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A Risk Analysis Based on a Two-Stage Model of Fuzzy AHP-DEA for Multimodal Freight Transportation Systems

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ABSTRACT Multimodal transportation has become a main focus of logistics systems due to environmental concerns, road safety issues, and traffic congestion. Consequently, research and policy interests in multimodal freight transportation problems are increasing. However, there are major challenges in the development of multimodal transportation associated with inherent risks and numerous uncertainties. Since risks are potential threats that directly impact logistics and transportation systems, comprehensive risk analysis should be carried out. Risk analysis is a critical process of identifying and analyzing significant issues to help industry mitigate those risks. However, identifying and prioritizing risks is more complex because of the ambiguity of the relevant data. This study proposes the integration of the fuzzy analytic hierarchy process (FAHP) and data envelopment analysis (DEA) for identifying and assessing quantitative risks. The proposed FAHP-DEA methodology uses the FAHP method to determine the weights of each risk criterion. The DEA method is employed to evaluate the linguistic variables and generate the risk scores. The simple additive weighting (SAW) method is used to aggregate risk scores under different risk criteria into an overall risk score. A case study of the coal industry demonstrates that the proposed risk analysis model is practical and allows users to more accurately prioritize risks while selecting an optimal multimodal transportation route. The process raises user's attention to the high-priority risks and is useful for industries in optimizing a multimodal transportation route under risk decision criteria.

INDEX TERMS Multimodal freight transportation, logistics, optimal route, risk analysis, risk assessment, DEA, FAHP.

I. INTRODUCTION

Freight transportation is an integral supply chain element for providing timely availability and effective movement of raw materials and finished goods [1]. Due to trade globalization, a traditional truck-only mode is no longer a feasible solution for all scenarios. Besides, traffic congestion, road safety and environmental issues are concerned on the agenda. Consequently, the EU transport policy aims to reduce road transport in favor of less polluting and more-energy efficient modes of transport. Multimodal transportation is currently a key element of modern transportation systems.

However, when focusing on the multimodal freight transportation system, many problems can be seen [1]–[5]. Since multimodal transportation comprises many factors and interactions among the different modes can be quite complex [2], leading to increased risk and uncertainty [3]. Risks are potential threats that instantly impact the transportation system [6]. Particularly in multimodal transportation, risks directly associated with accidents play a critical role not only in impacting cost and time but also in lessening competitive

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advantage [7]. Moreover, risks can disturb the logistics process, impact delivery timeliness and cause damage to freight and unexpected costs or delays [3], [7]–[9].

There are a large number of highly possible accident scenarios in the freight transportation system [10]–[12]. To evaluate and minimize the consequences of those scenarios, risk analysis is a crucial tool used to discuss the nature and impact of risks related to freight transportation. However, when considering risks perception in transportation, most studies focus only on road, ship, rail or air modes in isolation. There are very few studies concentrated on risks in multimodal transportation [3], [7], [13].

Risk analysis is a process for characterizing and determining hazards. It comprises two main stages: a qualitative stage of hazard classification and a quantitative stage of risk assessment. The latter stage includes estimating the possibility and severity of each hazard. Risk analysis in transportation can be defined as multi-criteria decision making (MCDM) problems and mainly propose qualitative models which are based upon subjective evaluations [7], [14], [15].

In addition, quantitative models are also complicated when involving the uncertainty and vagueness of the human decision process. Consequently, the dynamic nature of multimodal transportation leads to complex problems in the risk analysis process. For example, in the risk classification process, a method is required for risk prioritization considering many multiple experts' decisions.

Therefore, an appropriate MCDM should be realized for risk analysis in multimodal transportation while effectively solving multiple conflicting and interdependent issues [14]. To overcome the difficulty, this study proposes a novel framework for analyzing risks in multimodal freight transportation systems on the basis of the FAHP-DEA approach. The FAHP method is utilized to determine the weight of each criterion. Furthermore, FAHP can handle the vagueness and subjectivity of human judgments. The DEA method is used to define assessment grades in linguistic terms and to generate the local risk scores. Finally, the SAW method enables aggregation of local risk scores into an overall risk score for each decision alternative. The approach is illustrated on actual multimodal coal transportation routes in Thailand. To validate the model and result, Spearman's rank correlation and Pearson correlation analysis are carried out on each of the MCDM methods that are studied.

The significant contributions of this study can be summarized as follows:

1) The presented novel FAHP-DEA model has competitive performance compared with other techniques for evaluating multimodal transportation risks. To avoid a large number of pairwise comparisons in FAHP method, the proposed model requires the experts to only provide pairwise comparisons on decision criteria. Moreover, linguistic terms such as Very high, High, Medium, Low and Very low are used to simplify experts' assessment when selecting risk scores in DEA method. Therefore, the model has no synthesis of pairwise comparison matrices and requires only simple computation.
2) This study proposes a valid risk analysis framework to reduce bias in risk assessment and to help develop a new decision support system for assessing quantitative risk in multimodal transportation. It uses a qualitative expert opinion system to manage subjective risks in multimodal freight transportation. Moreover, the proposed model integrates a fuzzy set theory for reducing the complexity and uncertainty associated with risk analysis. The study offers useful insights to researchers and practitioners for analyzing and prioritizing transportation risks as well as optimizing routes under risk decision criteria.
3) The case study of risk analysis is presented along with its contributions to the literature by introducing a holistic list of potential factors affecting the five common risk types, including freight-damage risk, infrastructure risk, operational risk, security risk and environmental risk. Risks in multimodal transportation are identified in two sequential stages using both qualitative and quantitative research approaches. This comprehensive classification not only helps researchers and practitioners identify and classify the potential risk factors, but also provides a starting point for creating a transportation risk index model applicable to the multimodal transportation process.

The remainder of this article is organized as follows. Related work is briefly presented in Section II. Section III introduces the modeling framework of the FAHP and DEA models. Section IV illustrates the practical case study. Finally, conclusions, limitations, and future work are presented in Section V.

II. RELATED WORK

Risk analysis is a systematic process to assess the impact, occurrence and consequence of human activities or systems. The traditional risk analysis process consists of the following phases [3], [16]: risk identification, risk assessment and risk management and monitoring implementation. The diversity of risk analysis techniques ensures that there are many appropriate ones for any circumstance.

Various methodologies have been proposed in the risk analysis literature. Many studies have been carried out using MCDM methods to analyze significant risks. Karamoozian *et al.* [14] proposed a hybrid decision-making trial and evaluation laboratory and analytic network process (DEMATEL-ANP) models for risk prioritization in the construction projects. The result presented the important risk factors and defined the interdependencies between them in the case study. Ilangkumaran *et al.* [17] applied the analytic network process (ANP) and fuzzy linguistic approach to assess risks in the foundry industry's hot environments. Yazdi *et al.* [18] used the best-worst method (BWM) for reliable risk analysis based on the democratic-autocratic decision-making style. Lo *et al.* [19] proposed the failure mode and effects analysis (FMEA), which is based on MCDM and developed by integrating a rough best-worst method (BWM). Moreover, a technique for order preference by similarity to ideal solution (TOPSIS) is utilized for evaluating risk factors in machine tools. Matthews [20] studied risk management organization and practices using the DEA methodology. The result showed the importance of risk assessment in the banking industry. Shi *et al.* [21] utilized fuzzy logic with DEA to investigate the construction-program risk in China. Skevas *et al.* [22] used the DEA method to determine the performance of farms by incorporating environmental spillover of pesticides as well as other inputs related to production risks. Wang *et al.* [23] suggested the AHP-DEA methodology for risk assessment of bridges and showed that the method is simple and applicable to the case study. Kengpol and Tuammee [7] developed a risk assessment tool for determining multimodal logistics risks using the analytic hierarchy process (AHP) and data envelopment analysis (DEA). The abovementioned literature indicates the importance of risk analysis in different areas. Furthermore, most recent works have utilized the DEA model to develop risk analysis models.

Data envelopment analysis (DEA) is an assessment tool that involves different decision-making units (DMUs). It is capable of solving many complex problems by concurrently integrating multiple inputs and outputs using a ratio of the limited weight sum of outputs to the limited weight sum of inputs [7], [24]–[26]. Over the years, many studies have utilized DEA method to analyze risks in various fields. The DEA framework has been applied in a wide range of areas, including evaluation of service performance [25], [27], hospital efficiency [28], supplier selection [29] and transportation [30]–[33].

However, the DEA method is a nonparametric linear programming approach that evaluates DMU peers' relative efficiencies [7], [21]. Determining the weights of output indicators involves a multiple criteria decision-making (MCDM) problem [25]. Several MCDM methods have been used to determine the criteria weights, including the analytic hierarchy process (AHP). AHP is especially suitable for modeling and weighting qualitative data with a crisp 9-point rating scale [24] and utilizes pairwise comparison for each criteria [8]. It has been used in various research areas including evaluation, selection and forecasting [7], [8], [23], [34]. Nonetheless, AHP is not suitable when there are a large number of items to be determined and prioritized, as it can compare only a limited number of decision alternatives [24]. Besides, another limitation of traditional AHP is that experts cannot truly express their judgments by the crisp values in the rating scale. Fuzzy set theory can be utilized to solve the limitations since it provides the numerical strength to capture the uncertainties associated with the human cognitive process [24]. To overwhelm these problems, fuzzy set theory integrated with AHP are conducted to handle these uncertainty and complex problems involved in a decision-making environment [21], [31], [35]–[37].

Therefore, the integration of FAHP and DEA has become an effective method to deal with the multiple inputs and outputs of risk analysis. For example, Vencheh and Mohamadghasemi [24] used a hybrid model of FAHP and DEA for multiple criteria inventory classification. They showed that the integrated FAHP–DEA approach is very simple and applicable to the problems with a large number of decision alternatives. Shi *et al.* [21] applied fuzzy logic and DEA to investigate the management of delivery risk in construction and proved that those methods could reduce risk assessment bias. Diouf and Kwak [29] presented a conceptual model based on fuzzy set theory, AHP, and DEA for supplier selection.

The previous research studies indicate that integration of FAHP and DEA is widely used and appropriate for performing risk analysis. The combined FAHP and DEA models can deal with both qualitative and quantitative data [7]. Furthermore, it is more practical and easier for ranking decisions compared to a large number of alternatives.

The proposed integrated FAHP–DEA methodology has the following advantages over the methods of absolute priorities [23]–[25]:

1) The proposed FAHP-DEA method is more efficient and straightforward than other techniques. The implementation of FAHP-DEA considers the relative priorities of factors and represents the best alternative. Moreover, FAHP can confirm the response consistency by comparing objects with multiple attributes based on the hierarchical structure. In addition, the redundancy of pairwise comparison makes the FAHP-DEA model less sensitive to evaluation errors.
2) The proposed method can group risk alternatives into different risk categories for each criterion by characterizing the linguistic assessment grades. When faced with a large number of alternatives, this approach is much more practical for rank-ordering decision alternatives.
3) The proposed method requires solving only one linear programming model for each criterion, whereas the others require the solution of many linear programming models for every criterion.

To the best of found knowledge, there has been no study using this model to evaluate risks in multimodal transportation systems. Therefore, a hybrid model utilizing the FAHP and DEA method is introduced in this study. DEA is used to generate the local risk scores for each criterion. Additionally, FAHP is used to effectively assess the weight calculation for the risk factors' priorities.

III. MODELING FRAMEWORK

A. FUZZY SET THEORY

Fuzzy set theory was initially proposed by Zadeh [38]. A significant contribution of the theory is its capability to represent vague data. Fuzzy set theory is similar to a human's thought when expressing obscure words [24], for example, approximate, nearly, very, etc. A fuzzy set is a group of objects with a continuum of grades of membership, represented as values between 0 and 1. In this study, multimodal transportation risk analysis is carried out using experts' subjective judgments and fuzzy set concepts to determine the weights of different criteria. Fuzzy sets and linguistic variables are firstly introduced, followed by their applications to AHP [24], [38].

Definition 1: A fuzzy set $\tilde{A}$ in a universe of discourse X is defined by a membership function $u_{\tilde{A}}(x)$ which associates any $x \in X$, with a real number in the interval [0,1]. $u_{\tilde{A}}(x)$ expresses the membership degree of x in $\tilde{A}$.

Definition 2: The α-cut of fuzzy set $\tilde{A}$ is a crisp set $\tilde{A}_\alpha = \{x|u_{\tilde{A}}(x) \geq \alpha\}$. The support of $\tilde{A}$ is the crisp set $Supp(\tilde{A}) = \{x|u_{\tilde{A}}(x) \geq 0\}$. $\tilde{A}$ is normal if and only if $Supp_{x \in X} u_{\tilde{A}}(x) = 1$.

Definition 3: A fuzzy subset $\tilde{A}$ of the universe set X is convex if and only if $u_{\tilde{A}}(\lambda x + (1-\lambda)y) \geq \min(u_{\tilde{A}}(x), u_{\tilde{A}}(y))$, $\forall x, y \in X$, $\lambda \in [0, 1]$, where min denotes the minimum operator.

Definition 4: $\tilde{A}$ is a fuzzy number if and only if $\tilde{A}$ is a normal and convex fuzzy set of R.

Definition 5: A triangular fuzzy number (TFN) $\tilde{A}$ is defined with piecewise linear membership function $u_{\tilde{A}}(x)$ as follows:

$$u_{\tilde{A}}(x) = \begin{cases} \dfrac{x-l}{m-l}, & l \leq x \leq m, \\ \dfrac{u-x}{u-m}, & m \leq x \leq u, \\ 0, & otherwise, \end{cases} \tag{1}$$

where (l, m, u) is a triplet with l, u being the lower and upper bounds, respectively, and m being the most likely value of $\tilde{A}$.

Definition 6: Let $\tilde{A} = (l_1, m_1, u_1)$ and $\tilde{B} = (l_2, m_2, u_2)$ be two positive triangular fuzzy numbers and r be a positive real number. Then summation, subtraction, multiplication, distance, and inversion of the two triangular fuzzy numbers are defined as follows:

$$\begin{aligned} \tilde{A} \oplus \tilde{B} &= [l_1 + l_2, m_1 + m_2, u_1 + u_2], \\ \tilde{A} \ominus \tilde{B} &= [l_1 - l_2, m_1 - m_2, u_1 - u_2], \\ \tilde{A} \otimes \tilde{B} &= [l_1 \times l_2, m_1 \times m_2, u_1 \times u_2], \\ d(\tilde{A}, \tilde{B}) &= \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]}, \\ \tilde{A} \otimes r &= [l_1 \times r, m_1 \times r, u_1 \times r], \\ (\tilde{A})^{-1} &= (\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}). \end{aligned}$$

B. FUZZY AHP

The AHP method is the MCDM technique proposed by Saaty [39]. Generally, AHP uses comparison judgments and determines their relative importance weights. It is a significant technique for solving complex problems [25]. The AHP method's steps are as follows:

1) Construct the hierarchy structure of a decision and alternatives (See Fig 1.).
2) Compute the criteria weights at each level of the hierarchy.
3) Aggregate the normalized weights to obtain the final scores.

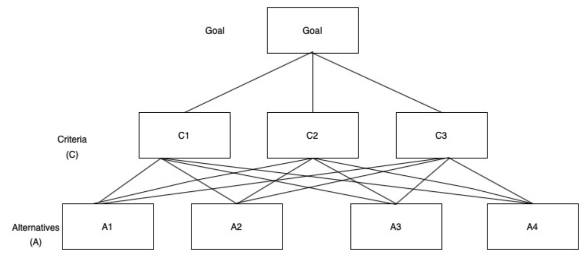

FIGURE 1. The hierarchy structure of decision.

However, the traditional AHP method is unable to deal with ambiguous problems. To relieve the shortcoming, fuzzy AHP is employed to solve uncertain problems more precisely. With fuzzy AHP, the pairwise comparisons of criteria and alternatives are performed through linguistic variables that are presented as triangular fuzzy numbers (TFNs). Various research [24], [35], [36] have applied FAHP to handle data uncertainty. Among the various methods, Chang [40] proposed an extent analysis method to derive weights for fuzzy comparison matrices. It has been adopted in several applications for its computational simplicity [41]–[43]. The algorithm can be described as follows:

Let $X = \{x_1, x_2, \ldots, x_n\}$ be an object set and $U = \{u_1, u_2, \ldots, u_m\}$ be a goal set. According to Chang's extent analysis method [40], each object is taken and an extent analysis for each goal g_i is performed, making it possible to obtain the values of m extent analysis that can be demonstrated as $M_{gi}^1, M_{gi}^2, \ldots, M_{gi}^m$ $i = 1, 2, \ldots, n$ where all the M_{gi}^j $(j = 1, 2, .., m)$ are TFNs.

The steps of Chang's extent analysis can be given as follows [43]:

Step 1: The value of a fuzzy synthetic extent with respect to the i^{th} object is defined as:

$$S_i = \sum_{j=1}^{m} M_{gi}^j \bigotimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right]^{-1} \tag{2}$$

To obtain $\sum_{j=1}^{m} M_{gi}^j$, the fuzzy addition operation of m extent analysis values for a particular matrix is performed such that

$$\sum_{j=1}^{m} M_{gi}^j = \left[\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right] \tag{3}$$

and to obtain $\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j$, the fuzzy addition operation is executed on $M_{gi}^j (j = 1, 2, \ldots, m)$ values such that

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j = \left[\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right] \tag{4}$$

The inverse of the vector in (4) can be computed as:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right]^{-1} = \left[\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right] \tag{5}$$

Step 2: If the M_1 and M_2 are two triangular fuzzy numbers, then the degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as follows:

$$V(M_2 \geq M_1) = \sup_{y \geq x}[\min(\mu_{M_1}(x), \mu_{M_2}(y))] \tag{6}$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d)$$
$$= \begin{cases} 1, & m_2 \geq m_1 \\ 0, & l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases} \tag{7}$$

where d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} (See Fig 2.)

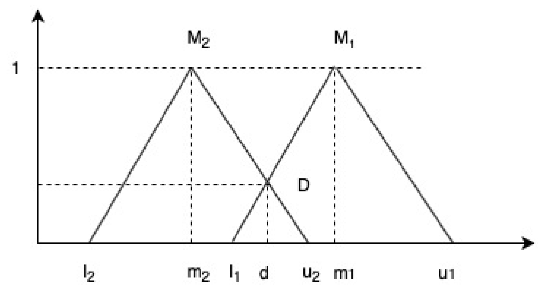

FIGURE 2. **The interaction between M_1 and M_2.**

To compare M_1 and M_2, the values of both $V(M_2 \geq M_1)$ and $V(M_1 \geq M_2)$ are required.

Step 3: Compute the overall degree of possibility for a convex fuzzy number greater than other convex fuzzy numbers M_i $(i = 1, 2, \ldots, k)$, which can be defined as

$$V(M \geq M_1, M_2, \ldots, M_k) = \min V(M \geq M_i), \quad i = 1, 2, \ldots, k \tag{8}$$

Assume that,

$$d'(M_i) = \min V(M_i \geq M_k) \tag{9}$$

for $k = 1, 2, \ldots, n$ and $k \neq i$. The following formula can give the weight vector:

$$W' = (d'(M_1), d'(M_2), \ldots, d'(M_n))^T \tag{10}$$

Step 4: Normalization step: the normalized weight vectors and results are non-fuzzy numbers which are given as:

$$W = (d(M_1), d(M_2), \ldots, d(M_n))^T, \tag{11}$$

where W is a non-fuzzy number.

Step 5: The graded mean integration approach is used to defuzzify the fuzzy weight, where a TFN $P = (l, m, u)$ can be defuzzified to a crisp number as follows:

$$P_{crisp} = \frac{(4m + l + u)}{6} \tag{12}$$

Step 6: It is essential to check the consistency index between the pairwise matrices. The consistency ratio (CR) is defined as the ratio between the consistency of an evaluation index (CI) and the consistency of a random index (RI). Eqs. (13)–(15) calculate the consistency ratio (CR):

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{13}$$

where λ_{max} is the largest eigenvalue of the comparison matrix, and n is the dimension of the matrix.

$$\lambda_{max} = \sum \left[\left(\sum C_j \right) \times \{W\} \right] \tag{14}$$

where $\sum C_j$ is the sum of the pairwise matrix, and W is the weight vector.

$$CR = \frac{CI}{RI(n)} \tag{15}$$

where $RI(n)$ is a random index that depends on n, as shown in Table 1. The acceptance limit for CR is 0.1 or 10%. If the CR is greater than 0.1, the judgment of the pairwise comparison needs to be carried out again to make the decision more consistent.

TABLE 1. **Random Index (*RI*) of random matrices [43].**

N	3	4	5	6	7	8	9
$RI(n)$	0.58	0.90	1.12	1.24	1.32	1.41	1.45

C. INTEGRATION OF THE FAHP AND DEA

DEA, introduced by Charnes [44], is an analytical technique for determining the relative efficiencies of DMUs using several inputs and outputs. There have been abundant applications of combining the FAHP and DEA methods because they are simple and applicable to complex problems with many decision alternatives. This study is developed from previous literature [7], [23], in order to improve the reduction of bias in risk analysis.

The study focuses on MCDM problems with l criteria and n decision alternatives. The normalized weight vector, W_p, is obtained through pairwise comparison in the FAHP.

To define the relative importance of each alternative with respect to each criterion, a set of assessment grades in linguistic terms (such as Very High, High, Medium, Low and Very Low) is constructed for each criterion as $G_p = \{L_{p_1}, .., L_{pK_j}\}$, $\{p = 1, .., l\}$, where $L_{p_1}, .., L_{pK_j}$ represents the linguistic terms of importance ranking from the most to the least important, and K_p is the number of assessment grades for criterion p. This definition evaluates the different numbers of assessment grades and identifies their relative importance for each criterion. Assume that criterion p is assessed by N_p experts. Then, the assessment vectors can be characterized as:

$$R(D_p(A_{ij})) = \{(L_{p_1}, NE_{ijp_1}), \ldots, (L_{pk_j}, NE_{ijpk_j})\} \tag{16}$$

where NE_{ijpk} $(k = 1, .., K_p)$ is the number of experts who assess alternative routes A_{ij} to grade L_{pk} under the

TABLE 2. Decision matrix.

Alternative routes	Decision criteria										
	D_1			$\dots$	D_2			$\dots$	D_l		
	L_{11}	$\dots$	L_{1K_1}	$\dots$	L_{p1}	$\dots$	L_{pK_j}	$\dots$	L_{l_1}	$\dots$	L_{lK_l}
A_{11}	NE_{1111}	$\dots$	NE_{111K_1}	$\dots$	NE_{11p1}	$\dots$	NE_{11pK_j}	$\dots$	NE_{11l_1}	$\dots$	NE_{11lK_l}
$\vdots$	$\vdots$	$\dots$	$\vdots$	$\dots$	$\vdots$	$\dots$	$\vdots$	$\dots$	$\vdots$	$\dots$	$\vdots$
A_{ij}	NE_{ij11}	$\dots$	NE_{ij1K_1}	$\dots$	NE_{ijp1}	$\dots$	NE_{ijpK_j}	$\dots$	NE_{ijl_1}	$\dots$	NE_{ijlK_l}
$\vdots$	$\vdots$	$\dots$	$\vdots$	$\dots$	$\vdots$	$\dots$	$\vdots$	$\dots$	$\vdots$	$\dots$	$\vdots$
A_n	NE_{n11}	$\dots$	NE_{n1K_1}	$\dots$	NE_{np_1}	$\dots$	NE_{npK_j}	$\dots$	NE_{nl1}	$\dots$	NE_{nlK_l}

criterion p. It is indicated that $\sum_{k=1}^{K_p} NE_{ijpk} = N_p$ for $i = 1, .., n; j = 1, .., m$. All the assessment vectors are derived from a decision matrix, listed in Table 2.

Let $S(L_{pk})$ be the scoring of grade $L_{pk}(k = 1, \dots, K_p)$. Thus, the local weight of each alternative with respect to each criterion can be defined as [7], [23]:

$$V_{ijp} = \sum_{k=1}^{K_p} S(L_{pk}) NE_{ijpk}, \quad \text{for} \quad i = 1, .., n; j = 1, .., m; p = 1, .., l \tag{17}$$

The local weight of each alternative with respect to every criterion is computed as a decision-making unit (DMU) using $S(L_{pk})$ as a decision variable and also the weight assigned to the output NE_{ijpk}. Thus, the local weight can be constructed as the following DEA model with common weights [7], [23]:

$$\begin{aligned} &\text{Maximize } \alpha \\ &\text{Subject to } \alpha \leq v_{ijp} = \sum_{k=1}^{K_p} S(L_{pk}) NE_{ijpk} \leq 1, \\ &\quad \text{for } i = 1, .., n; j = 1, .., m; p = 1, .., l \\ &\quad S(L_{p_1}) \geq 2S(L_{p_2}) \geq \dots \geq K_p S(L_{pK_p}) \geq 0 \end{aligned} \tag{18}$$

where $S(L_{p_1}), .., S(L_{pK_j})$ are decision variables and $S(L_{p_1}) \geq 2S(L_{p_2}) \geq \dots \geq K_p S(L_{pK_p}) \geq 0$ is the strong ordering condition imposed on assessment grades proposed by Noguchi *et al.* [45]

The local risk scores of each criterion and decision alternative can be determined by Eq. (18). Then, the local weight of each decision alternative with respect to criterion l is generated by Eq. (17). Subsequently, the simple additive weighting (SAW) method is utilized to aggregate the local weight into an overall weight, as follows [7], [23]:

$$\begin{aligned} V(A_{ij}) &= \sum_{p=1}^{l} W_p V_{ijp} \\ &= \sum_{p=1}^{l} W_p \left(\sum_{k=1}^{K_p} S(L_{pk}) NE_{ijpk} \right) \\ &\quad \text{for } i = 1, .., n; j = 1, .., m; p = 1, .., l \end{aligned} \tag{19}$$

where W_p is the criterion weight determined by the FAHP methodology, $S(L_{pk})$ are the optimal scores of the assessment grades solved by Eq. (18), and $V(A_{ij})$ is the overall weight of n decision alternatives, from which the alternatives are prioritized [7], [23].

IV. CASE STUDY

Multimodal freight transportation has become increasingly complex and vulnerable to various risks across all related activities, making it difficult to predict the process. The multimodal freight transportation system handles a wide range of freight for the main commodities, including coal—one of the world's most important natural resources as it is used in electrical generation and other manufacturing processes. Therefore, in order to identify and evaluate these risks effectively, the combined FAHP and DEA methodology has been proposed to analyze multimodal transportation risks. An actual case study is presented regarding multimodal coal transportation routes between Srichang, Thailand and the cement industry in Saraburi, Thailand. In the following sections, the conceptual framework is discussed the step by step instructions demonstrated in Fig 3.

A. IDENTIFY THE ROUTES

Multimodal transportation routes consist of different segmented routes, which can be classified into two types: where the goods are in motion by some mode of transportation, and where goods come to rest or change to another mode of transport. Thus, the possible routes as A_{ij} are defined where i is a segmented route of multimodal route j.

To study risks of coal logistical services originating from Srichang to a destination in the cement industry in Saraburi, Thailand, the data for possible multimodal transportation routes, including distances in different transport modes are collected through expert interviews. There are 8 possible multimodal logistics routes, which are presented in Table 3 and Appendix A. As an example, the details of the first segmented route in Table 3 are as follows: A_{11} is a route from Srichang to the Pasak River by ship. A_{21} is a route from the Pasak River to Nakornluang Port, also by ship. A_{31} is Nakornluang Port, the point for changing the mode of transport. A_{41} is the truck route from Nakornluang Port to Mittraphap Road. Finally, A_{51} is a route from Mittraphap Road to the cement plant in Saraburi.

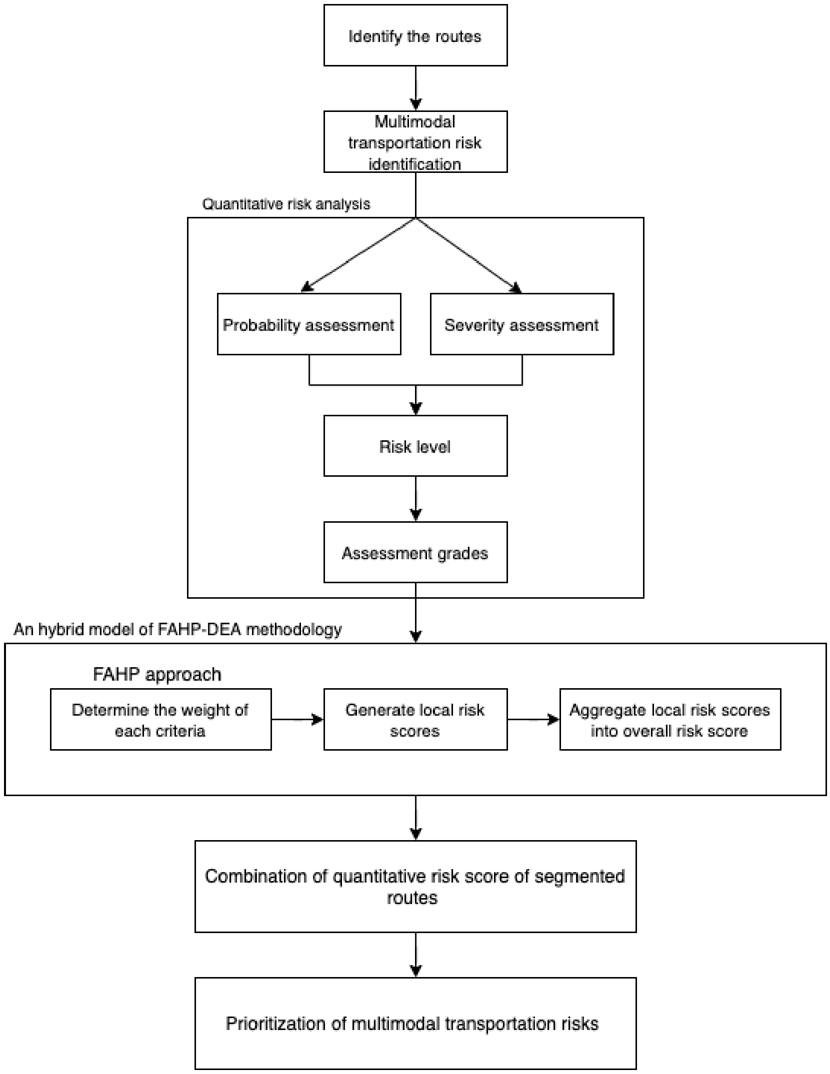

FIGURE 3. **The framework of quantitative risk assessment in multimodal transportation.**

B. RISK IDENTIFICATION

Risk identification is based on expert opinion and previous literature. This study utilizes a qualitative expert opinion system to manage risks in multimodal freight transportation. The expert team was composed of 10 experts who have a neutral understanding of the transportation risk, including logistics managers, shipping managers, academic researchers, etc. The main experts were directly involved in the process of transportation and logistics management for over 20 years (more details in Appendix B.).

The previous literature contained various studies on risk identification for transportation. Kengpol *et al.* [34] identified six risk factors in multimodal transportation including freight-damage risk, infrastructure risk, political risk, operational risk, macro risk, and environment risk. Pallis [46] classified 38 risk factors into five categories: human, machinery, environment, security, and natural. Shankar *et al.* [9] identified 18 categories of risks related to transportation systems. Vilko *et al.* [3] considered and classified risks into two categories of exogenous and endogenous risks (65 and 38 risks respectively).

The identified risks were analyzed by the highly qualified expert panel. Delphi method is the expert survey technique for identifying, prioritizing and aiding in the follow-up of expert interviews in decision-making [7], [14], [34]. To obtain a perspective on multimodal freight transportation risks, experts were asked repeatly until no further change occurs [7], [8].

With respect to experts' opinions, the given factors and their categories have been empirically validated in the multimodal transportation domain. Based on these results, the risk factors can be assessed in terms of the following criteria:

1) Freight-damage risk: This includes damaged or lost products during transfer, delivery at a warehouse, and delivery to a customer [7], [34].

TABLE 3. Possible multimodal transportation routes.

Possible multimodal routes	Segmented routes									
	1	2	3	4	5	6	7	8	9	10
1	A11	A21	A31	A41	A51					
2	A12	A22	A32	A42	A52	A62				
3	A13	A23	A33	A43	A53	A63				
4	A14	A24	A34	A44	A54	A64	A74	A84	A94	A104
5	A15	A25	A35	A45	A55	A65	A75	A85	A95	
6	A16	A26	A36	A46	A56	A66				
7	A17	A27	A37	A47						
8	A18	A28	A38	A48	A58					

2) Infrastructure risk: This includes road density, lanes, tunnels, the facility for handling equipment and material, railway density, transit utilization, etc. [7]
3) Operational risk: This involves document standardization, problems with documents or contracts, lack of skilled workers, strikes, lockouts, stoppage or restraint of labor from any cause, errors in server systems, etc. [34]
4) Security risk: This is a significant consideration in overall transportation risk planning and it includes theft from insiders, terrorism, fire and accidents.
5) Environmental risk: This includes natural phenomena which can have a negative effect on the transportation environment. Examples include natural disasters, climate change, floods, tropical storms and the rainy season [47].

C. QUANTITATIVE RISK ANALYSIS

Risk analysis is a process for identifying, determining, and assessing hazards [34]. It is applied extensively in a variety of applications, including logistics and transportation with a primary aim of minimizing accident occurrences by reducing their possibilities.

This study introduces a valid quantitative risk analysis approach for determining the value of decision variables. The quantitative risk assessment calculates the risk level of an activity which might raise hazards for people, environment, or systems [7]. In traditional transportation, risks can be calculated by multiplying the probability of accident occurrence by accident consequence as indicated in Eq. (20) [7], [48]:

$$R_{ij} = P_{ij} \times C_{ij} \tag{20}$$

where R_{ij} is the risk level along route segment i of multimodal route j, P_{ij} is the possibility of accident occurrence, and C_{ij} represents the consequences of the accident.

Multimodal transportation is a complex system with many categories of risk. The suggestions from experts indicate that the growing risk trend in multimodal transportation is based upon the mode of transportation and shipping distance. Thus, the shipping distance along each segment of a multimodal transportation route affects the quantitative risk analysis—longer distances can lead to higher risk levels. Besides, estimating risk scores relies on the consensus of conflicting expert opinions. Therefore, a proper risk assessment model has been developed to consider the weighted risk level based on shipping distances. The multimodal transportation risk assessment is a MCDM problem which consists of l criteria ($p = 1, .., l$). The ratio between each segmented route and the total multimodal transportation route distance is defined as $\triangle E_{A_{ijpk}}$. The quantitative risk assessment developed from Eq. (20) can be calculated as follows [7]:

$$R_{A_{ijpk}} = P_{A_{ijpk}} \times C_{A_{ijpk}} \times \triangle E_{A_{ijpk}} \tag{21}$$

where $R_{A_{ijpk}}$ is the risk level of segmented route i of multimodal route j for criteria p by expert k who assesses link A_{ij}. $P_{A_{ijpk}}$ is the probability assessment scale rank of A_{ij}. $C_{A_{ijpk}}$ is the severity impact assessment scale of A_{ij}. $\triangle E_{A_{ijpk}}$ is the ratio between distances of segmented route i and the total distance of multimodal route j.

The ranking scales in the probability and severity impact assessments were expressed using the percentage of increased cost and the increased time of logistics on the route, as illustrated in Table 4. This table was developed from previous studies and experts' opinions. In this study, there were 10 experts who have experience in transportation fields. The decision-making environment necessitates reliance on the opinions of multiple experts. However, expert decision-makers may not always give the same importance to the decision being made or specifics of a decision-making transaction because they may not always have equal degrees of relevancy, knowledge, and experience with respect to a specific decision.

To simplify experts' assessment while selecting scores, the measures of these criteria need to be converted into linguistic terms, defined as Very High, High, Medium, Low, and Very Low [24]. A visual representation is used to map multimodal transportation risks and define a set of assessment grades in linguistic terms. A risk matrix consists of a probability assessment scale rank (1–5) on the horizontal axis and a severity impact assessment scale rank (1–5) on the vertical axis, as shown in Fig. 4.

After identifying transportation risks, their quantitative values are calculated based on the risk level using Eq. (21). The risk matrix is then converted into assessment grades in linguistic variables. This process is necessary to define a set of assessment grades to describe multimodal transportation risk quantitatively. The risk assessment data are illustrated in Table 9 (more details in the next section).

TABLE 4. The rank of probability and severity assessment scale (adapted from Kengpol and Tuammee [7]).

Rank	Probability (% of accident or occurrence rate) (P)	Severity: Freight-damage risk (% of increased cost of logistics) (C)	Infrastructure risk (of increased time of logistics) (C)	Operational risk (of increased time of logistics) (C)	Security risk (% of increased cost of logistics) (C)	Environmental risk (of increased time of logistics) (C)
1	1%	<1%	1 day	1 day	<1%	1 day
2	<10%	1–5%	<1 week	<1 week	1–5%	1week
3	<20%	6–10%	2 weeks	2 weeks	6–10%	2 weeks
4	20–50%	11–20%	1 month	1 month	11–20%	1 month
5	>50%	>20%	>1 month	>1 month	>20%	>1 month

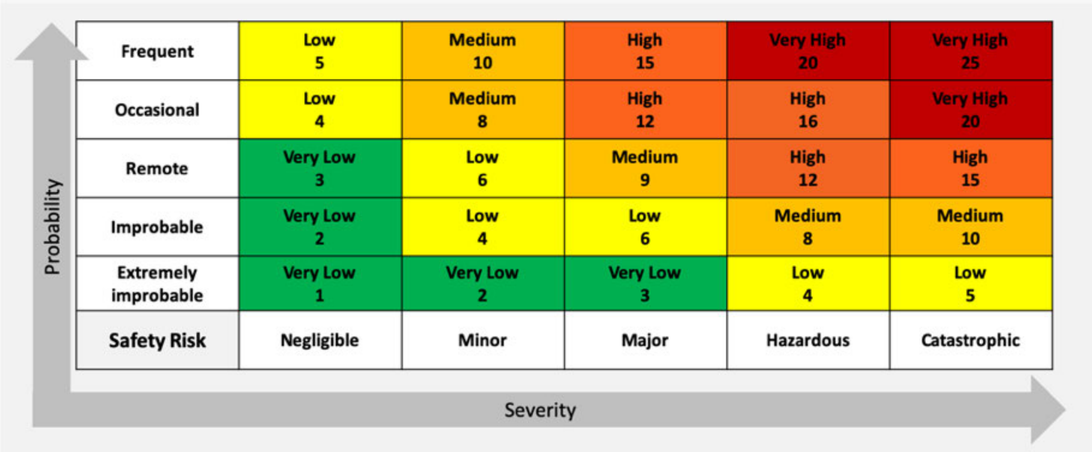

FIGURE 4. Risk matrix based on expert opinions.

The following illustrates the calculation of the risk level of the segmented route A_{11} shown in Table 3. For freight-damage risk, the segmented route A_{11} can be assessed as follows. The first expert defines the probability rank as $P_{A_{1111}} = 3$ and the impact severity rank as $C_{A_{1111}} = 3$. The ratio between the distance of segmented route and the total distance of the route is $\triangle E_{A_{1111}} = \frac{195km}{207km} = 0.942$. Thus, the risk level of $R_{A_{1111}}$ for freight-damage risk on segmented route A_{11} is $3 \times 3 \times 0.942 = 8.478$. Consequently, the risk score can be approximately measured by the risk magnitude in Fig. 4 as Medium. Furthermore, experts 1–5 assess it to be Medium and experts 6–9 assess risk as Low. The last expert evaluates it to be Very Low. The rest of the data for other cases can be described in a similar way in Table 9.

D. DETERMINATION OF THE WEIGHTS OF CRITERIA USING FAHP

In this study, risks in the context of multimodal transportation were identified based on literature review and expert interviews. Due to the meaning and similarities of transportation risks, these risks are grouped into five categories, namely freight-damage risk, infrastructure risk, operational risk, security risk, and environmental risk. The identified risks were analyzed to determine their importance weights using the FAHP method. The data collected will be converted into the Geometric Mean to measure the pairwise comparison.

In order to determine the criteria for the risk analysis process, decision-makers or experts consider the pairwise judgment matrices and evaluate their relative importance weights with respect to the goals, using linguistic terms. These linguistic evaluations are subsequently transformed into TFNs by means of the conversation scale presented in Table 5. Pairwise judgment matrices are finalized based on the experts' opinion and transformed into positive fuzzy numbers using the standard TFNs. The constructed fuzzy pairwise judgment matrices for various categories of risk are presented in Table 6.

TABLE 5. Fuzzy linguistic scale.

Uncertainty judgment	Triangular fuzzy scale	Triangular reciprocal scale
Equally important	(1,1,1)	(1,1,1)
Weakly important	(2,3,4)	(1/4,1/3,1/2)
Fairly important	(4,5,6)	(1/6,1/5,1/4)
Strongly important	(6,7,8)	(1/8,1/7,1/6)
Absolutely important	(9,9,9)	(1/9,1/9,1/9)

To test the consistency of the pairwise matrix, the consistency in a crisp comparison matrix are evaluated by following the criteria discussed in step 6 of Fuzzy AHP section. A triangular fuzzy number of the pairwise comparison matrix of the risk categories is defuzzified to a crisp number in Eq. (12). According to the result, the λ_{max} of the fuzzy crisp

TABLE 6. Risk factors pairwise comparison matrix.

	Freight-damage risk	Infrastructure risk	Operational risk	Security risk	Environmental risk
Freight-damage risk	**(1.00,1.00,1.00)**	(4.00,5.00,6.00)	(2.00,3.00,4.00)	(2.00,3.00,4.00)	(2.00,3.00,4.00)
Infrastructure risk	(0.17,0.20,0.25)	**(1.00,1.00,1.00)**	(4.00,5.00,6.00)	(4.00,5.00,6.00)	(4.00,5.00,6.00)
Operational risk	(0.25,0.33,0.50)	(0.17,0.20,0.25)	**(1.00,1.00,1.00)**	(6.00,7.00,8.00)	(6.00,7.00,8.00)
Security risk	(0.25,0.33,0.50)	(0.17,0.20,0.25)	(0.13,0.14,0.17)	**(1.00,1.00,1.00)**	(1.00,1.00,1.00)
Environmental risk	(0.25,0.33,0.50)	(0.17,0.20,0.25)	(0.13,0.14,0.17)	(1.00,1.00,1.00)	**(1.00,1.00,1.00)**

TABLE 7. Normalized matrix of risk factors.

	Freight-damage risk	Infrastructure risk	Operational risk	Security risk	Environmental risk
Freight-damage risk	**(1.00,1.00,1.00)**	(1.74,2.14,2.49)	(2.70,3.38,4.00)	(3.10,4.21,5.28)	(2.70,3.38,4.00)
Infrastructure risk	(0.40 0.47 0.57)	**(1.00,1.00,1.00)**	(4.70,5.72,6.73)	(4.70,5.72,6.73)	(3.03,4.08,5.10)
Operational risk	(0.25,0.30,0.37)	(0.15,0.17,0.21)	**(1.00,1.00,1.00)**	(3.37,4.00,4.59)	(1.43,1.48,1.52)
Security risk	(0.25,0.30,0.37)	(0.20,0.25,0.33)	(0.66,0.68,0.70)	**(1.00,1.00,1.00)**	(1.00,1.00,1.00)
Environmental risk	(0.19,0.24,0.32)	(0.15,0.17,0.21)	(0.22,0.25,0.30)	(1.00,1.00,1.00)	**(1.00,1.00,1.00)**

matrix is 5.301. The dimension of matrix is 5; thus the RI is 1.12 for $n = 5$ (Table 1). The calculation of the consistency index (CI) and the consistency ratio (CR) are represented in Eqs.(13)–(15). The value of CI is 0.075 and CR is 0.070, which is smaller than 10%. Thus, the pairwise comparison matrix developed for the multimodal risk factors is consistent and acceptable.

When the consistency in the comparison matrix is accepted, the fuzzy values of pairwise comparison are converted to crisp values through Chang's extent analysis as mentioned above (Table 7). First, the fuzzy synthesis extent values and the priority weights are calculated using Eq. (2). Equations (3)-(5) are used to present the degree of the synthetic extent values. An example of the weight calculation and these values are obtained:

$$\begin{aligned}\sum_{j=1}^{5} M_{g_1}^{j} &= (1.00, 1.00, 1.00) + (1.74, 2.14, 2.49)\\ &\quad + (2.70, 3.38, 4.00) + (3.10, 4.21, 5.28)\\ &\quad + (2.70, 3.38, 4.00) = (11.25, 14.11, 16.77)\end{aligned}$$

$$\begin{aligned}\sum_{i=1}^{5}\sum_{j=1}^{5} M_{g_i}^{j} &= (11.25, 14.11, 16.77)+(13.84, 16.98, 20.14)\\ &\quad + (6.20, 6.95, 7.69) + (3.11, 3.22, 3.40)\\ &\quad + (2.56, 2.66, 2.83)=(36.948, 43.926, 50.835)\end{aligned}$$

$$\begin{aligned}\left[\sum_{i=1}^{5}\sum_{j=1}^{5} M_{g_i}^{j}\right]^{-1} &= \left(\frac{1}{50.835}, \frac{1}{43.926}, \frac{1}{36.948}\right)\\ &= (0.020, 0.023, 0.027)\end{aligned}$$

Once the weight vector is derived by Eq. (6), the step of the normalized weight vector (N_i) is used to obtain the priority weight vector of each criteria by Eqs. (10)–(11). Thus, the minimum degree of possibility for each pairwise comparison is computed as:

$$d'(F) = \min V(F \geq I, O, S, E) = 0.329$$

$$d'(I) = \min V(I \geq F, O, S, E) = 0.398$$
$$d'(O) = \min V(O \geq F, I, S, E) = 0.162$$
$$d'(S) = \min V(S \geq F, I, O, E) = 0.075$$
$$d'(E) = \min V(E \geq F, I, O, S) = 0.062$$

Therefore, the weight vector is computed as $W' = (0.329, 0.398, 0.162, 0.075, 0.062)$. The preference weights are normalized for each risk as $W = (0.321, 0.388, 0.157, 0.073, 0.061)$. In other words, the relative weight criteria from FAHP for freight-damage risk, infrastructure risk, operational risk, security risk, and environmental risk are 0.321, 0.388, 0.157, 0.073 and 0.061 respectively, as shown in Table 8.

TABLE 8. Fuzzy weight of risk factors and their categories.

Categories	Important weight	Ranking
Freight-damage risk (F)	0.321	2
Infrastructure risk (I)	0.388	1
Operational risk (O)	0.157	3
Security risk (S)	0.073	4
Environmental risk (E)	0.061	5

E. AN HYBRID MODEL OF FAHP-DEA METHODOLOGY

The proposed model of FAHP-DEA can classify alternatives into different categories for each criterion, which are characterized by linguistic assessment grades [23]. Moreover, the integration of the FAHP and DEA methodology can solve an MCDM problem with a large number of decision alternatives.

This case study has five main criteria with 51 alternatives. The FAHP method is used to evaluate the criteria weights. It intends to determine the overall risk score of each segmented route. From the previous section, the importance weights of freight-damage risk, infrastructure risk, operational risk, security risk and environmental risk are 0.321, 0.388, 0.157, 0.073, and 0.061, respectively.

To quantitatively describe multimodal transportation risks, a set of assessment grades need to be defined for each of the five risk criteria. For example, the following set of assessment

TABLE 9. Risk assessment data.

Segmented route	Assessment criteria																								
	Freight-damage risk					Infrastructure risk					Operational risk					Security risk					Environmental risk				
	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL	VH	H	M	L	VL
A_{11}	0	0	5	4	1	0	0	0	10	0	0	2	5	3	0	0	2	6	1	1	0	0	5	3	2
A_{21}	0	0	5	5	0	0	0	0	0	10	0	0	5	5	0	1	2	3	2	2	4	6	0	0	0
A_{31}	0	0	2	3	5	3	4	1	1	1	1	1	4	2	2	0	0	10	0	0	0	4	6	0	0
A_{41}	0	0	0	0	10	0	4	4	1	1	1	5	4	0	0	1	1	8	0	0	2	2	4	1	1
A_{51}	0	0	5	5	0	0	0	0	0	10	0	4	6	0	0	0	1	9	0	0	2	2	6	0	0
A_{12}	2	3	3	1	1	1	2	7	0	0	0	1	6	3	0	2	5	2	1	0	0	10	0	0	0
A_{22}	0	0	0	5	5	0	1	5	2	2	1	1	8	0	0	0	0	10	0	0	0	10	0	0	0
A_{32}	0	0	10	0	0	2	2	2	2	2	0	0	2	4	4	0	2	3	5	0	0	3	7	0	0
A_{42}	1	2	4	2	1	2	4	4	0	0	0	1	9	0	0	0	0	2	4	4	0	4	3	2	1
A_{52}	0	0	0	10	0	3	2	2	2	1	0	0	0	0	10	1	1	2	3	3	0	5	5	0	0
A_{62}	2	5	2	1	0	2	1	5	1	1	0	1	1	4	4	0	0	0	3	7	0	10	0	0	0
A_{13}	0	0	3	7	0	2	1	2	2	3	0	2	8	0	0	0	1	5	4	0	0	10	0	0	0
A_{23}	0	2	2	6	0	0	0	0	5	5	0	1	9	0	0	0	0	10	0	0	0	10	0	0	0
A_{33}	0	0	10	0	0	0	3	4	3	0	0	0	10	0	0	0	0	10	0	0	0	2	4	4	0
A_{43}	0	0	0	5	5	0	0	5	5	0	0	0	10	0	0	0	1	9	0	0	2	1	3	2	2
A_{53}	0	0	3	7	0	0	0	0	5	5	0	0	4	6	0	0	0	10	0	0	0	2	3	0	5
A_{63}	0	0	1	9	0	0	0	2	8	0	0	0	3	7	0	0	0	5	5	0	2	1	5	1	1
A_{14}	0	0	0	0	10	0	0	0	4	6	0	0	0	8	2	0	0	6	4	0	0	2	8	0	0
A_{24}	2	1	7	0	0	0	0	10	0	0	0	1	5	4	0	0	0	4	6	0	0	1	9	0	0
A_{34}	1	1	5	2	1	1	2	3	2	2	0	1	8	1	0	0	0	10	0	0	2	3	3	1	1
A_{44}	1	2	1	3	3	0	1	9	0	0	0	3	7	0	0	0	2	3	5	0	0	3	6	0	1
A_{54}	2	2	2	2	2	0	1	7	2	0	0	0	10	0	0	2	2	2	2	2	0	2	2	3	3
A_{64}	0	4	1	3	2	0	1	8	1	0	0	0	10	0	0	0	0	0	0	10	0	3	7	0	0
A_{74}	1	1	1	4	3	0	1	9	0	0	0	0	9	1	0	2	0	4	4	0	0	0	10	0	0
A_{84}	0	2	5	3	0	0	0	10	0	0	2	6	2	0	0	0	2	8	0	0	0	0	5	5	0
A_{94}	2	1	5	2	0	0	0	10	0	0	0	0	10	0	0	0	1	4	5	0	0	0	0	5	5
A_{104}	0	0	2	4	4	0	1	8	1	0	0	0	0	5	5	1	2	3	2	2	0	1	4	5	0
A_{15}	1	1	6	1	1	0	1	9	0	0	0	6	2	2	0	0	3	2	5	0	0	2	6	2	0
A_{25}	0	0	7	3	0	0	0	10	0	0	0	0	10	0	0	2	4	2	1	1	2	3	3	1	1
A_{35}	1	1	8	0	0	1	1	3	3	2	0	2	8	0	0	1	2	4	2	1	1	1	5	2	1
A_{45}	1	2	5	2	0	1	2	4	2	1	0	3	4	3	0	0	1	5	4	0	2	2	6	0	0
A_{55}	3	2	5	0	0	0	0	8	2	0	0	1	9	0	0	0	3	6	1	0	0	1	9	0	0
A_{65}	1	2	4	3	0	0	0	0	5	5	0	1	5	2	2	0	2	3	5	0	1	1	8	0	0
A_{75}	1	1	4	2	2	0	0	6	4	0	1	1	3	4	1	0	0	10	0	0	0	1	9	0	0
A_{85}	0	0	5	5	0	1	1	2	6	0	2	1	5	1	1	0	0	10	0	0	0	0	10	0	0
A_{95}	2	1	7	0	0	0	0	7	3	0	2	2	4	1	1	0	0	5	5	0	0	0	10	0	0
A_{16}	0	0	5	5	0	2	2	4	1	1	0	0	10	0	0	0	0	5	5	0	0	0	10	0	0
A_{26}	2	1	4	3	0	3	2	3	2	0	0	0	0	0	10	0	0	7	3	0	0	0	10	0	0
A_{36}	0	3	4	3	0	0	0	3	7	0	5	5	0	0	0	0	1	8	1	0	0	0	10	0	0
A_{46}	2	2	6	0	0	1	1	6	1	1	0	5	5	0	0	2	2	4	1	1	0	1	9	0	0
A_{56}	2	0	7	1	0	0	1	9	0	0	0	0	10	0	0	1	1	3	3	2	1	1	8	0	0
A_{66}	0	1	8	1	0	0	0	10	0	0	0	4	3	3	0	2	2	5	1	0	2	2	5	1	0
A_{17}	0	0	5	5	0	0	2	8	0	0	1	1	8	0	0	2	3	3	1	1	0	10	0	0	0
A_{27}	0	3	4	3	0	3	5	2	0	0	4	6	0	0	0	2	4	2	2	0	2	2	4	1	1
A_{37}	2	2	3	2	1	0	0	5	5	0	0	8	2	0	0	0	4	4	2	0	0	0	10	0	0
A_{47}	1	2	6	0	1	0	5	5	0	0	0	3	5	2	0	0	2	5	3	0	0	0	0	0	10
A_{18}	0	0	4	3	3	0	0	10	0	0	0	0	10	0	0	0	0	2	2	6	0	8	2	0	0
A_{28}	5	5	0	0	0	5	5	0	0	0	2	8	0	0	0	0	0	3	7	0	1	1	5	2	1
A_{38}	0	0	5	5	0	4	6	0	0	0	3	5	2	0	0	0	0	0	2	8	2	1	6	1	0
A_{48}	0	0	10	0	0	1	2	5	1	1	0	10	0	0	0	0	2	6	2	0	3	5	1	1	0
A_{58}	0	0	6	4	0	0	3	3	2	2	0	0	8	2	0	0	0	7	3	0	0	1	9	0	0

Note: VH is Very High, H is High, M is Medium, L is Low and VL is Very Low.

grades is defined for the five criteria by $G = \{\text{Very High, High, Medium, Low, Very Low}\} = \{VH, H, M, L, VL\}$. The numbers and different sets of assessment grades were defined according to the risk matrix.

Table 9 presents the distribution decision matrix of assessment results for the 51 segmented routes, which were assessed by 10 experts. Consider freight-damage risk for the segmented route A_{11}, five experts assessed the grades as "Medium", four experts assessed it as "Low", and one expert assessed it as "Very Low". For the other segmented routes, assessment data can be described in the same way. The risk assessment data are subsequently used to generate the local risk scores for each criterion by the DEA model in Eq. (17).

The optimal solution for all decision variables $S(L_{pk})$ can be calculated as:

Let the freight-damage risk assessment in Table 9 be an example to calculate the optimal solution of decision variables $S(L_{pk})$, solving by Eq. (18). $S(L_{pk})$ is a decision variable and the weight assigned to the output NE_{ijpk}. Then, the DEA

TABLE 10. The optimal solution of each criterion.

	Optimal solutions					
Criteria	$S(VH)$	$S(H)$	$S(M)$	$S(L)$	$S(VL)$	α
Freight-damage risk	0.13333	0.066667	0.044444	0.033333	0.026666	0.999985
Infrastructure risk	0.13333	0.066667	0.044444	0.033333	0.026667	0.999985
Operational risk	0.13333	0.066666	0.044444	0.033333	0.026666	0.999985
Security risk	0.18462	0.092307	0.061537	0.046151	0.036917	0.867769
Environmental risk	0.14286	0.071428	0.047619	0.035714	0.028571	1.000000

model with common weights can be constructed as follows:

Maximize α

Subject to

$$
\begin{aligned}
&0S(VH_{11})+0S(H_{11})+5S(M_{11})+4S(L_{11})+1S(VL_{11}) \leq 1\\
&0S(VH_{11})+0S(H_{11})+5S(M_{11})+5S(L_{11})+0S(VL_{11}) \leq 1\\
&0S(VH_{11})+0S(H_{11})+2S(M_{11})+3S(L_{11})+5S(VL_{11}) \leq 1\\
&0S(VH_{11})+0S(H_{11})+0S(M_{11})+0S(L_{11})+10S(VL_{11}) \leq 1\\
&0S(VH_{11})+0S(H_{11})+5S(M_{11})+5S(L_{11})+0S(VL_{11}) \leq 1\\
&\vdots\\
&0S(VH_{11})+0S(H_{11})+6S(M_{11})+4S(L_{11})+0S(VL_{11}) \leq 1\\
&S(VH_{11})+0S(H_{11})+0S(M_{11})+0S(L_{11})+0S(VL_{11})\\
&\qquad \geq 2S(H_{11})\\
&0S(VH_{11})+2S(H_{11})+0S(M_{11})+0S(L_{11})+0S(VL_{11})\\
&\qquad \geq 3S(M_{11})\\
&0S(VH_{11})+0S(H_{11})+3S(M_{11})+0S(L_{11})+0S(VL_{11})\\
&\qquad \geq 4S(L_{11})\\
&0S(VH_{11})+0S(H_{11})+0S(M_{11})+4S(L_{11})+0S(VL_{11})\\
&\qquad \geq 5S(VL_{11})\\
&S(VH_{11}), S(H_{11}), S(M_{11}), S(L_{11}), S(VL_{11}) \geq 0 \qquad (22)
\end{aligned}
$$

where $S(VH)$, $S(H)$, $S(M)$, $S(L)$ and $S(VL)$ are the optimal scores of the assessment grades "Very High", "High", "Medium", "Low", "Very Low", respectively and α is the optimal local weight of each criterion. Additionally, the optimal solutions of decision variables $S(L_{pk})$ for other criteria can be computed in a similar way.

The local weight of each decision alternative with respect to every criterion is determined as a DMU, where $S(L_{pk})$ is a decision variable and also the weight assigned to the output NE_{ijpk}. The following optimal solutions of each criterion $S(L_{pk})$ are calculated using Eq. (18). For freight-damage risk, infrastructure risk, and operational risk, the optimal solutions are as follows:
$S(VH) = 0.13333$, $S(H) = 0.066667$, $S(M) = 0.044444$, $S(L) = 0.033333$, $S(VL) = 0.026666$ and $\alpha = 0.999985$

The following optimal solutions are obtained for security risk and environmental risk, respectively.
$S(VH) = 0.18462$, $S(H) = 0.092307$, $S(M) = 0.061537$, $S(L) = 0.046151$, $S(VL) = 0.036917$ and $\alpha = 0.867769$
$S(VH) = 0.14286$, $S(H) = 0.071428$, $S(M) = 0.047619$, $S(L) = 0.035714$, $S(VL) = 0.028571$ and $\alpha = 1.000000$

Thus, the optimal solutions of each criterion $S(L_{pk})$ are illustrated in Table 10. Consequently, these optimal solutions can be used to calculate the local risk scores of the 51 segmented routes with respect to each of the five criteria using Eq. (16), presented in Table 11.

The final step is to aggregate local risk scores into overall risk scores for each decision alternative using the SAW method in Eq. (19). The results, along with the risk priority ranking, are presented in Table 12.

The example of local risk calculation for segmented route A_{11} is shown below:

Freight-damage risk:
$(5\times0.044444)+(4\times0.033333)+(1\times0.026666) = 0.382218$
Infrastructure risk:
$10 \times 0.033333 = 0.333333$
Operational risk:
$(2\times0.066666)+(5\times0.044444)+(3\times0.033333) = 0.455551$
Security risk:
$(2 \times 0.092307) + (6 \times 0.061537) + (1 \times 0.046151) + (1 \times 0.036917) = 0.636904$
Environmental risk:
$(5\times0.047619)+(3\times0.035714)+(2\times0.028571) = 0.402379$

As stated in the previous section, the relative weight criteria from FAHP can be determined to complete the overall transportation risk scores in Table 12. The overall risk score can be solved by the SAW method in Eq. (19). Thus, the total risk score in segmented route A_{11} can be calculated as follows: $V(A_{11}) = (w_1v_{111}) + (w_2v_{111}) + (w_3v_{111}) + (w_4v_{111}) + (w_5v_{111}) = (0.321 \times 0.382) + (0.388 \times 0.333) + (0.157 \times 0.455) + (0.073 \times 0.637) + (0.061 \times 0.402) = 0.394$

The last step is to combine the risk scores in each segmented multimodal route. Table 12 represents the quantitative risk scores of multimodal routes with risk priority ranking.

Based on the ranking in Table 12, these risks can be prioritized: the highest risk score is 4.747 in route 4 and the lowest is 2.241 in route 1. The optimal multimodal transportation route is route 1 from Srichang to the Pasak River by ship. Then, to Nakornluang Port, also by ship; switching to truck transport to Mittraphap Road; and finally, shipping by truck from Mittraphap Road to the cement plant in Saraburi.

Table 12 provides a breakdown of the risk analysis results. Of the 5 risks identified in the interview and literature, possible multimodal routes have been evaluated on the basis of corresponding FAHP and DEA methods. It is apparent that the highest overall risk score is for route 4 because of several

TABLE 11. The overall multimodal transportation risk scores.

Segmented route	The overall multimodal transportation risk scores					Overall risk scores	Risk priority ranking
	Freight-damage risk (0.321)*	Infrastructure risk (0.388)*	Operational risk (0.157)*	Security risk (0.073)*	Environmental risk (0.061)*		
A_{11}	0.382218	0.333333	0.455551	0.636904	0.402379	0.394608	49
A_{21}	0.388885	0.266667	0.388885	0.719981	1.000008	0.402603	47
A_{31}	0.322217	0.771102	0.497777	0.615370	0.571426	0.560503	11
A_{41}	0.266666	0.504444	0.644436	0.769223	0.683337	0.480291	37
A_{51}	0.388885	0.266667	0.533328	0.646140	0.714290	0.402669	46
A_{12}	0.659992	0.577772	0.433329	1.000000	0.714280	0.620514	4
A_{22}	0.299995	0.408887	0.555548	0.615370	0.714280	0.430562	43
A_{32}	0.444444	0.608882	0.328884	0.599980	0.547617	0.507650	30
A_{42}	0.537772	0.711104	0.466662	0.455346	0.528568	0.587257	8
A_{52}	0.333333	0.715545	0.266660	0.649205	0.595235	0.510041	28
A_{62}	0.722216	0.615547	0.351106	0.396872	0.714280	0.598170	6
A_{13}	0.366663	0.568882	0.488884	0.769216	0.714280	0.514784	22
A_{23}	0.582216	0.566666	0.466662	0.615370	0.714280	0.568399	9
A_{33}	0.444444	0.557777	0.444444	0.615370	0.590472	0.509728	29
A_{43}	0.299995	0.388885	0.444444	0.646140	0.628575	0.402372	48
A_{53}	0.366663	0.566666	0.377774	0.615370	0.428568	0.467918	39
A_{63}	0.344441	0.355552	0.366663	0.538440	0.659528	0.385473	50
A_{14}	0.266666	0.293334	0.319996	0.553826	0.523808	0.321927	51
A_{24}	0.644435	0.444444	0.422218	0.523054	0.499999	0.514253	23
A_{34}	0.515549	0.519996	0.455551	0.615370	0.707146	0.526706	20
A_{44}	0.491105	0.466663	0.511106	0.599980	0.528569	0.494985	33
A_{54}	0.608888	0.444444	0.444444	0.843064	0.430949	0.525524	21
A_{64}	0.464443	0.455552	0.444444	0.369170	0.547617	0.455919	41
A_{74}	0.457771	0.466663	0.433329	0.799992	0.476190	0.483473	37
A_{84}	0.455553	0.444444	0.755544	0.676910	0.416665	0.512278	25
A_{94}	0.622213	0.444444	0.444444	0.569210	0.321425	0.503185	32
A_{104}	0.328884	0.455552	0.299995	0.719981	0.440474	0.408788	45
A_{15}	0.526666	0.466663	0.555555	0.630750	0.499998	0.513916	24
A_{25}	0.411107	0.444444	0.444444	0.944610	0.707146	0.486146	35
A_{35}	0.555549	0.486662	0.488884	0.744601	0.552382	0.531937	17
A_{45}	0.555555	0.537773	0.477773	0.584596	0.714290	0.548130	13
A_{55}	0.755544	0.422218	0.466662	0.692294	0.499999	0.560657	10
A_{65}	0.544439	0.300000	0.408884	0.599980	0.595240	0.435382	42
A_{75}	0.497771	0.399996	0.493326	0.615370	0.499999	0.467855	40
A_{85}	0.388885	0.488883	0.615545	0.615370	0.476190	0.485185	36
A_{95}	0.644435	0.411107	0.637767	0.538440	0.476190	0.534937	15
A_{16}	0.388885	0.637777	0.444444	0.538440	0.476190	0.510400	27
A_{26}	0.611102	0.733322	0.266666	0.569212	0.476190	0.593080	7
A_{36}	0.477776	0.366663	0.999988	0.630754	0.476190	0.527947	19
A_{46}	0.666658	0.526661	0.555555	0.883070	0.499999	0.600566	5
A_{56}	0.611101	0.466663	0.444444	0.673825	0.595240	0.532441	16
A_{66}	0.455552	0.444444	0.499995	0.907690	0.702385	0.506178	31
A_{17}	0.388885	0.488886	0.555548	0.913840	0.714280	0.511933	26
A_{27}	0.477776	0.822213	0.933316	0.953844	0.683337	0.730328	2
A_{37}	0.626658	0.388885	0.622216	0.707678	0.476190	0.530515	18
A_{47}	0.559994	0.555555	0.488884	0.630752	0.285710	0.535653	14
A_{18}	0.357773	0.444444	0.444444	0.436878	0.666662	0.429504	44
A_{28}	0.999985	0.999985	0.799988	0.507668	0.552382	0.905481	1
A_{38}	0.388885	0.933322	0.822208	0.387638	0.678576	0.685781	3
A_{48}	0.444444	0.548884	0.666666	0.646138	0.869053	0.560359	12
A_{58}	0.399996	0.586663	0.422218	0.569212	0.499999	0.494326	34

*Relative weights from FAHP.

changes in the mode of transportation and longer required lead time. The main aim of risk analysis is to reduce the impact of uncontrollable accidents on the working transportation process. The results could alert the user to select the appropriate corrective action and reduce time consumption.

This study supports the development of a valid decision support approach that is flexible and applicable to an industrial sector adopting multimodal transportation risk practices. In this perspective, the present work attempts to contribute to the reliable literature and expert knowledge by presenting the identification, analysis and prioritization of risks. The list of risks identified would certainly facilitate users in understanding the theory of risks. Moreover, coal industry companies were examined in the study. Comparing the risks arising from fundamentally different activities along a multimodel transportation route requires care in the wise selection of the appropriate route from the alternatives, which are ranked as routes 1, 7, 3, 8, 2, 6, 5, 4, from least to the most risky. Route 4 has the highest risk score and needs a higher level of managerial attention as compared to other routes.

TABLE 12. The quantitative risk scores of multimodal routes with risk priority ranking.

Possible multimodal routes	Segmented routes 1	2	3	4	5	6	7	8	9	10	Overall risk scores	Risk priority ranking
1	A11	A21	A31	A41	A51						2.241	8
2	A12	A22	A32	A42	A52	A62					3.254	4
3	A13	A23	A33	A43	A53	A63					2.849	6
4	A14	A24	A34	A44	A54	A64	A74	A84	A94	A104	4.747	1
5	A15	A25	A35	A45	A55	A65	A75	A85	A95		4.564	2
6	A16	A26	A36	A46	A56	A66					3.271	3
7	A17	A27	A37	A47							2.308	7
8	A18	A28	A38	A48	A58						3.075	5

The results show that the integrated FAHP-DEA for risk analysis in multimodal transportation can help users select a better decision on the optimal-risk route.

F. COMPARISON WITH OTHER DECISION-MAKING APPROACHES

Comparison and correlation analysis of the integrated FAHP-DEA model with results of other fuzzy multi-criteria decision making (MCDM) approaches are conducted to ensure greater consistency and validity of the model. The advantage of the integrated FAHP-DEA model is presented by its comparison with well-known fuzzy MCDM approaches for determining the criteria weight, a category to which the FAHP and DEA methods also belong. The fuzzy best-worst method (FBWM) [49] and fuzzy full consistency method (FFUCOM) [50] were investigated, since the validity of both MCDM methodologies are based on the concept of pairwise comparison and the degree of consistency, which are the fundamental foundation of the FAHP and DEA methods.

Each of the selected models was analyzed through the previous discussion in which the DEA, FAHP-DEA, FBWM-DEA and FFUCOM-DEA models were employed. For the purpose of validation, the obtained results will present the risk factor priority and the route ranking.

Mathematical models were performed in a similar way for the risk calculations. The weight coefficients for comparison with similar subject models—FAHP, FBWM and FFUCOM—were further utilized on as input data in the DEA model (Table 13), and the final results of DEA, FAHP-DEA, FBWM-DEA and FFUCOM-DEA models are illustrated in Table 14.

The alternative ranking discussed previously indicated that route 4 was selected due to its the highest weight with respect to other risk factors. Furthermore, the FAHP-DEA and FFUCOM-DEA models yielded the same ranking results, while the DEA and FBWM-DEA models gave different rankings.

From the results obtained in Table 13, it can be noted that these weights are different due to a number of reasons, summarized briefly below:

1) In the initial stage of determining the weight coefficients of the FAHP, FBWM, and FFUCOM models

TABLE 13. Alternative risk criteria weight ranks.

Methods		Risk factors F	I	O	S	E
FAHP	w_j	0.321	0.388	0.157	0.073	0.061
	Rank	2	1	3	4	5
FBWM	w_j	0.290	0.424	0.116	0.120	0.050
	Rank	2	1	4	3	5
FFUCOM	w_j	0.322	0.401	0.120	0.113	0.044
	Rank	2	1	3	4	5

(Table 13), FFUCOM only requires $n - 1$ pairwise comparisons, whereas FBWM requires $2n-3$ pairwise comparisons, and for FAHP, it is necessary to perform $n(n-1)/2$ pairwise comparisons.

2) When comparing the pairwise matrix, FBWM uses integer values, unlike FAHP, which requires the use of a ratio scale. On the contrary, FFUCOM can apply any scale (integer or decimal).

3) The FBWM and FAHP models rely on adherence to mathematical transitivity. FFUCOM allows satisfying the complete consistency of the model while respecting the conditions of transitivity.

G. RESULT VALIDATION USING SPEARMAN's RANK AND PEARSON CORRELATION COEFFICIENT

The correlation analysis is considered to describe the direction and strength of the relationship between two variables. Possible correlations range from $+1$ to -1. A zero correlation indicates that there is no relationship between the variables. A correlation of -1 indicates a perfect negative correlation, meaning that as one variable increases, the other decreases. A correlation of $+1$ indicates a perfect positive correlation, meaning that both variables move in the same direction.

The results obtained from Table 14 represent that risk scores and risk priority ranking were examined to evaluate the relationship between the results obtained by fuzzy MCDM methods. Generally, two main types of Spearman's rank correlation coefficient and Pearson correlation coefficient are measured. In this case, Spearman's rank correlation evaluates the ranked value for each variable, whereas Pearson correlation is used to evaluate the final score value.

TABLE 14. The results obtained using different methods.

Methods		Routes							
		1	2	3	4	5	6	7	8
DEA	Risk scores	13.170	16.569	15.533	24.985	24.414	17.027	12.275	15.074
	Risk priority ranking	7	4	5	1	2	3	8	6
FAHP-DEA	Risk scores	2.241	3.254	2.849	4.747	4.564	3.271	2.308	3.075
	Risk priority ranking	8	4	6	1	2	3	7	5
FBWM-DEA	Risk scores	2.283	3.327	2.914	4.811	4.592	3.316	2.346	3.076
	Risk priority ranking	8	3	6	1	2	4	7	5
FFUCOM-DEA	Risk scores	2.256	3.300	2.883	4.809	4.604	3.309	2.335	3.053
	Risk priority ranking	8	4	6	1	2	3	7	5

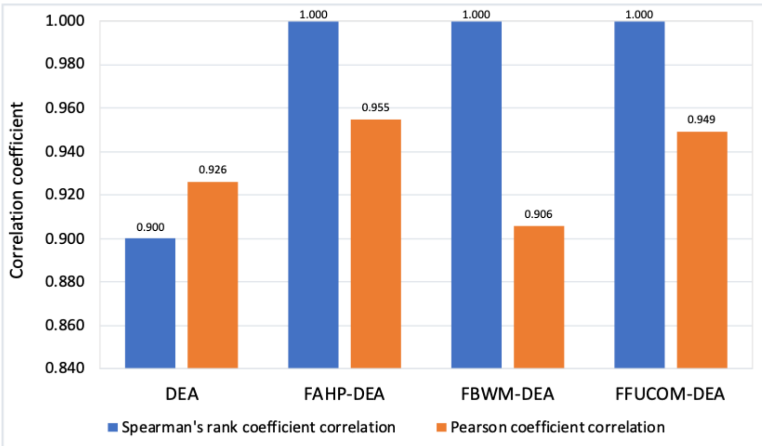

FIGURE 5. Correlation between the results of the risk priority ranking.

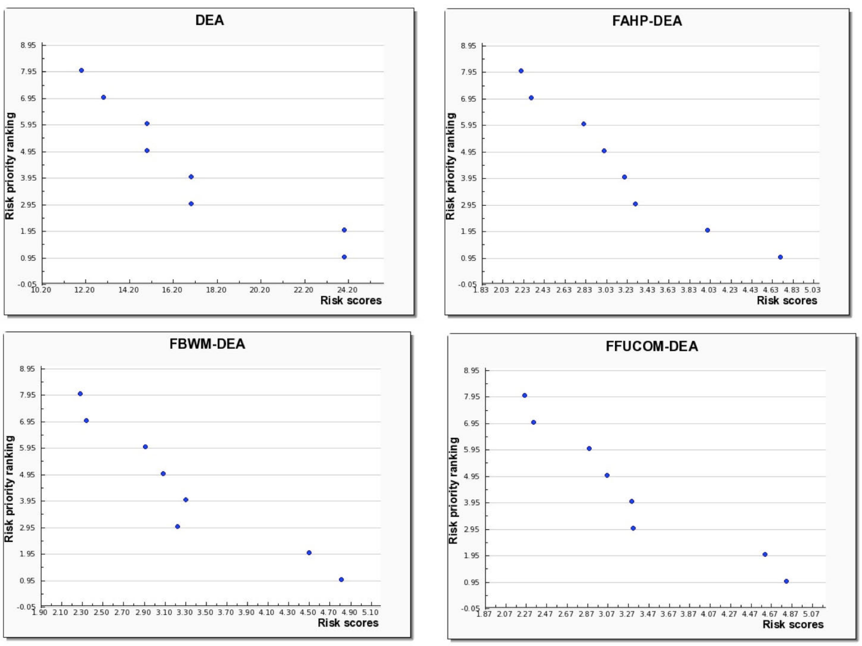

FIGURE 6. Scatter plots between the results of the risk scores and risk priority ranking.

The computation of Spearman's rank correlation and Pearson correlation are based on the following definitions [51]:

1) Spearman's rank correlation coefficient:

$$\text{Correlation} = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{23}$$

where d_i is the difference between two rankings and n is the number of observations.

2) Pearson correlation coefficient:
Correlation

$$= \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2}\sqrt{n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2}} \tag{24}$$

where n is the total number of values, x is the value in the first set of data, and y is the value in the second set of data.

The results from Spearman's rank correlation coefficient and Pearson correlation coefficient analysis, shown in Fig. 5, confirm the validity of the proposed FAHP-DEA method. The FAHP-DEA is most highly correlated with the final ranking while the DEA method is least correlated with the final ranking.

Furthermore, as opposed to other subjective models, the FAHP-DEA method has relatively less variation in the obtained risk scores than FFUCOM-DEA and other methods as shown in Table 14. The stability in the analysis of FAHP-DEA method makes evident that the priority of risk factors remain steady. On the other hand, the results from FFUCOM-DEA method indicate that the risk scores for route 2 and 6 are 3.300 and 3.309, respectively. This suggests that FFUCOM-DEA method produces almost identical risk scores, making it difficult to confidently rank the risk priorities. The scatter plots depicted in Fig 6 presented that the difference between adjacent risk scores of FAHP-DEA method are more uniformly distributed compared to other methods.

In conclusion, the FAHP-DEA method produces the best overall results. On the basis of case study findings, it clearly proves that the proposed FAHP-DEA method significantly outperforms other approaches.

V. CONCLUSION, LIMITATION AND FURTHER STUDY

Multimodal freight transportation is a complex problem sensitive to various risks. It is difficult to predict the process, as it faces risks in all activities. From the managerial perspective, risks are potential threats that can negatively impact normal activities or prevent actions. Multimodal freight transportation is the integration of two or more modes of transport to move goods from the source to the destination. Accidents can occur at any point along the transportation routes. Therefore, to raise user's attention to the high priority risks related to multimodal freight transportation, this study proposed the integrated FAHP-DEA process to model multimodal transportation risks quantitatively.

The proposed risk analysis model is the combination of quantitative risk analysis, FAHP, and DEA to prioritize and optimize the multimodal transportation routes. The FAHP technique is used to determine the weights of the risk criteria. The DEA method is employed to determine the values of the linguistic terms such as Very High, High, Medium, Low and Very Low to assess transportation risks under each criterion. Finally, the SAW method is applied to aggregate the risks under different criteria into an overall risk score. The literature review revealed that the integrated FAHP-DEA is very simple, applicable to many decision alternatives and particularly effective for complex MCDM problems.

A practical case study of the coal industry in Thailand has been conducted regarding multimodal transportation routes. The high visibility risks involved with complex multimodal freight transportation are identified. With prior literature and expert knowledge, 5 main multimodal transportation risk categories are investigated. Subsequently, the local risk scores of 51 segmented routes with respect to 5 criteria are generated. The FAHP-DEA approach is an effective tool for analyzing and prioritizing the critical risks in complex systems. The results of this study provide risk scores with priority ranking. Moreover, the risk assessment model can generate an optimal route in accordance with weights from the users.

The main contribution of this study is the development of reliable and practical risk model to support users in optimizing a route under risks. Furthermore, the results suggest that the users should consider the source and nature of risk impact to minimize the risks in multimodal freight transportation.

According to the correlation analysis using Spearman's rank correlation coefficient and the Pearson correlation coefficient, the proposed FAHP-DEA method clearly produces results that are consistent with the actual results. This clearly indicates that the proposed method is not only a practical decision-making approach but also highly reliable and accurate.

Nonetheless, there are limitations concerning the data. The majority of data acquired in this study is specific to the environment. These factors can be adjusted before applying to other cases. Therefore, the factors based on experts' preference scores need to be constructed carefully. The data and its analysis are typically subject to the context of industries.

For potential future research, this proposed risk analysis model can help support a new platform to systematically analyze risk and extend its applications to other complex and critical installations. The conceptual framework will be exploited by developing decision support software for quantitative risk analysis in transportation. It could provide an accurate, practical, and systematic decision support tool.

APPENDIX A
ROUTE IDENTIFICATION

Route 1: Srichang + Pasak River + Nakornluang Port – Mittraphap Road – Kaeng Khoi Cement Plant Saraburi
Route 2: Srichang + Pasak River + Nakornluang Port – Jumpa District – Mittraphap Road – Kaeng Khoi Cement Plant Saraburi
Route 3: Srichang + Pasak River + Nakornluang Port – Don Yanang District – Mittraphap Road – Kaeng Khoi Cement Plant Saraburi

TABLE 15. Profile of experts

Experts	Experience (years)	Position
Company A	32	CEO, Transport Manager
Company B	25	Logistics Manager
Company C	20	Safety and risk manager
Company D	21	Operation Manager
Company E	20	Consultant
Company F	24	Consultant
Technical office A	30	Bureau of Traffic Safety
Technical office B	35	Bureau of Road Maintenance
Technical office C	23	Chief Engineer
Technical office D	31	Engineer

Route 4: Srichang + Laem Chabang = Sri Racha = Chonburi = Chachoengsao = Bang Nam Piew = NakornNayok = Kaeng Khoi Train Station − Kaeng Khoi Cement Plant Saraburi
Route 5: Srichang − Laem Chabang = Sri Racha = Chonburi = Chachoengsao = Bang Nam Piew = NakornNayok = Kaeng Khoi Train Station − Kaeng Khoi Cement Plant Saraburi
Route 6: Srichang + Bang Pa Kong − Bang Nam Piew − NakornNayok − Mittraphap Road − Kaeng Khoi Cement Plant Saraburi
Route 7: Srichang + Bang Pa Kong − Mittraphap Road − Kaeng Khoi Cement Plant Saraburi
Route 8: Srichang + Bang Pa Kong − NongRong District − Mittraphap Road − Kaeng Khoi Cement Plant Saraburi
(Note: + is ship transport, = is train transport, − is truck transport.)

APPENDIX B

See table 15.

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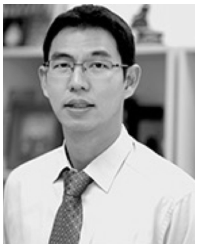

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