent in modern supply chain finance. Özek and Yildiz (2020) presented an interval type-2 fuzzy Technique for the Order Preference by Similarity to Ideal Solution (TOPSIS) approach (Hwang & Yoon, 1981) in digital supplier selection for the garment industry. Nasiri et al. (2020) discussed how companies can achieve greater visibility and transparency across their supply chains, which helps with better risk management. They provided a strategic roadmap for integrating smart technologies, such as the IoT, AI, blockchain, big data analytics, and robotics, into supply chain management. The roadmap outlines key steps and considerations for successful implementation. Khan et al. (2021) developed a structured interpretive structural modeling and MICMAC (impact matrix cross-reference multiplication applied to a classification) framework to identify critical factors in digital supply chains. Büyüközkan and Göçer (2021) aimed to develop a new evaluation model to improve the digital supplier selection process. They proposed a new hybrid AHP-COPRAS framework using Pythagorean fuzzy sets. Tavana et al. (2021) proposed a fuzzy methodology that combines BWM (Rezaei, 2015), MULTIMOORA (Brauers & Zavadskas, 2010), COPRAS, and TOPSIS. Fuzzy BWM was applied to the weights of the criteria, while fuzzy extensions of other MCDM methods were used to rank the digital suppliers. The criterion of agility and flexibility was determined as the most crucial for digital supplier selection. Sharma and Joshi (2023) employed an integrated Stepwise Weight Assessment Ratio Analysis (SWARA) (Keršulienė et al., 2010) and Weighted Aggregated Sum Product Assessment (WASPAS) (Zavadskas et al., 2012) model for digital supplier selection, which integrates with quality management systems. Alkan and Kahraman (2023) suggested a sophisticated and robust methodology for prioritizing digital transformation strategies in supply chains. By integrating interval-valued Fermatean fuzzy sets with an Analytic Hierarchy Process (AHP) and leveraging multi-expert input, their paper provided a comprehensive framework that enhances decision-making accuracy and strategic alignment. Benatiya Andaloussi (2024) conducted a bibliometric literature survey for 114 papers indexed in the Scopus database to highlight the key findings, research themes, and trends in the DSC field. His results revealed the transformative impact of digital tools in supply chains.

Table 1 presents a summary of the criteria regarding digital supplier evaluation and selection.

Table 1. Digital supplier selection criteria

Criteria	Type	Definition	Reference
Flexibility (C1)	Max	It means being able to fit in changing conditions easily. The risk of disruption in services offered to the end consumers is reduced thanks to flexibility.	Büyüközkan and Göçer (2018a, 2018b), Sharma and Joshi (2023), Alkan and Kahraman (2023)
Analytics tools (C2)	Max	Advanced analytical techniques enable the making of meaningful and reliable decisions with data more easily. Demand in the supply chain can also be better understood and predicted through the use of analytics tools.	Benatiya Andaloussi (2024), Tavana et al. (2021), Alkan and Kahraman (2023)
Technology integration (C3)	Max	Suppliers must be able to utilize cutting-edge technologies to learn and solve any problem within the digital supply chain. This promotes intelligent production and can help gain a competitive advantage.	Sahoo et al. (2024), Tavana et al. (2021), Özek and Yildiz (2020), Alkan and Kahraman (2023)
Automation in supply chain operations (C4)	Max	The digital supply chain offers numerous benefits, enabling automation to facilitate better collaboration. Furthermore, the efficiency of supply chain operations increases with the integration of human-machine interactions.	Büyüközkan and Göçer (2018b), Khan et al. (2021), Alkan and Kahraman (2023)
Technology capability (C5)	Max	This refers to activities that enable firms to select and utilize technologies to gain a competitive advantage. It also means being able to utilize technology in activities such as product development and service delivery.	Büyüközkan and Göçer (2018a, 2021), Tavana et al. (2021), Sahoo et al. (2024)
Digital innovation (C6)	Max	It defines the supplier's ability to innovate, helping to improve the supply chain. Companies can enhance their product innovation capabilities, processes, and knowledge by leveraging their digital suppliers.	Sharma and Joshi (2023), Alkan and Kahraman (2023), Khan et al. (2021)
Digital collaboration (C7)	Max	Digital transformation enables companies to connect and collaborate seamlessly. Working together fosters stronger relationships and facilitates the easier sharing of crucial information and resources.	Sahoo et al. (2024), Özek and Yildiz (2020), Tavana et al. (2021)
Digital education & training (C8)	Max	Through education and training, suppliers need to be equipped with the necessary digital supply chain management skills. Education and training programs support the development of the digital workforce.	Alkan and Kahraman (2023), Büyüközkan and Göçer (2018b), Sharma and Joshi (2023)
Lack of information security and privacy (C9)	Min	It refers to the tools the digital supply chain utilizes to secure its presence and technology in the virtual and real world. They are tools for transforming into smart value chains and aim to prevent security vulnerabilities.	Büyüközkan and Göçer (2021), Sharma and Joshi (2023)
Lack of information sharing (C10)	Min	Sharing information is one of the foremost pillars of integrating the digital supply chain. It enhances the agility of the entire supply chain and facilitates more straightforward integration with customers.	Sharma and Joshi (2023), Büyüközkan and Göçer (2018b), Alkan and Kahraman (2023)

2.2. Research gaps and contributions

A comprehensive literature review reveals that the number of studies addressing the digital supplier selection problem is relatively low, suggesting that this issue is still in its early stages of development. That is, digital supplier selection is an area that requires further investigation and development to enhance understanding and practice in digital supply chain management. Considering that suppliers integrated with advanced technologies such as IoT, digital twin, blockchain, and AI will make tremendous contributions to the competitiveness of companies, reliable, easy-to-understand, and practical decision tools are needed to solve the digital supplier selection problem. This research has the potential to bridge these gaps.

As a result of the literature review, it has been revealed that digital supplier selection is handled only in manufacturing (Tavana et al., 2021; Sharma & Joshi, 2023; Liao et al., 2019), transport (Büyüközkan and Göcer, 2018a, 2021; Khan et al., 2021), and garment (Özek & Yildiz, 2020) sectors. Thus, it is clear that more industry-specific research is needed to understand how digital supplier selection varies across different industries. This study fills a critical gap by focusing on digital supplier selection in the textile industry.

Recent studies have employed various MCDM techniques or their uncertain extensions, including COPRAS, ARAS, AHP, BWM, TOPSIS, MULTIMOORA, MICMAC, SWARA, and WASPAS. However, these methods have some structural issues and drawbacks (Ecer, 2024). For instance, they are particularly vulnerable to the rank reversal problem, and decision-makers often face the issue of inconsistency. As such, they are unlikely to provide satisfactory results as a credible decision-making method, particularly for complex decision problems such as selecting a digital supplier. Hence, this work introduces a new MCDM method, named MUNRA, to rank alternative digital suppliers. Further, the DIBR method is utilized to weight the selection criteria. Therefore, this study combines DIBR with the MUNRA method to identify the most suitable digital supplier. As a result, a considerable contribution is made to the existing literature.

Furthermore, there is no consensus among researchers in the literature regarding the criteria considered. They consider a variety of criteria in their papers. Identifying efficient and convenient criteria is crucial for accurately building a decision-making problem. In this work, therefore, the criteria are decided by the current literature survey and the experts' opinions. Addressing these research gaps will enhance the effectiveness and efficiency of digital supplier selection processes. It will also contribute to a more robust theoretical foundation and practical framework for organizations seeking to leverage digital technologies in their supply chain management.

3. Research methodology

This section aims to introduce the methods used in digital supplier selection. The DIBR method is used to weight the criteria in the selection process. The MUNRA method is developed to obtain the rankings of the alternatives. As depicted in Figure 1, this research has a four-stage methodological structure. In the first stage, the problem is defined and structured. The DIBR technique is revisited in the second stage, and the criteria are weighted. The third stage focuses on developing the cutting-edge multi-criteria MUNRA method, aiming to rank digital

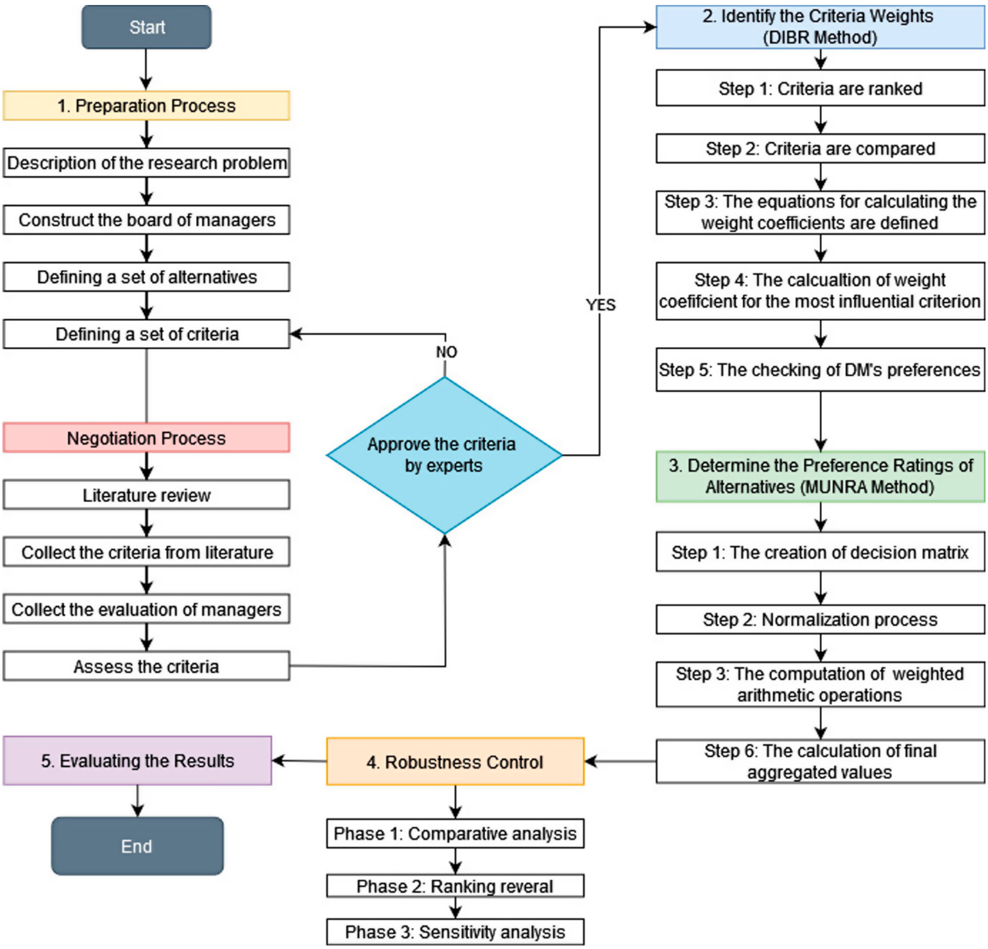

Figure 1. Flowchart of the introduced approach for digital supplier selection

suppliers and demonstrate its phases. The final stage involves testing the rankings of digital suppliers through a comprehensive sensitivity analysis. Moreover, comparisons are performed between ranking outcomes obtained by implementing various MCDM techniques.

3.1. The DIBR method

The DIBR method is a subjective weighting method proposed by Pamucar et al. (2021). After arranging the criteria in order of importance, it attempts to determine weights by quantifying the relationships between neighboring criteria. DIBR allows for consistent results in decision problems with a large number of criteria. Criterion weights can be calculated with a much smaller number of pairwise comparisons compared to the AHP and BWM methods. Using DIBR, Tešić and Marinković (2023) evaluated combat systems, Pamucar et al. (2022) prioritized mobility sharing systems, and Radovanović et al. (2023) evaluated unmanned aerial vehicles. The steps of the DIBR method are summarized below (Pamucar et al., 2021; Tešić et al., 2023).

Step 1: The criteria are ranked by experts as to their perceived level of importance.

Step 2: The Criteria are pairwise compared. The values that a DM (decision-maker) allocates to the criteria during comparisons will be represented as α_{12}, α_{23},..., $\alpha_{n-1,n}$, and $\alpha_{1,n}$. For instance, when comparing criterion CR_1 with CR_2, the value α_{12}. When comparing the criteria, all values α_{12}, α_{23},..., $\alpha_{n-1,n}$ and $\alpha_{1,n}$, must meet the condition that $\alpha_{n-1,n}$ and $\alpha_{1,n}$ are within the range [0, 1]. Based on the previously established settings, the following relationships between the criteria can be deduced:

$$w_1 : w_2 = \left(1-\alpha_{12}\right) : \alpha_{12}; \tag{1}$$

$$w_{n-1} : w_n = \left(1-\alpha_{n-1,n}\right) : \alpha_{n-1,n}; \tag{2}$$

$$w_1 : w_n = \left(1-\alpha_{1,n}\right) : \alpha_{1,n}. \tag{3}$$

As can be seen from the above Equations in each comparative analysis, the full 100% significance value is allocated between the two criteria being considered. For instance, if the relationship between criteria CR_1 with CR_2 is valued at 0.3 and α_{12} equals 0.3, this indicates that the importance of criterion CR_1 is 70%, while criterion CR_2 holds 30% significance.

Step 3: The equations for calculating the weight coefficients are defined as follows:

$$w_2 = \frac{\alpha_{12}}{\left(1-\alpha_{12}\right)} w_1; \tag{4}$$

$$w_3 = \frac{\alpha_{23}}{\left(1-\alpha_{23}\right)} w_2 = \frac{\alpha_{12}\alpha_{23}}{\left(1-\alpha_{12}\right)\left(1-\alpha_{23}\right)} w_1; \tag{5}$$

$$w_n = \frac{\prod_{i=1}^{n-1} \alpha_{i,i+1}}{\prod_{i=1}^{n-1} \left(1-\alpha_{i,i+1}\right)} w_1. \tag{6}$$

Step 4: The computation of the weight value for the foremost influential criterion, regarding Eqs. (4)–(6) and adhering to the condition that $\sum_{j=1}^{n} w_j = 1$, can be expressed by the following Equation:

$$w_1 \left(1 + \frac{\alpha_{12}}{\left(1-\alpha_{12}\right)} + \frac{\alpha_{12}\alpha_{23}}{\left(1-\alpha_{12}\right)\left(1-\alpha_{23}\right)} + \ldots + \frac{\prod_{i=1}^{n-1} \alpha_{i,i+1}}{\prod_{i=1}^{n-1} \left(1-\alpha_{i,i+1}\right)} \right) = 1. \tag{7}$$

From the above Equation, w_1 is calculated as follows:

$$w_1 = \frac{1}{\left(1 + \frac{\alpha_{12}}{\left(1-\alpha_{12}\right)} + \frac{\alpha_{12}\alpha_{23}}{\left(1-\alpha_{12}\right)\left(1-\alpha_{23}\right)} + \ldots + \frac{\prod_{i=1}^{n-1} \alpha_{i,i+1}}{\prod_{i=1}^{n-1} \left(1-\alpha_{i,i+1}\right)} \right)}. \tag{8}$$

Step 5: Checking DM's preferences. Using Eq. (3), the ratio between the most critical and the least significant criterion $\left(\alpha'_{1,n}\right)$ can be determined, and it is computed as follows:

$$\alpha'_{1,n} = \frac{w_n}{1+w_n}. \tag{9}$$

If the calculated ratio $\left(\alpha'_{1,n}\right)$ closely aligns with the ratio determined by the decision maker ($\alpha_{1,n}$), it indicates consistency in their evaluation of the criteria's importance. However, if the deviation between $\alpha_{1,n}$ and $\alpha'_{1,n}$ exceeds 10%, it suggests inconsistency in assessing the criteria ratios. In such cases, the value of $\alpha_{1,n}$ should either be redefined or the criteria's significance should be re-evaluated.

3.2. The MUNRA method

The MUNRA method arrives at the result by implementing three distinct normalization procedures. The motivation behind the MUNRA method is that a three-stage normalization process can produce more realistic results. Additionally, the method proposes an aggregation function appropriate to the nature of the benefit and non-benefit criteria. The following presents a detailed account of the steps of the MUNRA method.

Step 1: The initial step creates the decision matrix.

$$D = \left[d_{ij}\right]_{m\times n}. \tag{10}$$

Step 2: The following equations normalize the decision matrix presented in Eqs. (10)–(12) represent linear normalization procedures, whereas Eqs. (13)–(14) represent vector normalization procedures – finally, Eqs. (15)–(16) represent a nonlinear normalization procedure.

$$r_{ij} = \frac{d_{ij}}{\max\left(d_{ij}\right)} \quad \text{if } j \in BNF; \tag{11}$$

$$r_{ij} = \frac{\min\left(d_{ij}\right)}{d_{ij}} \quad \text{if } j \in NBNF; \tag{12}$$

$$y_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m}\left(d_{ij}\right)^2}} \quad \text{if } j \in BNF; \tag{13}$$

$$y_{ij} = 1 - \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m}\left(d_{ij}\right)^2}} \quad \text{if } j \in NBNF; \tag{14}$$

$$p_{ij} = \left(\frac{d_{ij}}{\max\left(d_{ij}\right)}\right)^2 \quad \text{if } j \in BNF; \tag{15}$$

$$p_{ij} = \left(\frac{\min\left(d_{ij}\right)}{d_{ij}}\right)^3 \quad \text{if } j \in NBNF. \tag{16}$$

In the Equations, BNF represents the benefit-based criteria, whereas NBNF represents the cost-based criteria. In the MUNRA framework, a hybrid normalization structure integrating linear, vector, and non-linear (squared and cubed) forms is adopted to achieve balanced sensitivity and stability in performance evaluation. The linear and vector normalizations (Eqs. (11)–(14)) provide proportional scaling and magnitude-based standardization, ensuring comparability across criteria. The non-linear (squared and cubed) normalization (Eqs. (15)–(16)) introduces an additional level of sensitivity that moderates the influence of extreme values and captures minor variations between alternatives. Specifically, squaring enhances the distinction among higher-performing alternatives under benefit criteria, while cubing amplifies penalization under non-benefit criteria, thus improving the discriminatory power and resilience of the method.

Step 3: Weighted arithmetic operations are computed as follows.

$$r_i' = \sum_{j \in BNF} w_j r_{ij} + \sum_{j \in NBNF} w_j r_{ij}; \tag{17}$$

$$y_i' = \sum_{j \in BNF} w_j y_{ij} + \sum_{j \in NBNF} w_j y_{ij}; \tag{18}$$

$$p_i' = \sum_{j \in BNF} w_j p_{ij} + \sum_{j \in NBNF} w_j p_{ij}. \tag{19}$$

Step 4: The results are aggregated to achieve the final results.

$$v_i = \alpha r_i' + \beta y_i' + \gamma p_i'. \tag{20}$$

In Eq. (20), parameters α, β, and γ are in the range of [0,1] and α + β + γ = 1. It is recommended that α, β, and γ be determined equally in Eq. (20). The final scores have been calculated, and the alternative with the highest final result has been identified as the optimal choice.

Eqs. (11)–(16), which represent the linear, vector, and nonlinear normalization schemes used in the MUNRA method, are grounded in well-established normalization practices widely adopted in the MCDM literature. The linear normalization formulas (Eqs. (11)–(12)) follow the structure used in classical methods, such as WASPAS (Chakraborty & Zavadskas, 2014) and MACONT (Wen et al., 2020), where benefit and cost-type criteria are scaled based on their minimum and maximum values to ensure comparability. The vector normalization formulas (Eqs. (13)–(14)) are inspired by methods that use Euclidean distance-based scaling, as seen in MOORA (Brauers & Zavadskas, 2006) and AROMAN-M (Balo et al., 2025), helping to preserve the relative magnitude of the alternatives while minimizing the effect of dimensionality. The nonlinear normalization procedures (Eqs. (15)–(16)), although not commonly used in traditional MCDM methods, offer valuable advantages in addressing issues such as scale distortion and the disproportionate impact of extreme values. These procedures utilize nonlinear transformations – typically involving squared or exponential operations – to adjust the influence of input values and ensure a more nuanced distribution of normalized data. This normalization technique was initially introduced to the literature by Peldschus et al. (1983) and has since been selectively applied in complex decision-making contexts where data variability is significant. Within the MUNRA framework, the inclusion of nonlinear normalization – alongside linear and vector approaches – aims to enhance robustness by leveraging complementary normalization effects and reducing biases that may arise from relying on a single scaling method. By integrating all three schemes, the MUNRA method aims to capitalize on their strengths, reduce normalization bias, and produce a more balanced and resilient scoring mechanism, particularly in multidimensional, real-world decision-making problems. Eq. (20), which involves the parameters α, β, and γ, has been reframed as a weighted composite utility function. In this function, these parameters represent equal importance assigned to the three normalization schemes. It should be noted that setting $\alpha = \beta = \gamma = 1/3$ balances the influence of all three procedures, thereby mitigating biases arising from data scale or distribution.

This choice is critical in decision matrices with heterogeneous value ranges, where relying on a single normalization approach may produce skewed rankings. By combining linear, vector, and nonlinear transformations under equal weights, the MUNRA method integrates the strengths of each scheme while minimizing their limitations. Moreover, the equal-weight configuration ensures a neutral decision environment when no prior domain knowledge or statistical justification exists to favor one normalization over another. Future research may investigate the use of adaptive or entropy-based weighting of α, β, and γ, potentially calibrated through machine learning or expert-driven feedback to reflect data-specific sensitivities.

In the MUNRA method, the equal assignment of the parameters (α, β, and γ) is adopted to ensure methodological neutrality and to prevent bias toward any single normalization technique. This equal allocation offers a baseline for robustness and comparability across applications. However, in specific contexts, unequal weighting may be more appropriate. For instance, domain-specific knowledge could justify prioritizing one normalization scheme over others if it better reflects the decision environment. Similarly, entropy-based calibration or data-driven optimization approaches may be employed to assign differential importance to α, β, and γ, thereby enhancing sensitivity to variability in decision matrices. Such adjustments could further refine decision accuracy while maintaining the flexibility of the MUNRA method.

4. Case study and findings

As digital technology transforms various aspects of textile value chains, from design and production to supply chain management and customer engagement, the textile industry and digital are becoming increasingly intertwined. Automation technologies, for instance, streamline production processes, improving efficiency and consistency while reducing labor costs and human error. IoT devices enable the real-time tracking and monitoring of goods throughout the supply chain, providing greater visibility and improved inventory management. IoTs and machine learning technologies can anticipate the need for maintenance, helping to reduce downtime and prolong the lifespan of the machinery. Blockchain technology helps verify the authenticity of materials and their ethical sourcing practices, ensuring transparency and traceability throughout the supply chain. AR and VR systems offer immersive shopping experiences, allowing clients to see products in their shopping environment or to try them on in a virtual environment. By enabling more accurate planning and resource allocation, data analytics and AI optimize production processes, predict demand, reduce waste, and improve sustainability. Further, digitalization enables mass customization, allowing consumers to personalize products according to their preferences, from design and color to fit and fabric choice. Advancements in digital technologies drive innovation in materials, including smart textiles, which incorporate sensors and conductive fibers to address various needs.

The textile sector has undergone a significant technological transformation in recent years, with many firms adopting digital tools to modernize their supply chains and enhance collaboration with suppliers. For instance, RFID technologies are increasingly used to monitor the flow of raw materials and inventory levels in real-time, enabling greater transparency and traceability. Similarly, automated fabric cutting and sewing machines, often integrated with ERP systems, have enhanced production accuracy and reduced lead times. Furthermore, platforms enabling cloud-based data sharing between suppliers and buyers have streamlined quality control, compliance monitoring, and forecasting processes. These developments justify the inclusion of technology-related criteria – such as system integration capability and digital responsiveness – in supplier evaluation models designed for the textile industry.

A textile company in Turkey is, therefore, used as a case study in this paper. The company wants to select the most suitable digital supplier. Its managers seek better management of criteria and a reliable and effective method for making evaluation decisions. Despite the methodological rigor of the proposed DIBR-MUNRA framework, it is crucial to acknowledge potential limitations related to the expert selection process, as expert judgments directly influence both the weighting of criteria and the evaluation of alternatives. In this study, the experts were intentionally selected from among the company's managerial staff, representing key departments such as production, purchasing, and R&D. Their academic backgrounds spanned textile, chemical, and industrial engineering, and all held at least a master's degree with 6 to 12 years of professional experience. This selection aimed to ensure that evaluations were grounded in practical, decision-oriented insights. Nevertheless, as with all expert-based assessments, a degree of subjectivity may remain. The data employed in the research were procured from five specialists (experts). The data were obtained from a textile engineer and a chemical engineer in the production department of the factory, an industrial engineer in the purchasing department, and a textile engineer and an industrial engineer in the R&D department. Table 2 provides an overview of the professional experience and educational background of the experts (EPs).

Based on a detailed literature review and experts' views, the criteria used to assess digital suppliers in the research are outlined in Table 3. The performances of six digital suppliers (DSs) are also conducted according to the criteria given in Table 3.

Table 2. Information about experts

Experts (EPs)	Education	Experience
EP1	BD: Textile Engineering, MD: Business Administration	12 Years
EP2	BD: Chemical Engineering, MD: Business Administration	6 Years
EP3	BD: Industrial Engineering, MD: Industrial Engineering	10 Years
EP4	BD: Textile Engineering, MD: Textile Engineering	8 Years
EP5	BD: Industrial Engineering, MD: Business Administration	9 Years

Notes: *BD: Bachelor's degree, MD: Master's degree.

Table 3. Criteria used in digital supplier selection studies

	Flexibility (C1)	Analytics tools (C2)	Technology integration (C3)	Automation in supply chain operations (C4)	Technology capability (C5)	Digital innovation (C6)	Digital collaboration (C7)	Digital education & training (C8)	Lack of information security and privacy (C9)	Lack of information sharing (C10)
Büyüközkan and Göçer (2021)			√		√	√	√	√	√	
Alkan and Kahraman (2023)	√	√	√	√		√		√	√	√
Büyüközkan and Göçer (2018a)	√	√	√		√		√			√
Tavana et al. (2021)	√	√	√		√		√			√
Khan et al. (2021)	√	√	√			√	√			√
Sharma and Joshi (2023)	√	√		√		√	√		√	√
Özek and Yildiz (2020)				√					√	
Liao et al. (2019)	√						√			
This research	√	√	√	√	√	√	√	√	√	√
Criteria type	B	B	B	B	B	B	B	B	C	C

Note: *B: Benefit, C: Cost.

In the criterion weighting phase using the DIBR method, expert input was collected through a structured survey. Five experts from relevant departments, including production, procurement, and R&D, were asked to rank the criteria based on their perceived importance in the digital supplier selection process. Although the Delphi method was not applied, consensus was achieved through iterative discussion rounds, during which experts refined their rankings based on collective feedback. To ensure transparency and reliability in the criteria weighting process, consensus on the DIBR ranking was achieved through multiple rounds of structured discussion among the participating experts. Initially, each expert provided an independent ranking of the criteria. The results were then collectively reviewed, and points of disagreement were discussed. In subsequent rounds, experts re-evaluated their rankings based on group feedback until a stable consensus was reached and no major differences remained. The aggregated ranks were then used as input to the DIBR algorithm to derive the final weights. This approach ensured both methodological rigor and practical relevance.

In the first stage, the significance of each criterion is calculated by DIBR. Experts rank the criteria according to their level of significance. Experts agree that the priority order of the criteria is C3, C1, C5, C8, C4, C7, C2, C6, C10, and C9. Then, the experts compare the foremost criterion pair wisely with the second foremost criterion, the second foremost criterion with the third foremost criterion, and so on. According to experts, the relationships between the criteria are as follows:

C3:C1 = 0.51, C1:C5 = 0.53, C5:C8 = 0.52, C8:C4 = 0.53, C4:C7 = 0.52, C7:C2 = 0.51, C2:C6 = 0.53, C6:10 = 0.54, and C10:C9 = 0.52. As a result, the criterion weights are found as follows: C3 (0.1427), C1 (0.1371), C5 (0.1216), C8 (0.1123), C4 (0.0995), C7 (0.0919), C2 (0.0883), C6 (0.0783), C10 (0.0667), and C9 (0.0616).

For example, the relations between the criteria can be defined as follows:
$\rho_{C3}:\rho_{C1}=0.49:0.51=0.961$; $\rho_{C1}:\rho_{C5}=0.47:0.53=0.887$; $\rho_{C5}:\rho_{C8}=0.48:0.52=0.923$; $\rho_{C8}:\rho_{C4}=0.47:0.53=0.887$; $\rho_{C4}:\rho_{C7}=0.48:0.52=0.923$; $\rho_{C7}:\rho_{C2}=0.49:0.51=0.961$; $\rho_{C2}:\rho_{C6}=0.47:0.53=0.887$; $\rho_{C6}:\rho_{C10}=0.46:0.54=0.852$; $\rho_{C10}:\rho_{C9}=0.48:0.52=0.923$.

The Equations for calculating the weight coefficients are obtained as follows:
$\rho_{C1}=0.961\cdot\rho_{C3}$; $\rho_{C5}=0.961\cdot 0.887=0.852$; $\rho_{C8}=0.852\cdot 0.923=0.786$;
$\rho_{C4}=0.786\cdot 0.887=0.697$; $\rho_{C7}=0.697\cdot 0.923=0.644$; $\rho_{C2}=0.644\cdot 0.961=0.619$;
$\rho_{C6}=0.619\cdot 0.887=0.549$; $\rho_{C10}=0.549\cdot 0.852=0.467$; $\rho_{C9}=0.467\cdot 0.923=0.431$.

From the condition $\sum_{j=1}^{n} w_j=1$ and Eq. (8), we can calculate the weight of C3 as follows.

$$w_{C3}=\frac{1}{0.961+0.852+\ldots+0.431}=0.1427,$$

$$w_{C1}=\frac{0.49}{(1-0.49)\cdot 0.1427}=0.1371,$$

$$w_{C5}=\frac{0.49\cdot 0.47}{(1-0.49)\cdot(1-0.47)\cdot 0.1427}=0.1216.$$

Similarly, the weights of the other criteria were calculated using the same method. More specifically, technology integration, flexibility, and technological capability are key factors in digital supplier selection, according to the study's findings. They are followed by "digital education and training," "automation in supply chain operations," "digital collaboration," "analytics tools," "digital innovation," and issues such as a lack of "information sharing" and "information security and privacy," respectively. Note that, since the MUNRA method is proposed in the study, the details of the DIBR method's analysis are not provided. Pamucar et al. (2021) can be a reference for those interested. The weight values obtained will aid in computing the weighted arithmetic operations of the MUNRA method.

In the second stage, MUNRA calculates the final scores of alternatives. The experts first evaluated the DS performance on a scale of 1 (very low) to 9 (very high). The arithmetic mean of the experts' opinions was calculated and used to construct the decision matrix presented in Table 4.

The decision matrix displayed in Table 4 has been normalized using Eqs. (11)–(16). The initial step is the linear normalization procedure, which utilizes Eqs. (11)–(12). The results of this procedure are presented in Table 5.

Table 4. The decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
DS1	6.8	7.4	7.0	7.4	6.2	6.8	6.4	7.2	3.8	3.0
DS2	7.2	7.6	6.2	7.4	8.0	8.0	6.6	7.4	4.2	3.4
DS3	7.2	6.8	6.0	7.8	7.6	7.8	6.2	5.0	3.0	3.8
DS4	6.8	7.6	6.8	6.6	7.0	6.8	7.6	6.8	2.6	3.0
DS5	7.4	7.0	7.4	7.4	7.8	6.8	6.6	6.8	3.0	2.6
DS6	8.0	7.6	7.0	7.2	7.0	6.4	7.0	6.4	3.2	3.6

Table 5. The results of linear normalization

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
DS1	0.8500	0.9737	0.9459	0.9487	0.7750	0.8500	0.8421	0.9730	0.6842	0.8667
DS2	0.9000	1.0000	0.8378	0.9487	1.0000	1.0000	0.8684	1.0000	0.6190	0.7647
DS3	0.9000	0.8947	0.8108	1.0000	0.9500	0.9750	0.8158	0.6757	0.8667	0.6842
DS4	0.8500	1.0000	0.9189	0.8462	0.8750	0.8500	1.0000	0.9189	1.0000	0.8667
DS5	0.9250	0.9211	1.0000	0.9487	0.9750	0.8500	0.8684	0.9189	0.8667	1.0000
DS6	1.0000	1.0000	0.9459	0.9231	0.8750	0.8000	0.9211	0.8649	0.8125	0.7222

The following two examples illustrate this procedure. In the first example, the value of supplier DS1 in beneficial criterion C1 is selected, while the value of the same supplier in cost criterion C9 is also selected.

$$r_{11} = \frac{d_{11}}{\max\left(d_{ij}\right)} = \frac{6.8}{8} = 0.85,$$

$$r_{19} = \frac{\min\left(d_{ij}\right)}{d_{19}} = \frac{2.6}{3.8} = 0.6842.$$

Subsequently, a vector normalization procedure is applied to the decision matrix, following the linear normalization process. This procedure is conducted using Eqs. (13)–(14). The outcomes of this procedure are shown in Table 6.

Table 6. The results of vector normalization

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
DS1	0.3832	0.4116	0.4233	0.4133	0.3471	0.3897	0.3871	0.4423	0.5360	0.6242
DS2	0.4057	0.4227	0.3749	0.4133	0.4479	0.4584	0.3992	0.4545	0.4872	0.5741
DS3	0.4057	0.3782	0.3628	0.4357	0.4255	0.4470	0.375	0.3071	0.6337	0.5240
DS4	0.3832	0.4227	0.4112	0.3687	0.3919	0.3897	0.4597	0.4177	0.6825	0.6242
DS5	0.417	0.3893	0.4475	0.4133	0.4367	0.3897	0.3992	0.4177	0.6337	0.6743
DS6	0.4508	0.4227	0.4233	0.4022	0.3919	0.3668	0.4234	0.3931	0.6093	0.5490

The following two examples illustrate the vector normalization procedure. In the first example, the value of supplier DS1 in beneficial criterion C1 is selected, while the value of the same supplier in cost criterion C9 is also selected.

$$y_{11} = \frac{d_{11}}{\sqrt{\sum_{i=1}^{m}\left(d_{ij}\right)^2}} = \frac{6.8}{\sqrt{\left(6.8\right)^2 + \left(7.2\right)^2 + \cdots + \left(8\right)^2}} = 0.3832,$$

$$y_{19} = 1 - \frac{d_{19}}{\sqrt{\sum_{i=1}^{m}\left(d_{ij}\right)^2}} = 1 - \frac{3.8}{\sqrt{\left(3.8\right)^2 + \left(4.2\right)^2 + \cdots + \left(3.2\right)^2}} = 0.536.$$

Following the vector normalization stage, the nonlinear normalization procedure is then applied to the decision matrix. The nonlinear normalization procedure is conducted using Eqs. (15)–(16). The results of this procedure are presented in Table 7.

Table 7. The results of nonlinear normalization

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
DS1	0.7225	0.9481	0.8947	0.9000	0.6006	0.7225	0.7091	0.9467	0.3203	0.6510
DS2	0.8100	1.0000	0.7019	0.9000	1.0000	1.0000	0.7541	1.0000	0.2372	0.4472
DS3	0.8100	0.8005	0.6574	1.0000	0.9025	0.9506	0.6655	0.4566	0.6510	0.3203
DS4	0.7225	1.0000	0.8444	0.7161	0.7656	0.7225	1.0000	0.8444	1.0000	0.6510
DS5	0.8556	0.8484	1.0000	0.9000	0.9506	0.7225	0.7541	0.8444	0.6510	1.0000
DS6	1.0000	1.0000	0.8947	0.8521	0.7656	0.6400	0.8484	0.7481	0.5364	0.3767

The following two examples represent the nonlinear normalization procedure. In the first example, the value of supplier DS1 in beneficial criterion C1 is selected, while the value of the same supplier in cost criterion C9 is also selected.

$$p_{11}=\left(\frac{d_{11}}{\max\left(d_{ij}\right)}\right)^2=\left(\frac{6.8}{8}\right)^2=0.7225,$$

$$p_{19}=\left(\frac{\min\left(d_{ij}\right)}{d_{19}}\right)^3=\left(\frac{2.6}{3.8}\right)^3=0.3203.$$

The weighted arithmetic operations are calculated using the formulas outlined in Eqs. (17)–(19). The final score for each digital supplier is obtained using Eq. (20). Consequently, the results of the MUNRA method are presented in Table 8.

Table 8. Final results and rankings

	r_i'	y_i'	p_i'	v_i	Ranking
DS1	0.8793	0.4231	0.7643	0.6882	5
DS2	0.9067	0.4340	0.8150	0.7178	3
DS3	0.8593	0.4138	0.7332	0.6681	6
DS4	0.9076	0.4362	0.8205	0.7207	2
DS5	0.9335	0.4477	0.8676	0.7489	1
DS6	0.9012	0.4332	0.8012	0.7112	4

To illustrate the methodology for determining the values of r_i', y_i', p_i', and v_i, the calculation of these values for the DS1 supplier will be presented below.

$$r_1'=\sum_{j\in BNF} w_j r_{ij}+\sum_{j\in NBNF} w_j r_{ij}=$$

$$\left(0.1371\times0.85+0.083\times0.9737+\cdots+0.1123\times0.973\right)+\left(0.0616\times0.6842+0.0667\times0.8667\right)=0.8793,$$

$$y_1' = \sum_{j \in BNF} w_j y_{ij} + \sum_{j \in NBNF} w_j y_{ij} =$$
$$(0.1371 \times 0.3832 + 0.083 \times 0.4116 + \cdots + 0.1123 \times 0.4423) + (0.0616 \times 0.536 + 0.0667 \times 0.6242) = 0.4231,$$

$$p_1' = \sum_{j \in BNF} w_j p_{ij} + \sum_{j \in NBNF} w_j p_{ij} =$$
$$(0.1371 \times 0.7225 + 0.083 \times 0.9481 + \cdots + 0.1123 \times 0.9467) + (0.0616 \times 0.3203 + 0.0667 \times 0.651) = 0.7643,$$

$$v_1 = 0.333 \cdot 0.8793 + 0.333 \cdot 0.4231 + 0.333 \cdot 0.7643 = 0.6882.$$

The outcomes of the MUNRA method reveal that the digital suppliers are ranked in the following order: DS5, DS4, DS2, DS6, DS1, and DS3.

The six evaluated digital suppliers (DS1–DS6) represent diverse solution providers operating in different domains of digital transformation within supply chain systems. Specifically, the suppliers include providers of Enterprise Resource Planning (ERP) – based analytics platforms, automation and process integration tools, and digital innovation services offering customized solutions for data-driven operations. Some suppliers emphasize advanced analytics and integration capabilities (C2, C3, C5), while others focus on automation efficiency, digital collaboration, and continuous training (C4, C7, C8). Although their identities remain confidential, this general characterization illustrates the technological diversity among the evaluated suppliers and supports the interpretation of their ranking outcomes.

The MUNRA method is evaluated in comparison with other MCDM methods to ascertain the accuracy of the results obtained. Table 9 presents the Spearman correlation coefficients between MUNRA and other MCDM methods.

Table 9. Spearman's rank correlation analysis results

	MUNRA	AROMAN	COPRAS	ARAS	MACONT	ARTASI	ALWAS	TODIFFA
MUNRA	1.0000	0.9430	1.0000	1.0000	0.8290	0.8290	1.0000	0.8290
AROMAN	0.9430	1.0000	0.9430	0.9430	0.9430	0.7710	0.9430	0.7710
COPRAS	1.0000	0.9430	1.0000	1.0000	0.8290	0.8290	1.0000	0.8290
ARAS	1.0000	0.9430	1.0000	1.0000	0.8290	0.8290	1.0000	0.8290
MACONT	0.8290	0.9430	0.8290	0.8290	1.0000	0.8290	0.8290	0.8290
ARTASI	0.8290	0.7710	0.8290	0.8290	0.8290	1.0000	0.8290	1.0000
ALWAS	1.0000	0.9430	1.0000	1.0000	0.8290	0.8290	1.0000	0.8290
TODIFFA	0.8290	0.7710	0.8290	0.8290	0.8290	1.0000	0.8290	1.0000
	MUNRA	WASPAS	CODAS	MARCOS	TOPSIS	CRADIS	ARLON	MCRAT
MUNRA	1.0000	1.0000	0.8860	1.0000	1.0000	1.0000	0.9430	0.8290
WASPAS	1.0000	1.0000	0.8860	1.0000	1.0000	1.0000	0.9430	0.8290
CODAS	0.8860	0.8860	1.0000	0.8860	0.8860	0.8860	0.7140	0.8290
MARCOS	1.0000	1.0000	0.8860	1.0000	1.0000	1.0000	0.9430	0.8290
TOPSIS	1.0000	1.0000	0.8860	1.0000	1.0000	1.0000	0.9430	0.8290
CRADIS	1.0000	1.0000	0.8860	1.0000	1.0000	1.0000	0.9430	0.8290
ARLON	0.9430	0.9430	0.7140	0.9430	0.9430	0.9430	1.0000	0.7710
MCRAT	0.8290	0.8290	0.8290	0.8290	0.8290	0.8290	0.7710	1.0000

The correlation coefficient between the developed MUNRA and ARLON and AROMAN methods was 0.9430, while the correlation coefficient between MUNRA and MACONT, ARTASI, TODIFFA, and MCRAT was 0.8290. Furthermore, the correlation coefficient between MUNRA and CODAS (Keshavarz Ghorabaee et al., 2016) was 0.8860. The correlation coefficient between MUNRA and other MCDM methods is 1.0000. In light of these findings, it can be concluded that the MUNRA method, as developed, produces accurate and consistent results. Figure 2 illustrates the correlation coefficients between the MUNRA approach and several MCDM methods, whereas Figure 3 shows the ranking outcomes of MUNRA in comparison to other MCDM methods.

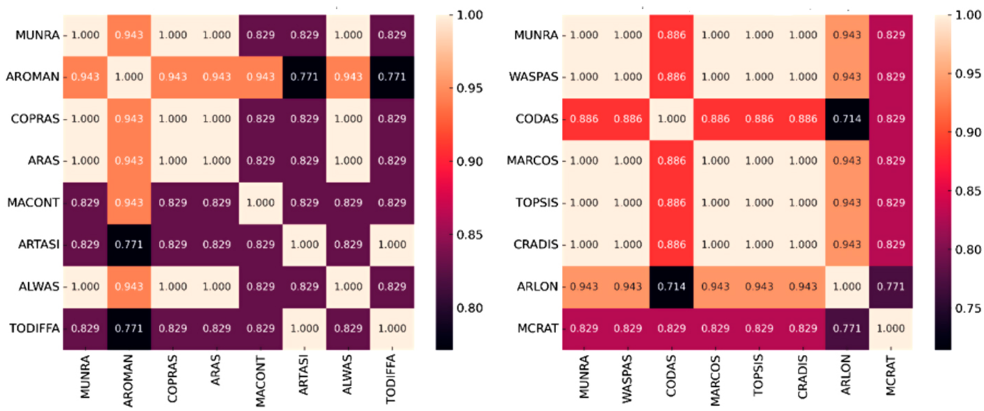

Figure 2. The correlation coefficients between MUNRA and the other MCDM methods

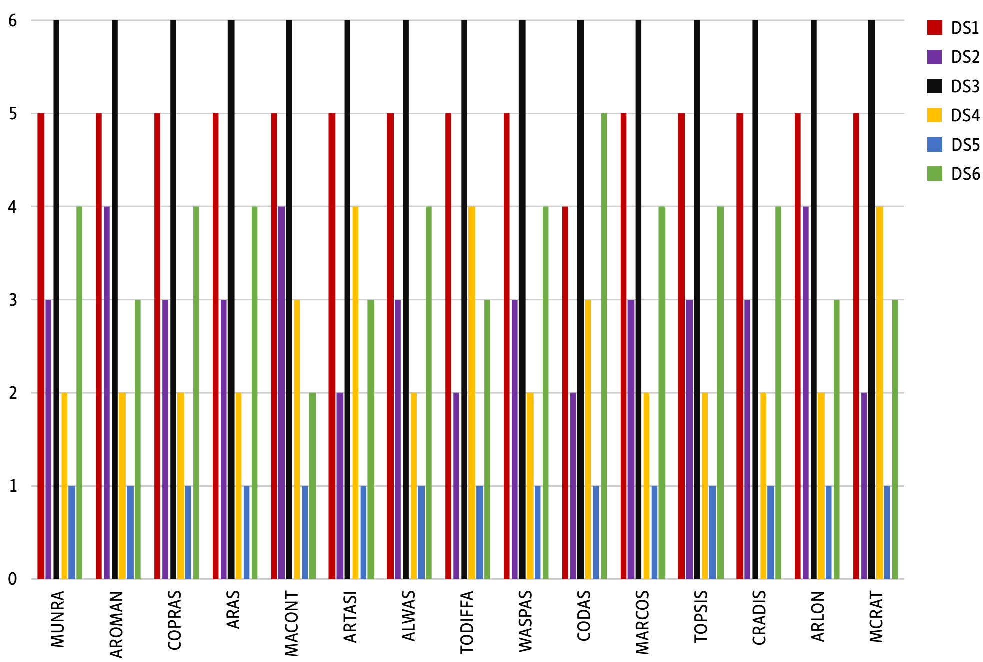

Figure 3. The comparison of MUNRA and other MCDM methods

To examine the effectiveness of the MUNRA method in a more diverse and multi-alternative MCDM problem, a selection problem presented by Ulutaş et al. (2023) was also addressed. The ranking of the alternatives regarding the MUNRA method and other MCDM methods is presented in Table 10.

Pearson Correlation Coefficients between MUNRA and other MCDM methods are as follows: MUNRA-MCRAT (0.9023), MUNRA-CRADIS (0.9474), MUNRA-MARCOS (0.9476), and MUNRA-ARAS (0.9744). Since the correlation coefficient between the MUNRA method and other MCDM methods is very high, it can be concluded that the MUNRA method yields accurate and reliable results.

Additionally, a comparison of the MUNRA method with other MCDM methods is provided in Table 11.

All MCDM methods have been known to yield highly satisfactory results. In contrast to alternative MCDM methods, the proposed method enables the attainment of more rigorous outcomes by incorporating three distinct normalization procedures. Despite the MACONT method's comprehensive nature, the calculation steps are not as straightforward as those of the MUNRA method.

Table 10. The results of MCDM methods

Alternatives	*MUNRA*	AROMAN	COPRAS	ARAS	MACONT
Cotton stalk fibers	*15*	15	14	14	14
Cotton waste	*10*	12	11	11	10
Hemp	*3*	3	3	3	3
Kenaf	*11*	11	12	12	12
Rice husk	*4*	5	4	4	4
Sheep wool	*1*	1	1	1	1
Wood fibre	*2*	2	2	2	2
Cellulose	*9*	13	10	10	9
Cork	*12*	10	13	13	11
Flax	*20*	14	15	15	16
Vacuum-insulated panel	*19*	20	20	20	20
Nano insulation materials	*5*	4	5	5	5
Aerogel	*13*	19	16	16	15
Fibreglass	*6*	6	6	6	6
Phenolic foam	*17*	18	17	17	19
Polyisocyanurate	*16*	17	18	18	18
Extruded polystyrene	*18*	16	19	18	17
Expanded polystyrene	*14*	9	9	9	13
Rock wool	*8*	8	8	8	8
Glass wool	*7*	7	7	7	7

Table 11. Distinctive features of MUNRA and other methods

	Linear Normalization	Vector Normalization	Nonlinear Normalization	Ease of Use	Practically
COPRAS (Zavadskas & Kaklauskas,1996)	Yes	No	No	Moderate	Moderate
ARAS (Zavadskas & Turskis, 2010)	Yes	No	No	High	High
WASPAS (Zavadskas et al., 2012)	Yes	No	No	High	High
AROMAN (Bošković et al., 2024)	Yes	Yes	No	Moderate	High
MACONT (Wen et al., 2020)	Yes	No	No	Low	Moderate
MUNRA (*Proposed*)	*Yes*	*Yes*	*Yes*	*High*	*High*

The MUNRA's resilience to the ranking reversal problem is also evaluated to ascertain its trustworthiness for practitioners in various industries. A total of *m-1* scenarios (SCNs) are constructed to achieve this analysis, with the lowest-ranked alternative removed. Subsequently, the remaining alternatives are re-ranked after repeating the computations. Ultimately, the ranking outcomes presented in Table 12 were examined across all scenarios. The findings in Table 12 indicate that the alternative rankings remain consistent, thereby substantiating the assertion that the MUNRA method offers a dependable, comprehensive, and resilient decision-making process.

Table 12. The results of the rank reversal analysis

Scenarios	Rankings
Current	DS5 > DS4 > DS2 > DS6 > DS1 > DS3
SCN-1	DS5 > DS4 > DS2 > DS6 > DS1
SCN-2	DS5 > DS4 > DS2 > DS6
SCN-3	DS5 > DS4 > DS2
SCN-4	DS5 > DS4
SCN-5	DS5

In the work, a sensitivity analysis is also performed by modifying the weights of the criteria. To this end, the weights of the four criteria having the highest weights (C1, C3, C5, and C8) are decreased, resulting in forty SCNs. Eq. (21) is used for scenario planning (Mešić et al., 2022).

$$W_{n\rho} = \left(1 - W_{n\theta}\right) . \frac{W_\rho}{\left(1 - W_n\right)}. \tag{21}$$

In Eq. (21), $W_{n\rho}$ represents a criterion's weight at a new value, whereas W_ρ illustrates the actual value of it. Moreover, $W_{n\theta}$ represents the reduced criterion weight, and W_n denotes the actual weight of a criterion with a reduced value (Mešić et al., 2022). The results of the sensitivity analysis are presented in Figure 4.

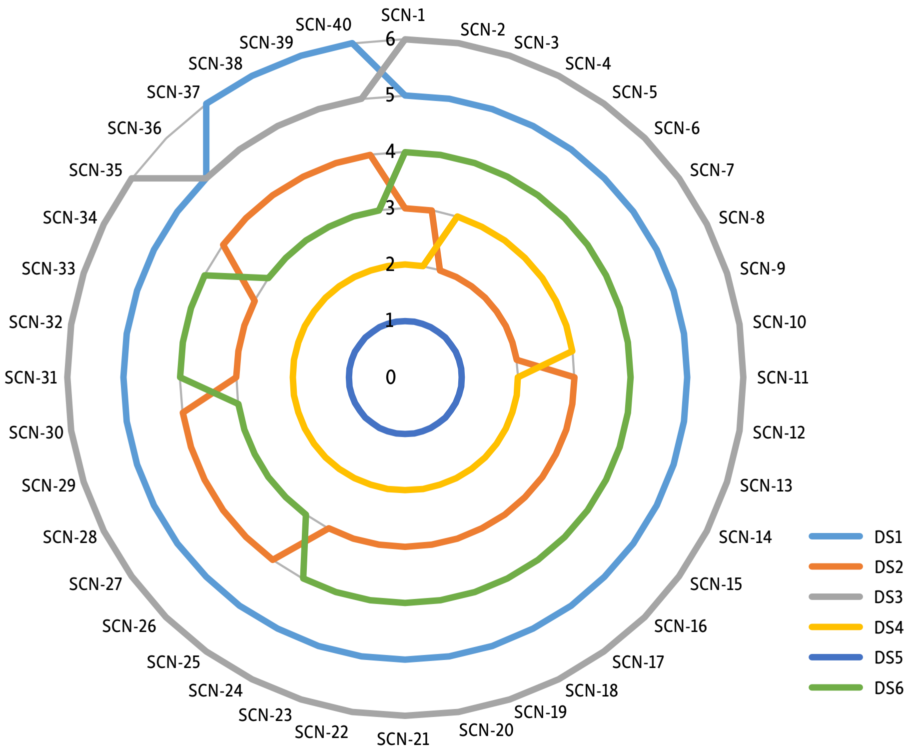

Figure 4. Radar chart of sensitivity analysis results

The sensitivity analysis reveals changes in the rankings of all suppliers except for DS5. Specifically, the ranking of the DS1 supplier dropped from fifth to sixth place in the SCN-37 to SCN-40 scenarios. DS2 was ranked third in other scenarios but climbed to second in the SCN-3 to SCN-10 scenarios and fell to fourth in the SCN-25 to SCN-30 and SCN-35 to SCN-40 scenarios. The DS3 supplier held sixth place in most scenarios but improved to fifth in the SCN-36 to SCN-40 scenarios. Similarly, DS4 secured second place in most scenarios but ranked third in the SCN-3 to SCN-10 scenarios. Lastly, DS6 took third place in the SCN-25 to SCN-30 and SCN-35 to SCN-40 scenarios while maintaining fourth place in all other cases.

The sensitivity analysis revealed that alterations to the criteria weights resulted in a change in the ranking of digital suppliers. In other words, the MUNRA method, as developed, is sensitive to changes in the criteria weights.

5. Discussion and implications

As mentioned above, the primary purpose of this research is to evaluate and select digital suppliers from alternative suppliers based on evaluation criteria. The study also develops a new MCDM method, MUNRA, for ranking alternatives. It should be noted that the DIBR technique is performed to obtain the criteria weight values.

Regarding the research findings, technology integration (C3; 0.1427), flexibility (C1; 0.1371), and technology capability (C5; 0.1216) are the most crucial drivers for digital supplier selection. However, digital education & training (C8; 0.1123), automation in supply chain operations (C4; 0.0995), digital collaboration (C7; 0.0919), analytics tools (C2; 0.0883), digital innovation (C6; 0.0783), lack of information sharing (C10; 0.0667), and lack of information security and privacy (C9; 0.0616) are also other significant factors for that selection process. These findings can provide managers, authorities, and researchers with valuable insights and recommendations for making more critical decisions about digital supplier selection.

Büyüközkan and Göçer (2021) found that digital innovation is the third critical factor for digital supplier selection, whereas digital education and training stand in the fourth position. Concerning the work of Büyüközkan and Göçer (2018a), technology integration, digital collaboration, and technology capability are among the top five crucial criteria for selecting digital suppliers. Tavana et al. (2021) identified flexibility, digital collaboration, and technology capability as the key drivers for selecting digital suppliers. Khan et al. (2021) noted that digital collaboration, information sharing, and analytics tools are among the most crucial factors in digital supply chain management. Sharma and Joshi (2023) highlighted the importance of digital innovation and knowledge sharing among digital suppliers, emphasizing their contribution to value creation in the digital supply chain. As a result of the literature review, Büyüközkan and Göçer (2018b) reached essential conclusions such as the digital supply chain increases cooperation among stakeholders, the integration of digital and non-digital supply chains is necessary, the digital supply chain enables information sharing, analytical tools provide undeniable support for decision making, the digital supply chain paves the way for innovations, and the flexibility of the digital supply chain makes configuration easier. Alkan and Kahraman (2022) concluded that innovation, automation, and integration are the foremost digital transformation strategies for the supply chain.

5.1. Research implications

This study entails a ranking analysis using the MUNRA method for multi-criteria problems. MUNRA is a cutting-edge ranking method introduced in this study. It offers a novel strategy for digital supplier selection by integrating three distinct normalization techniques: linear, vector, and nonlinear normalization. MUNRA notably distinguishes itself by combining a three-stage normalization procedure. This characteristic appears to be an essential feature that distinguishes it from other multi-criteria techniques. Vector and nonlinear normalizations ensure effective handling of data within the problem. Furthermore, three normalizations balance the dataset's influences of large and small values. The fewer the effects of extreme values in the dataset, the more confidence in the decision-making process. Thus, it facilitates the achievement of more accurate results in solving complex real-world problems. Hence, decision procedures based on vector and nonlinear normalizations enable the obtaining of more credible and robust decisions.

In this study, well-established MCDM methods such as TOPSIS and COPRAS were selected as benchmark models to evaluate the comparative performance of the proposed MUNRA approach. TOPSIS, based on the concept of distance to an ideal solution, and COPRAS, which utilizes a utility degree derived from the effects of positive and negative criteria, are among the most widely applied techniques in supplier selection problems. These methods provide a meaningful baseline due to their differing mathematical structures and interpretation logic. On the other hand, the MUNRA method offers several distinct advantages in this context. By incorporating three types of normalization schemes – linear, vector, and nonlinear – it addresses the scale-sensitivity and rank instability often observed in single-normalization models. This hybrid structure enhances robustness across diverse data distributions. Furthermore, MUNRA is free from the need for predefined ideal solutions or complex pairwise comparisons, making it both practical and scalable. The use of a composite normalization framework and straightforward score aggregation positions MUNRA as a flexible alternative for real-world decision-making scenarios involving digital suppliers.

The results indicate that the MUNRA technique ranks digital suppliers proficiently and yields consistent and precise outcomes compared to alternative MCDM methods. The strong correlation coefficients between the MUNRA and AROMAN methods, and between the MACONT and CODAS methods, validate the accuracy of the approach. Thus, Spearman's correlation analysis indicates that MUNRA yields more comprehensive and robust outcomes compared to alternative techniques. The MUNRA method is more advantageous than alternative approaches because of its straightforward computational processes. Moreover, MUNRA demonstrates resilience to rank reversal problems, affirming its efficacy as a dependable decision-making instrument. The approach is also designed to be responsive to changes in criterion weights. The ability of the MUNRA method to combine criteria by considering cost and benefit increases the flexibility of the decision-making process, offering potential applications in various scientific fields and areas. In particular, the features of the technique that distinguish it from other MCDM methods provide a unique perspective for decision-makers, leading to more reliable and balanced decisions.

5.2. Managerial/practical implications

Identifying the right supplier is a strategic decision for companies. This research can help senior managers and other executives in firms understand the strategic role of digital supplier selection. The most proper digital supplier might bring resilience to digital supply chains via their advanced technology tools. Limited studies in the literature have considered only a few factors in the digital supplier selection process, while neglecting others. However, the neglected factors could significantly impact the overall results. Hence, all factors are of utmost importance in the decision-making process. This study aims to identify the factors required in the selection process, determine the importance level of these factors in relation to the proposed model, and rank alternative digital suppliers. Thus, this research will facilitate supply chain managers and senior managers in understanding the importance levels of the factors involved in the selection process. This study may also be helpful for managers who are adopting a digital supply chain. This work guides the selection of qualified suppliers equipped with advanced technologies so that companies do not fall behind in competition in the digital age. Therefore, the research results provide practical insights and guidance for stakeholders, managers, and decision-makers to make more informed and effective decisions.

The research contributes to the practices of digital supply chains by identifying vital factors for the digital supplier selection process and achieving this through a novel MUNRA method.

Theoretically, the drivers of digital supplier selection, which are limited in the literature, are clarified. The methodology based on MUNRA can significantly enhance current digital supply chain management strategies in the literature due to its benefits in digital supplier selection. Digital supply chains have improved flexibility, visibility, and efficiency by implementing smart technologies, including AI, big data analytics, IoT, and cloud computing. Thanks to advanced digital technologies, managers can better connect with customers and adapt their strategies by developing digital supply chains in collaboration with digital suppliers. The MUNRA method facilitates more efficient utilization of these technologies in selecting digital suppliers. Incorporating normalizing approaches enhances the precision and robustness of supplier selection while mitigating the complexities and coefficient dependencies frequently found in alternative methods within the literature.

The MUNRA technique enables managers and decision-makers to evaluate and select suppliers based on their digitalization capabilities in the Industry 4.0 era. MUNRA and its possible extensions can be delivered as a decision support vehicle for further implementations in the supply chain management field. The results of this study provide a crucial foundation for exploring the effective integration of advanced technologies into the digital supplier selection process. The insights discussed can also help companies develop more effective and successful supply chain management action plans. Identifying factors and selecting the most suitable digital supplier can help companies operate their digital supply chains effectively and efficiently.

Moreover, the work provides some insights into the textile industry. The findings can help the textile industry identify the necessary skills and qualifications to successfully transform their supply chains into digital ones. Evaluation factors with high significance require managers' attention, as they directly influence decisions. Thus, decision-makers can focus more on essential selection factors and enable the digitalization of their supply chains through their suppliers.

Beyond its methodological contribution, the findings offer clear managerial implications for decision-makers in the textile industry. By highlighting technology integration, flexibility, and technological capability as the most critical evaluation factors, the proposed DIBR-MUNRA framework provides managers with actionable insights for supplier selection. In practice, this means that textile companies can use the method to structure supplier negotiations, ensuring that key technological competencies are prioritized when forming or maintaining strategic partnerships. Moreover, the robustness and transparency of the approach enable managers to justify supplier choices to stakeholders, reduce decision bias, and enhance long-term collaboration strategies in increasingly digitalized supply chains.

6. Conclusions

Digital supply chains enable seamless communication between supply chain partners, facilitating the effective management of all activities throughout the production process. Managers, decision-makers, and analysts can gain valuable insights from this study to inform their selection of suppliers with advanced technologies. In other words, the work can provide some insights into how companies can evaluate and choose digital suppliers mathematically to optimize the entire digital supply chain mechanism. The primary purpose of this study is to evaluate digital suppliers, a critical element of this chain. To this end, this work introduces the MUNRA method, incorporating three distinct normalization techniques: linear, vector, and nonlinear normalization. The motivation behind implementing these three strategies is to produce more robust outcomes. The MUNRA approach yielded outcomes indicating that digital providers are ranked as DS5, DS4, DS2, DS6, DS1, and DS3. To determine the significance of the factors, the DIBR method is also conducted. As a result, technology integration, flexibility, and technological capability are the paramount drivers of the digital supplier selection process, according to the work's findings. The accuracy of the MUNRA approach is also evaluated through a comprehensive sensitivity analysis. The results indicate that the MUNRA approach yields reliable and precise outcomes.

Although the case study provides valuable insights into the applicability of the proposed DIBR-MUNRA framework in a real-world setting, several limitations must be acknowledged. First, the analysis is based on data obtained from a single textile company located in Turkey, which may restrict the external validity and generalizability of the findings to other industries or geographical contexts. Second, while the selected experts represent diverse functions within the organization, their evaluations may still reflect the specific operational priorities and organizational culture of that particular firm. Additionally, since expert opinions were considered in evaluating the criteria and alternatives, this may have introduced bias. Third, the study focused exclusively on digital supplier selection within the textile sector, which may differ in its digital maturity and supply chain dynamics compared to other industries such as automotive, electronics, or healthcare. Finally, although sensitivity and robustness checks were performed, the framework has yet to be validated across multiple organizations or sectors, which limits the scope of cross-case comparison. Future research should consider applying the proposed methodology to a broader range of industries and contexts, involving larger expert panels and multi-site case studies to test the consistency and transferability of the results. Future studies are encouraged to broaden the expert panel, possibly using Delphi-based approaches, multi-round consensus techniques, or fuzzy group decision-making models to reduce bias further and enhance the robustness and generalizability of the results. While the DIBR-MUNRA framework demonstrated promising results in the textile sector, the focus on a single industry context may limit the generalizability of the findings. Industry-specific dynamics, such as digital maturity, supplier capabilities, and operational criteria, could influence how the method performs in other sectors.

This study focused on evaluating and selecting digital suppliers using a novel MCDM framework. Future studies are encouraged to examine how digital transformation strategies influence supplier performance and collaboration mechanisms in more dynamic environments. Whereas the current study adopts a deterministic decision framework, future extensions could incorporate fuzzy sets, intuitionistic fuzzy numbers, or grey systems to model uncertainty more realistically. This would enhance the adaptability and generalizability of the proposed method, especially in complex, multi-criteria digital supplier evaluation contexts. Future research is also recommended to apply the proposed framework to diverse industrial domains, including high-tech manufacturing, logistics, and consumer goods, to validate its scalability, adaptability, and cross-sector applicability. In future research, the MUNRA framework could also be extended by incorporating fuzzy logic or other uncertainty-handling techniques to better capture the inherent subjectivity and vagueness in expert evaluations and criteria weighting.

Competing interests

The author is the Editor-in-Chief for this journal and was not involved in the editorial review or the decision to publish this article.

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