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Enhancing Supplier Selection in Public Manufacturing: A Hybrid Multi-Criteria Decision-Making Approach

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ABSTRACT

In today's business world, outsourcing is a key strategy for organizations aiming to improve efficiency, reduce costs, and increase transparency. By using external experts, companies can quickly gain necessary resources and knowledge to better handle operational challenges. Therefore, choosing the right suppliers and contractors for manufacturing is essential. This study examines how public manufacturing organizations select suppliers and contractors, highlighting the importance of setting clear evaluation criteria before making selections. Following the Iranian Public Procurement Regulations, a strong set of criteria was created for effective supplier assessment. A combined Multi-Criteria Decision-Making (MCDM) approach was employed, integrating the Fuzzy DEMATEL method to analyze relationships among selection criteria, and the Best-Worst Method (BWM) to assign weights, with the best and worst criteria derived from the results of the Fuzzy DEMATEL analysis. The weighted criteria were then applied using three different MCDM techniques—COCOSO, MOORA, and TOPSIS—in a case study to rank potential suppliers. The results showed strong agreement among the methods, confirming the reliability of the evaluation framework and boosting stakeholder confidence in decision-making. This study demonstrates the effectiveness of MCDM strategies in promoting informed and strategic procurement decisions, ultimately leading to better operational efficiency and alignment with organizational goals in the public sector.

1. Introduction

In today's business environment, outsourcing has become a widely adopted strategy for organizations aiming to improve operational efficiency, control costs, and enhance transparency. Outsourcing allows organizations to quickly access critical resources and knowledge, helping them address operational challenges by leveraging external experience. This trend is driven by various factors, including competitive pressures, the increasing specialization of tasks, rising costs, and the excessive growth of organizations. As a result, organizations are increasingly turning to outsourcing to optimize performance, reduce expenses, focus on their primary objectives, and minimizing

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distractions from secondary activities. By delegating non-core tasks to external partners, businesses can tap into specialized expertise, streamline operations, and allocate resources more effectively, all while achieving their strategic goals. In different countries, organizations employ various methods for selecting suppliers, contractors, and task allocation to outsourcing. In recent years, the process of choosing the right suppliers and contractors has garnered significant attention in both academic and practical, as it is widely seen as a key factor in long-term success and sustainability. Choosing the right supplier or contractor involves evaluating both quantitative and qualitative factors, which can contribute to the long-term growth and competitiveness of the company. Furthermore, aligning contractors with the organization's strategic and commercial objectives is essential to achieving the desired outcomes [1].

It is essential for organizations to select the right suppliers for outsourcing in their manufacturing businesses. The selection of a sustainable supplier in any supply chain is one of the main reasons for the sustainability of the supply chain. Since every organization is part of one or more supply chain networks, and the efficiency of these networks often depends on sourcing goods from reliable suppliers at optimal costs and timelines. Effective production planning, inventory management, precise material planning, and cost-effective procurement are all vital to maintaining smooth production and response customer demands. A reliable supplier not only helps meet production targets but also improves operational flexibility and product quality customer satisfaction [2]. Furthermore, strategically selecting suppliers can lead to higher, lower procurement costs, and greater competitiveness in the market. The quality of raw materials provided by suppliers, along with their production capabilities, has a direct impact on the quality of the final product.

The primary objective of supplier selection is to identify a supplier that is compatible with the organization and capable of delivering maximum value [2]. Organizational decision-makers must carefully choose the appropriate supplier to effectively manage the supply chain from production to consumption. As such, organizations prioritize the systematic evaluation and selection of suppliers based on strict, predefined criteria [3]. Choosing the wrong supplier can impose costs such as money, time, customer dissatisfaction, and damage to the organization's reputation. Therefore, suppliers should be selected based on scientific and essential criteria. Strategic decisions that align with organizational goals are critical for fostering long-term growth. Furthermore, in organizations focused on large-scale projects, resource constraints and specialized tasks often necessitate outsourcing parts of the project. Selecting the right contractor is crucial, as it directly impacts project success, timely delivery, and quality standards. Like manufacturing firms, project-oriented organizations evaluate contractors based on set criteria to identify qualified partners and eliminate inefficient ones from the bidding process. Poor contractor selection can lead to resource inefficiency and significant losses, making it a priority for managers to maintain competitiveness. To identify a competent contractor, organizations must employ a comprehensive set of criteria and indicators. These criteria serve to assess the contractor's capability and qualifications, ensuring that the project is executed within the desired framework of time, cost, and quality [4]. Numerous criteria are used to select suppliers and contractors. Khalfan and Gough [5] across public and private sectors identified nine key criteria, including credibility, quality, pricing, flexible contracts, value-added capabilities, effective communication, available resources, and cultural-regional compatibility. These factors are essential for aligning suppliers and contractors with organizational goals and project needs.

This research focuses on examining the process of selecting suppliers for public manufacturing organizations and contractors for public sector projects. Consequently, it is essential to establish the necessary criteria for supplier and contractor selection prior to evaluating potential suppliers of raw materials and contractors. In this study, the criteria were derived from the Iranian Public Procurement Regulations (approved in 2009), which encompass a range of standards for selecting contractors in public projects and suppliers in public manufacturing organizations. In this study, a hybrid Multi-Criteria Decision-Making (MCDM) approach has been employed for supplier selection. To identify the most influential and the most influenced criteria among the set of evaluation criteria, as well as to analyze the interrelationships between these criteria, the Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) method was utilized. Following this, the Best-Worst Method (BWM) was applied to assign weights to the criteria used for supplier selection. The BWM requires the identification of the most important (best) and least important (worst) criteria, which are typically determined based on expert judgments. In this research, the best and worst criteria were derived from the results of the Fuzzy DEMATEL analysis. Specifically, the most influential criterion identified through Fuzzy DEMATEL was designated as the best criterion, while the most influenced criterion was designated as the worst criterion for the BWM.

Once the weights of the criteria were determined using the BWM, these weights were used as inputs for three distinct MCDM methods: Combined Compromise Solution (COCOSO), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), and Technique for Order Preference by Similarity to Ideal Solution **(**TOPSIS). These methods were applied to rank suppliers in a case study, with the aim of identifying the most suitable supplier. The proposed hybrid approach integrates the strengths of COCOSO, MOORA, TOPSIS and to provide a comprehensive evaluation framework. Finally, the results obtained from the three methods were compared to assess their consistency and to validate the robustness of the proposed approach.

2. Literature review

As highlighted in previous section, selecting an appropriate supplier or contractor is critically important across all business types, including intermediary businesses like Amazon, manufacturing enterprises, and project-oriented organizations. Within a business's supply chain, the process of choosing a suitable supplier is not only vital but also essential for ensuring the overall success and sustainability of the business. This emphasizes the need to establish robust evaluation criteria and strategic decision-making frameworks to identify and collaborate with suppliers or contractors who align with the business's objectives and quality standards.

Numerous studies have been conducted on supplier selection, reflecting the importance of the topic and the wide range of MCDM methods, which are crucial for evaluating suppliers. These studies aim to identify the best supplier among potential candidates based on various criteria across different industries. However, due to the continuous development of methods, frequent changes in criteria, and the diversity of criteria across industries, further research in this area remains necessary and essential.

The importance of selecting suppliers is reflected in the substantial number of review papers published in reputable journals over the years. For instance, studies [6-12] have extensively examined the application of MCDM methods for supplier evaluation and selection. Specifically, Sahoo and Goswami [13] focuses on this within the context of Industry 4.0 and green supplier selection. These studies collectively highlight the critical role of MCDM methods in enhancing the supplier selection process, emphasizing their relevance in addressing complex decision-making challenges in modern supply chain management.

In 2019, Tirkolaee *et al.,*[14] proposed a hybrid approach based on fuzzy logic to address the supplier selection problem, responding to the growing demand from companies to enhance the reliability and sustainability of their supply chains in light of customer requirements and environmental regulations. They employed the Fuzzy Analytic Network Process (FANP) to rank criteria and sub-criteria, the FDEMATEL method to identify interrelationships among the primary criteria, and the Technique for TOPSIS method to prioritize suppliers. The resulting weights were subsequently integrated as inputs into a multi-objective optimization model, designed to minimize total costs, maximize product value, and improve supply chain reliability. Finally, a case study involving a lamp supply chain was conducted to validate the proposed methodology. In 2021, Wu *et al.,* [15] proposed a hybrid framework for sustainable supplier selection (SSS) within the chemical industry, incorporating Fuzzy Grey Relational Analysis (FGRA), Failure Mode and Effects Analysis (FMEA), and the Entropy Weighting Method (EWM). The outcomes were integrated using the DEMATEL approach, which assists managers in selecting sustainable suppliers, addressing market demands, and sustaining competitiveness. The practical application of this proposed framework was validated through a case study conducted within a large petrochemical company in China.

Ortiz-Barrios *et al.,* [16] explored the supplier selection process in the mining industry, crucial for inventory, production, maintenance, financial, and environmental management, using a MCDM approach. The Fuzzy Analytic Hierarchy Process (FAHP) was initially applied to determine criterion weights under uncertainty, followed by Fuzzy DEMATEL to assess interrelationships among criteria. Fuzzy logic was used to capture uncertainty in both methods, and TOPSIS was employed to rank supplier alternatives. A case study on forklift filter suppliers found quality to be the most significant criterion. Similarly, Pamucar *et al.,* [17] also addressed the challenges faced by healthcare centers during the COVID-19 pandemic due to high demand for face masks and shields. The study introduced a decision-making approach combining MACBETH and a distance-based assessment method, using fuzzy rough numbers to manage uncertainty. A case study in Istanbul identified job creation and occupational health as key criteria, with Supplier A1 emerging as the optimal choice, based on a distance score of 3.308.

In 2023, Koc *et al.,* [18] proposed the use of probabilistic decision-making models for sustainable supplier selection, incorporating three key sustainability dimensions: economic, social, and environmental. In addition, they introduced three new, practical aspects: innovation, lean principles, and knowledge management into the supplier selection process. To address probabilistic uncertainties, they developed a novel hybrid multi-criteria decision analysis model, supported by Monte Carlo simulation. This simulation, combined with Beta-Pert distribution, was integrated with the AHP and the TOPSIS to identify the weights of criteria and evaluate suppliers [18].

Agrawal [19], the PROMETHEE II method was applied to supplier selection in three distinct case studies involving a large number of suppliers, and was compared with other MCDM methods (AHP and TOPSIS). Ecer and Torkayesh [20] focused on the selection of sustainable suppliers within a circular economy framework, accounting for the potential impacts of future events. A MCDM framework was employed, integrating layering theory to develop a novel Fuzzy Layering Method with Complete Coherence. This method identifies the optimal weights for criteria based on the anticipated impacts of future events. Additionally, an innovative extension of the composite aggregation method was introduced, utilizing comprehensive normalization in a fuzzy environment to prioritize suppliers according to sustainability and circular economy criteria. The proposed methodology was subsequently applied in a case study.

As highlighted, the significance of this topic is underscored by the numerous studies conducted annually on the evaluation and selection of suppliers, considering the diversity and complexity of products and services required across supply chains. This growing body of research stems from the varying criteria associated with different products and services, as well as the wide array of decision-making techniques available. Such diversity facilitates more comprehensive and nuanced supplier evaluations across different sectors within supply chains. Supplier selection criteria can vary significantly across different regions and countries due to diverse regulatory, economic, and cultural factors. As such, the process of selecting suppliers or contractors is not universally applicable and must be tailored to the specific context in which it is being applied. In light of this, the focus of this study is to explore the supplier selection process within the context of Iran. Specifically, this research will investigate the selection of suppliers or contractors based on the criteria outlined in the Iranian Public Procurement Regulations, which were officially approved in 2009. By analyzing these regulations, the study aims to provide a comprehensive understanding of how procurement criteria are structured and applied in the Iranian public sector. The findings will contribute to the broader field of supplier selection, offering insights into how national procurement frameworks influence decision-making processes and the overall efficiency of public procurement systems. This research will be valuable not only for academic purposes but also for practitioners involved in procurement management, as it will offer a detailed perspective on supplier selection within Iran's regulatory environment.

3. Methodology

To address complex problems using MCDM methods, it is essential to group approaches based on their underlying nature and the type of input data they require. Studies [21- 23] have introduced various MCDM methods to address such problems, which can be categorized into four main groups:

i. *Quantitative Methods*: These methods rely on numerical measurements and quantitative data for decision-making. Examples of such methods include TOPSIS, SAW, MOORA, ARAS, and COPRAS.
ii. *Qualitative Initial Methods*: These approaches are based on qualitative criteria and initial assessments. Methods like AHP and ANP fall under this category.
iii. *Comparative Preference Methods*: These methods facilitate the direct comparison of options side by side. Techniques such as PROMETHEE and ELECTRE belong to this group.
iv. *Non-numerical Qualitative Methods*: These methods are based on qualitative evaluations, which are not converted into numerical values. For instance, verbal decision analysis methods are categorized here.

This classification assists in selecting the most appropriate method for addressing complex decision-making problems.

In this study, some key criteria for supplier or contractor evaluation are outlined in the Iranian Public Procurement Regulations as general guidelines, though they may vary for specific projects. Therefore, this study will focus on the eight criteria specified in the regulations for public procurement in the Iranian public sector, providing a detailed discussion of each as follows:

i. *Proposed Price*: The proposed price from contractors is a primary criterion for selection. The contractor offering the most reasonable price is typically chosen.
ii. *Experience and Track Record*: The contractor's experience and proven track record in handling similar projects, coupled with their technical and managerial expertise, play a critical role in the selection process.
iii. *Resources and Capabilities*: Evaluating the contractor's resources—such as human capital, equipment, and financial capacity—is vital to ensure their ability to execute the project successfully.
iv. *Technical Quality and Performance*: The quality of the contractor's previous work and their adherence to required technical standards and specifications are essential for evaluation.
v. *Post-sale Support*: The contractor's capacity to provide post-project services, including repairs and maintenance, is a key factor in long-term satisfaction.
vi. *Compliance with Regulations and Standards*: It is crucial to assess the contractor's compliance with relevant regulations and public procurement standards for the project.

vii. *Financial Stability*: Ensuring that the contractor possesses the necessary financial stability to complete the project without encountering fiscal difficulties is an important criterion.

viii. *Social and Environmental Commitments*: The contractor's adherence to social and environmental responsibilities, including worker safety and environmental protection, should be thoroughly evaluated.

Table 1
Eight criteria in the regulations for public procurement in the Iranian public sector for selecting suppliers

	A	B	C	D	E	F	G	H
Criteria	Price	Experience	Quality	Resources	Support	Compliance with Rules	Financial Stability	Social and Environmental

For the above criteria (Table 1), the causal relationships between them were calculated using the fuzzy DEMATEL method to identify the most influential and most affected criteria.

3.1. Fuzzy DEMATEL Method

The Fuzzy DEMATEL method is a MCDM technique employed to analyze the relationships between criteria or factors within a complex system, using fuzzy inference. Originally developed at the Geneva Research Center to address complex problems in various domains, it has found widespread application in fields such as management, engineering, and economics [24]. Chang *et al.,* [25] was the first research to use Fuzzy DEMATEL to develop supplier selection criteria. The primary goal of the Fuzzy DEMATEL method is to identify the internal relationships between factors, distinguishing between those that are influential and those that are influenced. This approach enables researchers to construct a network structure of the factors under study, helping them identify the critical and most impactful elements within the system. The method is defined by four key features: causal-effect relationship analysis, network structure creation, quantification of relationship intensity, and applicability to complex systems. The steps involved in implementing this method are outlined in the flowchart presented in Figure 1.

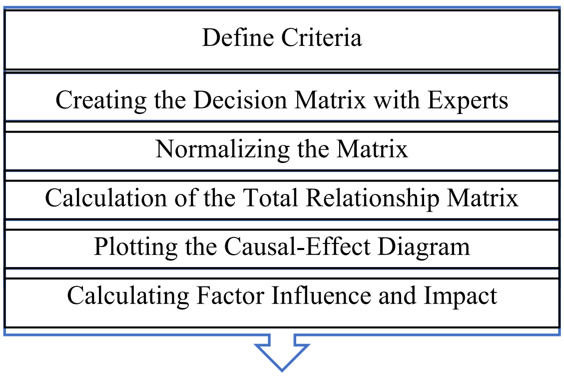

Fig. 1. Steps of the Fuzzy DEMATEL Method

Creating the Decision Matrix: To identify the relationships between N criteria, an N×N matrix, referred to as the direct relation matrix or decision matrix (denoted as M), is first constructed. Three experts are then asked to evaluate the influence of each criterion on the others using a pairwise comparison matrix, applying either a linguistic scale or a quantitative range from 1 to 4, as shown in Table 2. The average of the experts' opinions is then used to create the matrix M. Finally, the decision matrix is converted into a fuzzy decision matrix using Formula 1.

$$\widetilde{D} = \left[\tilde{d}_{ij}\right]_{n\times n}; \quad \tilde{d}_{ij} = \left(d_{ij}^{l};\ d_{ij}^{m}, d_{ij}^{r}\right) \tag{1}$$

Table 2
Five-Point Fuzzy DEMATEL Scale [23]

Linguistic Expression	No Influence	Very Low Influence	Low Influence	High Influence	Strongly Influence
Quantitative Value	0	1	2	3	4
Triangular Fuzzy Numbers	(0, 0, .0.25)	(0, 0.25, 0.5)	(0.25, 0.5, 0.75,)	(10.5, 0.75, 0.5)	(0.75, 1, 1)

Normalization of the Fuzzy Decision Matrix: The values of the initial decision matrix are normalized and transformed into a direct influence matrix. This normalization process is carried out using Equation (2).

$$\widetilde{N} = \left[\tilde{e}_{ij}\right]_{n\times n};\ \ \tilde{e}_{ij} = \left(e_{ij}^{l};\ e_{ij}^{m}, e_{ij}^{r}\right) \qquad (2)$$

The result of the normalized matrix in fuzzy DEMATEL method is presented in Table 3. This matrix shows the degree of influence and interrelationships between the various factors after applying the normalization process. The values in the table represent the normalized impacts, where each entry has been adjusted to reflect the relative importance of each factor in a consistent scale. This normalization allows for a more balanced and comparable evaluation of the fuzzy direct and indirect effects between the criteria involved in the analysis.

Table 3
Result of Normalized Fuzzy Decision Matrix

N	A			B			C			D		
A	0.00	0.00	0.00	0.12	0.10	0.09	0.10	0.08	0.07	0.10	0.08	0.07
B	0.13	0.11	0.10	0.00	0.00	0.00	0.13	0.11	0.10	0.10	0.08	0.07
C	0.13	0.11	0.10	0.11	0.09	0.08	0.00	0.00	0.00	0.13	0.11	0.10
D	0.15	0.15	0.13	0.02	0.02	0.02	0.12	0.10	0.09	0.00	0.00	0.00
E	0.13	0.11	0.10	0.13	0.11	0.10	0.13	0.11	0.10	0.07	0.05	0.03
F	0.15	0.15	0.13	0.15	0.15	0.13	0.13	0.11	0.10	0.15	0.15	0.13
G	0.10	0.09	0.07	0.13	0.11	0.10	0.12	0.10	0.09	0.10	0.08	0.07
H	0.05	0.04	0.03	0.07	0.05	0.03	0.02	0.02	0.02	0.07	0.05	0.03

N	E			F			G			H		
A	0.11	0.09	0.08	0.09	0.07	0.05	0.13	0.11	0.10	0.14	0.14	0.12
B	0.11	0.09	0.08	0.02	0.02	0.02	0.13	0.11	0.10	0.13	0.11	0.10
C	0.10	0.08	0.07	0.07	0.05	0.03	0.10	0.08	0.07	0.13	0.11	0.10
D	0.13	0.11	0.10	0.07	0.05	0.03	0.13	0.11	0.10	0.15	0.15	0.13
E	0.00	0.00	0.00	0.02	0.02	0.02	0.10	0.09	0.07	0.14	0.14	0.12
F	0.15	0.15	0.13	0.00	0.00	0.00	0.13	0.11	0.10	0.15	0.15	0.13
G	0.10	0.08	0.07	0.08	0.06	0.04	0.00	0.00	0.00	0.13	0.11	0.10
H	0.02	0.02	0.02	0.02	0.02	0.02	0.07	0.05	0.03	0.00	0.00	0.00

Calculation of the Fuzzy Total Relation Matrix: To calculate the total relation matrix (fuzzy total impact), first construct an identity matrix. Then, apply Equation (3) to subtract the normalized matrix from the identity matrix. After that, invert the resulting matrix (Table 4). Finally, multiply the inverted matrix by the normalized matrix to obtain the total relation matrix.

$$T = N \times (1 - N)^{-1} \qquad (3)$$

Table 4
Result of the Fuzzy Total Relation Matrix

T	A			B			C			D		
A	0.27	0.16	0.09	0.34	0.23	0.16	0.33	0.21	0.14	0.32	0.20	0.13
B	0.37	0.25	0.18	0.22	0.13	0.07	0.34	0.23	0.16	0.30	0.20	0.13
C	0.38	0.26	0.18	0.33	0.21	0.14	0.23	0.13	0.07	0.34	0.23	0.15
D	0.39	0.29	0.21	0.25	0.16	0.10	0.33	0.23	0.16	0.22	0.13	0.07
E	0.36	0.25	0.17	0.33	0.23	0.16	0.33	0.23	0.16	0.27	0.16	0.09
F	0.47	0.36	0.26	0.43	0.32	0.23	0.42	0.30	0.21	0.42	0.31	0.22
G	0.35	0.23	0.15	0.34	0.23	0.16	0.34	0.23	0.15	0.31	0.20	0.13
H	0.15	0.10	0.06	0.15	0.10	0.06	0.12	0.07	0.04	0.15	0.09	0.05
T	E			F			G			H		
A	0.32	0.22	0.14	0.20	0.13	0.08	0.37	0.25	0.17	0.44	0.32	0.22
B	0.31	0.21	0.14	0.13	0.08	0.05	0.36	0.24	0.17	0.41	0.29	0.20
C	0.31	0.20	0.13	0.18	0.11	0.06	0.34	0.22	0.14	0.42	0.29	0.20
D	0.33	0.23	0.16	0.18	0.11	0.07	0.36	0.25	0.17	0.43	0.33	0.24
E	0.20	0.11	0.06	0.13	0.08	0.05	0.33	0.21	0.14	0.41	0.30	0.21
F	0.42	0.32	0.23	0.15	0.09	0.05	0.44	0.31	0.21	0.53	0.41	0.29
G	0.31	0.20	0.13	0.19	0.12	0.07	0.25	0.14	0.08	0.42	0.29	0.20
H	0.11	0.07	0.04	0.07	0.04	0.03	0.17	0.10	0.06	0.13	0.07	0.04

Defuzzification to Certain Values: The fuzzy total relation matrix is transformed into a certain value matrix, resulting in the defuzzified total relation matrix. Table 5 displays the defuzzified matrix with precise values, derived from the fuzzy total relation matrix using Equation (4) for the four primary factors.

$$B = \frac{a_1 + 2a_2 + a_3}{4} \tag{4}$$

Table 5
Results of the Defuzzified Fuzzy Total Relation Matrix

	A	B	C	D	E	F	G	H
A	0.1688	0.241	0.224	0.214	0.2242	0.1363	0.261	0.324
B	0.2621	0.1376	0.243	0.205	0.2151	0.0859	0.2521	0.296
C	0.2673	0.2238	0.143	0.237	0.2108	0.1157	0.2288	0.301
D	0.2928	0.1655	0.238	0.136	0.2397	0.1188	0.2579	0.331
E	0.2541	0.2359	0.236	0.172	0.1232	0.0816	0.2223	0.304
F	0.36	0.3263	0.307	0.316	0.3197	0.0962	0.3194	0.407
G	0.2432	0.2435	0.237	0.209	0.2097	0.1238	0.1517	0.299
H	0.1012	0.1006	0.074	0.099	0.071	0.0442	0.1072	0.078

The sum of rows and columns: The sums of the rows and columns are represented as D and R in the total-relation matrix. Table 6 presents the results for D, R, D+R, and D−R.

Table 6
Results of sum of rows and columns

	A	B	C	D	E	F	G	H
D	1.793	1.697	1.727	1.779	1.629	2.451	1.717	0.675
R	1.9495	1.6743	1.701	1.588	1.6134	0.8024	1.8005	2.341
D+R	3.74	3.37	3.43	3.37	3.24	3.25	3.52	3.02
D-R	-0.16	0.02	0.03	0.19	0.02	1.65	-0.08	-1.67

Analysis of Causal Relationships: The sum of the elements in each row (D) for a given factor reflects the degree of influence that factor exerts on other factors within the system. Conversely, the sum of the elements in each column (R) for a factor indicates the extent to which it is influenced by other factors in the system. Consequently, the horizontal vector (D+R) represents the overall interaction and influence of the factor in question within the system. Thus, a higher value of D+R signifies greater interaction with other factors. The vertical vector (D−R) quantifies the strength of influence of each factor. In general, if D−R is positive, the variable is classified as an independent variable; if negative, it is classified as a dependent variable.

The analysis of Table 5 indicates that the criterion for compliance with regulations has an impact score of 2.451, the highest among all criteria. Its degree of influence from other criteria is 0.8024, the lowest, highlighting its pivotal role in the research. Thus, compliance with regulations is deemed the most critical criterion. The criterion for social commitments, with an average influence score of 2.341, is also recognized as an influential factor. In this context, compliance with regulations affects the other seven factors, while the social commitments factor does not influence any other factors. In selecting a supplier, eight key factors—price, track record, quality, resources, support, compliance with regulations, financial stability, and social commitments—should be carefully assessed. Managing the compliance criterion during supplier selection can effectively impact the other criteria, ultimately facilitating the identification of a superior supplier with reduced costs and time investments. Based on the analyses conducted on the influence and interdependencies among the factors in this research, a comprehensive model illustrating the relationships between these factors is presented in Figure 2.

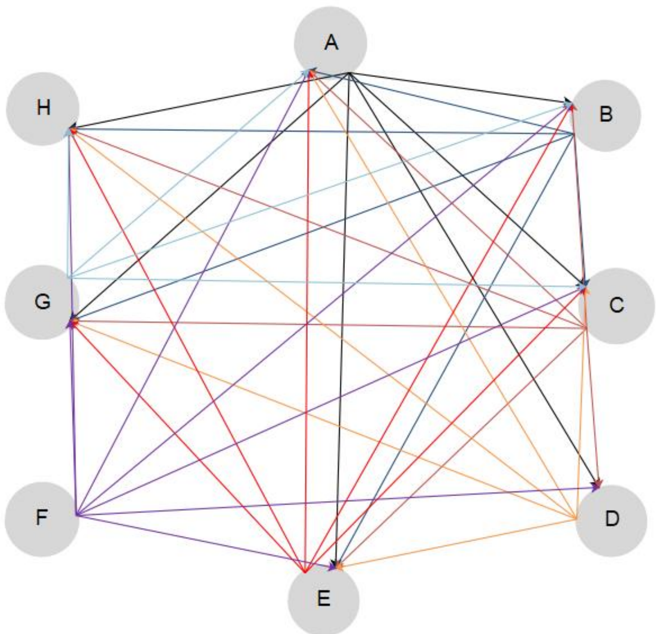

Fig. 2. The model derived from the data analysis

3.2. The Best-Worst Method (BWM)

In the next step, the BWM is employed to weigh the criteria for ranking suppliers. BWM is a multi-criteria decision-making approach that facilitates the weighting of decision-making criteria through pairwise comparisons. Introduced by Jafar Rezaei in 2015, this method aims to reduce the complexity of pairwise comparisons and enhance the accuracy of the decision-making process. BWM calculates the final weights with minimal inconsistency by comparing criteria against the best and worst options [26].

The implementation steps for this method are as follows:

i. *Identifying Criteria and Determining the Best and Worst Criteria*: A set of criteria related to the decision-making problem is identified. The criterion with the highest importance is designated as the best criterion (B), while the criterion with the lowest importance is designated as the worst criterion (W). In this study, the most impactful criterion (compliance with regulations), derived from the fuzzy DEMATEL method, is selected as the best criterion, and the most influenced criterion (social commitments) is chosen as the worst criterion for the BWM weighting method.

ii. *Pairwise Comparison of Criteria with the Best Criterion*: The importance of each identified criterion relative to the best criterion is specified using a scale (typically from 1 to 9).

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \tag{5}$$

iii. *Pairwise Comparison of Criteria with the Worst Criterion*: In this stage, the significance of the worst criterion is evaluated in relation to each of the other criteria.

$$A_W = (a_{W1}, a_{W2}, \dots, a_{Wn}) \tag{6}$$

iv. *Determining the Optimal Weight for Each Criterion*: The best weight is calculated using equations (7), (8), and (9).

$$\min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \tag{7}$$

S.t

$$\sum_j w_j = 1 \tag{8}$$

$$w_j \geq 0, for\ all\ j \tag{9}$$

This method was chosen because it requires fewer pairwise comparisons and yields more consistent results in this study. The results obtained from the BWM method are presented in Table 7.

Table 7
Results from the BWM Method for Criteria

WA	WB	WC	WD	WE	WF	WG	WH
0.111588	0.111588	0.083691	0.111588	0.111588	0.263948	0.167382	0.038627

Subsequently, five suppliers related to a case study in the industry were ranked separately using three methods: COCOSO, MORA, and TOPSIS. The results from each method were then compared with one another.

3.3. Combined Compromise Solution (COCOSO) Method

The COCOSO method is a MCDM technique used for ranking and prioritizing options based on multiple criteria. Introduced by Yazdani *et al.,* [27], this method employs a weighted aggregation approach using summation and exponentiation, aiming to identify the optimal option among several possibilities.

In the COCOSO method, options are first evaluated according to various criteria, followed by the application of three different functions for prioritization. In the final step, a combined linear-exponential function integrates these three functions to produce a final score for each option. This approach enhances the accuracy of ranking and optimizes the decision-making process by simultaneously considering multiple aspects of the decision criteria and pinpointing the best option through a specified compromise mechanism.

The steps for implementing this method are as follows:

Step 1: Formation of the Decision Matrix

This matrix is a fundamental tool in multi-criteria decision-making methods used to evaluate and compare different options based on a set of criteria. It is typically presented as a table (N×M), where:

- Rows (N) represent the options being considered.
- Columns (M) represent the evaluation criteria.
- Each cell in the matrix indicates the performance value of a specific option relative to a particular criterion.

$$X = \begin{bmatrix} x_{11} & x_{12} \dots & x_{1n} \\ x_{21} & x_{22} \dots & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \quad (9)$$

Step 2: Normalizing the Decision Matrix

The second step involves normalizing the decision matrix. In the COCOSO method, once the decision matrix is formed, normalization (dimensionless scaling) is essential to ensure that the criterion values fall within a standard range, facilitating direct comparison. This process is carried out using a compromise method, which is a common approach in data standardization.

Normalization is performed according to a specific formula, with each normalized element of the decision matrix represented as n_{ij}. This technique is widely applicable in various MCDM models and data standardization. By employing this normalization method, the values of different criteria can be compared without being influenced by their units of measurement. Normalization for positive criteria is calculated using Equation (10), while normalization for negative criteria is determined using Equation (11), Table 8.

$$\bar{n}_{ij} = \frac{X_{ij} - minX_{ij}}{maxX_{ij} - minX_{ij}} \quad (10)$$

$$\bar{n}_{ij} = \frac{maxX_{ij} - X_{ij}}{maxX_{ij} - minX_{ij}} \quad (11)$$

Table 8
Decision Matrix from COCOSO for Case Study

N	A	B	C	D	E	F	G	H
S1	0.408	0.796	0.797	0.796	1.000	0.781	1.000	0.799
S2	0.204	0.389	0.392	0.592	0.745	0.562	0.487	0.598
S3	0.408	0.796	0.594	1.000	0.745	1.000	0.743	1.000
S4	0.000	0.593	0.594	0.592	0.745	0.781	1.000	0.799
S5	0.613	1.000	1.000	0.796	1.000	0.781	0.743	0.598

In Table 8, S1 to S5 represent different suppliers that participated in a government tender and submitted their proposals. Therefore, Table 8 is formed based on the decision matrix established according to criteria A to H.

Step 3: Weighting the Normalized Matrix

In the third step, the normalized matrix must be weighted. To achieve this, two methods are employed: multiplication and exponentiation. At this stage, to apply weights to each criterion, the elements of the normalized decision matrix are combined with the criterion weights. This process is carried out in two phases:

i. *Multiplying the normalized decision matrix by the criterion weights*: In this phase, each value in the normalized decision matrix is multiplied by the corresponding weight of that criterion. This ensures that the impact of more important criteria, which have higher weights, is given greater consideration and is carried out using Equation (12).

$$S_i = \sum_{j=1}^{n} (W_j \times n_{ij}) \tag{12}$$

ii. *Exponentiating the normalized decision matrix with the criterion weights*: In this method, each value in the normalized decision matrix is raised to the power of the corresponding criterion weight. This approach not only considers the weights of the criteria but also amplifies the influence of more important criteria, and it is performed using Equation (13).

$$P_i = \sum_{j=1}^{n} (n_{ij})^{W_j} \tag{13}$$

To execute this step, the criterion weights must be predetermined based on the relative importance of each criterion compared to the others.

In the next step, the scores for the options need to be determined. This phase involves calculating the scores of the options using the three Equations (14 to 16) provided below (Tables 9-11).

$$K_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)} \tag{14}$$

Table 9
Results Obtained from Eq. (14)

Alt.	Ka
S1	0.2080
S2	0.1910
S3	0.2109
S4	0.1806
S5	0.2094

$$K_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{15}$$

Table 10
Results Obtained from Eq. (15)

Alt.	*Kb*
S1	2.6949
S2	2.0876
S3	2.8244
S4	2.3213
S5	2.7410

$$K_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\left(\lambda^{\max_i S_i} + (1-\lambda)^{\max_i P_i}\right)}; \quad 0 \leq \lambda \leq 1. \tag{16}$$

Table 11
Results Obtained from Eq. (16)

Alt.	Kc
S1	0.9861
S2	0.9057
S3	1.0000
S4	0.8564
S5	0.9926

In the final step of the COCOSO method, the final score for each option is calculated, allowing for the ranking of the options. At this stage, a combined formula is used to determine the final score for each option, which specifically represents the sum of the geometric mean and the arithmetic mean of the three equations from the previous step. This relationship is calculated as Equation (17):

$$K_i = (K_{ia}K_{ib}K_{ic})^{\frac{1}{3}} + \frac{1}{3}(K_{ia} + K_{ib} + K_{ic}) \qquad (17)$$

Table 12
Ranking Obtained from COCOSO method for Supplier 1 to supplier 5

CoCoSo	K	RANK
S1	2.1170	3
S2	1.7736	5
S3	2.1865	1
S4	1.8302	4
S5	2.1433	2

Table 12 presents the rankings of five suppliers based on the COCOSO method. The COCOSO method evaluates suppliers using a composite score (K) that reflects their overall performance across multiple criteria.

i. S3 achieves the highest score of 2.186541, securing the 1st rank as the top-performing supplier.
ii. S5 follows closely behind S3 with a score of 2.143329, earning the 2nd rank.
iii. S1 has a score of 2.117021, placing it in 3rd position.
iv. S4 scores 1.830228, which places it in 4th position.
v. S2, with a score of 1.773579, ranks 5th, indicating it has the lowest performance among the suppliers.

Overall, this ranking provides a clear comparison of supplier performance, enabling decision-makers to identify the best options for procurement based on the assessed criteria.

3.4. Multi-Objective Optimization based on Ratio Analysis (MOORA) Method

The MOORA method is a MCDM technique used to select the best option based on multiple criteria. Introduced by Brauers et al., [28]. The MOORA method begins with a decision matrix, where the performance of various options is evaluated based on a set of indicators or objectives. In multi-criteria decision-making models, there are generally two approaches: one focuses on weighting the criteria, and the other on ranking the options. The MOORA method primarily emphasizes ranking options, evaluating each option's performance relative to various criteria based on computed ratios. This method employs ratio analysis to compare and prioritize options within a multidimensional space, providing precise and reliable results.

The steps for implementing this method are as follows:

i. *Decision Matrix Formation*: The first step involves creating a criterion-option decision matrix, derived similarly to the decision matrix of the COCOSO method as shown in Equation (9). The elements of this matrix represent the scores of each option relative to its criterion.
ii. *Specification of Criteria*: In the MOORA decision matrix, both the type of criteria (positive or negative) and the weights of the criteria must be specified. Positive criteria are those

that improve the system when increased, while negative criteria are those that improve the system when decreased.

iii. *Normalization of the Decision Matrix*: The next step involves normalizing the decision matrix, using vector normalization as outlined in Equation (18), Table 13.

$$n_{ij} = \frac{X_{ij}}{\sqrt{\sum_1^m X_{ij}^2}} \tag{18}$$

Table 13
Normalized Decision Matrix from MOORA for the Case Study

N	A	B	C	D	E	F	G	H
S1	0.378	0.478	0.504	0.462	0.521	0.442	0.544	0.462
S2	0.504	0.239	0.252	0.346	0.391	0.331	0.272	0.346
S3	0.378	0.478	0.378	0.577	0.391	0.552	0.408	0.577
S4	0.630	0.359	0.378	0.346	0.391	0.442	0.544	0.462
S5	0.252	0.598	0.630	0.462	0.521	0.442	0.408	0.346

The criteria weights should be determined using alternative weighting methods and then provided as input to this process. Subsequently, by multiplying the criteria weights by the normalized matrix, as outlined in Equation (19), the weighted normalized matrix can be derived according to Equation (20), Table 14.

$$V = W_j \times N \tag{19}$$

$$V = \begin{bmatrix} v_{11} & v_{12} \dots & v_{1n} \\ v_{21} & v_{22} \dots & v_{2n} \\ \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & v_{mn} \end{bmatrix} \tag{20}$$

Table 14
Weighted Normalized Decision Matrix from MOORA for the Case Study

V=N*W	A	B	C	D	E	F	G	H
S1	0.039	0.042	0.034	0.047	0.040	0.191	0.056	0.013
S2	0.052	0.021	0.017	0.035	0.030	0.143	0.028	0.010
S3	0.039	0.042	0.026	0.059	0.030	0.239	0.042	0.016
S4	0.064	0.031	0.026	0.035	0.030	0.191	0.056	0.013
S5	0.026	0.052	0.043	0.047	0.040	0.191	0.042	0.010

In the final step, the options must be ranked using the ratio system approach. After normalizing the data, the first task is to calculate the sum of the positive criteria (representing the best performance for each criterion) and the sum of the negative criteria (indicating the worst performance for each criterion), as specified in Equation (21). Next, the difference between the sums of the positive and negative criteria for each option is computed. A higher result signifies the superiority of the option, indicating that it has outperformed others in the positive criteria relative to the negative ones and is overall optimal compared to the other options. This approach aids the decision-maker in selecting the option that most closely aligns with the desired criteria.

$$y_i = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^* \quad (j = 1,2,\dots,n) \tag{21}$$

Table 15
Ranking Obtained from MOORA method for Supplier 1 to supplier 5

MOORA	Positive	Negative	Score	RANK
S1	0.423	0.039	0.384	3
S2	0.284	0.052	0.233	5
S3	0.453	0.039	0.415	1
S4	0.382	0.064	0.318	4
S5	0.425	0.026	0.399	2

The rankings obtained from the MOORA (Table 15) method align with those derived from the CoCoSo method, indicating a consistent evaluation of supplier performance. Both methods assess suppliers based on multiple criteria, producing similar rankings that reflect each supplier's overall effectiveness. The agreement between the two methods suggests that the evaluated criteria are robust and that the suppliers' performances are stable across different analytical approaches.

3.5. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) Method

TOPSIS is a MCDM technique used for ranking and prioritizing options. Originally introduced by Hwang *et al.,* [29], it has since been enhanced by Hwang *et al.,* [30] and further expanded by Yoon [31] in 1993. This method employs two key concepts: Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS). The PIS represents the best possible option, excelling in every criterion, while the NIS represents the worst possible option. Although ideal solutions may not exist in practice, the goal of TOPSIS is to approach these ideal solutions as closely as possible.

Steps for Implementation

Forming the Decision Matrix: Similar to other methods, the first step involves constructing a decision matrix based on the criteria and alternatives being evaluated.

i. *Normalization*: The decision matrix is normalized using the vector normalization method, as expressed in Equation (18). The result of this normalization is organized into a matrix format, detailed in Equation (22), Table 16.

$$N = \begin{bmatrix} n_{11} & n_{12} \dots & n_{1n} \\ n_{21} & n_{22} \dots & n_{2n} \\ \vdots & \vdots & \vdots \\ n_{m1} & n_{m2} & n_{mn} \end{bmatrix} \quad (22)$$

Table 16
Normalized Decision Matrix from TOPSIS for the Case Study

N	A	B	C	D	E	F	G	H
S1	0.378	0.478	0.504	0.462	0.521	0.442	0.544	0.462
S2	0.504	0.239	0.252	0.346	0.391	0.331	0.272	0.346
S3	0.378	0.478	0.378	0.577	0.391	0.552	0.408	0.577
S4	0.630	0.359	0.378	0.346	0.391	0.442	0.544	0.462
S5	0.252	0.598	0.630	0.462	0.521	0.442	0.408	0.346

ii. *Weighting the Criteria*: The weight of each criterion, derived from appropriate weighting methods, is applied to all entries under its respective criterion to create a weighted normalized matrix, as indicated in Equation (20), Table 17.

Table 17
Weighted Normalized Decision Matrix from TOPSIS for the Case Study

N*W	A	B	C	D	E	F	G	H
S1	0.0387	0.0420	0.0344	0.0473	0.0400	0.1909	0.0557	0.0128
S2	0.0516	0.0210	0.0172	0.0355	0.0300	0.1432	0.0279	0.0096
S3	0.0387	0.0420	0.0258	0.0591	0.0300	0.2387	0.0418	0.0161
S4	0.0645	0.0315	0.0258	0.0355	0.0300	0.1909	0.0557	0.0128

iii. Calculating Ideal and Anti-Ideal Solutions (Table 18):
   - For criteria with positive impacts (where higher values are better):
      - *Positive Ideal Solution (A+):* The highest value for that criterion, indicating the best performance.
      - *Negative Ideal Solution (A-):* The lowest value for that criterion, representing the worst performance.
   - For criteria with negative impacts (where lower values are better):
      - *Positive Ideal Solution (A+):* The lowest value for that criterion, signifying the best condition.
      - *Negative Ideal Solution (A-):* The highest value for that criterion, indicating the worst condition.

Table 18
Calculating Ideal and Anti-Ideal Solutions by TOPSIS for the Case Study

A+	0.0258	0.0524	0.0430	0.0591	0.0400	0.2387	0.0557	0.0161
A-	0.0645	0.0210	0.0172	0.0355	0.0300	0.1432	0.0279	0.0096

iv. *Calculating Distances*: In the final step, the distances of each option from both the PIS and NIS are calculated. This step aims to determine how close each option is to the ideal conditions. The Euclidean distance formula is used for this calculation, as defined in Equations (23), (24), and (25).

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{23}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{24}$$

$$CL_i^* = \frac{d_i^-}{d_i^- + d_i^+} \tag{25}$$

By employing this systematic approach, TOPSIS enables decision-makers to effectively rank alternatives based on their proximity to ideal solutions, facilitating informed and strategic decision-making (Table 19).

Table 19
Ranking Obtained from TOPSIS method for Supplier 1 to supplier 5

TOPOSIS	D+	D-	CL	RANK
S1	0.05272	0.06860	0.56547	3
S2	0.11363	0.01290	0.10194	5
S3	0.02943	0.10530	0.78156	1
S4	0.07198	0.05700	0.44194	4
S1	0.05152	0.07659	0.59786	2

4. Results and Analysis

The comparison of rankings between the methods is presented in Table 20. This table illustrates that the rankings derived from each method are consistent, indicating a strong agreement across the different analytical approaches used in this study. The alignment of results reinforces the reliability of the evaluation process and suggests that the underlying criteria and data are robust. Such consistency not only enhances the credibility of the findings but also provides stakeholders with greater confidence in the decision-making process. This convergence across methods validates the effectiveness of the multi-criteria decision-making framework employed, ensuring that the selected suppliers are indeed the most suitable based on the established evaluation criteria.

Table 20
Comparison Ranking Between Methods

Alt.	CoCoSo	MOORA	TOPOSIS	RANK
S1	2.117021	0.384	0.56547	3
S2	1.773579	0.233	0.10194	5
S3	2.186541	0.415	0.78156	1
S4	1.830228	0.318	0.44194	4
S1	2.143329	0.399	0.59786	2

The alignment of rankings obtained from MOORA, CoCoSo, and TOPSIS signifies a strong consensus in evaluating supplier performance. This consistency across three distinct MCDM frameworks not only enhances the credibility of the findings but also instills greater confidence among stakeholders in the decision-making process. Each method employs different mathematical principles and approaches to assess supplier performance based on multiple criteria, yet they converge on the same rankings, suggesting that the underlying data and criteria are robust and accurately reflect suppliers' capabilities.

Such validation across different methodologies reduces the risk of bias or error that may arise from relying on a single assessment technique. Furthermore, the agreement in rankings facilitates a more streamlined decision-making process, enabling stakeholders to confidently identify top-performing suppliers, backed by corroborating analytical perspectives. This not only simplifies the selection process but also aids in justifying decisions to various stakeholders, including management and procurement teams.

In practical terms, this consistency allows organizations to leverage the strengths of their chosen suppliers effectively. By relying on validated rankings, companies can engage with suppliers that demonstrate superior performance, leading to enhanced operational efficiency and alignment with organizational goals. Overall, the convergence of rankings from MOORA, CoCoSo, and TOPSIS underscores the reliability of multi-criteria decision-making methods in supplier evaluation, promoting informed and strategic procurement decisions that can drive long-term success. This consistency across methodologies simplifies the decision-making process by providing a unified perspective on supplier performance, ultimately enhancing the effectiveness of evaluation techniques and supporting informed procurement decisions with greater assurance.

5. Conclusion

This research focused on the selection process for suppliers and contractors in public manufacturing organizations and projects. Establishing the necessary criteria is crucial, and this study derived them from the Iranian Public Procurement Regulations (2009), which provide standards for these selections. We employed a hybrid MCDM approach. The Fuzzy DEMATEL method was used to identify and analyze the interrelationships among the evaluation criteria. The BWM then assigned weights to these criteria, the BWM requires identifying the most important (best) and least important (worst) criteria, typically determined through expert judgment. In this study, the best and worst criteria were derived from the results of the Fuzzy DEMATEL analysis; the most influential criterion was designated as the best, while the most influenced criterion was designated as the worst for the BWM. The weights informed three MCDM methods: COCOSO MOORA, and TOPSIS, which were applied in a case study to rank suppliers. The alignment of results across these methods enhances confidence in the findings and reduces the risk of bias. This consistency facilitates a streamlined decision-making process, allowing stakeholders to confidently identify top-performing suppliers.

The alignment of rankings obtained from the COCOSO, MOORA, and TOPSIS methods signifies a strong consensus in the evaluation of supplier performance. This consistency across three distinct MCDM frameworks not only enhances the credibility of the findings but also instills a higher level of confidence among stakeholders in the decision-making process. Overall, the convergence of rankings from COCOSO, MOORA, and TOPSIS underscores the reliability of these methods in supplier evaluation, promoting informed procurement decisions that can drive long-term success. This comprehensive approach not only simplifies the selection process but also strengthens the justification for decisions made by management and procurement. This agreement across methodologies simplifies the decision-making process by providing a unified perspective on supplier performance. Ultimately, it underscores the effectiveness of the evaluation techniques and aids in making informed procurement decisions with greater assurance.

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Conflicts of Interest

The authors declare no conflicts of interest.

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