Fuzzy MCDM Framework for Risk Management in Construction Supply Chain

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Keywords: Risk Management, Construction Supply Chain, Fuzzy Sets, Multi-Criteria Decision Making, Supply Chain Management, Artificial Intelligence, Blockchain.

Abstract: Risk management in the construction supply chain (CSC) is vital in construction project risks. CSC has various risks affecting product quality and project timeline, such as operational, social, financial, technical, design, and safety risks. These risks should be mitigated in project construction. So, this paper proposed a set of technologies to overcome risks in CSC, like artificial intelligence (AI), blockchain, data analytics, and IoT, to select the best one. So, the multi-criteria decision-making (MCDM) methodology is used to deal with various risks. The Multi-Attribute Utility Theory (MAUT) method is used to rank technologies. The weights of risks are obtained by the average method by using the decision matrix. The MCDM methodology is integrated with a fuzzy set to overcome uncertainty data. Experts used triangular fuzzy numbers to express their opinions instead of exact numbers. These allow the model to overcome inconsistent and vague data. The MCDM methodology was applied to 18 risks and 5 technologies. The results show that social risks have the highest weight. AI is the best technology for overcoming risks in CSC. AI can integrate with CSC from raw data to final products to deliver to the usert.

1 INTRODUCTION

Supply chain management (SCM) controls the production flow of products and services from raw materials to the final product to deliver goods to clients. Firms and companies use various suppliers to deliver projects, from raw materials to final products and users. The role of SCM is to reduce the time of the production cycle and reduce cost. The effectiveness of the SCM maximizes the value of the supply chain. Various criteria are performed to increase the effectiveness of SCM, like identifying potential issues, optimizing price dynamically, and enhancing inventory allocation (Hmouda et al., 2024; Oyewole et al., 2024).

SCM was extended with various applications and case studies in healthcare, medical, retail, suppliers section(Sa'diyah et al., 2022), service companies, and food industries. Construction plays a vital role in the global marketplace. It can aid countries in creating opportunities for skilled and unskilled labor.

A construction project refers to using energy and raw materials, products, and hybrid nature. The quality of construction projects is increased by the performance of the project team and customer satisfaction with products.

Construction supply chain (CSC) refers to the process of a series of tasks from raw data to final goods in the construction industry. CSC is the process of sourcing, purchasing, and delivering materials. It is a network of suppliers that provide raw data into a final product to the user. It includes the flow of produce from suppliers to the construction site. It plays a vital role in the cost, time of projects, and quality of projects. CSC has various risks that affect the quality and performance of the system. These risks include cultural risks, social risks, financial risks, technical risks, and design risks. Various technologies are used with CSC to reduce these risks, like artificial intelligence (AI), blockchain, IoT, and data analysis (Chen et al., 2024; Gharaibeh et al., 2024).

AI is the common solution for addressing and minimizing risks in CSC. Each part in CSC forms raw data and the final product is managed by AI. The role of AI in CSC can optimize productivity and reduce

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Salamai, A. A.
Fuzzy MCDM Framework for Risk Management in Construction Supply Chain.
DOI: 10.5220/0013135700003956
In *Proceedings of the 7th International Conference on Finance, Economics, Management and IT Business (FEMIB 2025)*, pages 146-153
ISBN: 978-989-758-748-1; ISSN: 2184-5891

the effect of labor storage. AI can use the historical data of products and aid companies in predicting operational resources. AI can implement proactive maintenance methods and strategies. AI can analyze the unstructured data (Pournader et al., 2021; Singh et al., 2023).

Blockchain aids companies and firms in CSC by knowing the SC network, where the accumulation and exchange of value happen through a set of transactions, services, products, and information. Every business can add value for good before reaching the final step. Blockchain is interfaced with other technologies such as IoT and AI to deliver sustainable, secured, and safe CSC (Hijazi et al., 2019; Yoon & Pishdad-Bozorgi, 2022).

In decision-making, the experts and decision-makers are complex, and it is difficult to express their opinions in exact numbers in multi-criteria decision-making (MCDM) systems. So, the fuzzy set was applied to deal with vague data. The fuzzy set was used in various decision-making issues. So, the fuzzy set is a suitable framework for enabling decision-makers to express their opinions using v, uncertain data instead of exact numbers. Triangular fuzzy numbers (TFNs) are fuzzy sets that deal with vague data(Dong et al., 2021; Dubois et al., 2004). The MCDM methods are applied in various decision-making issues like renewable energy sources(Ali & Muthuswamy, 2023), green fuels evaluation(Elsayed, 2024), wastewater treatment(Saeed et al., 2024), and energy solar(Alharbi et al., 2024).

The Multi-Attribute Utility Theory (MAUT) approach is an MCDM methodology. The main advantage of the MAUT method is its simplicity in solving various criteria in decision-making problems. It can offer abundant freedom of action experts to make outcomes more effective and accurate. This method is applied in decision-making issues to select the best option. This method belongs to compensatory approaches; factors are independent, and qualitative factors are converted into quantitative ones(de Freitas et al., 2013; Işık, 2017).

1.1 Risk Management

Construction is quick and is a vital element in the supply chain. Delivering raw data from suppliers to sites is essential for a timely project. The main challenges of construction are sourcing and procurement of materials. There are various categories of materials in the supply chain (Shishehgarkhaneh et al., 2024; Yu & Ma, 2024). There are steps in risk management to reduce risks in CSC:

Identify and evaluate the potential risks in SC materials. It makes the SC more comprehensive in supply chain management. The project manager can investigate their vendor network to reduce risks. Identifying the risks can reduce the time of the project and deliver products and services on time.

Applying risk mitigation methods and strategies to reduce complex timelines in construction projects. The construction projects have risk mitigation strategies to deliver projects on time.

1.2 Contributions of this Study

The primary contributions of this work are:

- This work presents the risk management for the construction supply chain. We introduced the risks of CSC and how to reduce these risks.
- We introduce some trend technologies to overcome CSC risks. We introduce five trend technologies to select the best one.
- We used the MCDM concept to manage multiple risks in CSC and the MCDM method to select the best technology.
- We used a triangular fuzzy set to deal with vague data in the selection problem. This study uses five main technologies and 18 CSC risks.
- We show that AI is the best technology to reduce CSC risks by analyzing the historical data and predicting the demand of supply to overcome risks.

1.3 Organization of this Paper

The rest of this paper is organized as follows: Section 2 shows the previous studies in CSC for risk management. Section 3 shows the materials and methods of this study; we introduce the MCDM methodology with the fuzzy set to deal with vague data. Section 4 shows the results and discussion of this study. Section 5 shows the sensitivity analysis. Section 6 shows the conclusions of this work.

2 LITERATURE REVIEW

Risk management plays an important role in CSC for effective performance and operation with uncertainty degrees. Various models and frameworks are used to reduce risks in CSC, like supply risks and risks of SCM. Pham et al. (Pham et al., 2023) aimed to reduce and overcome risks in CSC. They presented a complete review to show different risks and how to reduce them in CSC. They focused on risk management for the CSC process and operation.

Shojaei and Haeri (Shojaei & Haeri, 2019) proposed a framework to reduce risks in CSC. They used fuzzy cognitive mapping and gray relational analysis. They applied their model in real cases to show the performance and effectiveness of their model. They evaluated various risks by their model. They applied their model to reduce complexity and risks in the construction process, avoid time and cost, and project failure.

Tah and Carr (Tah & Carr, 2001) defined the limitations in risk management for CSC tools, and methods. They used the methods for describing risks for the development stable knowledge-driven method for risk management. They defined the generic risk and remedial action in descriptive terms. They implemented their model in the data management system. They adopted a prototype system to support risk management in CSC.

Aloini et al. (Aloini et al., 2012) proposed work to analyze the CSC with various factors in the construction industry. They provided a complete review of risk management in CSC. They provided case studies and tests to show the limitations results of CSC.

Hernadewita and Saleh (Hernadewita & Saleh, 2020) enhanced tools and approaches for risk management and evaluation in CSC. They used the literature review methodology to find tools and methods, including AHP, FMEA, SCOR, and HAZOP. They show the limitations and advantages of defining and evaluating CSC for risk management.

Abas et al. (Abas et al., 2022) aimed to identify the risks and factors impacting CSC. They adopted a methodology for identifying risk and success criteria. They created questionnaires to collect the opinions of firms and project managers. They show the highest risk in CSC financials, followed by storage materials, cash flow, and bad weather. Their study shows the enhancement of the construction industry.

Senthil and Muthukannan (Senthil & Muthukannan, 2022) introduced a complete survey to focus on quality management and quality assurance processes in the construction industry. They reviewed the risk management for CSC and showed that a neural network depends on a network by weight training input.

Rudolf and Spinler (Rudolf & Spinler, 2018) introduced a ranked view on the CSC for risk management. They provide a contextualized risk for engineering and construction projects. They showed the highest risk is inherent risk in large-scale projects and behavior risks.

Obayi et al. (Obayi & Ebrahimi, 2021) provided a study to show the role of external pressures in risk management in CSC. They showed a case study of regulatory strategies in CSC. They showed that relational costs have the highest weight, followed by transportation costs.

Deng et al. (Deng et al., 2019) presented a framework to analyze the CSC risks. They used the fuzzy synthetic evaluation to evaluate the risks in CSC. They presented nine risks with high weight and discussed the criteria risks in CSC.

3 MATERIAL AND METHODS

MCDM methods are used in decision-making issues to make the best decision. This section shows the steps of the MCDM framework under TFNs to select the best technology in CSC risk management (Dong et al., 2021; Işık,, 2017). Figure 1 shows the MCDM framework. Also, we show some definition of TFNs as:

Definition 1

We introduce some definition of triangular fuzzy numbers (TFNs) as:

TFNs defined as: $b = (b^l, b^m, b^u)$ is a fuzzy set defined on the set R of real numbers whose membership is:

$$z_b(x) = \begin{cases} \frac{(b^u - x)}{(b^u - b^m)}, & if\ b^m \le x \le b^u \\ \frac{(x - b^l)}{(b^m - b^l)}, & if\ b^l \le x \le b^m \\ 0, & if\ x > b^u\ or\ x < b^l \end{cases} \quad (1)$$

Where b^l, b^m, b^u define as a low, mode, and upper bound of TFNs.

Definition 2

We can compute the graded mean integration representation:

$$R(b) = \frac{1}{6}(b^l + 4b^m + b^u) \quad (2)$$

Definition 3

The fuzzy weights vector of TFNs can be defined as:

$$\sum_{j=1}^{n} w_j^m = 1, w_j^u + \sum_{i=1, i \neq j}^{n} w_j^l \le 1, w_j^l + \sum_{i=1, i \neq j}^{n} w_j^u \ge 1 \quad (3)$$

Step 1. Data collection

The step invited the experts to evaluate the criteria and alternatives. This study invited 5 experts with high experience. These experts have more than 20 years of experience in supply construction chain management.

Step 2. Build assessment matrix

The assessment matrix is built between factors and options by using the options of experts. The experts used the linguistic terms of triangular fuzzy sets. Then we used the triangular fuzzy numbers to build the assessment matrix. Then we convert these numbers into crisp numbers.

Step 3. Combine the assessment matrix.

The assessment matrix is combined by using the average method to attain one matrix.

Step 4. Compute the factors' weights.

The experts evaluated the factors and options. Then we used the average method to combine these factors to attain factor weights.

Step 5. Normalize the assessment matrix.

The assessment matrix is normalized by using the beneficial and non-beneficial factors such as:

$$x_{ij} = \frac{q_{ij} - \min(q_{ij})}{\max(q_{ij}) - \min(q_{ij})}; i = 1, \dots, m; j = 1, \dots, n \quad (4)$$

$$x_{ij} = 1 + \left(\frac{\min(q_{ij}) - q_{ij}}{\max(q_{ij}) - \min(q_{ij})}\right); i = 1, \dots, m; j = 1, \dots, n \quad (5)$$

Where q_{ij} refers to the value in the assessment matrix.

Step 6. Compute the marginal utility score

$$y_{ij} = \frac{e^{(x_{ij})^2} - 1}{1.71}; i = 1, \dots, m; j = 1, \dots, n \quad (6)$$

Step 7. Computing the final utility score

$$R_{ij} = \sum_{j=1}^{n} w_j y_{ij}; i = 1, \dots, m \quad (7)$$

Step 8. Rank the alternatives.

The final utility score is ranked descending to obtain the final rank of options.

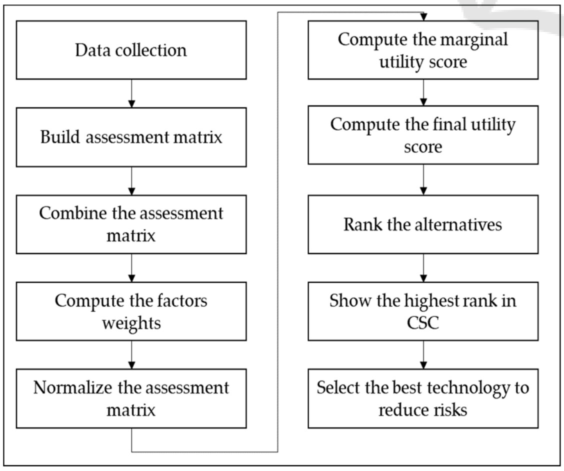

Figure 1: The steps of MCDM methodology.

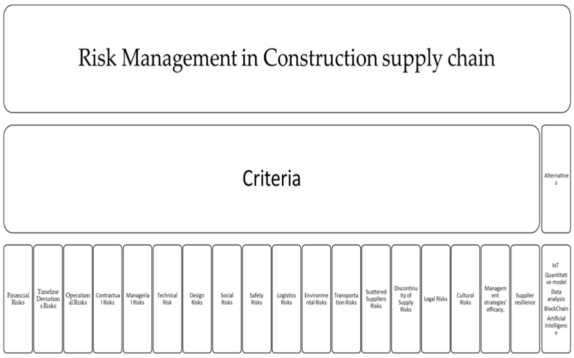

Figure 2: List of factors and technologies.

4 RESULTS AND DISCUSSION

This section shows the results of the MCDM framework for selecting the best technology to reduce risks in CSC through risk management. This study used the MCDM method to rank alternatives. The fuzzy set is used to overcome vague data through evaluation steps.

CSC is the process used to control the flow of sources and materials in the construction area. CSC has various components and steps, such as project management, logistic operations, manufacturing elements, and raw materials procurement. CSC aims to preserve and maintain strong relations between manufacturers and suppliers. The best SCM with cost-effective products delivered on time and project-building effectiveness. However, several risks the CSC faces affect its process, performance, and effectiveness. CSC has various risks and challenges, such as multiple fragmented processes, long production times, balancing inventory levels, legal risks, safety risks, environmental risks, financial risks, and culture risks.

Risks in CSC can lead to a complex SC process and bad quality products and performance. Construction firms must select technology to aid them in the SC process, complete their projects on time, and preserve a competitive edge in the construction industry. AI can overcome and reduce the risks in CSC. AI aids construction firms in reducing safety risks, operational risks, and costs. AI can be used throughout the CSC process, from planning to the final steps. AI has various models and algorithms that can analyze large amounts of data from multiple sources to show predictive results. These models can solve the risk of prediction delays. AI models can aid in the preservation of business continuity. AI models can analyze and train large amounts of data, like historical project data, customer needs, and market trends, to predict accurate demand predictions. Construction firms can use the demand prediction results to predict the upcoming materials and data to overcome the risks.

AI models and algorithms can aid a firm's construction to assess suppliers with some factors like time of delivery, dependability, and quality of goods. AI models can evaluate the performance of each supplier in CSC and select the best one. This can increase the performance and effectiveness of each supplier in CSC. AI models and algorithms can reduce risks in CSC by empowering firms to design risk mitigation methods and strategies. Firms can use AI models for early detection of risks to mitigate the effect of one project's time and cost.

Step 1. Criteria are collected from previous studies based on CSC risks, and five main technologies are used to select the best one to reduce risks in CSC. Figure 2 shows the risks and technologies for CSC. This study invited five experts to assess the factors and technologies. These experts used the linguistic terms of triangular fuzzy sets.

Step 2. The assessment matrix is built between factors and technologies using the TFNs. Then, these numbers are converted to crisp numbers as shown in Table 3.

Step 3. The assessment matrix combines factors and technologies to obtain a single matrix with TFNs.

Step 4. The factor weights are obtained by using the average method. Figure 3 shows the factor's weights.

From the weights results, we show that social risks are the most important, with a weight of 0.066922, followed by discontinuity of supply risks, with a weight of 0.066922, Transportation Risks, with a weight of 0.06266; Financial Risks, with a weight of 0.061807, Scattered Supplier Risks, with a weight of 0.060102, and Logistics Risks, with a weight of 0.058397.

We show the management strategies' efficacy has the lowest importance with a weight of 0.041347, followed by Cultural Risks with a weight of 0.042199, followed by safety risks with a weight of 0.04902, Operational Risks with a weight of 0.050725, and Timeline Deviations Risks with a weight 0.05243.

Step 5. Eq. (4) is used to normalize the decision matrix between factors and technologies as shown in Table 1.

Step 6. Eq. (6) is used to compute the marginal utility score as shown in Table 2.

Step 7. Eq. (7) is used to compute the final utility score as shown in Figure 4.

Step 8. Technologies are ranked based on the highest value in the final utility score. We show that AI has the highest rank followed by IoT, Blockchain, data analytics, and quantitative models.

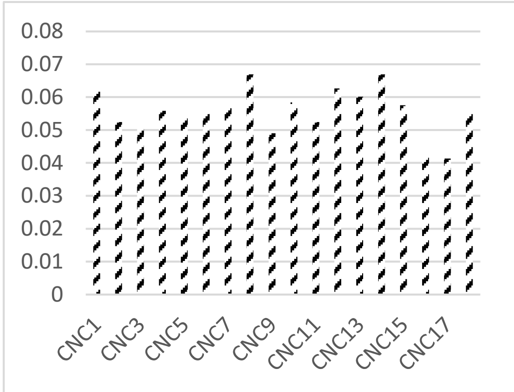

Figure 3: Factors weights.

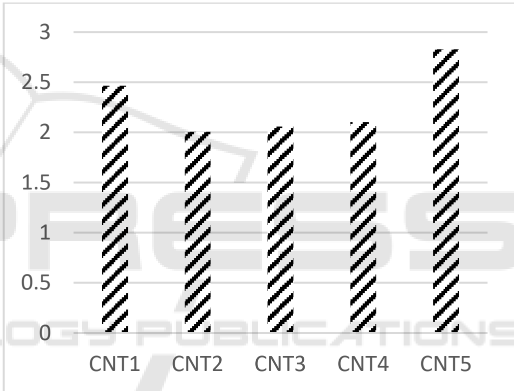

Figure 4: Final utility score values for each technology.

Table 1: The Normalized Decision Matrix.

	CNT_1	CNT_2	CNT_3	CNT_4	CNT_5
CNC_1	0.875	0	1	0.375	0.25
CNC_2	1	0.5	0.083333	0	0.416667
CNC_3	0	0.526316	0.631579	0.315789	1
CNC_4	0.3	0.9	0.6	0	1
CNC_5	0.416667	0.833333	1	0.333333	0
CNC_6	1	0	0.5	0.9	0.3
CNC_7	1	0.5625	0.9375	0.625	0
CNC_8	1	0	0.375	1	0.875
CNC_9	0	1	0.666667	0.75	0.916667
CNC_{10}	0.181818	1	0.181818	0	1
CNC_{11}	0	0	0.545455	0.636364	1
CNC_{12}	0	0.166667	0.833333	0.666667	1
CNC_{13}	1	0.25	0	1	1
CNC_{14}	1	0.625	0	0.125	0.875
CNC_{15}	0.777778	1	0.333333	0	0.666667
CNC_{16}	1	0	0.636364	0.545455	0.272727
CNC_{17}	0	1	0.8	1	0.8
CNC_{18}	0	0.375	0.6875	1	0.875

Table 2: The marginal utility score.

	CNT_1	CNT_2	CNT_3	CNT_4	CNT_5
CNC_1	3.365265	0.584795	4.321085	1.238012	0.964164
CNC_2	4.321085	1.589638	0.690854	0.584795	1.3456
CNC_3	0.584795	1.675545	2.068171	1.099753	4.321085
CNC_4	1.065567	3.537806	1.941589	0.584795	4.321085
CNC_5	1.3456	3.096193	4.321085	1.139026	0.584795
CNC_6	4.321085	0.584795	1.589638	3.537806	1.065567
CNC_7	4.321085	1.801296	3.813345	2.041136	0.584795
CNC_8	4.321085	0.584795	1.238012	4.321085	3.365265
CNC_9	0.584795	4.321085	2.218519	2.620871	3.65772
CNC_{10}	0.841258	4.321085	0.841258	0.584795	4.321085
CNC_{11}	0.584795	0.584795	1.740924	2.088057	4.321085
CNC_{12}	0.584795	0.816148	3.096193	2.218519	4.321085
CNC_{13}	4.321085	0.964164	0.584795	4.321085	4.321085
CNC_{14}	4.321085	2.041136	0.584795	0.750892	3.365265
CNC_{15}	2.770595	4.321085	1.139026	0.584795	2.218519
CNC_{16}	4.321085	0.584795	2.088057	1.740924	1.009001
CNC_{17}	0.584795	4.321085	2.89651	4.321085	2.89651
CNC_{18}	0.584795	1.238012	2.31291	4.321085	3.365265

5 SENSITIVITY ANALYSIS

We conducted a sensitivity analysis to ensure the validity of the proposed model by showing the rank of alternatives under different situations. We proposed nineteen situations of criteria weights, as shown in Figure 5. In the first situation, all criteria were given equal weight. Then, in the second situation, the first criterion was given 0.1 weight, and all criteria had the same weight.

Then, we show the rank of alternatives under different situations, as shown in Figure 6. We show that alternative 5 is the best in all situations. So, the rank of other options is stable under different situations.

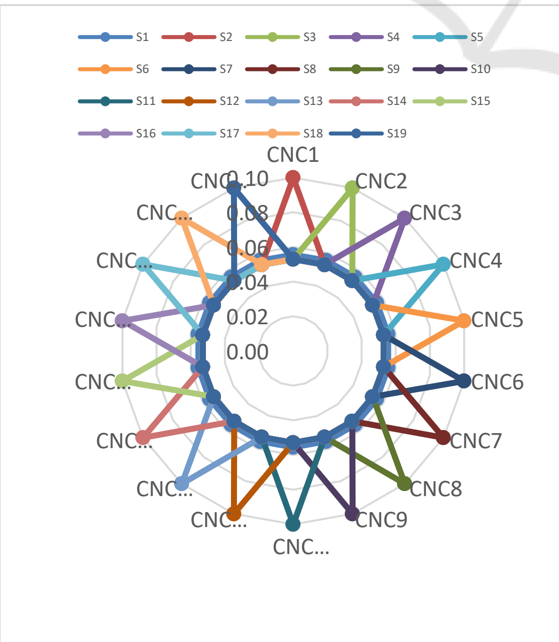

Figure 5. The different situations of criteria weights.

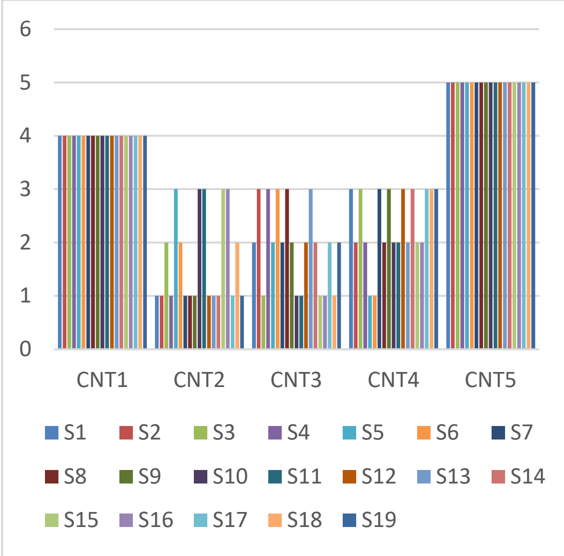

Figure 6: The rank of alternatives under different situations.

6 CONCLUSIONS

This study proposed an MCDM model for reducing risks in CSC using the risk management framework. This study used the MCDM method, and MAUT was used to rank options. The average method using the decision matrix obtains the factors' weights. Five experts with experience in CSC and risk management evaluated the factors and technologies. There are 18 risks, and 5 technologies were used in this study. The assessment matrix is built between factors and 5 technologies. The triangular fuzzy numbers are used to evaluate the factors and options. Then, these numbers are converted to the crisp number. Then, we combined this matrix into one matrix. The criteria weights are obtained. The results show that social risk has the highest weight. The MAUT is applied to rank the options. The results show that AI has the highest rank. AI can aid CSC by reducing the risks by predicting historical data to show the best demand in the future to deliver products on time.

The limitations of this paper are a few criteria and alternatives. So, in future work, we will maximize the number of criteria and alternatives. Another limitation is the number of experts, in future study, the number of experts will increase.

Various MCDM methods, such as AHP, BWM, and DEMATEL, will be used to obtain the factor's weight in future studies. The 5 technologies can be extended to include multiple technologies to reduce risks in CSC.

Table 3: The assessment matrix between factors and technologies.

	CNT_1	CNT_2	CNT_3	CNT_4	CNT_5
CNC_1	(5,7,9)	(3,5,7)	(7,9,11)	(1,3,5)	(5,7,9)
CNC_2	(7,9,11)	(1,1,1)	(1,3,5)	(1,1,1)	(3,5,7)
CNC_3	(1,1,1)	(1,3,5)	(7,9,11)	(1,1,1)	(7,9,11)
CNC_4	(1,3,5)	(5,7,9)	(7,9,11)	(1,3,5)	(5,7,9)
CNC_5	(3,5,7)	(7,9,11)	(5,7,9)	(1,1,1)	(1,3,5)
CNC_6	(5,7,9)	(1,1,1)	(5,7,9)	(7,9,11)	(1,3,5)
CNC_7	(7,9,11)	(1,3,5)	(7,9,11)	(7,9,11)	(1,1,1)
CNC_8	(7,9,11)	(3,5,7)	(7,9,11)	(5,7,9)	(5,7,9)
CNC_9	(1,1,1)	(5,7,9)	(1,1,1)	(1,3,5)	(5,7,9)
CNC_{10}	(1,3,5)	(7,9,11)	(1,3,5)	(1,3,5)	(7,9,11)
CNC_{11}	(1,3,5)	(1,1,1)	(5,7,9)	(1,1,1)	(7,9,11)
CNC_{12}	(3,5,7)	(1,3,5)	(7,9,11)	(7,9,11)	(5,7,9)
CNC_{13}	(5,7,9)	(3,5,7)	(1,1,1)	(5,7,9)	(7,9,11)
CNC_{14}	(7,9,11)	(5,7,9)	(1,3,5)	(3,5,7)	(5,7,9)
CNC_{15}	(5,7,9)	(7,9,11)	(1,1,1)	(1,3,5)	(3,5,7)
CNC_{16}	(5,7,9)	(1,1,1)	(1,3,5)	(1,1,1)	(1,3,5)
CNC_{17}	(1,1,1)	(1,3,5)	(3,5,7)	(5,7,9)	(1,1,1)
CNC_{19}	(1,1,1)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)
Second expert	CNT_1	CNT_2	CNT_3	CNT_4	CNT_5
CNC_1	(5,7,9)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)
CNC_2	(1,3,5)	(5,7,9)	(7,9,11)	(1,1,1)	(3,5,7)
CNC_3	(1,1,1)	(1,3,5)	(5,7,9)	(7,9,11)	(7,9,11)
CNC_4	(1,3,5)	(5,7,9)	(7,9,11)	(1,3,5)	(5,7,9)
CNC_5	(3,5,7)	(1,3,5)	(5,7,9)	(7,9,11)	(1,3,5)
CNC_6	(5,7,9)	(1,1,1)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_7	(1,3,5)	(5,7,9)	(7,9,11)	(7,9,11)	(1,1,1)
CNC_8	(7,9,11)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)
CNC_9	(1,3,5)	(5,7,9)	(7,9,11)	(1,3,5)	(5,7,9)
CNC_{10}	(1,3,5)	(7,9,11)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_{11}	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)	(7,9,11)
CNC_{12}	(3,5,7)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)
CNC_{13}	(1,3,5)	(5,7,9)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_{14}	(7,9,11)	(5,7,9)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_{15}	(1,3,5)	(5,7,9)	(7,9,11)	(1,3,5)	(3,5,7)
CNC_{16}	(5,7,9)	(1,3,5)	(5,7,9)	(7,9,11)	(1,3,5)
CNC_{17}	(1,1,1)	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_{18}	(1,1,1)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)
Third Expert	CNT_1	CNT_2	CNT_3	CNT_4	CNT_5
CNC_1	(5,7,9)	(3,5,7)	(7,9,11)	(1,1,1)	(1,3,5)
CNC_2	(7,9,11)	(7,9,11)	(1,1,1)	(1,3,5)	(3,5,7)
CNC_3	(1,1,1)	(7,9,11)	(7,9,11)	(1,1,1)	(7,9,11)
CNC_4	(7,9,11)	(7,9,11)	(1,1,1)	(1,3,5)	(5,7,9)
CNC_5	(3,5,7)	(7,9,11)	(7,9,11)	(7,9,11)	(1,1,1)
CNC_6	(5,7,9)	(7,9,11)	(7,9,11)	(1,1,1)	(1,3,5)
CNC_7	(7,9,11)	(7,9,11)	(7,9,11)	(1,1,1)	(1,1,1)
CNC_8	(7,9,11)	(7,9,11)	(1,1,1)	(5,7,9)	(5,7,9)
CNC_9	(1,1,1)	(5,7,9)	(7,9,11)	(7,9,11)	(1,1,1)
CNC_{10}	(7,9,11)	(7,9,11)	(1,1,1)	(1,3,5)	(7,9,11)
CNC_{11}	(1,3,5)	(1,1,1)	(7,9,11)	(7,9,11)	(1,1,1)
CNC_{12}	(3,5,7)	(7,9,11)	(7,9,11)	(1,1,1)	(5,7,9)
CNC_{13}	(5,7,9)	(3,5,7)	(7,9,11)	(7,9,11)	(1,1,1)
CNC_{14}	(7,9,11)	(7,9,11)	(7,9,11)	(1,1,1)	(5,7,9)
CNC_{15}	(5,7,9)	(7,9,11)	(7,9,11)	(1,1,1)	(3,5,7)
CNC_{16}	(5,7,9)	(1,1,1)	(1,3,5)	(1,1,1)	(1,3,5)
CNC_{17}	(1,1,1)	(7,9,11)	(7,9,11)	(1,1,1)	(1,1,1)
CNC_{18}	(1,1,1)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)
Fourth expert	CNT_1	CNT_2	CNT_3	CNT_4	CNT_5
CNC_1	(5,7,9)	(3,5,7)	(7,9,11)	(5,7,9)	(1,1,1)
CNC_2	(7,9,11)	(5,7,9)	(1,1,1)	(1,3,5)	(3,5,7)
CNC_3	(1,1,1)	(5,7,9)	(1,1,1)	(1,3,5)	(7,9,11)
CNC_4	(1,3,5)	(5,7,9)	(1,1,1)	(1,3,5)	(5,7,9)
CNC_5	(3,5,7)	(7,9,11)	(5,7,9)	(1,1,1)	(1,3,5)
CNC_6	(5,7,9)	(1,1,1)	(1,3,5)	(7,9,11)	(1,3,5)
CNC_7	(7,9,11)	(1,3,5)	(5,7,9)	(1,1,1)	(1,3,5)
CNC_8	(5,7,9)	(1,1,1)	(1,3,5)	(5,7,9)	(5,7,9)
CNC_9	(1,1,1)	(5,7,9)	(1,1,1)	(1,3,5)	(5,7,9)
CNC_{10}	(1,3,5)	(7,9,11)	(5,7,9)	(1,1,1)	(1,3,5)
CNC_{11}	(1,3,5)	(5,7,9)	(1,1,1)	(1,3,5)	(7,9,11)
CNC_{12}	(3,5,7)	(5,7,9)	(1,1,1)	(1,3,5)	(5,7,9)
CNC_{13}	(5,7,9)	(3,5,7)	(5,7,9)	(1,1,1)	(1,3,5)
CNC_{14}	(7,9,11)	(5,7,9)	(1,1,1)	(1,3,5)	(5,7,9)
CNC_{15}	(5,7,9)	(5,7,9)	(1,1,1)	(1,3,5)	(3,5,7)
CNC_{16}	(5,7,9)	(1,1,1)	(1,3,5)	(1,1,1)	(1,3,5)
CNC_{17}	(1,1,1)	(5,7,9)	(1,1,1)	(1,3,5)	(1,1,1)
CNC_{18}	(1,1,1)	(5,7,9)	(1,1,1)	(1,3,5)	(5,7,9)
Fifth expert	CNT_1	CNT_2	CNT_3	CNT_4	CNT_5
CNC_1	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(5,7,9)
CNC_2	(7,9,11)	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)
CNC_3	(1,1,1)	(1,3,5)	(1,3,5)	(1,3,5)	(5,7,9)
CNC_4	(1,3,5)	(1,3,5)	(5,7,9)	(1,3,5)	(5,7,9)
CNC_5	(1,3,5)	(1,3,5)	(5,7,9)	(1,1,1)	(1,3,5)
CNC_6	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(1,3,5)
CNC_7	(7,9,11)	(1,3,5)	(1,3,5)	(5,7,9)	(1,1,1)
CNC_8	(1,3,5)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)
CNC_9	(1,1,1)	(1,3,5)	(1,3,5)	(5,7,9)	(5,7,9)
CNC_{10}	(1,3,5)	(1,3,5)	(5,7,9)	(1,3,5)	(7,9,11)
CNC_{11}	(1,3,5)	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_{12}	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)
CNC_{13}	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_{14}	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)
CNC_{15}	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_{16}	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)	(1,3,5)
CNC_{17}	(1,1,1)	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)
CNC_{18}	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,11)	(5,7,9)

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