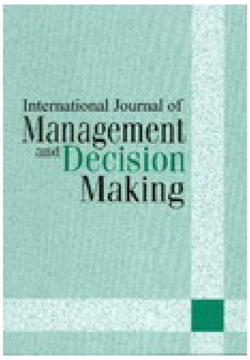


International Journal of Management and Decision Making

ISSN online: 1741-5187 - ISSN print: 1462-4621
https://www.inderscience.com/ijmdm

A decision-support framework for evaluating supplier performance in the trial production stage of new car model development: a hybrid multi-criteria decision-making approach

Detcharat Sumrit, Kamphon Pingsusaen

DOI: 10.1504/IJMDM.2023.10050404

Article History:

Received:	10 June 2022
Accepted:	25 July 2022
Published online:	04 December 2023

A decision-support framework for evaluating supplier performance in the trial production stage of new car model development: a hybrid multi-criteria decision-making approach

Detcharat Sumrit* and Kamphon Pingsusaen

The Cluster of Logistics and Rail Engineering,
Faculty of Engineering,
Mahidol University,
25/25 Phuttamonthon 4 Road, Salaya,
Nakhon Pathom, 73170, Thailand
Email: detchara.sum@mahidol.ac.th
Email: armkamphon@gmail.com
*Corresponding author

Abstract: This study proposes a decision support framework using a hybrid multi-criteria decision making (MCDM) approach for evaluating supplier performance in the trial production stage of new car model development. First, 18 evaluation criteria are identified through rigorous literature review and confirmed by two groups of industrial experts. Second, consistent fuzzy preference relations (CFPRs) and fuzzy-based criteria importance through inter-criteria correlation (fuzzy CRITIC) are integrated to determine the subjective weights and objective weights of evaluation criteria. Next, a fuzzy-based Vlse Kriterijumska Optimizacija I Kompromisno Resenje (fuzzy VIKOR) approach is employed to rank the performance of suppliers. Thereafter, the sensitivity analysis is conducted to verify the stability and robustness of the proposed decision-making framework. Finally, the comparative study with other MCDM approaches. One of the largest Japanese car manufacturing in Thailand is used as a case study to demonstrate the applicability of the proposed framework.

Keywords: multi-criteria decision making; MCDM; CRITIC; consistent fuzzy preference relation; CFPR; VIKOR; supplier performance.

Reference to this paper should be made as follows: Sumrit, D. and Pingsusaen, K. (2024) ‘A decision-support framework for evaluating supplier performance in the trial production stage of new car model development: a hybrid multi-criteria decision-making approach’, *Int. J. Management and Decision Making*, Vol. 23, No. 1, pp.1–32.

Biographical notes: Detcharat Sumrit is currently a Lecturer of the Faculty of Engineering, Mahidol University, Thailand. He graduated an Engineering Bachelor’s degree from the Kasetsart University, Thailand. He holds two Master’s degrees: Master of Engineering from the Chulalongkorn University, Thailand and MBA from Thammasat University. Also, he obtains his PhD from Technopreneurship and Innovation Management, Chulalongkorn University. His current research interests are in multi-criteria decision making (MCDM), supply chain management, performance measurement and optimisation.

Kamphon Pingsusaen graduated from the Silpakorn University with a Bachelor of Engineering Program in Petrochemicals and Polymeric Materials. He is currently a Master's student at The Cluster of Logistics and Rail Engineering, Faculty of Engineering, Mahidol University, Thailand. His research topic is based on supplier performance evaluation in automotive manufacturing in Thailand. He has experience developing automotive parts with local suppliers in Thailand and global suppliers, reviewing and approving proposals for global business contracts, including with established import – export parts criteria to enhance international collaboration.

1 Introduction

It has been broadly recognised that new product development (NPD) is one of the key strategies that play an important role in bringing competitiveness to an organisation. However, growing product complexity, fast technological innovation, shrinking product life cycle and volatility of customer demands in today's market dynamics pressure manufacturers to develop new products faster, more efficient, and launch them into the market in a timely manner (Sumrit, 2020). NPD is a complex process surrounded by an uncertain environment leading manufacturers to strengthen collaboration with external parties such as suppliers (Melander, 2018). In principle, suppliers are responsible for developing parts/processes and providing services to NPD. They can also share resources, investments, information, capabilities, ideas and knowledge with manufacturers (Wowak et al., 2016; Zhao et al., 2018). Thus, the success of the NPD depends mainly on the performance of suppliers involved in the projects because they have specialised product and process capabilities (Im et al., 2019). Previous studies highlighted the importance of incorporating suppliers into NPD projects. The early supplier involvement (ESI) in NPD literature highlights that partnering with suppliers with strong technical capabilities reduces the risks associated with design delay problems (Mackelprang et al., 2018). Underlying transaction cost economics (TCE) theory, integration suppliers in NPD can benefit the manufacturers such as lower development costs, improve product quality, reduce development time and foster innovation (Schoenherr and Swink, 2015). It is an increasing trend that manufacturers attempt to engage suppliers into NPD as early as possible. Numerous academic studies posit that there is a positive correlation between the performance of suppliers and the success of NPD projects (Yan and Kull, 2015; Rajeev et al., 2017; Im et al., 2019). The evaluation of supplier performance in NPD is one of the most important supply chain decisions. Thus, evaluating supplier performance in NPD is a challenging task for many manufactures. This is not accepted for automobile manufacturing sector. The success of a new car model development is greatly relied on the performance of the first-tier suppliers.

The aim of performance evaluation should not solely emphasise on supplier selection but also the development of suppliers in new car model development processes. According to the extensive literature review, almost of the existing studies in evaluating supplier performance in NPD focus on either fuzzy front-end process or mass production stage rather than trial production stage. Even an evaluation of supply performance in trial production stage is crucial importance, especially in new car model development. Because, the improper supplier performance in trial production stage can lead to additional development costs and times, inferior product quality and delays in introduction of new car model to the market. This study aims to contribute to the body of knowledge on ESI in NPD literature by proposing an evaluation framework of supplier performance in trial production stage of new car model development.

Basically, the nature of supplier performance evaluation is complex due to the consideration of various criteria in decision making process. In addition, this problem also involves the degree of uncertainty and imprecise information input from decision makers. Multi-criteria decision making (MCDM) approaches under fuzzy environments are widely used to deal with such problem. This study reports some of the example papers from literature using fuzzy MCDM application to evaluate supplier performance in various industries as: clean energy sector (Liang et al., 2022), automotive sector (Ghadimi et al., 2019), electronics sector (Chatterjee et al., 2018), logistics sector (Wang et al., 2019) and construction sector (Zarbakhshnia et al., 2020).

In this study, evaluating supplier performance in trial production stage of new car model development is treated as a MCDM under fuzzy environment problem. A hybrid MCDM composed of consistent fuzzy preference relations (CFPRs) and fuzzy-based criteria importance through inter-criteria correlation (fuzzy CRITIC) are integrated to determine the subjective weights and the objective weights of evaluation criteria respectively. Next, a fuzzy-based Vlse Kriterijumska Optimizacija I Kompromisno Resenje (fuzzy VIKOR) approach is employed to rank the performance of suppliers. One of the largest Japanese car manufacturing in Thailand is used as a case study to demonstrate the applicability of the proposed framework.

This paper addresses the following objectives:

- To identify the criteria of for evaluating supplier performance in trial production stage of new car model development.
- To develop/propose a hybrid multi-criteria decision support framework for evaluating supplier performance in trial production stage of new car model development.
- To implement the proposed framework by evaluating the performance of five-wheel disc suppliers in a new car model development for one of the largest Japanese car manufacturing in Thailand.

1.1 Research contributions

This study provides several important contributions to the extant literature and managerial practices as follows:

- This work bridges the gap in the lack of research on evaluating supplier performance in trial production stage. To do this, a hybrid MCDM framework is proposed by integrating CFPR, fuzzy-based CRITIC and fuzzy-based VIKOR approaches. Such a combination approach is the first time to be introduced in the literature.
- In this study, the performance criteria for supplier evaluation in trial production stage for new car model development are firstly explored and reviewed through the lenses of experts from car manufacturer.

- The important weights of performance criteria are obtained using a combination between subjective and objective weights. As a result, the criteria weights are more accurate.
- Using different MCDM methods for solving the same problem can sometimes produce to a different result. To verify the conformity of the proposed framework, this study conducts a comparative study with other fuzzy MCDM approaches including weighted aggregated sum product assessment (WASPAS), preference ranking organisation method for enrichment evaluation (PROMETHEE), elimination and choice expressing reality (ELECTRE) and technique for order of preference by similarity to ideal solution (TOPSIS).
- Apart from those aforementioned academic contributions, this study also makes a practical contribution. This finding in this study provides depth insight to scholars and practitioners involved in evaluating supplier performance in trial production stage for new car model development. As well as, they can use the proposed framework as a guideline for systematically evaluating supplier performance in trial production stage.

The remaining of this paper is organised as follows. Section 2 provides a brief of relevant literature review. The methods used in this study are presented in Section 3. The proposed decision-support framework is shown in Section 4. In Section 5, the application of the proposed decision-support framework is performed. The discussion and managerial implications are portrayed in Section 6. The conclusions and future research directions are outlined in Section 7.

2 Literature review

This section is divided into two subsections. Section 2.1 presents relevant literature on supplier performance in NPD and MCDM related supplier performance evaluation exhibits in Section 2.2.

2.1 Supplier performance in NPD

It is essential to monitor suppliers' performance to ensure overall supply chain performance. As a result, buyer firms must continuously monitor supplier performance and collaborate with them on improvement strategies. The participation of a supplier in an NPD project is used to evaluate supplier performance in trial production stage. The ultimate goal of project performance development is to increase effectiveness and efficiency. NPD efficiency refers to completing a project on time and within budget since each project has different success variables necessitating various approaches (Um and Kim, 2019). Dweiri et al. (2016) supported that price, quality, delivery, and service are frequently used as performance indicators in supplier selection. Organisational practices, risk management, environmental and social practices are among the leading criteria for identifying those factors in which stakeholders are involved. As a result, we need techniques, criteria, and sub-criteria that are customised to each scenario. To keep a balance between literature and practice in an automotive NPD project, sub-criteria such as knowledge integration, engineering changes, information sharing, and others were added to performance indicators focusing on flexibility, special requirements, and close collaboration with concurrent engineering systems.

One of the most important activities during the trial production stage is the frequent sharing of information, such as technical information, new product information and market information. The product development process is a highly integrated, complicated process in which numerous activities must be completed in concurrently and in constant collaboration across many departments (such as marketing, pre-development and production) (Fürst and Vietor, 2019). Even though, information sharing with a supplier can enhance supplier performance and encourage more collaborative cooperation (Maestrini et al., 2018). On the other hand, sharing knowledge is a double-edged sword. It is advantageous to the relationship between exchange partners. Another indicator is supplier flexibility, which is defined as the supplier's ability to adjust the aggregated output level based on customer requirements, as well as the supplier's ability to change the planned or assumed delivery schedule to cope with all changes (Yang et al., 2019).

In the automotive supply chain, where materials and information flow from various chains all over the world, this process change becomes more complicated. The most important tool for efficiently managing change in NPD is 'engineering change management' (ECM), which is looking for improvements in quality improvement, cost savings, and standing in market strongly against competitors reaching on time in market (Shivankar and Deivanathan, 2021). The capabilities of the automotive supply chain are highly dependent on the efficiency of both car manufacturers and suppliers. Thus, they must monitor and assess not just the long-term profitability of their operations, but also the sustainability of their suppliers and other stakeholders (Giannakis et al., 2020).

2.2 MCDM related supplier performance evaluation

Decision making is an inevitable part of life. In real-world, data is frequently inadequate, unavailable, or inaccurate, and thus not deterministic. Complicated decision making problems often involve a large number of criteria with different degrees of importance. For this reason, it is difficult for humans can make the appropriate decisions (Shekhovtsov and Sałabun, 2020). MCDM are effective tools to help decision makers obtain the optimum solution in their decision processes (Biscaia et al., 2021). The most widely used MCDM approaches in evaluating and selecting suppliers usually integrate fuzzy-based approaches into MCDM because human judgements are typically imprecise when selecting an alternative from multiple criteria (Memari et al., 2019). In formulating the problem, decision makers might be difficult to give accurate numerical numbers. The linguistic variables such as very low, low, medium, high, very high, or something similar are also easier to cope with when attempting to make a decision (Ploskas and Papathanasiou, 2019). As a result, fuzzy sets are suitable for this purpose. A triangular fuzzy number (TFN) is widely used to represent a fuzzy number in most research (Hosseini et al., 2021). The implementation of various fuzzy MCDM applications in the context of automotive supplier evaluation has recently been documented in the literature; such as Memari et al. (2019) used an intuitionistic fuzzy TOPSIS method to select the right automotive spare parts supplier. Dweiri et al. (2016) applied hierarchy process (AHP) to select automotive suppliers in Pakistan. Dwivedi et al. (2017) modified fuzzy interpretive structural modelling (fuzzy-ISM) method to rank the barriers of the usage of additive manufacturing (AM) in the Indian automotive industry. Giannakis et al. (2020)

used the analytic network process (ANP) method to develop framework for sustainability performance supplier evaluation and selection thorough study of 144 supply chain specialists in the UK and France. Most previous studies have concentrated on performance in the mass production stage for monitoring and evaluating supplier performance in order to maintain production stability. Afrasiabi et al. (2022) assessed supplier performance in the context of sustainable resilience under fuzzy environments. Nonetheless, very few research has been conducted on the trial production stage. For example, Wang and Yang (2021) investigated the role of supplier involvement in trial stage of sustainable NPD. In this study, MCDM under fuzzy environment is used to evaluate supplier performance in trial production stage of new car model development.

3 Methods

In this section, the methods used in this study, including CFPR, fuzzy-based CRITIC and fuzzy-based VIKOR, are presented as follows.

3.1 CFPR

Herrera-Viedma et al. (2004) proposed an efficient method with consistency results called CFPR. This method not only allows decision-makers to present their alternatives with minimal judgement, but it also eliminates the need to check for consistency throughout the decision making process (Park et al., 2019) and makes weighing severity simple (Alias et al., 2019). Furthermore, the CFPR questionnaire is relatively simple and short for respondents to answer, increasing the chances of receiving responses (Lu et al., 2019). Compared with extent analysis (EA) and fuzzy preference programming (FPP), these methods are a huge number of pairwise, $n * [(n - 1) / 2]$ nevertheless, CFPR is only use $n - 1$ to confirm consistency where n is the number of criteria (Wahyuningrum et al., 2019). CFPR steps are described as follows:

Step 1 Form a pairwise comparison matrix of each expert using Table 1. A pairwise comparison matrix is represented as equation (1):

$$A^k = \begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \\ \vdots \\ C_n \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \dots & C_n \end{array} \\ \begin{bmatrix} 1 & a_{12}^k & \times & \times & \times \\ \times & 1 & a_{23}^k & \times & \times \\ \times & \times & 1 & a_{34}^k & \times \\ \vdots & \vdots & \vdots & \ddots & a_{n-1n}^k \\ \times & \times & \times & \times & 1 \end{bmatrix} \end{array} \tag{1}$$

where a_{ij}^k stands for a pairwise preference score between evaluation criterion i and j judged by expert k^{th}, $a_{ij} \in \left[\frac{1}{9}, 9\right]$ and $a_{ij} \cdot a_{ji} = 1, \forall i, j \in \{1, 2, \dots, n\}$.

Step 2 Aggregate all pairwise comparison matrices into a single matrix $\tilde{A} = (\tilde{a}_{ij})$ using equation (2):

$$\tilde{a}_{ij} = \frac{1}{k}\left(a_{ij}^1 + a_{ij}^2 + \cdots + a_{ij}^k\right) \tag{2}$$

where $\tilde{a}_{ij}$ is an element in aggregated pairwise comparison matrix.

Step 3 Use the multiplication preference relation properties to convert all element values in aggregated pairwise matrix from $\tilde{a} \in \left[\frac{1}{9}, 9\right]$ to $P = (p_{ij})$ with $p_{ij} \in [0, 1]$ and then construct a preference matrix as follows:

$$p_{ij} = g\left(a_{ij}\right) = \frac{1}{2}\left(1 + \log_9 a_{ij}\right) \tag{3}$$

$$p_{ij} + p_{ji} = 1 \quad \forall i, j \in \{1, 2, \ldots, n\} \tag{4}$$

$$p_{ij} + p_{jk} + p_{ki} = \frac{3}{2} \quad \forall i, j, k = 1, 2, \ldots, n \tag{5}$$

$$p_{ij} + p_{jk} + p_{ki} = \frac{3}{2} \quad \forall i < j < k = 1, 2, \ldots, n \tag{6}$$

$$p_{i(i+1)} + p_{(i+1)(i+2)} + \cdots + p_{(j-1)j} + p_{ji} = \frac{j-i+1}{2} \quad \forall i < j \tag{7}$$

Step 4 Construct a preference matrix based on results from Step 3 as follows:

$$P = \begin{array}{c} \\ F_1 \\ F_2 \\ F_3 \\ \vdots \\ F_n \end{array} \begin{array}{c} \begin{array}{ccccc} F_1 & F_2 & F_3 & \cdots & F_n \end{array} \\ \begin{bmatrix} 0.5 & p_{12}^k & \times & \times & \times \\ 1-p_{12}^k & 0.5 & p_{23}^k & \times & \times \\ \times & 1-p_{23}^k & 0.5 & p_{34}^k & \times \\ \vdots & \vdots & \vdots & \ddots & p_{n-1n}^k \\ \times & \times & \times & \times & 0.5 \end{bmatrix} \end{array} \tag{8}$$

If some element values in preference matrix are in the interval $[a, 1 + a]$, a transformation function is used to convert them in the interval $[0, 1]$. The transformation function is determined by equation (9).

$$f\left(p_{ij}^k\right) = \frac{p_{ij}^k + a}{1 + 2a} \tag{9}$$

Step 5 Normalised all elements in the preference matrix by equation (10):

$$g_{ij} = \frac{p_{ij}}{\sum_{i=1}^{n} p_{ij}} \tag{10}$$

Step 6 Compute the subjective weight (w_j^s) by equation (11):

$$w_j^s = \frac{\sum_{j=1}^{n} g_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} g_{ij}} \tag{11}$$

Table 1 Scale of relative importance weight

Relative importance	*Meaning*
1	Equally importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values between two adjacent judgements

Source: Alias et al. (2019)

3.2 Fuzzy-based CRITIC

'Criteria importance through inter-criteria correlation' known as CRITIC is a MCDM method that uses to determine the objective weights of criteria. The basic principle of CRITIC is that the criteria can be considered as a source of information. In decision matrix, the amount of information contained in each criterion can be represented the degree of importance weight. CRITIC divides the sources of information in each criterion into contrast intensity and conflict between criteria. The contrast intensity is defined by standard deviation while the conflict between criteria is represented by correlation coefficient. Recently, CRITIC was applied to solve real-world problems such as supply risk management of subsea pipelines (Li et al., 2022); evaluate wearable health technology application (Haktanir and Kahraman, 2022). The objective weight calculation by fuzzy CRITIC can be obtained as follows:

Step 1 Formulate fuzzy performance rating matrix $(\tilde{z})$ for each expert k^{th} by using linguistic expressions in Table 2:

$$\tilde{z} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m1} & \dots & \tilde{x}_{mn} \end{bmatrix} \end{array} \tag{12}$$

where $\tilde{x}_{ij}^k$ is performance rating score of alternatives A_i with respect to criterion C_j, evaluated by k^{th} expert, $\tilde{x}_{ij}^k = (\alpha_{1ij}^k, \alpha_{mij}^k, \alpha_{uij}^k)$, $i = 1, 2, 3, \dots, m$ and $j = 1, 2, 3, \dots, n$.

Step 2 Aggregate all fuzzy performance decision matrices into a group decision matrix as follows:

$$\tilde{x}_{ij} = \frac{1}{K}\left(\tilde{x}_{ij}^{1} \oplus \cdots \oplus \tilde{x}_{ij}^{k} \oplus \cdots \oplus \tilde{x}_{ij}^{K}\right) \tag{13}$$

Step 3 Obtain the normalised decision matrix $D = [d_{ij}]_{m\times n}$.

$$D = \begin{cases} \dfrac{\tilde{x}_{ij} - x_j^-}{x_j^* - x_j^-} & \text{if } j \in B \\ \dfrac{x_{jk}^- - \tilde{x}_{ij}}{x_j^- - x_j^*} & \text{if } j \in C \end{cases} \tag{14}$$

where B represents a set of beneficial criteria while C represents a set of cost criteria, d_{ij} represents the normalised values of fuzzy performance rating matrix for i^{th} alternative with respect to j^{th} criterion. If $j \in B$, then $x_j^* = \max[\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_m]$ and $x_j^- = \min[\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_m]$, and if $j \in C$, then $x_j^* = \min[\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_m]$ and $x_j^- = \max[\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_m]$.

Step 4 Measure the contrast intensity represented by standard deviation (σ_j) for each criterion j, as follows:

$$\sigma_j = \sqrt{\sum_{i=1}^{m} \frac{\left(x_{ij} - \overline{x}_j\right)^2}{m-1}} \tag{15}$$

where σ_j stands for the standard deviation of the j^{th} criterion.

Step 5 Measure the conflict between criteria represented by correlation coefficient matrix $R = (r_{jj'})_{n\times n}$ as follows:

$$r_{jj'} = \frac{\sum_{x=1}^{m}\left(x_j - \overline{x}_j\right)\left(x_{j'} - \overline{x}_{j'}\right)}{\sqrt{\sum_{x=1}^{m}\left(x_j - \overline{x}_j\right)^2}\sqrt{\sum_{x=1}^{m}\left(x_{j'} - \overline{x}_{j'}\right)^2}} \tag{16}$$

Step 6 Calculate the information measures of each criterion as follows:

$$H_j = \sigma_j \sum_{j'=1}^{n}\left(1 - r_{jj'}\right) \tag{17}$$

Step 7 Obtain the fuzzy objective weight of each j^{th} criterion as follows:

$$\omega_j = \frac{H_j}{\sum_{j=1}^{n} H_j} \tag{18}$$

where w_j is the objective weight of the j^{th} criterion, $\omega_j = (\omega_j^l, \omega_j^m, \omega_j^u)$.

Step 8 De-fuzzy the objective weight of each j^{th} criterion to crisp number as follows:

$$w_j^o = \frac{\omega_j^l + 4\left(\omega_j^m\right) + \omega_j^u}{6}. \tag{19}$$

Table 2 Linguistic expressions for alternatives performance ratings

Linguistic expressions	*Symbol*	*Fuzzy scores*
Very poor	VP	0.00, 0.00, 1.00
Poor	P	0.00, 1.00, 3.00
Medium poor	MP	1.00, 3.00, 5.00
Fair	F	3.00, 5.00, 7.00
Medium good	MG	5.00, 7.00, 9.00
Good	G	7.00, 9.00, 10.00
Very good	VG	9.00, 10.00, 10.00

Source: Demirel et al. (2020)

3.3 Combination weight

The combination weight is computed by aggregated subjective weight (obtained by CFPR) and objective weight (obtained by fuzzy CRITIC) as follows:

$$w_j^{com} = \frac{w_j^s \times w_j^o}{\sum_{j=1}^{n} w_j^s \times w_j^o} \tag{20}$$

where ω_j is a combination weight, $\varphi \in [0, 1]$.

3.4 Fuzzy-based VIKOR

The Vlse Kriterijumska Optimizacijia I Kompromisno Resenje (VIKOR) was developed by Opricovic in 1998. This method focuses on ranking and selecting a range of alternatives based on conflicting and non-commensurable decision criteria (Hosseini et al., 2021; Demirel et al., 2020). It relies on an aggregating function by being the closest to the ideal solution of the decision-maker in reaching a final decision (Hezer et al., 2021). Fuzzy VIKOR is the best method that is widely used in the multi-criteria environment of complex systems (Parvez, 2020). In the presence of conflicting criteria, the user can directly input judgement data and define the list of alternatives used for ranking and selecting alternatives (Suganthi, 2018). There are several MCDM methods, including VIKOR, TOPSIS, PROMETHEE, COMET, COPRAS, and others. It can be used to rank and select the best alternatives. TOPSIS and VIKOR are two of the most commonly used methods for ranking decision variants and obtaining a reliable result (Shekhovtsov and Sałabun, 2020). TOPSIS is considered in determining an ideal and an anti-ideal solution by comparing the distances of each alternative to those. WASPAS evaluates the maximisation and minimisation criteria simultaneously. It is also appropriate for both qualitative and quantitative criteria (Al-Barakati et al., 2022). While, ELECTRE takes full advantage of data and transforms it into a decision matrix, as well as outstanding use in comparing alternatives ranking (Chen et al., 2022). Conversely, VIKOR was developed to provide compromise solutions to discrete multiple criteria issues with non-commensurable and conflicting criteria (Ploskas and Papathanasiou, 2019). Furthermore, Sennaroglu and Celebi (2018) compare PROMETHEE to VIKOR. In ranking and selecting the best alternative, PROMETHEE is used as an outranking method while VIKOR is used as a compromise ranking method. The VIKOR method is frequently used to various international literatures (Papathanasiou, 2021). It is commonly applied in supplier selection, material selection, risk assessment, customer satisfaction, supply chain management, healthcare management, and tourism management (Ploskas and Papathanasiou, 2019; Demirel et al., 2020). Such as Sennaroglu and Celebi (2018) used VIKOR to assess alternative locations for military airports in Turkey. Parvez (2020) assessed the performance of original equipment manufacturers using the fuzzy VIKOR technique, and Ayyildiz and Taskin (2022) applied VIKOR to select serving petrol stations during COVID-19 lockdown.

The fuzzy VIKOR proposed in this research is based on Taylan et al. (2020) and utilises fuzzy linguistic expressions to evaluate alternatives ratings are shown in Table 2.

Step 1 Assumed that $\tilde{A} = A^l, A^m, A^u$ is a fuzzy number, where $\tilde{A}^{def}$ is the defuzzification value of $\tilde{A}$ (Hosseini et al., 2021)

$$\tilde{A}^{def} = \frac{A^l + 4\left(A^m\right) + A^u}{6} \tag{21}$$

Step 2 Determine the best (positive ideal) f_i^* and the worst f_i^- (negative ideal) values of all criteria functions, $i = 1, 2, \ldots, n$ as follows:

$$f_i^* = \max_i \left\{f_{ij}\right\}, f_i^- = \min_i \left\{f_{ij}\right\} \tag{22}$$

Step 3 Compute the highest utility value of the majority S_i and the distinct regret of the opponent R_i for the benefit criteria as follows:

$$S_i = \sum\nolimits_{i=1}^{n} w_i \left[\frac{f_i^* - \left(f_{ij}\right)}{f_i^* - f_i^-}\right] \tag{23}$$

$$R_i = \max_i \left\{w_i \left[\frac{f_i^* - \left(f_{ij}\right)}{f_i^* - f_i^-}\right]\right\} \tag{24}$$

where w_i represents the weight of criteria.

Step 4 Calculate the value of merit function Q_i as follows:

$$Q_i = v\left[\frac{S_i - S^*}{S^- - S^*}\right] + (1 - v)\left[\frac{R_i - R^*}{R^- - R^*}\right] \tag{25}$$

where v represents the strategy of maximum group benefit weight, $1 - v$ is the weight of particular regretand.

Whereas $S^- = \max_i \{S_i\}, S^* = \min_i \{S_i\}, R^- = \max_i \{R_i\}, R^* = \min_i \{R_i\}$.

Step 5 Rank the alternatives in ascending order by the values S, R and Q.

Step 6 Propose the alternative (a') that is best ranked by the measure Q (minimum) as a compromise solution, if the following two conditions are met.

Condition 1 'Acceptable advantage'

If alternatives a' and a'' are ranked first and second, respectively. Where m is the number of alternatives. Relation (26) must be true:

$$Q(a'') - Q(a') \geq \frac{1}{m-1} \tag{26}$$

Condition 2 'Acceptable stability in decision making'

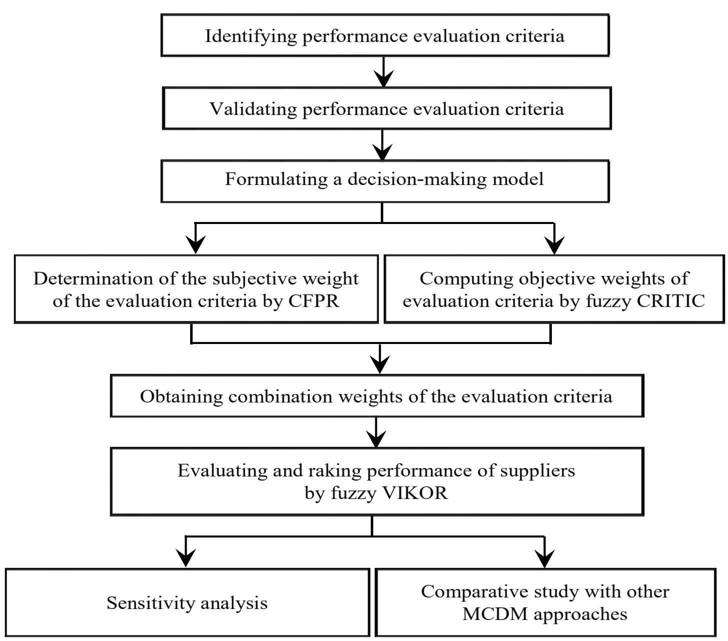
Alternative a' is the best alternative, and it must also be ranked based on the S and/or R values. During the decision making process, this compromise solution remains steady. The weight of the decision making method is represented by v. If one of these conditions is not satisfied, a set of compromise solutions is suggested. Then, a set of compromise solutions are included the following:

- Alternatives a' and a'' only if the Condition 2 is not met.
- Alternatives a', a'', …, a^m if the Condition 1 is not met; a^m is determined for maximum m with $Q(a^m) - Q(a') < \frac{1}{m-1}$ (closeness to the positions of these alternatives).

4 Proposed decision-support framework

The proposed decision-support framework is illustrated in Figure 1.

Figure 1 Proposed decision-support framework



5 Application of the proposed decision-support framework

This section provides a demonstration of the proposed decision-support framework using XYZ company as a case study.

5.1 Problem description

Case company is one of the largest Japanese car manufacturers in Thailand. The name of the case company cannot be disclosed to maintain confidentiality. Hence, for the rest of this paper the case company is named as XYZ company. Currently, the company has two car assembly factories that produce only passenger cars for domestic sales and export to many countries around the world. The company plans to produce approximately 130,000 passenger cars in 2021. According to new product planning, XYZ company has regularly developed a range of new car models every two and a half years. A new car model development process of the XYZ company can be divided into three stages including design stage, trial production stage and mass production stage as shown in Table 3. Although, suppliers are actively interfaced in all stages of the development of new car model but many problems owned by suppliers cannot be resolved before the mass production stage begins. Such problems lead to high difficulties in troubleshooting and clarifying the responsibility of the problems, higher resolution costs in mass production, and delays in bringing new car models into the market. Currently, XYZ company has a supplier performance evaluation process only in mass production stage. New car model development project team need to implement a supplier performance evaluation process in trial production stage in order to proactively address supplier issues in advance. Thus, the decision-support framework proposed from this study can help XYZ company' to systematically evaluate supplier performance in trial production stage of new car model development. In this regard, a new hybrid MCDM under fuzzy environment is introduced by combining CFPR, CRITIC and VIKOR approaches to address this issue. The five first-tier wheel disc suppliers referred as A_1, A_2, A_3, A_4 and A_5 are selected to validate the proposed decision-support framework.

Table 3 A new car model development process of the XYZ company

Design stage	*Trial production stage*			*Mass production stage*
	Event X	*Event Y*	*Event Z*	
Investment and product design	Tooling design and durability test	Process capability	Standardisation and pre-mass production	High volume production

5.2 Identifying performance evaluation criteria

Based on the analysis of the literature, 18 criteria of supplier performance evaluation in trial production stage of new car model development are identified as shown in Table 4.

Table 4 The evaluation criteria of supplier performance

Criteria	*Description*	*Authors*
Part quality (C1)	Parts developed by suppliers meet customer's accepted quality standards.	Dweiri et al. (2016), Giannakis et al. (2020), Khan et al. (2018), Zhao and Cao (2015)
Quality commitment (C2)	Suppliers are committed to continually improving their manufacturing processes to meet customer acceptable levels of quality.	Benton et al. (2020), Corsten et al. (2011), Ruiz and Ravindran (2018), Schoenherr and Wagner (2016)
Knowledge integration (C3)	Suppliers are willing to integrate essential knowledge of developed parts such as technological innovation and engineering design.	Kumara and Rahmanb (2015), Schoenherr and Wagner (2016), Sumrit (2020)
Technical support (C4)	Suppliers can provide full support to solve technical problems. quality problem and change requirements.	Benton et al. (2020), Schoenherr and Wagner (2016), Zhao and Cao (2015)
FMEA activities (C5)	Suppliers can perform 'failure modes and effects analysis' (FMEA) effectively.	Sumrit (2020), Zhao and Cao (2015)
Delivery reliability (C6)	Suppliers can carry out reliable delivery of parts according to customer requirements.	Corsten et al. (2011), Kannan (2018), Görener et al. (2017), Zhao and Cao (2015), Khan et al. (2018)
Engineering changes management (C7)	Suppliers provide an effective 'engineering change management' (ECM) for developed parts.	Sumrit (2020)
Part certification (C8)	Suppliers can manage 'part certification' in accordance with laws/regulations and effectively complying with customer's lead time.	Poltronieri et al. (2019), Zhao and Cao (2015)
Documentations (C9)	Suppliers can provide required documents such as 'production part approval process' (PPAP) accurately and completely.	Corsten et al. (2011), Görener et al. (2017)
Warehouse management (C10)	Suppliers have a good warehousing management system to guarantee reliable stock and to prevent incorrectly procured parts.	Görener et al. (2017), Liou et al. (2019)
Reliable pricing (C11)	The prices quoted for parts and services by suppliers are reliable.	Corsten et al. (2011), Görener et al. (2017)
Flexible pricing (C12)	The prices quoted for parts and services provided by the supplier are flexible.	Görener et al. (2017), Dweiri et al. (2016)
Cost assistance (C13)	Suppliers can assist in optimising project costs.	Corsten et al. (2011), Zhao and Cao (2015)
Business compatibility (C14)	The supplier's business model is compatible with the customer.	Ruiz and Ravindran (2018), Dweiri et al. (2016), Um and Kim (2019), Schoenherr and Wagner (2016), Maestrini et al. (2018)
Flexible management (C15)	Suppliers have flexibility in project management such as production flexibility, sourcing flexibility and communication flexibility.	Um and Kim (2019), Delic and Eyers (2020), Khan et al. (2018), Maestrini et al. (2018), Yang et al. (2019)
Information sharing (C16)	Suppliers are willing to share essential information about development projects.	Benton et al. (2020), Corsten et al. (2011), Görener et al. (2017), Kumara and Rahmanb (2015), Schoenherr and Wagner (2016), Yang et al. (2019)
Health and safety (C17)	The supplier's health and safety regulations/policy are in accordance with their customers.	Giannakis et al. (2020), Khan et al. (2018), Memari et al. (2019)
Green policy (C18)	The supplier's green policies such as environmental protection, emissions and waste management are compiled with their customers.	Poltronieri et al. (2019), Memari et al. (2019)

5.3 Validating performance evaluation criteria

In order to validate the performance evaluation criteria, thirteen qualified experts from automotive industry having knowledge and experiences are formed. All of experts have at least 15 years in the field of new car model development. Experts are divided into two groups. The first group (referred as 'Group I') consists of six middle management staffs responsible for new component parts development such as interior and exterior parts, body parts, chassis parts and electronic parts. The second group (referred as 'Group II') consists of seven senior executives comprising three Thai directors and four Japanese directors. Details and qualifications of experts are presented in Table 5. An in-depth interview is conducted with experts from 'Group I' regarding the suitability of evaluation criteria as mentioned in Table 4. After gathering the results from 'Group I', the experts from 'Group II' are asked to validate of evaluation criteria. Finally, all criteria in Table 4 are affirmed for further use in the next phase of this study.

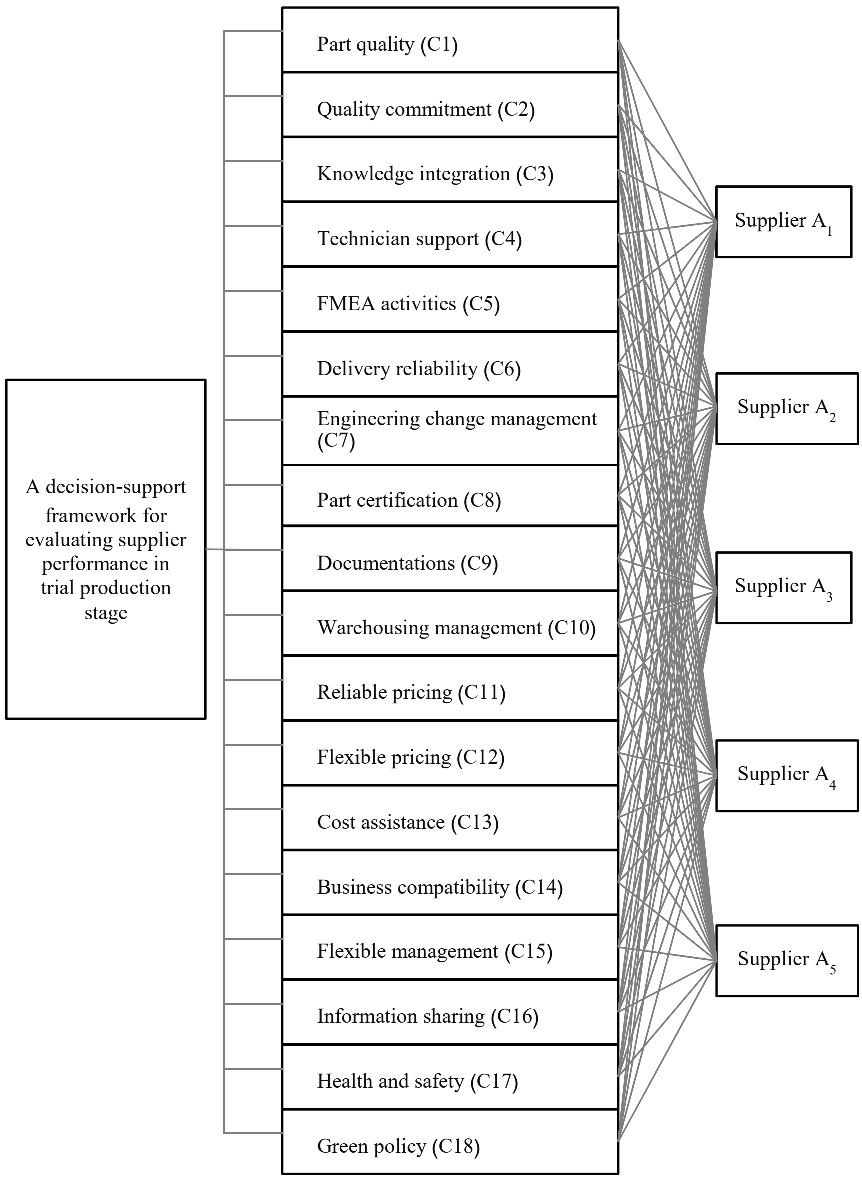
Table 5 Details and qualifications of experts

Group	*Expert*	*Position*	*Experiences (years)*	*Area of expertise*
Group I (middle management)	E1.1	Section manager	22	Interior and exterior part development
	E1.2	Section manager	25	Body part development
	E1.3	Section manager	24	Chassis part development
	E1.4	Section manager	21	Electronic part development
	E1.5	Section manager	27	Strategy of new part development
	E1.6	Section manager	18	Strategy of purchasing planning
Group II (top management/senior executives)	E2.1	Department manager	21	Operation of new car guarantee
	E2.2	Division manager	25	Strategy of car guarantee
	E2.3	Deputy-chief engineering of quality	24	Quality of car guarantee
	E2.4	Quality coordinator (Japanese)	22	Quality executive of car guarantee
	E2.5	Delivery coordinator (Japanese)	24	Delivery executive of car guarantee
	E2.6	New model executive (Japanese)	25	Strategy of car guarantee
	E2.7	General manager (Japanese)	27	Strategy of car guarantee

5.4 Formulating a decision making model

Based on the result in Section 5.2, a decision making model for supplier performance evaluation in trial production stage of new car model development is formulated as depicted in Figure 2.

Figure 2 A decision making model for supplier performance evaluation in trial production stage of new car model development



5.5 Determination of the subjective weight of the evaluation criteria

In this section, the subjective weights of the evaluation criteria are determined by CFPR approach as described in Section 3.1. First, each expert from Group II is assigned to assess the importance of evaluation criteria using linguistic terms in Table 1. The linguistic terms are then converted into corresponding numbers. The pairwise comparison matrix of each expert is formulated for a set of $n - 1$ pairs of neighbouring criteria $\{C_{12}, C_{23}, \ldots, C_{17,18}\}$. The pairwise comparison matrices from all experts are formed by equation (1). Then, equation (2) is utilised to aggregate all pairwise comparison matrices into a single matrix. Using equation (3), all elements in aggregated pairwise comparison matrix are converted to [0, 1] as illustrated by the following example:

$$p_{12} = 0.5 \times (1 + \log_9 2.925) = 0.744,$$
$$p_{23} = 0.5 \times (1 + \log_9 1.91) = 0.647,$$
$$p_{34} = 0.5 \times (1 + \log_9 0.763) = 0.439,$$
$$p_{45} = 0.5 \times (1 + \log_9 0.870) = 0.468, \ldots,$$
$$p_{16,17} = 0.5 \times (1 + \log_9 1.419) = 0.580,$$
$$p_{17,18} = 0.5 \times (1 + \log_9 2.529) = 0.711.$$

Next, the remain elements in aggregated pairwise matrix can be computed using equations (4)–(8). The completed aggregated pairwise matrices for criteria are shown in Table 6. Some numerical examples for criteria are illustrated as follows:

$$p_{21} = 1 - p_{12} = 1 - 0.744 = 0.256,$$

$$p_{32} = 1 - p_{23} = 1 - 0.647 = 0.353,$$

$$p_{75} = \frac{(j - i + 1)}{2} - p_{56} - p_{67} = \frac{(7 - 5 + 1)}{2} - 0.840 - 0.556 = 0.104,$$

$$p_{18,15} = \frac{(j - i + 1)}{2} - p_{15,16} - p_{16,17} - p_{17,18}$$
$$= \frac{(18 - 15 + 1)}{2} - 0.568 - 0.580 - 0.711 = 0.141$$

Since some element values in Table 6 are not in the range [0, 1], therefore the transformation function as equation (9) is applied to maintain reciprocal and additive consistency properties. The criteria matrices are derived from transformation functions shown in Table 7. Finally, equations (10)–(11) are used to calculate the subjective weights of criteria (w_j^s) as illustrated in Table 7.

Table 6 The completed aggregated pairwise matrices for criteria

Criteria	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*	*C10*	*C11*	*C12*	*C13*	*C14*	*C15*	*C16*	*C17*	*C18*
C1	0.000	0.744	0.891	0.830	0.798	1.138	1.194	1.163	1.560	1.765	1.977	2.279	2.214	1.972	2.096	2.164	2.244	2.455
C2	0.256	0.000	0.647	0.586	0.554	0.894	0.950	0.919	1.315	1.521	1.733	2.034	1.970	1.728	1.851	1.920	2.000	2.211
C3	0.109	0.353	0.000	0.439	0.407	0.747	0.803	0.771	1.168	1.374	1.586	1.887	1.823	1.581	1.704	1.773	1.852	2.063
C4	0.170	0.414	0.561	0.000	0.468	0.808	0.864	0.833	1.230	1.435	1.647	1.949	1.884	1.642	1.766	1.834	1.914	2.125
C5	0.202	0.446	0.593	0.532	0.000	0.840	0.896	0.865	1.261	1.467	1.679	1.980	1.916	1.674	1.797	1.866	1.945	2.156
C6	–0.138	0.106	0.253	0.192	0.160	0.000	0.556	0.525	0.921	1.127	1.339	1.640	1.576	1.334	1.457	1.526	1.606	1.817
C7	–0.194	0.050	0.197	0.136	0.104	0.444	0.000	0.469	0.865	1.071	1.283	1.585	1.520	1.278	1.402	1.470	1.550	1.761
C8	–0.163	0.081	0.229	0.167	0.135	0.475	0.531	0.000	0.897	1.102	1.314	1.616	1.551	1.309	1.433	1.501	1.581	1.792
C9	–0.560	–0.315	–0.168	–0.230	–0.261	0.079	0.135	0.103	0.000	0.705	0.918	1.219	1.155	0.913	1.036	1.104	1.184	1.395
C10	–0.765	–0.521	–0.374	–0.435	–0.467	–0.127	–0.071	–0.102	0.295	0.000	0.712	1.014	0.949	0.707	0.831	0.899	0.979	1.190
C11	–0.977	–0.733	–0.586	–0.647	–0.679	–0.339	–0.283	–0.314	0.082	0.288	0.000	0.801	0.737	0.495	0.618	0.687	0.767	0.978
C12	–1.279	–1.034	–0.887	–0.949	–0.980	–0.640	–0.585	–0.616	–0.219	–0.014	0.199	0.000	0.436	0.194	0.317	0.385	0.465	0.676
C13	–1.214	–0.970	–0.823	–0.884	–0.916	–0.576	–0.520	–0.551	–0.155	0.051	0.263	0.564	0.000	0.258	0.381	0.450	0.529	0.741
C14	–0.972	–0.728	–0.581	–0.642	–0.674	–0.334	–0.278	–0.309	0.087	0.293	0.505	0.806	0.742	0.000	0.623	0.692	0.771	0.982
C15	–1.096	–0.851	–0.704	–0.766	–0.797	–0.457	–0.402	–0.433	–0.036	0.169	0.382	0.683	0.619	0.377	0.000	0.568	0.648	0.859
C16	–1.164	–0.920	–0.773	–0.834	–0.866	–0.526	–0.470	–0.501	–0.104	0.101	0.313	0.615	0.550	0.308	0.432	0.000	0.580	0.791
C17	–1.244	–1.000	–0.852	–0.914	–0.945	–0.606	–0.550	–0.581	–0.184	0.021	0.233	0.535	0.471	0.229	0.352	0.420	0.000	0.711
C18	–1.455	–1.211	–1.063	–1.125	–1.156	–0.817	–0.761	–0.792	–0.395	–0.190	0.022	0.324	0.259	0.018	0.141	0.209	0.289	0.000

Table 7 The transformation function of pairwise matrices

Criteria	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*	*C10*	*C11*	*C12*	*C13*	*C14*	*C15*	*C16*	*C17*	*C18*	g_{ij}	w_j^s	*Ranking*
C1	0.000	0.562	0.600	0.584	0.576	0.663	0.678	0.670	0.771	0.824	0.878	0.955	0.938	0.877	0.908	0.926	0.946	1.000	0.742	0.087	1
C2	0.438	0.000	0.538	0.522	0.514	0.601	0.615	0.607	0.709	0.761	0.815	0.892	0.876	0.814	0.846	0.863	0.884	0.938	0.680	0.080	2
C3	0.400	0.462	0.000	0.484	0.476	0.563	0.577	0.569	0.671	0.723	0.778	0.855	0.838	0.776	0.808	0.826	0.846	0.900	0.642	0.076	5
C4	0.416	0.478	0.516	0.000	0.492	0.579	0.593	0.585	0.687	0.739	0.793	0.871	0.854	0.792	0.824	0.841	0.862	0.916	0.658	0.077	4
C5	0.424	0.486	0.524	0.508	0.000	0.587	0.601	0.593	0.695	0.747	0.802	0.879	0.862	0.800	0.832	0.849	0.870	0.924	0.666	0.078	3
C6	0.337	0.399	0.437	0.421	0.413	0.000	0.514	0.506	0.608	0.660	0.715	0.792	0.775	0.713	0.745	0.762	0.783	0.837	0.579	0.068	6
C7	0.322	0.385	0.423	0.407	0.399	0.486	0.000	0.492	0.593	0.646	0.700	0.777	0.761	0.699	0.731	0.748	0.768	0.822	0.564	0.066	8
C8	0.330	0.393	0.431	0.415	0.407	0.494	0.508	0.000	0.601	0.654	0.708	0.785	0.769	0.707	0.739	0.756	0.776	0.830	0.572	0.067	7
C9	0.229	0.291	0.329	0.313	0.305	0.392	0.407	0.399	0.000	0.553	0.607	0.684	0.667	0.606	0.637	0.655	0.675	0.729	0.471	0.055	9
C10	0.176	0.239	0.277	0.261	0.253	0.340	0.354	0.346	0.447	0.000	0.554	0.631	0.615	0.553	0.585	0.602	0.622	0.676	0.418	0.049	10
C11	0.122	0.185	0.222	0.207	0.198	0.285	0.300	0.292	0.393	0.446	0.000	0.577	0.561	0.499	0.530	0.548	0.568	0.622	0.364	0.043	12
C12	0.045	0.108	0.145	0.129	0.121	0.208	0.223	0.215	0.316	0.369	0.423	0.000	0.484	0.422	0.453	0.471	0.491	0.545	0.287	0.034	17
C13	0.062	0.124	0.162	0.146	0.138	0.225	0.239	0.231	0.333	0.385	0.439	0.516	0.000	0.438	0.470	0.487	0.508	0.562	0.304	0.036	15
C14	0.123	0.186	0.224	0.208	0.200	0.287	0.301	0.293	0.394	0.447	0.501	0.578	0.562	0.000	0.532	0.549	0.569	0.623	0.365	0.043	11
C15	0.092	0.154	0.192	0.176	0.168	0.255	0.269	0.261	0.363	0.415	0.470	0.547	0.530	0.468	0.00	0.517	0.538	0.592	0.334	0.039	13
C16	0.074	0.137	0.174	0.159	0.151	0.238	0.252	0.244	0.345	0.398	0.452	0.529	0.513	0.451	0.483	0.000	0.520	0.574	0.316	0.037	14
C17	0.054	0.116	0.154	0.138	0.130	0.217	0.232	0.224	0.325	0.378	0.432	0.509	0.492	0.431	0.462	0.480	0.000	0.554	0.296	0.035	16
C18	0.000	0.062	0.100	0.084	0.076	0.163	0.178	0.170	0.271	0.324	0.378	0.455	0.438	0.377	0.408	0.426	0.446	0.000	0.242	0.028	18

Table 8 Aggregated a group of decision making matrix

	Criteria					
	C1	*C2*	*C3*	*C4*	*C5*	*C6*
A_1	(4.000, 6.000, 8.000)	(3.667, 5.667, 7.500)	(5.334, 7.334, 9.000)	(3.667, 5.667, 7.500)	(4.334, 6.334, 8.334)	(4.334, 6.334, 8.167)
A_2	(6.667, 8.667, 9.834)	(4.334, 6.334, 8.167)	(5.000, 7.000, 8.834)	(5.334, 7.334, 9.000)	(5.334, 7.334, 9.000)	(6.000, 8.000, 9.500)
A_3	(6.667, 8.334, 9.334)	(7.667, 9.167, 9.834)	(4.667, 6.667, 8.500)	(5.667, 7.667, 9.167)	(5.000, 7.000, 8.834)	(6.000, 8.000, 9.500)
A_4	(3.667, 5.667, 7.500)	(4.667, 6.667, 8.334)	(6.334, 8.167, 9.500)	(6.000, 7.834, 9.167)	(4.334, 6.334, 8.167)	(4.000, 6.000, 8.000)
A_5	(3.667, 5.667, 7.500)	(3.334, 5.334, 7.334)	(4.334, 6.334, 8.167)	(6.000, 7.834, 9.334)	(3.667, 5.667, 7.667)	(5.000, 7.000, 9.000)
	Criteria					
	C7	*C8*	*C9*	*C10*	*C11*	*C12*
A_1	(5.000, 7.000, 8.834)	(5.000, 7.000, 8.667)	(3.334, 5.334, 7.334)	(5.334, 7.167, 8.667)	(6.334, 8.334, 9.667)	(5.000, 7.000, 9.000)
A_2	(5.000, 7.000, 8.834)	(5.000, 7.000, 8.834)	(6.334, 8.334, 9.500)	(5.334, 7.334, 9.000)	(6.334, 8.334, 9.667)	(5.000, 7.000, 9.000)
A_3	(4.667, 6.667, 8.500)	(5.667, 7.667, 9.167)	(4.334, 6.334, 8.167)	(4.667, 6.667, 8.500)	(6.667, 8.500, 9.667)	(4.667, 6.667, 8.500)
A_4	(5.667, 7.667, 9.167)	(4.667, 6.667, 8.667)	(4.334, 6.334, 8.334)	(4.667, 6.667, 8.667)	(5.667, 7.667, 9.334)	(4.667, 6.667, 8.500)
A_5	(3.667, 5.667, 7.667)	(5.334, 7.334, 9.000)	(5.334, 7.334, 9.000)	(4.334, 6.334, 8.167)	(5.334, 7.334, 9.167)	(4.667, 6.667, 8.500)
	Criteria					
	C13	*C14*	*C15*	*C16*	*C17*	*C18*
A_1	(4.334, 6.334, 8.167)	(3.334, 5.334, 7.334)	(2.667, 4.667, 6.667)	(3.667, 5.667, 7.667)	(6.000, 7.834, 9.167)	(5.667, 7.667, 9.167)
A_2	(4.667, 6.667, 8.500)	(5.334, 7.334, 9.167)	(5.667, 7.500, 9.000)	(6.000, 7.834, 9.334)	(5.334, 7.334, 9.000)	(5.334, 7.334, 9.000)
A_3	(4.667, 6.667, 8.500)	(5.000, 7.000, 8.834)	(6.334, 8.000, 9.167)	(7.334, 8.834, 9.667)	(4.334, 6.334, 8.167)	(4.000, 6.000, 7.834)
A_4	(4.667, 6.667, 8.334)	(5.000, 7.000, 8.834)	(5.667, 7.667, 9.167)	(6.000, 8.000, 9.500)	(3.667, 5.667, 7.500)	(4.334, 6.334, 8.167)
A_5	(4.000, 6.000, 8.000)	(4.667, 6.667, 8.667)	(4.000, 6.000, 7.834)	(5.667, 7.667, 9.334)	(4.334, 6.334, 8.167)	(4.334, 6.334, 8.167)

5.6 Computing objective weights of evaluation criteria

The objective weights of the evaluation criteria can be obtained by fuzzy CRITIC as described in Section 3.2. First, all experts from Group II are invited to evaluate five-wheel disk suppliers (A_1, A_2, A_3, A_4, A_5) using the linguistic expressions as presented in Table 2. The linguistic terms are then converted into fuzzy scores as equation (12). Next, input data from all experts are aggregated into a group of decision making matrix by equation (13) as shown in Table 8. All elements in group decision making matrix are normalised by equation (14). Subsequently, the information measures of each criterion are calculated by equations (15)–(17). The fuzzy objective weights are obtained by equation (18). Finally, the objective weights are converted to crisp numbers by equation (19) as shown in Table 9.

Table 9 The objective weights of criteria by fuzzy CRITIC

Criteria	σ_j			$H_j = \sigma_j \sum_j^n (1 - r_{ij})$			ω_j			w_j^o
	σ_j^l	σ_j^m	σ_j^u	H_j^l	H_j^m	H_j^u	ω_j^l	ω_j^m	ω_j^u	
C1	0.447	0.447	0.435	4.407	4.417	4.169	0.037	0.038	0.039	0.039
C2	0.411	0.424	0.434	5.944	6.221	6.666	0.053	0.054	0.062	0.055
C3	0.435	0.456	0.435	6.744	7.002	5.321	0.060	0.061	0.049	0.059
C4	0.548	0.548	0.548	8.771	8.836	9.176	0.077	0.078	0.085	0.078
C5	0.354	0.354	0.408	4.283	4.262	4.603	0.037	0.038	0.043	0.038
C6	0.548	0.548	0.447	6.735	6.798	5.322	0.058	0.059	0.049	0.058
C7	0.354	0.354	0.408	4.283	4.262	4.603	0.037	0.038	0.043	0.038
C8	0.447	0.447	0.548	9.006	9.030	11.271	0.079	0.080	0.105	0.083
C9	0.354	0.354	0.365	4.868	4.855	5.177	0.042	0.043	0.048	0.043
C10	0.548	0.548	0.548	6.785	6.678	5.719	0.058	0.060	0.053	0.058
C11	0.418	0.447	0.548	5.902	6.267	7.860	0.052	0.055	0.073	0.057
C12	0.548	0.548	0.548	7.609	7.615	7.860	0.066	0.067	0.073	0.068
C13	0.548	0.548	0.548	7.609	7.615	7.860	0.066	0.067	0.073	0.068
C14	0.548	0.548	0.548	6.785	6.678	5.719	0.058	0.060	0.053	0.058
C15	0.447	0.447	0.447	5.573	5.621	5.615	0.048	0.049	0.052	0.050
C16	0.380	0.390	0.408	5.561	5.783	6.392	0.049	0.050	0.059	0.052
C17	0.354	0.355	0.149	4.207	5.693	1.774	0.037	0.050	0.016	0.042
C18	0.418	0.419	0.183	8.137	7.268	2.635	0.063	0.072	0.024	0.058

5.7 Obtaining combination weights of the evaluation criteria

The combination weights of evaluation criteria (w_j^{com}) can be obtained based on the weights from CFPR and fuzzy CRITIC using equation (20) as shown in Table 10. A numerical example for criterion C_1 is illustrated below.

$$w_1^{com} = \frac{0.087 \times 0.039}{(0.087 \times 0.039) + (0.080 \times 0.055) \cdots + (0.028 \times 0.058)}$$
$$= 0.062$$

Table 10 The combination weights of the evaluation criteria

Criteria	w_j^s	w_j^o	w_j^{com}	*Ranking*
C1	0.087	0.039	0.062	6
C2	0.080	0.055	0.078	4
C3	0.076	0.059	0.084	3
C4	0.077	0.078	0.111	1
C5	0.078	0.038	0.054	7
C6	0.068	0.058	0.072	5
C7	0.066	0.038	0.047	10
C8	0.067	0.083	0.103	2
C9	0.055	0.043	0.046	11
C10	0.049	0.058	0.051	8
C11	0.043	0.057	0.041	12
C12	0.034	0.068	0.036	14
C13	0.036	0.068	0.048	9
C14	0.043	0.058	0.041	12
C15	0.039	0.050	0.035	15
C16	0.037	0.052	0.037	13
C17	0.035	0.042	0.022	17
C18	0.028	0.058	0.031	16

5.8 Evaluating and raking performance of suppliers

In this section, fuzzy VIKOR approach (described in Section 3.4) is employed to evaluate and rank the performance of suppliers in trial production stage. Based on Table 8, all elements in the aggregated evaluation matrix are defuzzied into crisp numbers by equation (21) as shown in Table 11. The best positive ideal (f_i^*) and the worst negative ideal (f_i^-) values of all criteria are determined by equation (22) as shown in Table 12. Based on the combination weights (w_j^{com}) in Table 10, the highest utility values of the majority (S_i), the distinct regret of the opponent (R_i) and the value of merit function of each supplier's performance (Q_i) are calculated by equations (23)–(25) respectively, as shown in Table 13. In this study, v value is defined as 0.5. A computation of Q_i values are illustrated below.

$$Q_1 = 0.5 \times \left[\frac{0.653 - 0.253}{0.672 - 0.253}\right] + (1 - 0.5)\left[\frac{0.111 - 0.069}{0.111 - 0.069}\right] = 0.977$$

$$Q_2 = 0.5 \times \left[\frac{0.253 - 0.253}{0.672 - 0.253}\right] + (1 - 0.5)\left[\frac{0.069 - 0.069}{0.111 - 0.069}\right] = 0.00$$

$$Q_3 = 0.5 \times \left[\frac{0.253 - 0.253}{0.672 - 0.253}\right] + (1 - 0.5)\left[\frac{0.069 - 0.069}{0.111 - 0.069}\right] = 0.00$$

$$Q_4 = 0.5 \times \left[\frac{0.518 - 0.253}{0.672 - 0.253}\right] + (1 - 0.5)\left[\frac{0.103 - 0.069}{0.111 - 0.069}\right] = 0.722$$

$$Q_5 = 0.5 \times \left[\frac{0.672 - 0.253}{0.672 - 0.253}\right] + (1 - 0.5)\left[\frac{0.084 - 0.069}{0.111 - 0.069}\right] = 0.681$$

Then, the compromise solution conditions are checked using equation (26) as follows:

Condition 1

$$Q(a'') - Q(a') \geq \frac{1}{m-1}$$

$$0.681 - 0.000 \geq \frac{1}{5-1}$$

$$0.681 \geq 0.25$$

Condition 2 Based on S_i and R_i values indicate that $A_2 = A_3 > A_5 > A_4 > A_1$. Both conditions are satisfied, therefore the final suppliers' performances ranking is $A_2 = A_3 > A_5 > A_4 > A_1$.

Table 11 The defuzzification of aggregated evaluation matrix

	Criteria								
	C1	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*
A_1	6.000	5.639	7.278	5.639	6.333	6.306	6.972	6.944	5.333
A_2	8.528	6.306	6.972	7.278	7.278	7.917	6.972	6.972	8.194
A_3	8.222	9.028	6.639	7.583	6.972	7.917	6.639	7.583	6.306
A_4	5.639	6.611	8.083	7.750	6.306	6.000	7.583	6.667	6.333
A_5	5.639	5.333	6.306	7.778	5.667	7.000	5.667	7.278	7.278
	Criteria								
	C10	*C11*	*C12*	*C13*	*C14*	*C15*	*C16*	*C17*	*C18*
A_1	7.111	8.222	7.000	6.306	5.333	4.667	5.667	7.750	7.583
A_2	7.278	8.222	7.000	6.639	7.306	7.444	7.778	7.278	7.278
A_3	6.639	8.389	6.639	6.639	6.972	7.917	8.722	6.306	5.972
A_4	6.667	7.611	6.639	6.611	6.972	7.583	7.917	5.639	6.306
A_5	6.306	7.306	6.639	6.000	6.667	5.972	7.611	6.306	6.306

Table 12 The $w_i\left[\frac{f_i^* - (f_{ij})}{f_i^* - f_i^-}\right]$ values

	Criteria								
	C1	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*
A_1	0.054	0.072	0.038	0.111	0.032	0.061	0.015	0.072	0.046
A_2	0.000	0.057	0.053	0.026	0.000	0.000	0.015	0.069	0.000
A_3	0.000	0.057	0.053	0.026	0.000	0.000	0.015	0.069	0.000
A_4	0.062	0.051	0.000	0.001	0.033	0.072	0.000	0.103	0.030
A_5	0.062	0.078	0.084	0.000	0.054	0.034	0.047	0.034	0.015

	Criteria								
	C10	*C11*	*C12*	*C13*	*C14*	*C15*	*C16*	*C17*	*C18*
A_1	0.009	0.006	0.000	0.025	0.041	0.035	0.037	0.000	0.000
A_2	0.000	0.006	0.000	0.000	0.000	0.005	0.011	0.005	0.006
A_3	0.000	0.006	0.000	0.000	0.000	0.005	0.011	0.005	0.006
A_4	0.032	0.029	0.036	0.002	0.007	0.004	0.010	0.022	0.025
A_5	0.051	0.041	0.036	0.048	0.013	0.021	0.013	0.015	0.025

Table 13 The S_i, R_i and Q_i value

Suppliers	S_i	R_i	Q_i	*Rank*
A_1	0.653	0.111	0.977	4
A_2	0.253	0.069	0.000	1
A_3	0.253	0.069	0.000	1
A_4	0.518	0.103	0.722	3
A_5	0.672	0.084	0.681	2

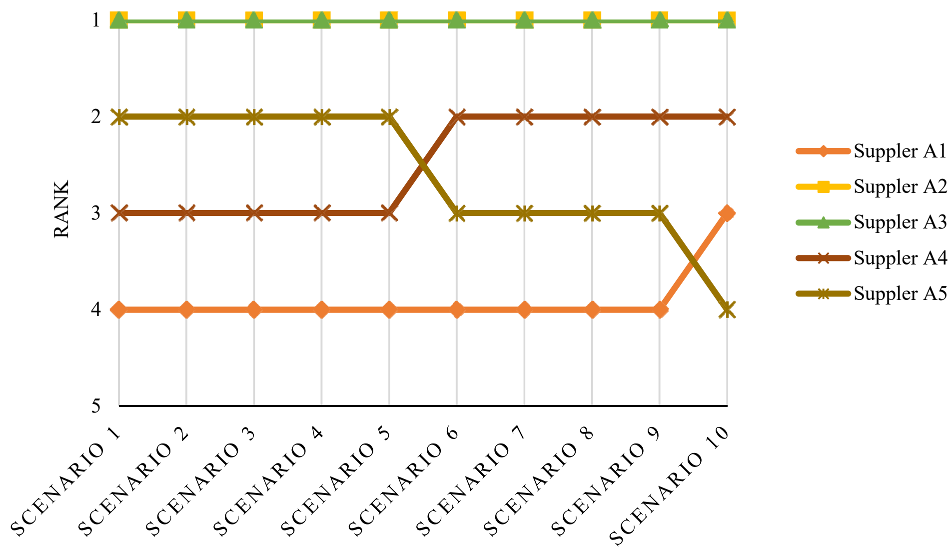
Table 14 The Q_i values for ten scenarios

Suppliers	*Scenarios*									
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
	v = 0.1	*v = 0.2*	*v = 0.3*	*v = 0.4*	*v = 0.5*	*v = 0.6*	*v = 0.7*	*v = 0.8*	*v = 0.9*	*v = 1.0*
	Q_i *values*									
A_1	0.995	0.991	0.986	0.982	0.977	0.973	0.968	0.964	0.959	0.955
A_2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A_3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A_4	0.793	0.776	0.758	0.740	0.722	0.705	0.687	0.669	0.651	0.634
A_5	0.426	0.490	0.554	0.617	0.681	0.745	0.809	0.872	0.936	1.000

5.9 Sensitivity analysis

In this section, a sensitivity analysis is carried out to verify the stability and robustness of decision makers towards the proposed decision making framework. To do this, ten scenarios are formulated by altering v values to 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0 to examine the impact on ranking of suppliers. Table 14 presents the Q_i values, while Figure 3 presents the ranking of suppliers for ten scenarios. It can be seen that when v values are changed the ranking of suppliers mostly remains unchanged through all scenarios ($A_2 = A_3 > A_5 > A_4 > A_1$). It indicates that the proposed decision making framework is robust and stable.

Figure 3 The ranking of suppliers for ten scenarios (see online version for colours)



5.10 *Comparative study with other MCDM approaches*

In this study, a comparative study between the proposed framework and four selective MCDM methods as WASPAS, PROMETHEE, ELECTRE, and TOPSIS under fuzzy environment is carried out to validate the conformity of the proposed framework using the same case study. The comparative ranking results of the different MDCM methods for evaluating supplier performance are presented in Table 15. Utilising equation (27), Spearman's correlation coefficient between a pair of MCDM methods is computed to determine the degree of conformity as shown in Table 17. From Table 16 indicates that supplier A_2 is the best supplier for all comparison MCDM methods. Using Table 15 and Table 17, the correlation results can be interpreted that the proposed framework (fuzzy VIKOR) is very strong conformity with fuzzy TOPSIS (R = 0.849), also strong conformity with fuzzy ELECTRE (R = 0.765), fuzzy WASPAS (R = 0.606) and fuzzy PROMETHEE (R = 0.606). It implies that the proposed framework in this study conforms with other MCDM approaches.

$$R = 1 - \frac{6\sum D^2}{N\left(N^2 - 1\right)} \tag{27}$$

Table 15 Interpretation degree of correlation by Spearman's correlation coefficient

Spearman's correlation coefficients	*Degree of conformity*
$R < 0.2$	Very weak
$0.2 \leq R < 0.4$	Weak
$0.4 \leq \underline{R} < 0.6$	Moderate
$0.6 \leq R < 0.8$	Strong
$R \geq 0.8$	Very strong

Source: Keshavarz-Ghorabaee et al. (2020)

Table 16 Comparative ranking results of different MDCM methods

Suppliers	*Ranking the different MCDM methods under fuzzy environment*				
	VIKOR	*WASPAS*	*PROMETHEE*	*ELECTRE*	*TOPSIS*
A_1	4	4	4	4	5
A_2	1	1	1	1	1
A_3	1	2	2	2	2
A_4	3	3	3	3	3
A_5	2	5	5	4	4

Table 17 Spearman's correlation coefficient between a pair of MCDM methods

MCDM methods under fuzzy environment	*VIKOR*	*WASPAS*	*PROMETHEE*	*ELECTRE*	*TOPSIS*
VIKOR	1.000	0.606	0.606	0.765	0.849
WASPAS	-	1.000	1.000	0.970	0.900
PROMETHEE	-	-	1.000	0.970	0.900
ELECTRE	-	-	-	1.000	0.970
TOPSIS	-	-	-	-	1.000

6 Discussion and managerial implications

Due to lack of criteria to evaluating suppliers' performance in trial production stage from the existing literature, this study therefore identifies eighteen criteria and validates them through industrial experts' review. Based on the results from combination weights of criteria in Table 10, the findings indicate that 'technical support' (C_4) is the most important performance criteria followed by 'compliance part certification' (C_8) and 'engineering change management' (hereafter ECM) (C_7) for supplier performance evaluation in trial production stage for new car model development for case study. Thus, this finding suggests that a car manufacturer should give the high priority for these three criteria when evaluating the performance of suppliers in trial stage of new car model development. Considering suppliers' technical support during the trial production stage, this suppliers' performance can benefit to car manufacturer in a number of ways such as resolving the hidden parts quality issues, advising value analysis/value engineering (VA/VE) for costs reduction, reducing production trial lead time, cooperating design for manufacturing/design for assembly (DFM/DFA) activities. Technical support from suppliers includes 'design for X' (DFX) that can help automakers deal with specific engineering contexts such as manufacturability, maintainability, assimilability, recyclability and sustainability (Favi et al., 2022). Next, 'compliance part certification' is the second most importance performance criteria. Therefore, suppliers must ensure that the parts supplied are complied with the specific quality and safety standards governed by the laws and regulations of the country of manufacture. Suppliers who are unable to produce supplied parts to meet such regulations in a timely manner leading to a delay in the development of new car model development. ECM is the third most important performance criteria. This finding is in accordance with Sumrit (2020), who stated that the work flow of ECM is a complex task, especially in the early stages of a NPD project due to the numerous engineering changes. An effective ECM is essential to reduce the negative impact of design on automotive components.

Controversially, ECM can cause substantial economic losses in product development if not managed properly (Yin et al., 2022). ECM often suffers from long lead times and non-transparent information flow causing delays in implementation (Pan and Stark, 2022). Therefore, car manufacturers and suppliers need to work together to properly control and implement the ECM to avoid unnecessary NPD time delays and costs. Therefore, an efficient ECM is one of key performance of suppliers in trial production stage of new car model development. Based on the results of five-wheel disk suppliers ranking by fuzzy VIKOR, this study reveals that supplier A_2 together with supplier A_3 are the best performance suppliers followed by supplier A_5, supplier A_4 and supplier A_1, respectively.

7 Conclusions and future research directions

The integrating of suppliers into NPD can open up opportunities to reduce the development costs, enhance the product quality, shorten the development times, and foster the higher degree of innovation. Hence, properly evaluate supplier performance in the NPD stage is one of challenges for manufacturers. As well as car manufactures, developing a new car model is heavily relied on suppliers' performance at all stages of NPD. From the academic's point of view, most of studies focused on evaluating the performance of suppliers at mass production stage but little attention has been paid to the trial production stage. Supplier performance evaluation in trial production stage is clearly a critical decision for scholars and practitioners involving in a new car model development. This study proposes a comprehensive framework to evaluate performance of supplier in trial production stage of new car model development. The reason for the emphasis on the trial production stage is that improper supplier management and control activities at this stage can lead to additional development costs and times, inferior product quality and delays in introduction of new car model to the market. On the other hand, implementing a proper mechanism to evaluate supplier performance in trial production stage can prevent risks posed by suppliers transferring to mass production. In this study, evaluating the suppliers' performance in trial production stage of new car model development can be treated as MCDM problem. In this regard, a hybrid MCDM approach is introduced by combining CFPR, fuzzy CRITIC and fuzzy VIKOR. The applicability of the proposed framework is demonstrated by using one of the largest

Japanese car manufacturing in Thailand as a case study. There are four main contributions of this study. First, evaluation of suppliers' performance in trial production stage does not appear to be explored in existing literature. Even in the automotive industry, it is one of the most important NPD stages for the development of new car model. To the authors' best knowledge, this is the first study to introduce a framework for supplier performance in trial production stage. Second, proposed method incorporates uncertain and imprecise data provided by decision-makers using fuzzy set theory. Third, to obtain a better and more accurate calculation of important weights of performance criteria, the combination weight method is used in this study by integrating subjective and objective weights. Finally, the scholars and practitioners involving in the development of new car model can use the proposed framework as a guideline for systematically evaluating supplier performance in trial production stage. This study has some restrictions that open the window of opportunities for future research. First, the complexity of the proposed decision making model should be reduced by grouping performance criteria into relevant dimensions. In this regard, the statistical technique such as exploratory factor analysis (EFA) can be applied. Second, the interdependence between performance criteria should be investigated, therefore some MCDM techniques such as decision making trial and evaluation laboratory (DEMATEL) or ANP can be employed. Finally, it will be interesting to conduct a comparative study/benchmarking between eastern and western car manufacturers by applying the proposed framework.

References

Afrasiabi, A., Tavana, M. and Di Caprio, D. (2022) 'An extended hybrid fuzzy multi-criteria decision model for sustainable and resilient supplier selection', *Environmental Science and Pollution Research* [online] https://doi.org/10.1007/s11356-021-17851-2.

Al-Barakati, A., Mishra, A.R., Mardani, A. and Rani, P. (2022) 'An extended interval-valued Pythagorean fuzzy WASPAS method based on new similarity measures to evaluate the renewable energy sources', *Applied Soft Computing*, Vol. 120 [online] https://doi.org/10.1016/j.asoc.2022.108689.

Alias, F.M.A., Abdullah, L., Gou, X., Liao, H. and Viedma, E.H. (2019) 'Consistent fuzzy preference relation with geometric Bonferroni mean: a fused preference method for assessing the quality of life', *Applied Intelligence*, Vol. 49, pp.2672–2683, https://doi.org/10.1007/s10489-019-01415-6.

Ayyildiz, E. and Taskin, A. (2022) 'A novel spherical fuzzy AHP-VIKOR methodology to determine serving petrol station selection during COVID-19 lockdown: a pilot study for Istanbul', *Socio-Economic Planning Sciences* [online] https://doi.org/10.1016/j.seps.2022.101345.

Benton, W.C.J., Prahinski, C. and Fan, Y. (2020) 'The influence of supplier development programs on supplier performance', *International Journal of Production Economics*, Vol. 230, https://doi.org/10.1016/j.ijpe.2020.107793.

Biscaia, R.V.B., Braghini, A.J. and Colmenero, J.C. (2021) 'Selection of projects for automotive assembly structures using a hybrid method composed of the group-input compatible, best-worst method for criteria weighting and TrBF-TOPSIS', *Expert Systems with Applications*, Vol. 184 [online] https://doi.org/10.1016/j.eswa.2021.115557.

Chatterjee, K., Pamucar, D. and Zavadskas, E.K. (2018) 'Evaluating the performance of suppliers based on using the R'AMATEL-MAIRCA method for green supply chain implementation in electronics industry', *Journal of Cleaner Production*, Vol. 184, pp.101–129, https://doi.org/10.1016/j.jclepro.2018.02.186.

Chen, F., Zhu, Y., Zu, J., Lyu, J. and Yang, J. (2022) 'Appraising road safety attainment by CRITIC-ELECTRE-FCM: a policymaking support for Southeast Asia', *Transport Policy*, Vol. 112, pp.104–118 [online] https://doi.org/10.1016/j.tranpol.2022.04.014.

Corsten, D., Gruen, T. and Peyinghaus, M. (2011) 'The effects of supplier-to-buyer identification on operational performance – an empirical investigation of inter- organizational identification in automotive relationships', *Journal of Operations Management*, Vol. 29, https://doi.org/10.1016/j.jom.2010.10.002.

Delic, M. and Eyers, D.R. (2020) 'The effect of additive manufacturing adoption on supply chain flexibility and performance: an empirical analysis from the automotive industry', *International Journal of Production Economics*, Vol. 228, https://doi.org/10.1016/j.ijpe.2020.107689.

Demirel, H., Sener, B., Yildiz, B. and Balin, A. (2020) 'A real case study on the selection of suitable roll stabilizer type for motor yachts using hybrid fuzzy AHP and VIKOR methodology', *Ocean Engineering*, Vol. 217 [online] https://doi.org/10.1016/j.oceaneng.2020.108125.

Dweiri, F., Kumar, S., Khan, S.A. and Jain, V. (2016) 'Designing an integrated AHP based decision support system for supplier selection in automotive industry', *Expert Systems with Applications*, Vol. 62, pp.273–283, https://doi.org/10.1016/j.eswa.2016.06.030.

Dwivedi, G., Srivastava, S.K. and Srivastava, R.K. (2017) 'Analysis of barriers to implement additive manufacturing technology in the Indian automotive sector', *International Journal of Physical Distribution & Logistics Management*, Vol. 47, No. 10, pp.972–991.

Favi, C., Campi, F., Germani, M. and Mandolini, M. (2022) 'Engineering knowledge formalization and proposition for informatics development towards a CAD-integrated DfX system for product design', *Advanced Engineering Informatics*, Vol. 51 [online] https://doi.org/10.1016/j.aei.2022.101537.

Fürst, A. and Vietor, T. (2019) 'A methodical approach for improved control of safety-related product properties in early phases of the automotive product development process', *Procedia CIRP*, Vol. 84, pp.605–610, https://doi.org/10.1016/j.procir.2019.04.209.

Ghadimi, P., Wang, C. and Lim, M.K. (2019) 'Intelligent sustainable supplier selection using multi-agent technology: theory and application for Industry 4.0 supply chains', *Computers & Industrial Engineering*, Vol. 127, pp.588–600, https://doi.org/10.1016/j.cie.2018.10.050.

Giannakis, M., Dubey, R., Vlachos, I. and Ju, Y. (2020) 'Supplier sustainability performance evaluation using the analytic network process', *Journal of Cleaner Production*, Vol. 247 [online] https://doi.org/10.1016/j.jclepro.2019.119439.

Görener, A., Ayvaz, B., Kuşakcı, A.O. and Altınok, E. (2017) 'A hybrid type-2 fuzzy based supplier performance evaluation methodology: the Turkish Airlines technic case', *Applied Soft Computing*, Vol. 56, https://doi.org/10.1016/j.asoc.2017.03.026.

Haktanir, E. and Kahraman, C. (2022) 'A novel picture fuzzy CRITIC & REGIME methodology: wearable health technology application', *Engineering Applications of Artificial Intelligence*, Vol. 113 [online] https://doi.org/10.1016/j.engappai.2022.104942.

Herrera-Viedma, E., Herrera, F., Chiclana, F. and Luque, M. (2004) 'Some issues on consistency of fuzzy preference relations', *European Journal of Operational Research*, Vol. 154, pp.98–109 [online] https://doi.org/10.1016/S0377-2217(02)00725-7.

Hezer, S., Gelmez, E. and Özceylan, E. (2021) 'Comparative analysis of TOPSIS, VIKOR and COPRAS methods for the COVID-19 regional safety assessment', *Journal of Infection and Public Health*, Vol. 14, pp.775–786, https://doi.org/10.1016/j.jiph.2021.03.003.

Hosseini, S.M., Paydar, M.M. and Keshteli, M.H. (2021) 'Recovery solutions for ecotourism centers during the Covid-19 pandemic: utilizing fuzzy DEMATEL and fuzzy VIKOR methods', *Expert Systems with Applications*, Vol. 185 [online] https://doi.org/10.1016/j.eswa.2021.115594.

Im, G., Rai, A. and Lambert, L.S. (2019) 'Governance and resource sharing ambidexterity for generating relationship benefits in supply chain collaborations', *Decision Sciences Journal*, Vol. 50, No. 4, pp.656–693.

Kannan, D. (2018) 'Role of multiple stakeholders and the critical success factor theory for the sustainable supplier selection process', *International Journal of Production Economics*, Vol. 195, https://doi.org/10.1016/j.ijpe.2017.02.020.

Keshavarz-Ghorabaee, M., Amiri, M., Hashemi-Tabatabaei, M., Zavadskas, E.K. and Kaklauskas, A. (2020) 'A new decision-making approach based on Fermatean fuzzy sets and WASPAS for green construction supplier evaluation', *Mathematics*, Vol. 8, No. 12, p.2202.

Khan, S.A., Sarpong, S.K., Arhin, F.K. and Sarpong, H.K. (2018) 'Supplier sustainability performance evaluation and selection: a framework and methodology', *Journal of Cleaner Production*, Vol. 205, https://doi.org/10.1016/j.jclepro.2018.09.144.

Kumara, D. and Rahman, Z. (2015) 'Sustainability adoption through buyer supplier relationship across supply chain: a literature review and conceptual framework', *International Strategic Management Review*, Vol. 3, https://doi.org/10.1016/j.ism.2015.04.002.

Li, X., Han, Z., Yazdi, M. and Chen, G. (2022) 'A CRITIC-VIKOR based robust approach to support risk management of subsea pipelines', *Applied Ocean Research*, Vol. 124 [online] https://doi.org/10.1016/j.apor.2022.103187.

Liang, Y., Ju, Y., Martínez, L. and Tu., Y. (2022) 'Sustainable battery supplier evaluation of new energy vehicles using a distributed linguistic outranking method considering bounded rational behavior', *Journal of Energy Storage*, Vol. 48 [online] https://doi.org/10.1016/j.est.2021. 103901.

Liou, J.J.H., Chuang, Y.C., Zavadskas, E.K. and Tzeng, G.H. (2019) 'Data-driven hybrid multiple attribute decision making model for green supplier evaluation and performance improvement', *Journal of Cleaner Production*, Vol. 241, https://doi.org/10.1016/j.jclepro.2019.118321.

Lu, W., Park, S.H., Huang, T. and Yeo, G.T. (2019) 'An analysis for Chinese airport efficiency using weighted variables and adopting CFPR', *The Asian Journal of Shipping and Logistics*, Vol. 35, pp.230–242, https://doi.org/10.1016/j.ajsl.2019.12.010.

Mackelprang, A.W., Bernardes, E., Burke, G.J. and Welter, C. (2018) 'Supplier innovation strategy and performance: a matter of supply chain market positioning', *Decision Sciences Journal*, Vol. 49, No. 4, pp.660–689.

Maestrini, V., Maccarrone, P., Caniato, F. and Luzzini, D. (2018) 'Supplier performance measurement systems: communication and reaction modes', *Industrial Marketing Management*, Vol. 74, pp.298–308, https://doi.org/10.1016/j.ijpe.2018.07.008.

Melander, L. (2018) 'Customer and supplier collaboration in green product innovation: external and internal capabilities', *Business Strategy and the Environment*, Vol. 27, No. 6, pp.677–693.

Memari, A., Dargi, A., Jokar, M.R.A., Ahmad, R. and Rahim, A.R.A. (2019) 'Sustainable supplier selection: a multi-criterion intuitionistic fuzzy TOPSIS method', *Journal of Manufacturing Systems*, Vol. 50, pp.2–24, https://doi.org/10.1016/j.jmsy.2018.11.002.

Pan, Y. and Stark, R. (2022) 'An interpretable machine learning approach for engineering change management decision support in automotive industry', *Computers in Industry*, Vol. 138 [online] https://doi.org/10.1016/j.compind.2020.103633.

Papathanasiou, J. (2021) 'An example on the use and limitations of MCDA: the case of fuzzy VIKOR', *Examples and Counterexamples*, Vol. 1 [online] https://doi.org/10.1016/j.exco.2020. 100001.

Park, Y.I., Lu, W., Nam, T.H. and Yeo, G.T. (2019) 'Terminal vitalization strategy through optimal route selection adopting CFPR methodology', *The Asian Journal of Shipping and Logistics*, Vol. 35, pp.41–48, https://doi.org/10.1016/j.ajsl.2019.03.006.

Parvez, S. (2020) 'Application of fuzzy VIKOR and cluster analysis for performance evaluation of original equipment manufacturers', *Materials Today: Proceedings*, Vol. 27, pp.1411–1416, https://doi.org/10.1016/j.matpr.2020.02.785.

Ploskas, N. and Papathanasiou, J. (2019) 'A decision support system for multiple criteria alternative ranking using TOPSIS and VIKOR in fuzzy and nonfuzzy environments', *Fuzzy Sets and Systems*, Vol. 377, pp.1–30, https://doi.org/10.1016/j.fss.2019.01.012.

Rajeev, A., Pati, R.K., Padhi, S.S. and Kannan, G. (2017) 'Evolution of sustainability in supply chain management: a literature review', *Journal of Cleaner Production*, Vol. 162, pp.299–314 [online] http://dx.doi.org/10.1016/j.jclepro.2017.05.026.

Ruiz, A.T. and Ravindran, A.R. (2018) 'Multiple criteria framework for the sustainability risk assessment of a supplier portfolio', *Journal of Cleaner Production*, Vol. 172, https://doi.org/10.1016/j.jclepro.2017.10.304.

Schoenherr, T. and Swink, M. (2015) 'The roles of supply chain intelligence and adaptability in new product launch success', *Decision Sciences Journal*, Vol. 46, No. 5, pp.901–936.

Schoenherr, T. and Wagner, S.M. (2016) 'Supplier involvement in the fuzzy front end of new product development: an investigation of homophily, benevolence and market turbulence', *International Journal of Production Economics*, Vol. 180, https://doi.org/10.1016/j.ijpe.2016.06.027.

Sennaroglu, B. and Celebi, G.V. (2018) 'A military airport location selection by AHP integrated PROMETHEE and VIKOR methods', *Transportation Research Part D*, Vol. 59, pp.160–173, https://doi.org/10.1016/j.trd.2017.12.022.

Shekhovtsov, A. and Sałabun, W. (2020) 'A comparative case study of the VIKOR and TOPSIS rankings similarity', *Procedia Computer Science*, Vol. 176, pp.3730–3740, https://doi.org/10.1016/j.procs.2020.09.014.

Shivankar, S.D. and Deivanathan, R. (2021) 'Product design change propagation in automotive supply chain considering product life cycle', *CIRP Journal of Manufacturing Science and Technology*, Vol. 35, pp.390–399, https://doi.org/10.1016/j.cirpj.2021.07.001.

Suganthi, L. (2018) 'Multi expert and multi criteria evaluation of sectoral investments for sustainable development: an integrated fuzzy AHP, VIKOR/DEA methodology', *Sustainable Cities and Society*, Vol. 43, pp.144–156, https://doi.org/10.1016/j.scs.2018.08.022.

Sumrit, D. (2020) 'An integrated fuzzy multi-criteria decision making approach for evaluating suppliers' co-design ability in new product development', *International of Journal Applied Decision Sciences*, Vol. 13, No. 2, pp.215–246.

Taylan, O., Alamoudi, R., Kabli, M., AlJifri, A., Ramzi, F. and Viedma, E.H. (2020) 'Assessment of energy systems using extended fuzzy AHP, fuzzy VIKOR, and TOPSIS approaches to manage non-cooperative opinions', *Sustainability*, Vol. 12, DOI: 10.3390/su12072745.

Um, K.H. and Kim, S.M. (2019) 'The effects of supply chain collaboration on performance and transaction cost advantage: the moderation and nonlinear effects of governance mechanisms', *International Journal of Production Economics*, Vol. 217, pp.97–111, https://doi.org/10.1016/j.ijpe.2018.03.025.

Wahyuningrum, T., Azhari, A. and Suprapto (2019) 'Improving e-commerce severity rating measurement using consistent fuzzy preference relation', *Improving e-Commerce Severity Rating Measurement, SCDS 2019*, CCIS 1100, pp.28–39.

Wang, H., Jiang, Z., Zhang, H., Wang, Y. and Li, Y. (2019) 'An integrated MCDM approach considering demands-matching for reverse logistics', *Journal of Cleaner Production*, Vol. 208, pp.199–210 [online] https://doi.org/10.1016/j.jclepro.2018.10.131.

Wang, Y. and Yang, J. (2021) 'Role of supplier involvement and project leader in SNPD: a conceptual model and exploratory case study', *International Journal of Managing Projects in Business*, Vol. 14, No. 4, pp.960–981 [online] https://doi.org/10.1108/IJMPB-07-2020-0206.

Wowak, K., Craighead, C., Ketchen, D. and Hult, G. (2016) 'Toward a 'theoretical toolbox' for the supplier enabled fuzzy front end of the new product development process', *Journal of Supply Chain Management*, Vol. 52, No. 1, pp.66–81.

Yan, T. and Kull, T.J. (2015) 'Supplier opportunism in buyer-supplier new product development: a China-US study of antecedents, consequences, and cultural/institutional contexts', *Decision Sciences Journal*, Vol. 46, No. 2, pp.403–445.

Yang, Z., Jiang, Y. and Xie, E. (2019) 'Buyer-supplier relational strength and buying firm's marketing capability: an outside-in perspective', *Industrial Marketing Management*, Vol. 82, pp.27–37, https://doi.org/10.1016/j.indmarman.2019.03.009.

Yin, L., Sun, Q., Tang, D., Xu, Y. and Shao, L. (2022) 'Requirement-driven engineering change management in product design', *Computers & Industrial Engineering*, Vol. 168 [online] https://doi.org/10.1016/j.cie.2022.108053.

Zarbakhshnia, N., Wu, Y., Govindan, K. and Soleimani, H. (2020) 'A novel hybrid multiple attribute decision-making approach for outsourcing sustainable reverse logistics', *Journal of Cleaner Production*, Vol. 242 [online] https://doi.org/10.1016/j.jclepro.2019.118461.

Zhao, Y. and Cao, H. (2015) 'Risk management on joint product development with power asymmetry between supplier and manufacturer', *International Journal of Project Management*, Vol. 33, pp.1812–1826, DOI: 10.1016/j.ijproman.2015.08.008.

Zhao, Y., Feng, T. and Shi, H. (2018) 'External involvement and green product innovation: the moderating role of environmental uncertainty', *Business Strategy and the Environment*, Vol. 27, No. 8, pp.1167–1180.