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A NEW FRAMEWORK FOR RISK ASSESSMENT OF ROAD TRANSPORTATION OF HAZARDOUS SUBSTANCES

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Abstract. *Various elements including environmental, public safety, economic, and security concerns define the evaluation of threats connected with the movement of dangerous materials. It is imperative to undertake a comprehensive investigation to address the multifaceted problem of risk assessment concerning the road transportation of dangerous materials. The primary aim of this study is to present a framework for threat assessment in this domain. To achieve this objective, an integrated approach involving stepwise weight assessment ratio analysis (SWARA) with the multi-attributive border approximation area comparison (MABAC) approach under the Z-number theory is introduced. Preliminary investigations and expert opinions are taken into consideration, and 17 risks are identified for developing the failure mode and effect analysis (FMEA) technique for rural roads located in Cosenza, a region in southern Italy. A qualified analysis is conducted between the outcomes of the FMEA approach implemented by Z-SWARA-MABAC and those of the conventional FMEA method. This investigation is undertaken to achieve sustainable mobility goals by evaluating the risks and enhancing the safety of the transportation of dangerous substances via roadways. Therefore, it is essential to re-evaluate the laws and measures required to mitigate hazards on the regional road network of southern Italy.*

Key words: *Risk assessment, Hazardous substances, Sustainable mobility, SWARA, Z-number theory*

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1. INTRODUCTION

Road safety guarantees are essential for preventing crashes and protecting lives [1-3]. This is especially critical when carrying dangerous substances, as any occurrence could have serious consequences. The transportation of dangerous materials is a complex issue in road transportation that requires careful consideration from various perspectives [4-5]. Hazardous substances are utilized in numerous industries as raw materials for industrial production, such as petrochemicals used in plastic industries or various chemical derivatives utilized in the health and cosmetic industries [6]. Consequently, the transportation of dangerous materials is considered a critical matter for various industries to operate efficiently from an economic standpoint [7]. However, with the growth of various industries and their need for abundant raw materials for increased production, the escalation in the volume of transportation of hazardous materials is indisputable [8]. Thus, particularly in developed and developing countries, concerns about the safety of individuals who are directly and indirectly involved in the transportation of these materials on roads arise [9]. In recent years, there has been an increased emphasis on the transportation of dangerous substances, with a specific emphasis on road transportation [10]. The transportation of dangerous substances through densely populated and confined spaces has experienced a rise, prompting concerns about the likelihood of mishaps and their ramifications. Moreover, the ecological consequences of transporting dangerous substances have emerged as a significant issue. The possibility of spills or leaks occurring during transportation has the potential to result in lasting harm to both the environment and public health [11-12].

MCDM models are crucial in risk assessment due to their ability to handle complex decision-making scenarios involving multiple conflicting criteria [13]. The use of integrated fuzzy MCDM methods allows for the consideration of subjective assessments, thereby refining risk rankings and prioritization [14]. The systematic approach of MCDM models leads to more informed and effective risk management strategies, ultimately contributing to better project outcomes and safety measures [15]. MCDM frameworks facilitate the aggregation of diverse expert insights, which incorporates multiple decision-makers to identify and prioritize alternatives [16].

The extended Z-number based MCDM methods enhance this capability by incorporating uncertainty and reliability into the decision-making process, which is particularly important in risk assessment. These methods provide a more nuanced approach to evaluating risks by considering both the fuzziness of information and its reliability, thus offering a comprehensive framework for decision-making under uncertainty. Z-numbers, introduced by Zadeh, are used to manage the fuzziness and reliability of information, which is crucial in risk assessment where data is often uncertain or incomplete [17]. The use of Z-numbers in MCDM allows for a more accurate representation of uncertainty, as demonstrated in the evaluation of driving behavior risks, where dual perspectives and credibility values are calculated to assess risk scores [18].

The integration of Z-numbers in MCDM enhances the decision-making process by providing additional certainty and guidance, as seen in the valuation of uncertain information, which leads to more confident and comprehensive judgments [19]. A likelihood-based approach to ranking Z-numbers further refines decision-making by comparing the randomness and reliability of information, thus supporting more informed decisions in complex scenarios [13].

Given the multifaceted nature of the issue, it is imperative to undertake a thorough investigation into the associated risks [20]. To this end, a comprehensive understanding and evaluation of the processes governing the transportation of hazardous materials are essential for effective risk prevention and mitigation [21]. The transportation of such materials by road involves a multitude of variables, necessitating the incorporation of various data inputs, including information on the type of materials being transported, geometric road data, vehicle data, and other pertinent details, in the risk assessment process [22]. Many strategies have been developed to assess the possible risks connected to the movement of hazardous products [23-25]. Multi-criteria decision-making (MCDM) approaches and failure modes and effects analysis (FMEA) are widely adopted techniques for assessing risk [26-29].

Despite the extensive efforts in this domain, a number of challenges remain unsolved. Specifically, most of the existing methods in risk assessment cannot handle the uncertainty and reliability of information simultaneously. Classical fuzzy approaches consider only uncertainty and do not take into account the reliability of data, which is an important factor in decision-making. This has resulted in incomplete evaluations and unstable outcomes in many cases.

In that respect, this paper fills these gaps by developing a new framework that incorporates both stepwise weight assessment ratio analysis (SWARA) and multi-attributive border approximation area comparison (MABAC) methods into the fuzzy environment. The key novelty is using the theory of Z-number in handling uncertainty and reliability of information together, which is an important feature of the approach for assessing risks in hazardous materials transportation because data are often incomplete or fuzzy under real-life conditions. Subsequently, a team of experienced technicians identified 17 potential risks associated with the transportation of dangerous materials. To evaluate these risks and compare the outcomes of the proposed approach, a real-life case study was conducted alongside two other approaches. It is noteworthy that the novelty of this research lies in the utilization of the Z-number theory to address the uncertainties associated with these factors. This approach considers the reliability of the factors, as well as their fuzziness, in the evaluation process. The main contributions, their impacts, and their insights to this study are as follows:

- This paper represents a new framework that combines SWARA and MABAC methods under a fuzzy environment. The integration of these methods into one would provide a systematic and structured approach to the evaluation and prioritization of risks, hence enhancing overall accuracy and consistency in risk assessments concerning the complex domain of hazardous materials transportation.
- This paper applies the theory of Z-number, put forward by Zadeh, which accounts simultaneously for the fuzziness and the reliability of information. The presented dual consideration of uncertainty and reliability is an important limit of the methodologies at present available that increases the potential applicability of the proposed framework under real-world operative conditions characterized by incomplete, imprecise, or uncertain data.
- The proposed framework eliminates the limitations of classical fuzzy methods, which take into consideration only uncertainty without respect to data reliability. Overcoming such weaknesses, the framework gives more full and reliable risk assessments with smaller odds on unstable outcomes and incomplete analyses.

- The framework was then validated by a real case study in which 17 potential risks associated with hazardous materials transportation were identified and evaluated. The practical application of the framework proves its effectiveness and adaptability to real-world scenarios, hence providing evidence of relevance for industry professionals and decision-makers.
- The performance of the proposed framework was compared to two different existing approaches in order to emphasize its strengths and advantages. This comparative analysis reinforces not only the reliability and robustness of the proposed model but also its superiority in handling the complexities related to risk assessment under uncertainty.

The subsequent sections of this investigation are structured in an ensuing manner: Section 2 presents a succinct compendium of the literature review. The methodologies, comprising the fuzzy sets concept, Z-number theory, the Z-SWARA method, and the Z-MABAC method are expounded upon in Section 3. Section 4 explores the suggested approach. Section 5 explicates the distinguishing features of a case study. Section 6 examines the use of three strategies and discusses the ranking of the most important risks in the road traffic of hazardous materials.

2. Literature Review

The transportation of dangerous materials has been the subject of valuable research [30-35]. Deng et al. [36] proposed a generic approach for preventing dangerous chemical accidents, which utilizes K-means clustering analysis of incident data to address the associated challenges. To demonstrate the effectiveness of their approach, they developed a database of dangerous chemical incidents and employed a K-means clustering algorithm to categorize them. The results obtained revealed that the suggested approach significantly enhances accident categorization and enables the identification of the most suitable order of crucial objectives to prioritize, the prerequisites for accident prevention, and the development of preventive measures. On the other hand, Hong et al. [37] utilized the association rules mining (ARM) method to detect the contributory crash-risk effects of hazardous material (HAZMAT) vehicle-involved accidents on expressways. They conducted a case study and analyzed accident data from the crash database of the Korea Expressway Corporation between 2008 and 2017. According to their findings, the use of ARM as a data mining methodology established correlations between crashes involving hazardous material vehicles and crucial factors that increase the risk of such incidents. Moreover, the implementation of ARM held promise for producing easily understandable results and valuable insights to improve the safety of expressways.

Extensive research has been conducted on the parameters that influence accidents during the transportation of dangerous substances, the severity of injuries, and the risks that contribute to such accidents [38-42]. Büyüközkan et al. [43] introduced a comprehensive and structured MCDM approach based on the analytical hierarchy process (AHP) and VIKOR in an intuitionistic fuzzy (IF) environment to evaluate the selection process of hazardous waste transportation. To overcome bias, uncertainties, and partiality in decision-making processes, they adopted a group decision-making approach using IF. The efficacy of this proposed framework was validated by applying it to a real-world case study in Turkey. Ma et al. [44] analyzed the statistical distribution features of several factors, including hazardous materials, transport crashes, driver attributes, vehicle attributes, environmental factors, and road conditions. To handle unobserved variability among data, they proposed an ordered logit regression model. The findings of their model estimation revealed a significant correlation between the harshness of accidents involving dangerous material transportation and 10 elements, including violations, risky driving behaviors, and vehicle faults.

Noguchi et al. [45] developed an innovative methodology for examining accident scenarios relating to HAZMAT transportation. Their proposed technique utilized network theory as a means to represent the intricate crash process. The methodology employed in their research involved the selection of accident scenarios from accident processes through the amalgamation of the HAZMAT transportation crash network and transportation-related environmental features based on crash statistics. The research applied the methodology to conduct a case study on the transportation of liquefied petroleum gas (LPG) via roadways in Japan. The findings suggested that the methodology presented for the investigation of crash scenarios had the potential to expedite the process of risk assessment in the transport of hazardous materials while also facilitating the transition from risk assessment to risk management. Weng et al. [46] built a quantitative risk assessment (QRA) model to evaluate the risk of hazmat transportation accidents. The QRA model combined the frequency and consequences of all potential accident scenarios. An event tree, which consisted of six intermediate events, was utilized to identify the potential accident scenarios. To prove the efficacy of the proposed QRA model in evaluating the danger of hazardous material transportation accidents, a case study was carried out using relevant hazmat transportation data from Shanghai. The outcomes showed that the proposed model had reliable performance.

Ren and Yang [47] analyzed the risk factors of hazmat road transportation accidents with a Bayesian network model, HRT-BN, developed upon Tree Augmented Naive Bayes (TAN), reflecting dependencies such as those of accident types and rescue times. The results point out that human factors are the main cause of slight accidents with short rescue times, while the interaction of multiple factors results in more serious and varied accidents. Other factors, such as seasonal and regional factors, come into play such as longer rescue times during summer. Their analysis concluded with targeted recommendations to reduce risks. Kanj et al. [48] proposed a novel method to enhance transportation safety related to hazardous goods with the help of real-time information. They have worked out a hybrid methodology called fuzzy AHP-TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) for risk analysis and optimized route selection on three criteria, namely: cost, duration, and risk. The approach proposed aimed at finding the safest route by assigning calculated weights to these criteria through pairwise comparisons. They examined both static and dynamic environments where the static decisions remained fixed while dynamic decisions changed with the flow during transport. Their outcome indicated an enhancement of safety and reduced risks on hazardous material transportation. Hsu et al. [49] proposed the integrated quality function deployment and multicriteria decision-making (QFD-MCDM) framework for selecting the key drivers to I5.0 in order to enhance supply chain resilience while concurrently handling hazardous material transportation risk. Some of the proposed measures that will contribute to sustainability and stability of firms, as proposed by them, include safe and inclusive working environments, customized products and services, improved flexibility of production, enhanced control redundancy, and full utilization of real-time data analysis. Their findings showed how the integration of I5.0 and SCR can have a synergistic effect in mitigating HMTR. The findings also provided useful insights and implications for enterprises from different industries.

3. METHODOLOGY

In this section, we will outline the concepts of fuzzy set theory and Z-number theory, followed by a discussion of the Z-SWARA and Z-MABAC methodologies. Additionally, we will elucidate the advantages of employing the SWARA and MABAC methods in comparison to other weighting and ranking approaches, respectively.

The SWARA method involves a hierarchical ranking of criteria, prioritizing the most significant criteria over those of lesser importance. The participation of experts in assessing the weight of these criteria is essential to this process. SWARA allows decision-makers to establish priorities aligned with predefined policies, particularly in contexts where these priorities reflect known situations. It effectively assesses the relative significance of multiple criteria concurrently. Its versatility makes SWARA suitable for various decision-making scenarios, and its use among researchers has notably increased in recent years. In terms of contextual consideration, comprehensive evaluation of multiple criteria, and broad applicability, the SWARA method presents several advantages over other methods such as the Analytic Hierarchy Process (AHP), the Analytic Network Process (ANP), and the Best Worst Method (BWM) [16].

The MABAC method offers several advantages in MCDM over traditional methods. It is particularly effective in handling complex decision-making scenarios by incorporating various innovative approaches, such as time-series analysis, fuzzy logic, and probabilistic linguistic terms. These enhancements allow MABAC to provide more accurate and reliable decision-making outcomes. The MABAC method can incorporate time-series data, allowing it to handle dynamic decision-making scenarios where criteria and preferences may change over time. This is achieved through time weights, which enhance the reliability of the decision-making process by accounting for temporal variations. It allows for bidirectional adjustments, enabling decision-makers to refine and adjust criteria weights and preferences dynamically, which is not typically possible with traditional static methods [50].

Moreover, integrating fuzzy numbers and dual probabilistic linguistic term sets allows MABAC to effectively manage uncertainty and fuzziness in decision-making. This capability is crucial for scenarios where decision criteria are not precisely defined or are subject to interpretation. The method's ability to incorporate fuzzy logic and probabilistic assessments provides a more nuanced and comprehensive evaluation of alternatives, enhancing decision accuracy [51]. Additionally, MABAC's approach of ranking alternatives based on their distances from an approximate boundary region limits unconditional compensation among attribute values, leading to more balanced and fair evaluations [50]. The method has been successfully applied in various practical scenarios, such as determining winners in competitions and selecting sustainable suppliers, demonstrating its versatility and effectiveness in real-world applications [52].

The MABAC method offers distinct advantages in terms of robustness, flexibility, and ease of implementation, making it a compelling choice for multi-criteria decision-making. While methods like TOPSIS, VIKOR, and others have their strengths, MABAC’s focus on border approximation and comprehensive evaluation positions it effectively for scenarios where nuanced decision-making is critical.

3.1. Fuzzy Set Theory

The idea of fuzziness presents a membership function to manage many language variables [53–55]. Within the realm of individuals' internal cognition, inference, and perception, a certain extent of ambiguity exists. Fuzzy sets handle sources of imprecision and uncertainty that are non-statistical and ambiguous in nature. The fundamental descriptions of fuzzy number sets used in this work are clarified in the next part.

Definition 1: A set *A* that is fuzzy, and is defined on the reference set *X*, can be expressed through the use of Eq. (1):

$$A = \{(x, \mu_A(x)) | x \in X\} \tag{1}$$

The membership function denoted as $\mu_A(x): X \to [0,1]$ in Eq. (1) characterizes the fuzzy set *A*. The value of membership $\mu_A(x)$ signifies the extent to which $x \in X$ pertains to *A*. The membership degree is the extent that an element, $x \in R$, belongs to the fuzzy set $\widetilde{A}$. This parameter conveys the level of assent or conviction in *x* being a member of the fuzzy set $\widetilde{A}$, or the degree of conformity of *x* with the intended concept of the set $\widetilde{A}$.

Definition 2: A triple (*l*, *m*, *u*) can be employed to denote a triangular fuzzy number $\widetilde{A}$, with its membership function being articulated in Eq. (2).

$$\mu_A(x) = \begin{cases} 0 & x \le l \\ \frac{x-l}{m-l} & l \le x \le m \\ \frac{u-x}{u-m} & m \le x \le u \\ 0 & x \ge u \end{cases} \tag{2}$$

Definition 3: Let $\widetilde{A} = (l_1, m_1, u_1)$ and $\widetilde{B} = (l_2, m_2, u_2)$ represent two triangular fuzzy numbers, and let λ be a positive constant. In this scenario, mathematical actions on these fuzzy numbers are executed based on Eqs. (3–7):

$$\tilde{A} \oplus \tilde{B} = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{3}$$

$$\tilde{A} \otimes \tilde{B} = (l_1 . l_2, m_1 . m_2, u_1 . u_2), \tag{4}$$

$$\tilde{A} - \tilde{B} = (l_1 - u_2, m_1 - m_2, u_1 - l_2), \tag{5}$$

$$\frac{\tilde{A}}{\tilde{B}} = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right), \tag{6}$$

$$\lambda\tilde{A} = \lambda(l_1, m_1, u_1) = (\lambda l_1, \lambda m_1, \lambda u_1), \tag{7}$$

Definition 4: Let $\widetilde{A} = (l_1, m_1, u_1)$ and $\widetilde{B} = (l_2, m_2, u_2)$ denote two positive triangular fuzzy numbers. The measure of separation among $\widetilde{A}$ and $\widetilde{B}$ is ascertained by means of Eq. (8):

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{((l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2)}{3}} \tag{8}$$

Definition 5: A triple (*l*, *m*, *u*) is utilized to define a triangular fuzzy number. The change of said number to a crisp number is achieved through the utilization of Eq. (9):

$$A = \frac{l + 4 \times m + u}{6} \tag{9}$$

3.2. Z-Number Theory

The Z-number theory was anticipated as a thorough representation of uncertainty theory, which addresses the calculation of non-reliable numbers [56]. Unlike fuzzy theory, the Z-number theory considers the concept of reliability. It can be merged with MCDM approaches, such as VIKOR [57–58].

The Z-number represented as a custom pair *Z = (A, B)*, is a type of fuzzy data that is utilized to characterize the value of the random variable *X*. It is important to note that in the aforementioned statement, *A* is a form of fuzzy constraint that is applied to the value of the random variable *X*, while *B* is the partial dependability of probability criteria connected with *A*.

Eq. (10) presents the triad (*X*, *A*, *B*) as a comprehensive constraint on *X*, and designates it as Z-valuation, akin to an assignation statement:

$$\text{Prob}(X \text{ is } A) \quad \text{is} \quad B \tag{10}$$

This particular constraint is acknowledged as a probability constraint that connotes a function of probability distribution. Additionally, it can be given in the following manner:

$$R(X){:}\, X \quad is \rightarrow poss(X = u) = \mu_A(u) \tag{11}$$

In the aforementioned equation, the symbol μ_A represents the membership function of *A*, while *u* denotes a generic value of *X*. The function μ_A can be interpreted as a limitation on *R(X)*, signifying that it encompasses $\mu_A(u)$, denoting the extent to which *u* can be satisfied. Consequently, *X* presents a stochastic variable with a probability distribution which acts as a potential restriction on *X*. The potential constraints and probability density function are illustrated in Eqs. (12) and (13), respectively:

$$R(X){:}\, X \quad is \quad p \tag{12}$$

$$R(X){:}\, X \quad is \quad p \rightarrow prob(u \leq X \leq u + du) = p(u)du \tag{13}$$

In Eq. (13), the term *du* denotes the constituent of *u*'s derivatives. To effectuate the conversion of a Z-number into a fuzzy number, one must execute the ensuing mathematical operations: If *Z=(A, B)* represents a Z-number (where *A* has been identified as the verbal variable illustrated in Table 1, while *B* has been identified as the verbal variable accessible in Table 2 and $A = \{(X, \mu_{\tilde{A}}) | X \in [0,1]\}$ and $B = \{(X, \mu_{\tilde{B}}) | X \in [0,1]\}$ denote fuzzy triangular numbers, then the conversion of fuzzy number reliability to a certain number can be accomplished in the following manner:

$$\alpha = \frac{\int x \mu_{\tilde{B}}(x) dx}{\int \mu_{\tilde{B}}(x) dx} \tag{14}$$

and the second part is added to the first part as follows:

$$\tilde{Z}^{\alpha} = \{(X, \mu_{\tilde{A}^{\alpha}}) | \mu_{\tilde{A}^{\alpha}}(x) = \alpha \mu_{\tilde{A}^{\alpha}}, X \in [0,1]\} \tag{15}$$

In the aforementioned Eqs. (14) and (15), α denotes the reliability weight, $\mu_B(x)$ is an indicator of the degree of dependence of $x \in X$ in *B*, and $\mu_{\tilde{A}^{\alpha}}(x)$ is an indicator of the degree of dependence of $x \in X$ in A^{α}.

Table 1 Risk prioritization in FMEA with extended SWARA

Linguistics terms	Membership functions
Equally-significant (ES)	(1,1,1)
Moderately-less-significant (MOS)	(2/3,1, 3/2)
Less-significant (LS)	(2/5,1/2,2/3)
Very-less-significant (VLS)	(5/2,3,7/2)
Much-less-significant (MUS)	(2/7,1/3,2/5)

Table 2 Conversion guidelines of linguistics variables of reliability

Linguistic variables	Very Weak (VW)	Weak (W)	Medium (M)	Strong (S)	Very Strong (VS)
TFNs	(0,0,0.3)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.7,1.0,1.0)

3.3. Z-SWARA Method

Achieving best results in challenging situations depends on evaluating many approaches of decision-making. These techniques enable methodically evaluating and ranking many elements engaged in the decision-making process [59-61]. The technique known as SWARA is a method for making decisions by determining values for weight that play a pivotal role in the process [62-63]. Keršuliene et al. [64] developed this approach, and it has a major advantage in that it allows one to evaluate the opinions of professionals on criteria of relevance all the while figuring their relative weights. In the context of a fuzzy environment, the fuzzy SWARA technique serves as an adapted decision-making approach that is leveraged to calculate the weights of criteria and sub-criteria. The fuzzy SWARA methodology operates in a way that is like to that of the SWARA method. However, it has been extended to accommodate uncertainties in decision-making or a dearth of knowledge, hence the term "fuzzy" [65–66]. The weights of the criteria in the fuzzy SWARA method are established according to expert judgments, underscoring the indispensable role of researchers in the process. To heighten the level of confidence in the resultant outcomes, the fuzzy SWARA method has been extended to encompass the Z-SWARA technique, which takes into account a reliability factor. The Z-SWARA methodology involves the ensuing steps:

Step 1: Academics in the field of expertise commonly sort criteria in a descending manner based on their level of significance, where the utmost crucial factors are assigned greater precedence than their less noteworthy counterparts. This approach is attributed to their vast knowledge and proficiency.

Step 2: During the preliminary assessment stage, proficient individuals should allocate linguistic qualities to the comparative significance of criterion j concerning the preceding j–1 criteria. Subsequently, the specialists employ Table 1 to ascertain the worth of the primary component ($\tilde{F}_j$). Table 2 is utilized for the computation of the dependability component ($\tilde{L}_j$). The outcome is a Z-value allocated to every individual state.

Step 3: To obtain a precise numerical value for the second aspect, which is reliability, the utilization of Eq. (14) is deemed necessary in order to transform the Z-number that was obtained during Step 2 into a triangular fuzzy number (TFN) as elaborated in Eq. (12). Upon completion of the equation, the weight is subsequently integrated into the original component as stipulated in Eq. (13).

To determine the relative significance of linguistic variables on the *j*-th criteria, the Z-number transforms by adjusting the appropriate TFN values, as presented in Tables 1–2, respectively. Furthermore, Table 3 provides additional Z-number to TFN conversions for a comprehensive understanding of the phenomenon.

Table 3 Guidelines are provided for transforming Z-number linguistics variables into fuzzy numbers

Linguistics terms	Membership functions	Linguistics terms	Membership functions
(ES, VW)	(1,1,1)	(ES, W)	(1,1,1)
(ES, M)	(1,1,1)	(ES, S)	(1,1,1)
(ES, VS)	(1,1,1)	(MOS, VW)	(0.212,0.316,0.474)
(MOS, W)	(0.367,0.548,0.822)	(MOS, M)	(0.474,0.707,1.061)
(MOS, S)	(0.561,0.837,1.255)	(MOS, VS)	(0.636,0.949,1.423)
(LS, VW)	(0.126,0.158,0.212)	(LS, W)	(0.219,0.274,0.367)
(LS, M)	(0.283,0.354,0.474)	(LS, S)	(0.355,0.418,0.561)
(LS, VS)	(.379,0.474,.0636)	(VLS, VW)	(0.092,0.104,0.126)
(VLS, W)	(0.159,0.181,0.219)	(VLS, M)	(0.205,0.233,0.283)
(VLS, S)	(0.243,0.276,0.335)	(VLS, VS)	(0.275,0.313,0.379)
(MUS, VW)	(0.069,0.079,0.092)	(MUS, W)	(0.120,0.137,0.159)
(MUS, M)	(0.155,0.177,0.205)	(MUS, S)	(0.184,0.209,0.243)
(MUS, VS)	(0.209,0.237,0.275)		

Step 4: To determine the coefficient $\tilde{k}_j$, refer to Eq. (16):

$$K_j = \begin{cases} 1 & j = 1 \\ S_j + 1 & j > 1 \end{cases}, j = 1,2,\ldots,n. \tag{16}$$

Step 5: The weight coefficient $\tilde{q}_j$, which is indistinct, is established in the following manner, considering the outcomes obtained from Step 4:

$$\tilde{q}_j = \frac{\tilde{q}_{j-1}}{\tilde{z}_j}, j = 1,2,\ldots,n, \tag{17}$$

where $\tilde{q}_j$ is TFN and $\tilde{q}_j$= (1, 1, 1).

Step 6: Lastly, the scheming of the relative weights of the *j*-th evaluation criteria is performed, which carefully considers all *n* evaluation criteria. This is achieved by applying Eq. (18):

$$\widetilde{w}_j = \frac{\tilde{q}_j}{\sum_{j=1}^{n} q_j}, j = 1,2,\ldots,n, \tag{18}$$

where $\widetilde{w}_j$ is a TFN.

3.4. Z-MABAC Method

The MABAC method [67] is a contemporary approach to decision-making that was formulated in 2015. Ever since its inception, the MABAC method has been extensively utilized and adapted to tackle a plethora of problems within the realm of MCDM [68-69]. The MABAC method's foundational framework involves the assessment of the criterion function's distance for each alternative observed from the boundary approximation domain.

The ensuing section expounds on the six-step procedure for the application of the MABAC method.

The Z-MABAC technique is a solution to address the issue of decision-making within a fuzzy environment. Following the acquisition of attribute weights, the MABAC method is utilized to compute the value of the standard function for each alternative, with the distance of said function from the margin approximation area subsequently defined. Once the distance of the standard function from the margin approximation area is determined, the alternatives are ranked, and the optimal choice is selected.

Step 1: involves the construction of an initial decision matrix Z utilizing the application of Z-numbers**.** In the formation of the primary decision matrix (Z), a crucial step involves the assessment of m alternatives based on n criteria. These alternatives are appropriately represented as vectors, denoted by $A_i = (X_{i1}, X_{i2}, \dots, X_{in})$, where X_{ij} represents the value of the j-th alternative by the i-th criterion ($i = 1,2, \dots, m; j = 1,2, \dots n$):

$$Z = \begin{array}{c} \\ A_1 \\ A_2 \\ \dots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{array}, \tag{19}$$

Step 2: involves the conversion of Z-numbers into fuzzy numbers, with the intent of facilitating informed decision-making. The initial decision matrix (Z) contains inherent linguistic values (Table 4) that undergo a conversion process into fuzzy numbers, resulting in the matrix $\tilde{Z}$.

Table 4 Language-based variables for ranking the failure modes

Linguistic variables	Very Weak (VW)	Weak (W)	Moderately Weak (MW)	Medium (M)	Moderately Strong (MS)	Strong (S)	Very Strong (VS)
TFNs	(0,0,1)	(0,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,10)	(9,10,10)

In order to adequately address the language-based elements present in Z-numbers, while the second element B is turned into a triangle fuzzy number, the initial element A becomes a trapezoidal fuzzy number (Table 5).

A Z-number is a mathematical entity comprising two unique constituents. Within the current framework, the $\tilde{Z}$ matrix is first solved employing the centroid approach of the second segment, subsequently amalgamating into an assemblage of trapezoidal fuzzy numbers, designated as $\tilde{Z}^{\alpha}$:

$$\tilde{Z}^{\alpha} = \begin{array}{c} \\ A_1 \\ A_2 \\ \dots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} \tilde{Z}^{\alpha}{}_{11} & \tilde{Z}^{\alpha}{}_{12} & \dots & \tilde{Z}^{\alpha}{}_{1n} \\ \tilde{Z}^{\alpha}{}_{21} & \tilde{Z}^{\alpha}{}_{22} & \dots & \tilde{Z}^{\alpha}{}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{Z}^{\alpha}{}_{m1} & \tilde{Z}^{\alpha}{}_{m2} & \dots & \tilde{Z}^{\alpha}{}_{mn} \end{bmatrix} \end{array}, \tag{20}$$

Table 5 Conversion guidelines for Z-number linguistics based variables to fuzzy numbers

Linguistics terms	Membership functions	Linguistics terms	Membership function
(VW, VW)	(0,0,0.32)	(VW, W)	(0,0,0.55)
(VW, M)	(0,0,0.71)	(VW, S)	(0,0,0.84)
(VW, VS)	(0,0,0.95)	(W, VW)	(0,0.32,0.95)
(W, W)	(0,0.55,1.64)	(W, M)	(0,0.71,2.12)
(W, S)	(0,0.84,2.51)	(W, VS)	(0,0.95,2.85)
(MW, VW)	(0.32,0.95,1.58)	(MW, W)	(0.55,1.64,2.74)
(MW, M)	(0.71,2.12,3.54)	(MW, S)	(0.84,2.51,4.18)
(MW, VS)	(0.95,2.85,4.74)	(M, VW)	(0.95,1.58,2.21)
(M, W)	(1.64,2.74,3.83)	(M, M)	(2.12,3.54,4.95)
(M, S)	(2.51,4.28,5.86)	(M, VS)	(2.85,4.74,6.64)
(MH, VL)	(1.58,2.21,2.85)	(MS, W)	(2.74,3.84,4.93)
(MS, M)	(3.54,4.95,6.36)	(MS, S)	(4.18,5.86,7.53)
(MH, VH)	(4.74,6.64,8.54)	(S, VW)	(2.21,2.85,3.16)
(S, W)	(3.84,4.93,5.48)	(S, M)	(4.95,6.36,7.07)
(S, S)	(5.86,7.53,8.37)	(S, VS)	(6.64,8.54,9.49)
(VS, VW)	(2.85,3.16,3.16)	(VS, W)	(4.93,5.48,5,48)
(VS, M)	(6.36,7.07,7.07)	(VS, S)	(7.53,8.37,8.37)
(VS, VS)	(8.54,9.49,9.49)		

Step 3: The process of normalizing the aggregated fuzzy matrix yields the matrix $\tilde{Z}^{'}$, which conforms to a standard measurement range as an alternative to the conventional [0,1]. For every benefit criterion j in the decision matrix $\tilde{Z}^{\alpha}$, the trapezoidal fuzzy number element $\tilde{Z}_{ij}^{\alpha}$= $(Z_{ij1}, Z_{ij2}, Z_{ij3})$ is subjected to normalization by separating the maximum value in Z_{ij3}:

$$\tilde{Z}_{ij}^{'} = \left(\frac{Z_{ij1}}{max_i(Z_{ij3})}, \frac{Z_{ij2}}{max_i(Z_{ij3})}, \frac{Z_{ij3}}{max_i(Z_{ij3})}\right), j \in \text{benefit-related criteria} \quad (21)$$

For each j-th cost criterion in the decision matrix $\tilde{Z}^{\alpha}$, standardization is carried out by separating the minimum value of Z_{ij1} for each component $\tilde{Z}_{ij}^{\alpha}$= $(Z_{ij1}, Z_{ij2}, Z_{ij3})$ and subsequently taking the inverse in order:

$$\tilde{Z}_{ij}^{'} = \left(\frac{min_i(Z_{ij1})}{Z_{ij3}}, \frac{min_i(Z_{ij1})}{Z_{ij2}}, \frac{min_i(Z_{ij1})}{Z_{ij1}}\right), j \in \text{cost-related criteria} \quad (22)$$

Step 4: The computation of the constituent element of a more intricate matrix denoted as (V) is performed through the utilization of Eq. (24):

$$v_{ij} = w_j\left(\tilde{C} + \tilde{Z}_{ij}^{'}\right)\tilde{C}, j = 1,2, \dots, n, i = 1,2, \dots, m, \quad (23)$$

$$V = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1.\tilde{C} + \tilde{Z}_{11}^{'} & w_2.\tilde{C} + \tilde{Z}_{11}^{'} & \cdots & w_n.\tilde{C} + \tilde{Z}_{1n}^{'} \\ w_1.\tilde{C} + \tilde{Z}_{21}^{'} & w_2.\tilde{C} + \tilde{Z}_{22}^{'} & \cdots & w_n.\tilde{C} + \tilde{Z}_{2n}^{'} \\ \cdots & \cdots & \cdots & \cdots \\ w_1.\tilde{C} + \tilde{Z}_{m1}^{'} & w_2.\tilde{C} + \tilde{Z}_{m2}^{'} & \cdots & w_n.\tilde{C} + \tilde{Z}_{mn}^{'} \end{bmatrix} \quad (24)$$

Step 5: The computation of the matrix of bordering approximative fields (G) is undertaken herein. The bordering approximative field is established as follows:

$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m}, i = 1,2, \dots, m. \tag{25}$$

The components of the weighted matrix (V) are denoted by v_{ij}, while m signifies the total number of alternatives. Upon computation of the value g_i, a matrix of approximative fields is constructed per criteria G (as expressed in Eq. (26)) in the format of n, which denotes the total number of criteria utilized in selecting the alternatives:

$$\tilde{G} = (g_1, g_2, \dots, g_n). \tag{26}$$

Step 6: An alternative methodology for ascertaining the boundary approximative area (Q) involves the computation of the distance matrix element:

$$Q = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ q_{m1} & q_{m2} & \cdots & q_{mn} \end{bmatrix}. \tag{27}$$

The determination of the distance of every alternative from the boundary approximative area (q_{ij}) is achieved through the subtraction of the values of the bordering approximative areas (G) from the corresponding elements in the heavier matrix (V):

$$Q = V - G = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} - [g_1 \quad g_2 \quad \cdots \quad g_n], \tag{28}$$

$$Q = \begin{bmatrix} v_{11} - g_1 & v_{12} - g_2 & \cdots & v_{1n} - g_n \\ v_{21} - g_1 & v_{22} - g_2 & \cdots & v_{2n} - g_n \\ \cdots & \cdots & \cdots & \cdots \\ v_{m1} - g_1 & v_{m2} - g_2 & \cdots & v_{mn} - g_n \end{bmatrix} = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ q_{m1} & q_{m2} & \cdots & q_{mn} \end{bmatrix},$$

whereas g_i denotes the contiguous approximative regions for criterion C_i, and v_{ij} denotes the constituents of the denser matrix (V).

Alternative A_i may pertain to a contiguous approximative region (G), an upper contiguous approximative region (G^+), or a lower contiguous approximative region (G^-). For each i, A_i is a member of the set $\{G \vee G^+ \vee G^-\}$. In order to identify the region where the ideal alternative A^+ is located, the upper approximative area (G^+) must be determined. Similarly, the lower approximative area (G^-) must be identified to represent the space where the anti-ideal alternative (A^-) is located. This is described in Fig. 1 [57].

The determination of the affiliation of alternative A_i with respect to the approximative area G, G^+ or $G^-$is conducted through the utilization of Eq. (29):

$$A_i \in \begin{cases} G^+ \ if \ q_{ij} > g_i \\ G \ if \ \ q_{ij} = g_i \\ G^- \ if \ q_{ij} < g_i \end{cases}, i = 1,2, \dots, m. \tag{29}$$

For a specific set, the optimal solution is chosen only if it is a member of the upper approximating field (G^+) for as many criteria as possible.

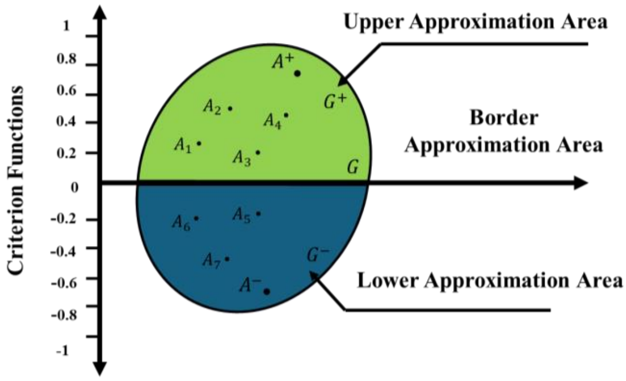

Fig. 1 Styles and sizes for equations

Step 7: The prioritizing of the alternatives is determined through a computing of the values of the criteria functions, as per Eq. (30). This equation involves the summation of distances between the alternatives and the surrounding approximative fields, indicated as (q_i). To arrive at the final values of the criterion functions, one must add the elements of the Q matrix along the rows in accordance with Eq. (30). This process ultimately facilitates the prioritizing of the alternatives.

$$S_i = \sum_{j=1}^{n} q_{ij}\,, j = 1,2,\dots,n, i = 1,2,\dots,m. \tag{30}$$

4. PROPOSED APPROACH

In this particular section, the proposed methodology for prioritizing risks is introduced by utilizing FMEA, fuzzy-SWARA-MABAC, and Z-MABAC approaches. The suggested method is delineated in three stages. The preliminary stage of this recommended approach entails the identification of risks within the ambit of risk evaluation by the FMEA team, while the values of the three factors are assigned based on Table 6. Furthermore, in this phase, the pertinent team determines the dependability of each identified risk.

Table 6 Traditional ratings for SOD factors

Rating	Severity (S)	Occurrence (O)	Detection (D)
10 9	Hazardous-without-warning Hazardous-with-warning	Very-high: ″failure is almost inevitable″	″Absolute uncertainty″
8 7	Very-high High	High: ″repeated failures″	High: ″repeated failures″
6 5 4	Moderate Low Very-low	Moderate: ″occasional failures″	Moderate: ″occasional failures″
3 2	Minor Very-minor	Low: ″relatively few failures″	Low: ″relatively few failures″
1	None	Remote: ″failure is unlikely″	Remote: ″failure is unlikely″

In the subsequent phase, the employment of the fuzzy SWARA approach is implemented to account for varying levels of significance pertaining to the triple criteria. Upon identification of the most favorable and unfavorable criteria by the proficient team, pairwise comparisons of the criteria are carried out utilizing linguistic variables. The linguistic variables proffered by the experts are subsequently subjected to conversion into fuzzy numbers utilizing Table 1. Subsequently, the execution of the fuzzy SWARA mathematical model is performed on the aforementioned values, yielding the optimal weights of the triple factors.

In the next phase of the study, the Z-MABAC method is utilized to rank the identified risks. This methodology takes into account the differing levels of significance of the triple criteria, according to the outputs of the initial and secondary phases. This method combines the fuzzy values with the dependability of each criterion for the three elements of each risk, in contrast to the conventional MABAC technique. As demonstrated in this study, this more nuanced approach yields superior results.

In the suggested approach, Table 5 transforms the values into fuzzy numbers after the development of the decision matrix, which consists of both fuzzy and Z-numbers. Thereafter, various models are executed within a fuzzy environment. The outcome from the application of these models yields an indistinguishable result from that of the primary ranking of the identified risks in the preliminary phase. The definitive ranking of the risks is established based on the dominance ranking theory, with the triple approaches being juxtaposed against one another. Fig. 2 shows the application procedure of the proposed approach.

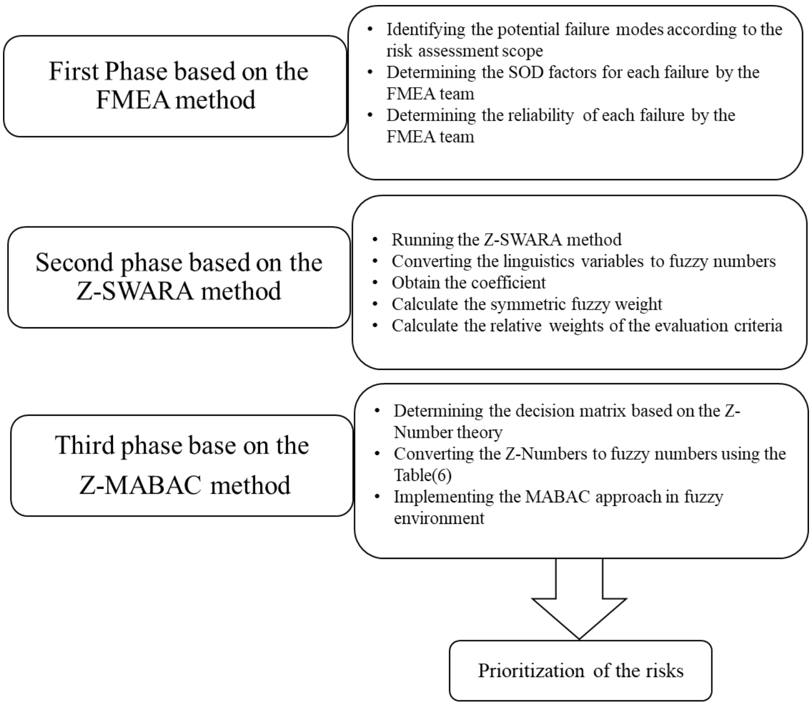

Fig. 2 An overview of the proposed methodology

5. CASE STUDY

The research region falls in the province of Cosenza's municipality of Rende (Fig. 3). [70]. The territory of the city of Rende has an extension of 55 sq km and is located north of Cosenza between the municipalities of Montalto Uffugo, Castiglione Cosentino, Castrolibero, Cosenza, San Vincenzo La Costa, San Fili, Marano Principato, Rose [71].

Fig. 3 Location of the municipality of Rende (CS)

Rende has a population of about 36,500 inhabitants. Within the modern city, which developed downstream from the historic center, numerous commercial activities have sprung up in recent decades and public services and equipment of general interest, both public and private, are concentrated. To the north-east of the municipal area, there is also an industrial zone, which represents a strong attraction pole for commercial vehicles. This zone, localized in Contrada Lecco, is part of the city's Industrial Development Area, and therefore characterized by a high volume of vehicles which, on a daily basis, transport freights with origin or destination in the urban area of the city of Rende [72-73].

The main road axes are oriented along the South-North direction, also influenced by the morphology of the territory. However, significant vehicular flows also occur on the transversal routes along the East-West axis (particularly on State Road 107), which cross the city, connecting locations on the Ionian coast with those on the Tyrrhenian coast, and vice versa. Within the municipal territory of Rende, there is an interchange of the A2 Mediterranean Motorway (Cosenza Nord-Rende), which provides a connection to State Road 107 Silana-Crotonese.

In the urban area, Provincial Road 241 (formerly State Road 19/19bis) plays an important role, serving as the structural axis of Rende's settlement development along the Crati plain. The A2 Motorway and SP241 simultaneously function as collectors for supra-municipal traffic, particularly for the Montalto Uffugo-Cosenza connection, and as primary roads connecting Cosenza and Rende.

Some roads serve as transversal links but face significant performance issues (low capacity values compared to high demand peaks), leading to instances of congestion at times, especially on routes connecting to the university campus, which accommodates thousands of daily trips. A strong polarization of people's mobility between the territories of Cosenza and Rende is evident.

The estimation of vehicular traffic volumes affecting the area was derived from on-site surveys and an analysis of data from the "15th General Census of Population and Housing regarding commuter movements for study or work purposes" (ISTAT). The analysis reveals that the area is affected by a total of 10,320 internal trips (with origins and destinations within the municipal territory), 21,497 inbound trips (with origins outside the municipal territory and destinations within it), and 6,050 outbound trips (with origins within the municipal territory and destinations outside it).

The total number of road accidents occurred in the last 5 years (2020-2024) in the study area is equal to 482, involving 735 injured and 5 dead.

Fig. 4 shows the heavy vehicles impact on traffic flow in the whole study area. The percentage of heavy vehicles on the total volume of vehicles observed in the road network varies from 3% (secondary roads) to 30% (access/exit roads to the industrial area).

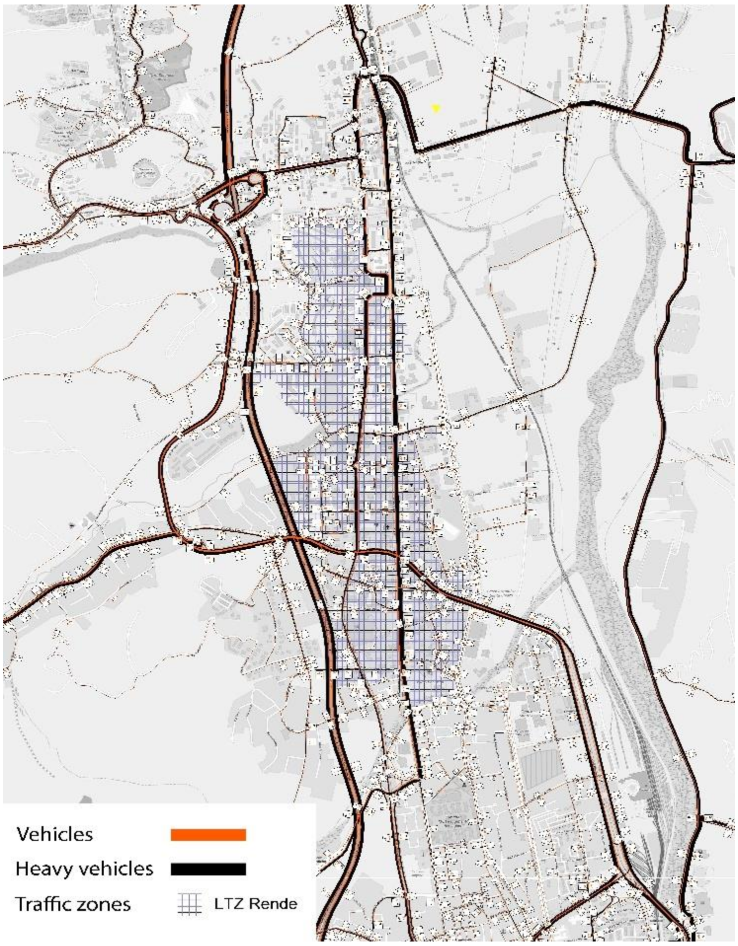

Fig. 4 An overview of traffic flows on the road network in the case study

Among the goods transported in the case study area, a share between 5% and 8% is related to hazardous substances, which are mainly toxic waste, electronic equipment with release of polluting substances, exhausted vegetable oils. The transportation of these types of substances in the area is due to the presence of a waste storage and treatment plant. These values lead to an analysis of the effects that the transport of dangerous substances can generate on the environment and human health.

6. RESULTS

This specific section focuses on the outcomes of the suggested strategy used to assess possible risks resulting from the transporting of hazardous substances on highways. In accordance with the initial phase of this approach, the team responsible for FMEA endeavors to detect and pinpoint all plausible risks that may surface during the process. Besides this, the team also defines triple factor values for every identified risk, which are shown in Table A.1 in the Appendix.

It is worth noting that identifying the 17 risks related to the carriage of hazardous substances was not a linear process. To begin with, we conducted a critical review of related literature to identify widely reported risks in the transportation of hazardous materials. Complementary to this were expert consultation sessions with persons with substantial experience in logistics, transportation safety, and hazardous materials handling. Their input was important to ascertain that the identified risks were not only of practical relevance but also representative of realistic situations. We analyzed historical data on past incidents and accidents involving dangerous goods to further support and consolidate this selection process. The following risks were fully identified through a multi-step process, as shown in Table A.1. These risks could be used as a basis for the next steps in assessing and ranking risks.

The Z-number theory is applied aptly to accommodate the uncertainty imbued inherently in these factors. In this way, dependability and ambiguity of these factors are remarkably acknowledged. Table A.2 illustrates the Z-number values of the triple factors of each risk based on input from the FMEA team.

Following the use of the SWARA approach in the second phase of the study's methodology, the evaluation of risks described in Table 7 is carried out for each decision-maker by determining the values of coefficient k and the weights q and w derived using Eqs. (16–18).

Table 7 The weights of the threat factors by SWARA

Team number	Risk factor	Comparative importance			Coefficient			Recalculated weight			Weight		
TM-1	S				1	1	1	1.000	1.000	1.000	0.428	0.444	0.466
	O	0.285	0.333	0.4	1.285	1.333	1.4	0.714	0.750	0.778	0.306	0.333	0.362
	D	0.4	0.5	0.666	1.4	1.5	1.666	0.429	0.500	0.556	0.183	0.222	0.259
TM-2	S				1	1	1	1.000	1.000	1.000	0.414	0.425	0.440
	D	0.285	0.333	0.4	1.285	1.333	1.4	0.714	0.750	0.778	0.295	0.319	0.342
	O	0.222	0.25	0.285	1.222	1.25	1.285	0.556	0.600	0.636	0.230	0.255	0.280
TM-3	O				1	1	1	1.000	1.000	1.000	0.434	0.454	0.483
	S	0.4	0.5	0.666	1.4	1.5	1.666	0.600	0.667	0.714	0.260	0.303	0.345
	D	0.222	0.25	0.285	1.222	1.25	1.285	0.467	0.533	0.584	0.202	0.242	0.282

The transformation of linguistic variables into triangular fuzzy numbers is accomplished during this stage. Upon successful conversion, the coefficient k_j from Eq. (16), the fuzzy weight q_j from Eq. (17), and the final weight of the factors in the form of fuzzy numbers w_j from Eq. (18) can be ascertained. Table 8 includs the final fuzzy weight of the main criteria for each decision-maker (DM).

Table 8 Ultimate SWARA weights of the threat factors

Risk factors	Ultimate weights		
S	0.3680	0.3910	0.4176
O	0.3238	0.3477	0.3757
D	0.2275	0.2612	0.2949

Following the application of the SWARA and Z-number approaches in the third phase of the study methodology, the rate of the coefficient k and the weights of q and w were calculated for every decision-maker assessing the offered risks in Table 9. Throughout this particular procedure, the linguistic variables undergo a transformation into triangular fuzzy numbers by virtue of the equations that have been explicitly outlined in Tables 1–2.

Once fuzzy numbers have been generated from the linguistic variables, the coefficient, fuzzy weight, and ultimate weight of the components in the structure of fuzzy numbers are all determined. Table 10 shows each decision-maker's final fuzzy weight for every important criteria.

Table 9 The weights of the risk factors by Z-SWARA

Team number	Risk factor	Comparative importance			Coefficient			Recalculated weight			Weight		
TM-1	S				1	1	1	1.000	1.000	1.000	0.407	0.419	0.438
	O	0.205	0.233	0.283	1.205	1.233	1.283	0.799	0.811	0.830	0.317	0.340	0.364
	D	0.335	0.418	0.561	1.335	1.418	1.561	0.499	0.572	0.622	0.203	0.240	0.272
TM-2	S				1	1	1	1.000	1.000	1.000	0.379	0.385	0.395
	D	0.159	0.181	0.219	1.159	1.181	1.219	0.820	0.847	0.863	0.311	0.326	0.341
	O	0.12	0.137	0.159	1.12	1.137	1.159	0.708	0.745	0.770	0.268	0.287	0.304
TM-3	O				1	1	1	1.000	1.000	1.000	0.419	0.436	0.463
	S	0.335	0.418	0.561	1.335	1.418	1.561	0.641	0.705	0.749	0.268	0.308	0.347
	D	0.184	0.209	0.243	1.184	1.209	1.243	0.515	0.583	0.633	0.216	0.254	0.293

Table 10 Final Z-SWARA weights of the threat factors

Risk factors	Final weights		
S	0.3522	0.3712	0.3939
O	0.3355	0.3549	0.3776
D	0.2439	0.2739	0.3025

Upon the completion of normalizing the fuzzy assessment matrix, which is represented in Table A.3, the ensuing step involves deriving the weighted normalized matrix Z-SWARA. This is accomplished by assimilating the weights of the distinct threat factors, as elaborated in Table A.4.

Finally, after the completion of the normalization process for the final weights, the risks are subjected to a ranking procedure utilizing the fuzzy SWARA-MABAC, Z-MACAB, and FMEA techniques. This particular section of the study implements three distinct approaches in accordance with Table A.3–A.4, whereby the outcomes are subsequently presented, while also considering the general dependability of the risks and the inherent uncertainty related with the SOD variables. Upon conclusion of this analysis, the various options are meticulously compared and contrasted by means of their respective rankings, which are presented in Table 11.

Based on the findings presented in Table 11, it can be determined that the FMEA approach identified risk modes R14, R7, and R8 as the top three risks, with RPN scores of 280.77, 186.666, and 144.444, respectively. These risks are deemed critical and necessitate the implementation of corrective or preventive measures. Conversely, risk mode R1, with an RPN score of 37.333, is ranked last and is currently not in need of corrective actions due to financial constraints. Additionally, the fuzzy SWARA-MABAC approach ranked risk modes R12, R13, and R7 as the top three risks, with scores of S_{12}=0.1313, S_{13}=0.1140, and S_7=0.1040, respectively. Risk mode R2, with a score of S_2=–0.1656, was ranked last using this approach. Furthermore, it is worth noting that Z-MABAC ranked risk modes R16, R12, and R9 as the top three risks, with scores of S_{16}=0.1350, S_{12}=0.1333, and S_9=0.1196, respectively. Lastly, risk mode R2 has been ranked seventeenth with a score of S_2=–0.2022 by the Z-MABAC approach.

Table 11 Comparison of risk prioritization based on three approaches

Risk	Conventional FMEA		Fuzzy SWARA-MABAC		Z-MABAC	
	RPN	Rank	S_i	Rank	S_i	Rank
R1	37.333	16	-0.1258	16	-0.124	16
R2	95.333	8	-0.1656	17	-0.202	17
R3	69	12	0.0654	6	0.0917	7
R4	46.666	14	0.0212	10	-0.400	11
R5	65	13	-0.0758	15	-0.072	15
R6	125	4	0.0253	9	0.0556	8
R7	186.666	2	0.1040	3	0.1029	5
R8	144.444	3	0.0415	8	0.0472	9
R9	125	4	0.0593	7	0.1196	3
R10	83.333	9	-0.0475	14	-0.059	14
R11	120.888	6	0.0047	11	-0.013	10
R12	82.962	10	0.1313	1	0.1333	2
R13	124.444	5	0.1140	2	0.1023	6
R14	280.777	1	-0.0368	13	-0.048	12
R15	80	11	-0.0255	12	-0.048	13
R16	100	7	0.0862	4	0.1350	1
R17	41.481	15	0.0703	5	0.1101	4

In Fig. 5, we present the outcomes of the prioritization of risks based on three different approaches. Furthermore, we executed the assessment and prioritization of risks. The results of the analysis highlight the distinctions in prioritization among the three proposed approaches. In fact, the fuzzy approach has triumphantly overcome the inadequacies of the traditional FMEA methodology and provided an absolute priority by considering different weights for each of the 17 risks, utilizing diverse weights for prioritization, and applying fuzzy theory to leverage uncertainty. This approach brings the subject closer to the real-world and engages expert opinions more than ever to obtain accurate results.

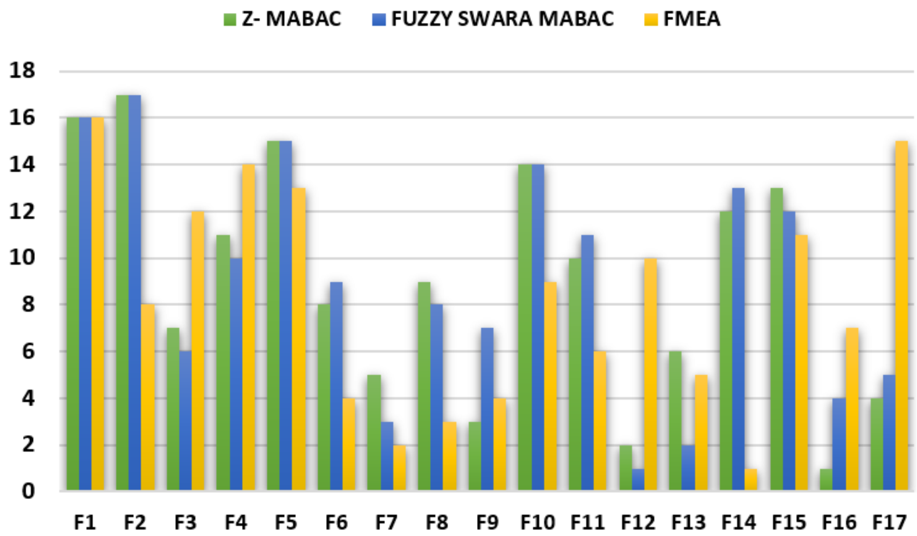

Fig. 5 A comparison between the prioritization of risks based on three different approaches

In contrast, the approach proposed in this study extends the notion of data reliability for each criterion by employing the Z-number theory, in addition to covering the benefits of Z-MABAC and fuzzy SWARA-MABAC techniques. The opinions of experts are incorporated with greater accuracy in calculations, and consequently, our responses will be more dependable. Apart from obtaining outcomes that are close to the real-world, the proposed approach is also simple in its solution method.

6.1. Validation of Proposed Approach

This section presents two validation studies designed to evaluate the reliability and validity of the rankings derived from the proposed Z-SWARA-MABAC approach. The first study involved a comparative analysis with two established methods, Z-WASPAS and Z-MARCOS, to assess the consistency and effectiveness of Z-SWARA-MABAC in prioritizing risks associated with hazardous material transportation. The second study employed Pearson's correlation analysis to further validate the results produced by the MCDM methods.

6.1.1. Comparative Analysis

The objective of this section is to provide empirical evidence regarding the reliability, accuracy, and efficacy of the proposed methodology. To achieve this, a thorough comparative analysis has been conducted, contrasting the results obtained from the Z-SWARA-MABAC technique with those derived from established methods, specifically the extended Z-number with Weighted Aggregated Sum Product Assessment (Z-WASPAS) and the extended Z-number with measurement of alternatives and ranking according to compromise solution (Z-MARCOS).

The results derived from the application of diverse methodologies underscore the efficacy of the Z-WASPAS and Z-MARCOS approaches, as illustrated in Table 12 and Figure 6. A detailed examination reveals that criteria A16, A12, and A9 consistently ranked first, second, and third, respectively, across all employed methods, highlighting the robustness of these findings. The comprehensive analysis of risk prioritization using the WASPAS and MARCOS methodologies reveals significant parallels in the identified risks. Notably, the top four risks consistently rank the same across all three approaches, indicating a strong consensus. While minor variations do exist in the prioritization of other risks, these generally do not exceed two ranks, which is considered acceptable given the low magnitude of the discrepancies. Therefore, it can be concluded that the proposed method is both valid and reliable, producing results that closely align with those from the comparative methodologies.

Table 12 Risks rankings based on three various ranking methodologies

Risk	**Z-MABAC**		**Z-MARCOS**		**Z-WASPAS**	
	Score	Rank	Score	Rank	Score	Rank
A1	-0.124	16	0.4562	15	0.591	17
A2	-0.202	17	0.4348	17	0.596	16
A3	0.0917	7	0.5382	9	0.675	8
A4	-0.4	11	0.5114	12	0.646	10
A5	-0.072	15	0.4901	13	0.604	15
A6	0.0556	8	0.5763	8	0.677	7
A7	0.1029	5	0.6157	6	0.709	5
A8	0.0472	9	0.5882	7	0.649	9
A9	0.1196	3	0.7136	2	0.718	3
A10	-0.059	14	0.4384	16	0.606	14
A11	-0.013	10	0.5183	11	0.646	11
A12	0.1333	2	0.7092	3	0.725	2
A13	0.1023	6	0.6577	5	0.686	6
A14	-0.048	12	0.5289	10	0.628	12
A15	-0.048	13	0.4564	14	0.626	13
A16	0.135	1	0.7356	1	0.736	1
A17	0.1101	4	0.6955	4	0.718	4

The consistent identification of risks across the MABAC, WASPAS, and MARCOS methods reinforces the robustness and validity of the proposed approach. This alignment enhances confidence in the accuracy of the prioritization process and affirms the reliability of the findings. By employing multiple techniques that yield consistent results, this study underscores its credibility in risk assessment. Such agreement among diverse methodologies bolsters the conclusion that the proposed approach is both valid and dependable for effective risk evaluation.

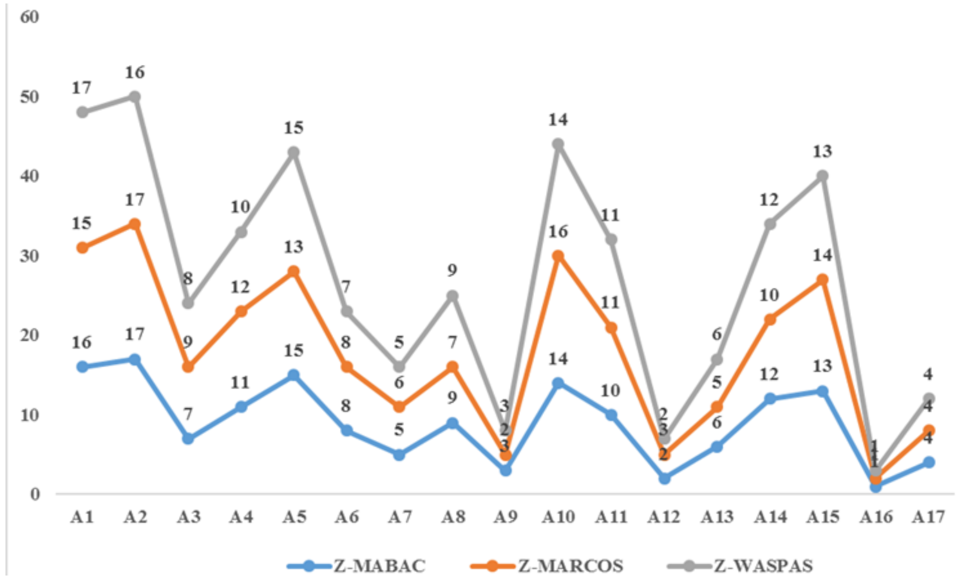

Fig. 6 Chart of risks rankings based on three various ranking methodologies

6.1.2. Pearson's Correlation

The Pearson correlation coefficient is one of the most important statistical tools that describes the strength and direction of the linear relationship between two continuous variables. In the MCDM framework, Pearson's correlation bears great relevance and importance both as a useful tool in analysis and interpretation and as a support method in decision-making for choosing the best alternative according to the preset criteria.

Usually, the decision-makers have to select the best alternative among various options on the basis of multiple criteria. Pearson's correlation coefficient plays a very important role not only in the selection but also in the comparison and validation of different ranking methods applied in the MCDM frameworks. Decision-makers may employ different MCDM methods (e.g., MABAC, WASPAS, and MARCOS). Pearson’s correlation can be used to compare the rankings produced by these methods by analyzing the correlations among the scores derived from different methods. This comparative analysis can highlight inconsistencies or affirm the robustness of the rankings. Pearson's correlation is an efficient tool that can be used to verify the relationship between ranking and scoring functions. In this way, it is possible to determine if the rankings created by different methods of scoring are either consistent or correlated, which gives a better understanding of the reliability of the decision-making process. The use of Pearson's correlation in assessing the aforementioned relationship in MCDM will provide the ability for decision-makers to assess the stability and dependability of the outcomes. Consistent rankings from the various scoring methods confirm the validity of the decision-making process, while inconsistencies in the rankings may signal a need to revisit criteria weighting or the scoring methodologies themselves.

The decision-maker will be able to identify which methods yield similar results and which may lead to divergent rankings by calculating the correlation coefficients between the rankings produced by different methods. A high value of the correlation coefficient between two methods will indicate that these methods produce consistent rankings, while a low coefficient will point to significant differences. This evaluation is important for establishing the robustness of the alternatives identified. The decision-maker could be less uncertain about the reliability of the selections when several techniques are suggesting similar top choices.

Pearson's Correlation coefficient formula is presented below.

$$r = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})*(y_i-\bar{y})}{\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2\right)*(\frac{1}{n}\sum_{i=1}^{n}(y_i-\bar{y})^2)}} \tag{31}$$

The results (Figure 7) from the Pearson's correlation analysis between three different ranking methods—MABAC, MARCOS, and WASPAS—provide valuable insights into the accuracy and appropriateness of these methods for evaluating risks in transporting hazardous materials.

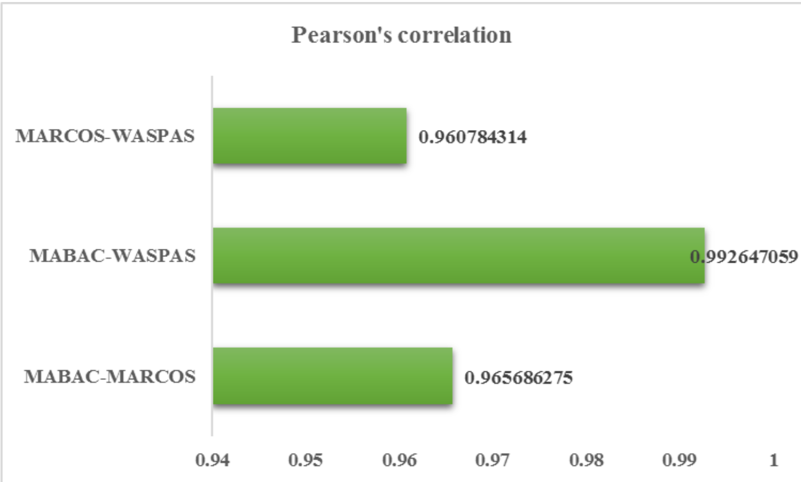

Fig. 7 Pearson's correlations between MABAC, MARCOS, and WASPAS

The Pearson's correlations between MABAC and the other two methods (MARCOS and WASPAS) indicate a strong degree of alignment in the rankings produced. Specifically:

- A correlation of 0.9926 between MABAC and WASPAS suggests an extremely close resemblance in the rankings generated by these two methods. This high correlation indicates that both methods assess alternatives similarly in terms of their effectiveness in addressing the criteria for evaluating risks.
- A correlation of 0.9657 between MABAC and MARCOS also reflects a robust agreement, indicating that both methods yield comparable rankings for the alternatives considered.

The consistency between MABAC and the other ranking methods suggests that the MABAC method is generating stable and reliable rankings for the evaluation of risks associated with transporting hazardous materials. A strong correlation implies that the method is not only accurate but also resilient to variations in input data across different methods. This reliability is important for risk assessment because the decision-makers should rely on a valid and believable result.

Both MARCOS and WASPAS also show strong correlations amongst themselves, from the Pearson correlation coefficient of 0.9608. That means the three methods operate on kindred principles to evaluate risks, hence building a case towards the use of any of them. However, since MABAC shows the highest correlation with WASPAS (0.9926), it positions MABAC as a particularly accurate and effective method within this group for this specific application.

Based on the analysis of Pearson's correlation coefficients, we validate that the MABAC method provides accurate ranking results for evaluating risks in transporting hazardous materials. The high correlation coefficients among MABAC with the other ranking methods, MARCOS and WASPAS, denote a high level of agreement in results from risk evaluations and show that MABAC correctly captured the inherent relationships among risk factors. Further, in tune with other methods and having the robustness in providing consistent rankings, the method of MABAC is recommended to be most appropriate in this study. It allows drawing accurate results that enhance decision-making capabilities in the realm of hazardous material transportation and, finally, to safer and more effective risk management.

7. Discussion

The current study reveals some convergences and divergences in risk prioritization by applying different methodologies in the assessment of risk in hazardous material transportation. FMEA, based on quantitative data and historical trends, gives operational risks like unfitness of personnel on appropriate training in safety matters and poor maintenance of vehicles. On the other hand, the fuzzy SWARA-MABAC approach that integrated expert judgment listed organizational risks related to management inefficiency, such as R12 and R13, in the highest rank order for priority. Furthermore, the Z-SWARA-MABAC method has identified vehicle compatibility with hazardous materials (R16), drawing on an important perspective rooted in regulatory considerations and contextual factors. The differences among these approaches are due to their methodological frameworks. FMEA focuses strongly on measurable factors, often disregarding such qualitative elements as organizational culture. On the other hand, the fuzzy SWARA-MABAC method captures those qualitative dimensions of risk. Integration of Z-number theory in the Z-SWARA-MABAC approach introduces sophisticated modeling of uncertainty that allows the risks to be reevaluated in light of contextual and regulatory considerations. For example, certain risks-like R2-that have been rated low in conventional methods start assuming great significance when viewed through the prism of compliance and contextual relevance.

These results highlight how much the success of risk assessment depends on methodology. While FMEA represents one systematized data-driven approach, with roots in historical insights, the fuzzy SWARA-MABAC and Z-SWARA-MABAC methods make use of expert opinions and uncertainty modeling in order to uncover risks that otherwise may be overlooked. Each method adds something different, which indicates that a comprehensive assessment framework is vital when taking into consideration the complex nature of hazardous material transportation risks.

The study also carries practical implications for stakeholders. Transportation planners can use these insights to enhance infrastructure and optimize routing strategies, particularly in high-risk areas. Safety regulators can revise the priority listing of standards and training that must be made mandatory. Logistics operators can take up risk mitigation measures based on their particular needs, such as in-vehicle monitoring and emergency response plans. Emergency responders can focus resources on high-hazard areas and improve multiagency coordination. Combining findings from all three approaches gives the decision-maker a comprehensive view of the priorities of risk and thus the safest, most efficient ways of transporting hazardous materials.

8. Policy Implications

To mitigate the critical risks associated with hazardous material transportation, policymakers must adopt a multi-dimensional strategy informed by the study's findings. The integration of diverse methodologies provides a robust framework for risk assessment, enabling targeted interventions to enhance safety and operational efficiency. Some of the most important of these measures are as follows:

- Strengthening Training and Safety Protocols: The drivers and personnel who come into contact with the hazardous materials are to undergo extensive training courses on safe handling, emergency response, and compliance with local and international regulations. This would be further developed through regular updates and practical drills in order to avoid human error.
- Implementing Rigorous Vehicle Maintenance Standards: Vehicle safety requires planned inspections, proper maintenance records, and real-time monitoring. It will identify the majority of imminent risks long before they can cause an accident. Additional utilization of telematics and predictive analytics will achieve even more efficiencies and reliability for maintenance.
- Enhancing Regulatory Compliance: Policymakers should establish strict audits and incentives for adhering to safety standards. Working in collaboration with transportation companies to develop specific benchmarks with regard to regulatory compliance can provide a culture of accountability and continuous improvement.
- Improving Risk Communication and Public Awareness: Safety risks associated with hazardous material transportation should be made transparent. Communities will be informed through public awareness campaigns; the involvement of local authorities and emergency services will increase their risk management and preparedness. Public confidence will also be aided by regular reporting on safety practices and incidents.
- Developing Robust Contingency Plans: Contingency planning will minimize the effects of any probable accident. To this end, comprehensive emergency response plans-developing evacuation plans and resource allocation, among others-are to be developed with frequent simulation tests. Coordinated collaboration between transportation operators and emergency services ensures that responses are effective.
- Leveraging Advanced Technologies: Safety may be significantly enhanced by technological investment. It preserves real-time monitoring systems, automatic reporting tools, and predictive analytics that detect developing threats and guarantee compliance. Algorithms for route planning that include risk evaluations may further reduce exposure to high-risk zones.

These strategies will, therefore, allow stakeholders to mitigate most of the critical risks identified in this study while engendering a safety and accountability culture in the industry. These policies will continuously need to be evaluated and adapted to respond to evolving challenges in hazardous material transportation, assuring long-term sustainability and public safety.

9. CONCLUSIONS

The transportation of hazardous materials by road is a very complex issue and demands rigorous analysis from different perspectives. This work proposed an integrated approach that used the SWARA and MABAC methods under Z-number theory for the assessment and prioritization of risks. By applying expert judgment, critical risks were identified and developed in a tailored FMEA approach with regard to rural roads in Cosenza, southern Italy. Results underlined clearly the differences between the three proposed approaches in prioritizing risks, being more performative: the fuzzy approach treated the uncertainty and overcame the limitations set by traditional FMEA. By using distinct weights for all criteria, this provided a strong priority ranking that is really useful for decision making under uncertainty. The study significantly provides new insights to enhance methodologies in risk evaluation for transportation of hazardous material. Its results provide practical insights for possible future applications on different roadway systems or risk assessment scenarios.

The present study predominantly relates to the conditions of rural roads in Cosenza, Italy, and for this reason, the regional effects it may present will not be directly applicable in other areas or networks of urban roads. The narrowness of the scope limits generalization since the road infrastructure, traffic patterns, and regulatory environment can vary a lot across different regions. It is further recommended that the proposed framework be put to test in heterogeneous environments, including urban as well as other areas with different road conditions, to ensure generalization and adaptability. Conducting comparative studies across different geographical and regulatory contexts can provide deeper insights into the framework's robustness. Involving more stakeholders in expert opinions, such as local authorities, transport companies, and affected communities, will be attempted in future work in order to decrease the subjectivism of reliance on expert opinions. Such a mechanism would enable the framework to embrace any change in regulation, technological development, and changing societal expectations and remain relevantly effective for a longer period.

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Appendix

Table A.1 Identified risks in the process of road transport of hazardous substances

Symbols	Risk names	Severity (S)			Occurrence (O)			Detection (D)		
		TM-1	TM-2	TM-3	TM-1	TM-2	TM-3	TM-1	TM-2	TM-3
R1	Unsuitable condition of the roads	6	7	5	6	4	4	1	2	1
R2	Unsuitable meteorological conditions	4	3	4	7	5	6	5	4	4
R3	Improper packaging	8	8	7	4	2	3	3	2	4
R4	Improper loading and unloading	5	7	6	3	3	4	3	1	3
R5	Lack of protective equipment	5	4	6	3	2	4	4	5	4
R6	Depreciation of vehicles	9	9	7	4	6	5	2	4	3
R7	Failure to monitor and maintain vehicles	7	7	6	4	5	3	8	6	7
R8	Failure to comply with the special requirements for transporting hazardous materials by vehicle	6	6	8	5	3	5	6	4	5
R9	Lack of awareness of the driver	9	8	8	7	5	3	2	3	4
R10	Failure to comply with traffic regulations	4	5	6	2	5	3	4	6	5
R11	Failure to comply with the requirements related to the transportation of hazardous substances by the driver	6	4	7	4	5	3	5	5	6
R12	Over transport	5	8	7	2	3	2	4	5	7
R13	Poor management of facilities	4	7	5	3	5	2	8	6	7
R14	Inadequate safety training	8	6	5	7	6	6	7	6	8
R15	Illegal operation	5	5	6	2	4	3	6	4	5
R16	Vehicle does not match hazmat	8	9	8	4	6	2	3	2	4
R17	Natural disaster	3	2	3	1	2	2	9	10	9

Table A.2 The decision matrix that utilizes Z-numbers

Symbols	Severity (S)			Occurrence (O)			Detection (D)		
	TM1	TM2	TM3	TM1	TM2	TM3	TM1	TM2	TM3
R1	(M,W)	(MS,M)	(M,M)	(M,W)	(MW,M)	(M,M)	(VW,VW)	(W,W)	(VW,W)
R2	(M,W)	(MW,W)	(M,S)	(S,M)	(MS,S)	(M,VS)	(MS,W)	(M,M)	(MW,S)
R3	(S,S)	(VS,S)	(M,S)	(MW,VW)	(W,W)	(MW,M)	(W,W)	(W,W)	(MW,M)
R4	(MS,M)	(S,S)	(MS,W)	(W,VW)	(MW,W)	(M,M)	(W,VW)	(VW,W)	(MW,M)
R5	(MW,W)	(W,W)	(MS,M)	(MW,VW)	(W,M)	(MW,M)	(W,VW)	(MW,W)	(MW,M)
R6	(VS,S)	(H,VS)	(S,VS)	(MW,W)	(MS,M)	(M,M)	(W,W)	(MW,W)	(MW,M)
R7	(S,M)	(MS,S)	(M,S)	(M,W)	(M,M)	(MW,S)	(S,M)	(MS,S)	(MS,VS)
R8	(MS,S)	(MS,M)	(S,VS)	(M,M)	(W,M)	(MS,S)	(M,W)	(MW,M)	(M,S)
R9	(VS,VS)	(S,S)	(S,VS)	(MS,W)	(MW,W)	(W,M)	(W,W)	(W,M)	(MW,M)
R10	(MW,M)	(MW,W)	(M,W)	(W,W)	(MW,W)	(MW,M)	(MW,W)	(M,M)	(MW,M)
R11	(M,VW)	(MW,M)	(MS,S)	(MW,W)	(MW,W)	(W,M)	(MW,W)	(MW,M)	(M,M)
R12	(MW,W)	(S,M)	(MS,S)	(W,VW)	(W,VW)	(W,VW)	(MW,M)	(M,M)	(MS,S)
R13	(M,W)	(S,M)	(M,S)	(W,VW)	(M,W)	(W,M)	(S,M)	(M,M)	(M,S)
R14	(S,M)	(M,M)	(MW,S)	(MS,M)	(M,M)	(M,S)	(M,M)	(M,M)	(S,S)
R15	(MW,VW)	(MW,M)	(M,M)	(W,M)	(MW,M)	(W,M)	(M,W)	(MW,M)	(MW,S)
R16	(S,H)	(VS,VS)	(S,VS)	(MW,W)	(M,M)	(W,M)	(W,W)	(W,W)	(MW,M)
R17	(W,VW)	(W,VW)	(W,W)	(VW,VW)	(W,W)	(W,W)	(VS,S)	(VS,VS)	(VS,VS)

Table A.3 The matrix of normalized fuzzy evaluations

Symbol		S			O			D	
R1	0.5029	0.6126	0.7377	0.4109	0.5216	0.6502	0.2275	0.2700	0.3440
R2	0.4538	0.5604	0.6820	0.3238	0.4146	0.5346	0.2958	0.3919	0.5013
R3	0.6010	0.7038	0.7934	0.4856	0.6018	0.7225	0.2351	0.3048	0.4030
R4	0.5765	0.6908	0.8073	0.4607	0.5751	0.6936	0.2351	0.2961	0.3833
R5	0.4415	0.5344	0.6542	0.4856	0.6018	0.7225	0.2427	0.3222	0.4226
R6	0.6501	0.7559	0.8352	0.3860	0.4949	0.6213	0.2427	0.3222	0.4226
R7	0.5519	0.6647	0.7795	0.4109	0.5216	0.6502	0.3565	0.4616	0.5701
R8	0.5765	0.6908	0.8073	0.4109	0.5216	0.6358	0.2806	0.3745	0.4816
R9	0.6501	0.7559	0.8352	0.4358	0.5483	0.6647	0.2351	0.3048	0.4030
R10	0.4293	0.5344	0.6542	0.4856	0.6018	0.7225	0.2654	0.3571	0.4620
R11	0.4783	0.5865	0.7099	0.4856	0.6018	0.7225	0.2654	0.3571	0.4620
R12	0.5274	0.6386	0.7516	0.5354	0.6553	0.7514	0.2958	0.3919	0.5013
R13	0.5274	0.6386	0.7516	0.4856	0.6018	0.7080	0.3261	0.4267	0.5308
R14	0.5029	0.6126	0.7238	0.3611	0.4681	0.5924	0.3261	0.4267	0.5308
R15	0.4293	0.5344	0.6542	0.5105	0.6286	0.7369	0.2654	0.3571	0.4620
R16	0.6501	0.7559	0.8352	0.4607	0.5751	0.6936	0.2351	0.3048	0.4030
R17	0.3680	0.4301	0.5428	0.5604	0.6687	0.7514	0.4323	0.5225	0.5897

Table A.4 Weighted normalized purpose approach matrix

Symbol		**S**			**O**			**D**	
R1	0.4462	0.5237	0.6120	0.4764	0.5694	0.6757	0.2439	0.2794	0.3303
R2	0.4148	0.4953	0.5845	0.3355	0.4264	0.5422	0.2947	0.3729	0.4580
R3	0.5569	0.6451	0.7194	0.5642	0.6493	0.7368	0.2502	0.3061	0.3779
R4	0.5085	0.5334	0.6021	0.5345	0.6179	0.7077	0.2502	0.2983	0.3582
R5	0.4049	0.4681	0.5486	0.5566	0.6466	0.7368	0.2551	0.3147	0.3825
R6	0.6202	0.7167	0.7879	0.4364	0.5325	0.6419	0.2551	0.3170	0.3901
R7	0.4938	0.5828	0.6718	0.4663	0.5629	0.6734	0.3675	0.4627	0.5584
R8	0.5371	0.6339	0.7307	0.4589	0.5560	0.6545	0.2872	0.3654	0.4488
R9	0.6231	0.7182	0.7879	0.5164	0.6063	0.6966	0.2502	0.3077	0.3832
R10	0.3895	0.4595	0.5395	0.5459	0.6377	0.7327	0.2740	0.3470	0.4267
R11	0.4274	0.5010	0.5852	0.5510	0.6431	0.7356	0.2740	0.3470	0.4267
R12	0.4768	0.5594	0.6437	0.6260	0.6937	0.7551	0.3064	0.3901	0.4797
R13	0.4694	0.5528	0.6353	0.5620	0.6468	0.7260	0.3293	0.4159	0.5003
R14	0.4540	0.5397	0.6273	0.3998	0.4964	0.6099	0.3339	0.4202	0.5046
R15	0.3928	0.4609	0.5390	0.5481	0.6506	0.7425	0.2723	0.3477	0.4302
R16	0.6476	0.7311	0.7879	0.5160	0.6113	0.7077	0.2502	0.3061	0.3779
R17	0.3522	0.3874	0.4449	0.6141	0.6914	0.7551	0.4633	0.5478	0.6050