Applied Soft Computing Journal 201 (2026) 115404

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

A neutrosophic MACONT-LOPCOW decision support model for emergency logistics center selection during humanitarian crises

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HIGHLIGHTS

- Provides DSS for emergency logistics center selection during crises.
- Integrates the MACONT and LOPCOW methods in the type-2 neutrosophic context.
- Selects ELCs by taking the Kahramanmaraş earthquake as a reference.
- Presents recommendations for disaster logistics and humanitarian professionals.
- Offers practical guidance for logistical planners in disaster-prone regions.

ARTICLE INFO

Keywords:
Disaster Management
Humanitarian Logistics
Emergency Logistics Centers
Type-2 Neutrosophic Fuzzy Sets
Mixed Aggregation by Comprehensive Normalization Technique

ABSTRACT

This paper examines disaster preparedness and response, focusing on challenges encountered during natural disasters such as earthquakes. Therefore, we aim to develop a new and powerful tool based on type-2 neutrosophic numbers (T2NNs) for the selection of emergency logistics centers (ELCs). In this context, mixed aggregation based on a comprehensive normalization technique (MACONT) and logarithmic percentage change-driven objective weighting (LOPCOW) are systematically integrated with expert-based subjective weighting under a type-2 neutrosophic environment to construct a coherent decision-making framework for the ELC selection problem. We extend the MACONT method, which handles multiple normalization techniques, to incorporate the benefits into the T2NN-based environment. We combine the objective weights obtained using the LOPCOW method with the subjective weights derived from the T2NNs' structural features to accurately and rationally determine the weights of the criteria affecting the selection of the ELC. The proposed model offers a systematic decision-making process that incorporates criteria weighting and alternative ranking steps, effectively managing ambiguity and inconsistency in expert judgments. Based on real field data and expert opinions from the Kahramanmaraş earthquake, the proposed approach was applied to 19 criteria across four main categories and five possible ELC alternatives. The findings show that the proposed T2NN-based integrated approach produces more consistent, decision-maker-oriented results than traditional methods. In this context, the study makes meaningful contributions to the disaster management literature and practice by providing a methodological reference for decision-making problems under uncertainty in emergency logistics.

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https://doi.org/10.1016/j.asoc.2026.115404
Received 25 April 2025; Received in revised form 30 January 2026; Accepted 5 May 2026
Available online 16 May 2026

List of Acronyms

AI	Artificial Intelligence
ANP	Analytic Network Process
AHP	Analytic Hierarchy Process
CR	Consistency Ratio
CRITIC	Criteria Importance Through Intercriteria Correlation
DEA	Data Envelopment Analysis
DM	Decision Maker
ELC	Emergency Logistics Center
ELCSP	Emergency Logistics Center Selection Problem
GIS	Geographic Information Systems
HL	Humanitarian Logistics
IoT	Internet of Things
IVFS	Interval-Valued Fuzzy Set
LOPCOW	Logarithmic Percentage Change-Driven Objective Weighting
MACONT	Mixed Aggregation by Comprehensive Normalization Technique
MCDM	Multi-Criteria Decision-Making
NIS	Negative Ideal Solution
PIS	Positive Ideal Solution
SWARA	Step-Wise Weight Assessment Ratio Analysis
T2NN	Type-2 Neutrosophic Number
T2NS	Type-2 Neutrosophic Set
T2N	Type-2 Neutrosophic
T2NNWA	Type-2 Neutrosophic Number Weighted Averaging
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje

1. Introduction

Decision-makers (DMs) regarding natural disasters, such as public and local authorities and related units of the countries, plan and carry out critical preparedness measures to protect the country's citizens and economic, cultural, and social assets, and to mitigate the impact of a possible natural disaster with minimal damage. For instance, in Türkiye's plan, as part of the disaster readiness procedure, each working group, comprising employees from all departments within the Ministry of Interior Disaster and Emergency Management Presidency (AFAD), devises its logistics plans beforehand and scales up its capacity as necessary. Despite the extraordinary efforts of relevant institutions and organizations in this regard, it is incredibly difficult to anticipate the location, timing, and severity of natural disasters such as earthquakes and take precautions accordingly. For example, on February 6, 2023, the province of Kahramanmaraş, Türkiye, experienced two consecutive catastrophic earthquakes, both with magnitudes of 7.7. These events affected over 12 million people across ten provinces, resulting in hundreds of thousands of injuries, millions being displaced nationwide, and tens of thousands of fatalities [1,2]. The scale of the aftershocks, especially the Kahramanmaraş earthquake, was astonishing for seismologists and caused significant loss of life, including search and rescue teams, and many humanitarian aid officials and employees could not continue their duties [3,4]. After these earthquakes, which can be considered the biggest natural disaster of recent years, infrastructure elements such as roads, railways, and airlines, as well as hospitals, public buildings, and other necessary facilities, were widely destroyed, causing severe problems and difficulties in terms of the continuity and sustainability of logistics activities [5].

To manage these challenges, large-scale construction equipment and lifting equipment, such as cranes and heavy transport vehicles, were needed to transport them. At the same time, the earthquake victims' urgent and immediate health, first aid, food, and shelter needs were required. By the time the initial quake ended, the scale of the disaster was not entirely clear, as critical transport and communications infrastructure had been extensively damaged. However, as the scale of the disaster became increasingly apparent, the Government quickly declared a state of emergency in eleven affected cities. Then, humanitarian aid materials and search-and-rescue teams began to be delivered to the region from across Turkey.

These experiences clearly reveal that the effectiveness of disaster response operations is highly dependent on the pre-disaster planning and strategic location of emergency logistics centers. Despite increasing awareness of the critical role of emergency logistics centers in disaster response operations, decision-making processes regarding their location are often conducted under severe time pressure, with incomplete information, and high levels of uncertainty. In practice, many emergency logistics center location decisions are still based on heuristic judgments, fragmented expert opinions, or simplified deterministic models that fail to adequately capture the dynamic and uncertain nature of post-disaster environments. This gap between the complexity of real-world disaster conditions and the limited representational capability of existing decision-support tools may lead to delayed responses, inefficient resource allocation, and ultimately increased human and economic losses. Particularly in disaster-prone countries such as Türkiye, where large-scale earthquakes pose recurring, high-impact risks, there is a pressing need for scientifically grounded, robust, and uncertainty-aware decision-making frameworks to support authorities in identifying strategically optimal emergency logistics center locations before and during disasters. Delays or inefficiencies in the early stages of humanitarian logistics can significantly increase human and economic losses, underscoring the urgent need for scientifically grounded, robust decision-support tools for ELC location planning.

In this regard, selecting the appropriate site is extremely important to ensure that the humanitarian logistics (HL) of an ELC are carried out quickly, effectively, and continuously. The problem, which is defined as the emergency logistics center location problem (ELCLSP) in the relevant literature, becomes a more meaningful and critical problem, especially in times of crisis when natural disasters occur [6]. Proper positioning of ELCs significantly reduces the costs associated with the HL while facilitating much faster access to disaster areas. Classical optimization problems such as routing, assignment, and transportation models have long provided the theoretical foundation for decision-making frameworks in logistics and location-selection problems, particularly where cost minimization and operational efficiency are primary objectives [2]. The ELCLSP is inherently a complex decision-making problem, as it involves multiple conflicting criteria, significant uncertainty, limited information, and the need to make rapid yet critical decisions under extreme conditions.

The core problem addressed in this study is the lack of an integrated and robust decision-support framework capable of simultaneously handling uncertainty, indeterminacy, expert heterogeneity, and normalization sensitivity in emergency logistics center location decisions. Existing approaches predominantly treat weighting and ranking as sequential and weakly coupled processes, often assuming stable information structures and homogeneous expert judgments. However, in real post-disaster environments, decision-makers must operate under highly inconsistent, incomplete, and sometimes contradictory information, where the reliability of expert opinions and the influence of normalization procedures can substantially alter decision outcomes. Consequently, the lack of a unified modeling framework that explicitly accounts for these interconnected challenges undermines the reliability and practical applicability of current ELCLSP solutions, particularly in high-risk, time-critical disaster response contexts.

Traditional mathematical frameworks often fail to capture and address uncertainty or indeterminacy, leading to the development of fuzzy concepts such as Intuitionistic and Pythagorean fuzzy, and their different measures [7]. Unlike its classical counterpart, FTP allows the allocation of fractional goods between sources and destinations, introducing a nuanced dimension in transportation planning [8,9]. Selecting an appropriate PCM for any given application is a complex task, as it involves considering multiple factors such as melting temperature, thermal conductivity, specific heat capacity, and energy density, among others. In addition, appropriately located ELCs can improve the effectiveness of emergency response and humanitarian response while enabling faster disaster relief [6]. On the other hand, since it is challenging to predict the magnitude, severity, precise location, and number of individuals affected by a natural disaster, it is not practical to construct and implement action plans adapted to specific scenarios in real-life conditions [10].

Since the magnitude, precise location, and areas impacted by a disaster cannot be predicted in advance, it is impractical to design action plans tailored to specific scenarios [10]. It is especially crucial for Türkiye, given its status as a high-risk disaster zone. This study is motivated by the limited literature and field-specific knowledge regarding the optimal establishment of ELCs during disasters. Currently, there is insufficient information on the key factors to consider when selecting ELC locations, the relative importance of these factors, or how alternative sites should be evaluated. Given that the ELCLSP is inherently a selection problem, this study applies multi-criteria decision--making (MCDM) methods to address the issue effectively. However, the core challenge is not the application of MCDM itself, but how to construct an integrated weighting–ranking structure capable of handling indeterminacy, expert heterogeneity, and normalization sensitivity simultaneously.

However, a critical review of the existing literature reveals several significant gaps. Although several studies have combined neutrosophic sets with objective weighting or ranking techniques independently, most existing fuzzy-MCDM frameworks treat weighting and ranking as sequential but weakly coupled processes. In contrast, the present study emphasizes the interaction between objective dispersion-based weighting (logarithmic percentage change-driven objective weighting (LOPCOW)) and normalization-sensitive ranking (mixed-aggregation by comprehensive normalization technique (MACONT)) under a unified type-2 neutrosophic (T2N) structure, which has not been explicitly operationalized in emergency logistics center location problems. Most existing studies either rely on deterministic or type-1 fuzzy approaches, which are insufficient to capture the high level of uncertainty, indeterminacy, and inconsistency inherent in disaster-related decision environments.

In response to the aforementioned challenges and research gaps, the primary objective of this study is to develop a comprehensive and MCDM framework based on type-2 neutrosophic numbers (T2NNs) to support the selection of emergency logistics centers under post-disaster uncertainty. Specifically, the study aims to (i) model the uncertainty, indeterminacy, and inconsistency inherent in expert evaluations through a type-2 neutrosophic representation, (ii) construct an integrated weighting structure by coherently combining subjective expert-based weights and objective data-driven weights using the LOPCOW method, (iii) enhance the robustness of alternative ranking by adopting the normalization-sensitive MACONT technique, and (iv) validate the applicability and effectiveness of the proposed framework through a real post-disaster case study derived from the 2023 Kahramanmaraş earthquakes in Türkiye.

Despite the growing body of research on emergency logistics and location selection problems, several critical gaps remain insufficiently addressed. First, existing studies predominantly employ deterministic or type-1 fuzzy frameworks that are unable to explicitly represent indeterminacy and inconsistency in expert judgments, which are prevalent in post-disaster decision environments. Second, although objective and subjective weighting methods are widely used, they are typically applied as isolated or sequential steps, without considering their mutual interactions or potential instability arising from data dispersion and normalization. Third, the majority of current MCDM-based emergency logistics studies neglect the sensitivity of alternative ranking results to normalization procedures, despite evidence that normalization-induced bias can significantly alter decision outcomes in complex and uncertain settings. Finally, the integration of expert heterogeneity and reputation into a unified neutrosophic decision-making framework remains largely unexplored, particularly in real post-disaster applications. These gaps highlight the need for an integrated, uncertainty-aware, and normalization-robust decision-support framework tailored specifically to emergency logistics center location selection problems.

Although various fuzzy-based approaches have been proposed to address ambiguity in complex decision-making problems, their representational capabilities remain limited in highly uncertain and crisis-driven environments. Hesitant fuzzy sets (HFS) are effective for capturing situations in which decision-makers hesitate among several possible membership degrees; however, they do not explicitly distinguish indeterminacy as a separate component nor account for the reliability of the provided information. Classical type-2 fuzzy systems, on the other hand, enhance uncertainty modeling by allowing imprecision in membership functions, yet they remain confined to a truth-based uncertainty structure and lack an explicit mechanism to represent the coexistence of truth, falsity, and indeterminacy simultaneously.

In disaster-related decision environments, such as emergency logistics center location selection, decision-makers are confronted not only with incomplete and vague information but also with conflicting expert opinions and uncertainty regarding the credibility and consistency of available data. Under these conditions, uncertainty is not limited to membership vagueness alone; rather, it exhibits a strong epistemic nature stemming from indeterminacy and inconsistency in expert judgments. T2NNs provide a more comprehensive modeling framework by simultaneously incorporating uncertainty, indeterminacy, and inconsistency via independent membership functions for truth, indeterminacy, and falsity under a second-order uncertainty structure. This capability enables T2NNs to more realistically reflect the complex cognitive and informational conditions characterizing post-disaster decision-making processes, thereby offering a superior and more robust alternative to HFS and classical Type-2 Fuzzy approaches in emergency logistics applications.

Recent advances in neutrosophic theory further support the suitability of neutrosophic-based modeling frameworks for complex, multilayered systems characterized by high uncertainty, interdependence, and ambiguous relational structures. In this context, the implementation of single-valued neutrosophic soft hypergraphs has demonstrated strong representational capability in modeling highly complex systems with uncertain interactions. For example, Akram & Nawaz [11] employed single-valued neutrosophic soft hypergraphs to model the human nervous system, showing that neutrosophic representations can effectively capture intricate relational patterns and indeterminate interactions that classical fuzzy and intuitionistic fuzzy models fail to adequately address. Similarly, Akram & Nawaz [12] developed efficient algorithms for regular single-valued neutrosophic soft hypergraphs and successfully applied them to the analysis of supranational Asian decision-making bodies, highlighting the robustness of neutrosophic frameworks in handling heterogeneous actors, incomplete information, and conflicting decision structures.

These studies provide strong methodological evidence that neutrosophic-based representations are particularly well suited for complex decision environments involving multiple stakeholders and high levels of epistemic uncertainty. Consequently, they provide solid theoretical support for adopting a T2N modeling structure in the proposed MCDM framework, thereby reinforcing its ability to address the indeterminacy, inconsistency, and expert heterogeneity inherent in emergency logistics center location selection problems.

Moreover, the integration of objective and subjective weighting mechanisms in a T2N framework remains very limited. In addition, few studies incorporate expert reputation and decision-maker characteristics into the evaluation process, particularly in real post-disaster contexts. Crisp MCDM approaches fall short of adequately addressing complex decision problems due to their inability to handle inherent uncertainty and imprecision [8].

Therefore, the primary objective of this study is to develop a robust and integrated MCDM framework based on T2NNs to effectively address the emergency logistics center location selection problem under uncertainty. Selecting the optimal location for an ELC during a disaster is a complex, time-consuming task due to numerous competing criteria and multiple potential sites. Additionally, the location of an emergency center is a strategic decision in the HL, requiring careful planning, efficient resource allocation, and a swift response to alleviate suffering and save lives. This study identified the relevant criteria for the ELCLSP through a literature review and expert consultations. These criteria were organized into a hierarchical structure, and their weights were determined using the T2N operator. This operator was chosen for its ability to better handle the logistical uncertainties associated with natural disasters.

Objective weighting techniques such as Entropy, CRITIC, and standard deviation-based methods are commonly used to derive criterion importance from data dispersion [13,14]. Nevertheless, these approaches may suffer from scale dependency and sensitivity to extreme values, leading to unstable weighting results in complex decision matrices. LOPCOW was proposed by Ecer & Pamucar [15] as an alternative objective weighting approach that effectively addresses these limitations by utilizing logarithmic percentage changes to more accurately reflect the relative variation of criteria.

Previous studies have shown that LOPCOW produces more balanced and interpretable weights, particularly in decision-making problems characterized by heterogeneous criteria and nonlinear data distributions [16]. Given the multidimensional and dynamic structure of emergency logistics center location problems, employing the LOPCOW method enables the extraction of objective information from the data while maintaining computational stability and methodological rigor, as evidenced in recent MCDM literature [17].

In addition, to avoid ignoring objective information that effectively determines the relative weights of the criteria, the criterion weights were calculated using the objective, practical, and highly functional LOPCOW method. The subjective weights of the criteria were calculated using the structural properties of T2N sets. The final weight values for the measures were determined by combining the objective and subjective weights.

Although previous studies have independently applied neutrosophic sets, objective weighting techniques, or advanced ranking methods in location selection and logistics-related decision problems [18,19]. An integrated framework combining T2N modeling with the LOPCOW and MACONT methods has not yet been reported in the literature. The proposed hybrid methodology addresses this gap by simultaneously incorporating expert-driven uncertainty through neutrosophic sets, objective data-based weighting via LOPCOW [20], and robust alternative ranking with MACONT [21] within a unified decision-support structure. Therefore, the methodological contribution of this study lies not only in the individual application of these techniques but also in their systematic integration to solve the emergency logistics center location problem under post-disaster conditions [22].

Additionally, the suggested model can incorporate DM characteristics and abilities into the evaluation process. For this purpose, it assigns relative weights to the experts participating in the assessment process. Since an expert's reputation can provide a more accurate and reasonable basis for decision-making, each expert's weight is determined by the degree of their reputation.

Alternative sites were generated based on a specific infrastructure framework and expert recommendations. The study used MACONT to evaluate these alternatives, using T2NNs to identify the most effective option. As a result, the MACONT method is adapted and extended within a T2N environment to improve robustness against normalization-induced ranking instability, rather than being proposed as an entirely new ranking paradigm. Conventional MCDM ranking techniques such as TOPSIS, VIKOR, ARAS, and COPRAS rely heavily on normalization procedures, which may result in information loss and ranking instability when applied to complex and uncertain decision environments [23,24]. In contrast, the MACONT (Mixed Aggregation by Comprehensive Normalization Technique) method integrates multiple aggregation strategies through comprehensive normalization, allowing for a more flexible and discriminative evaluation of alternatives [25].

Recent methodological studies indicate that MACONT improves ranking robustness and reduces the dependency of results on a single normalization rule [26]. These characteristics make MACONT particularly suitable for emergency logistics applications, where decision alternatives must be assessed under multiple conflicting criteria and uncertain information structures [27]. Consequently, the use of MACONT in this study enhances the reliability of alternative ranking results and strengthens the methodological foundation of the proposed decision-support framework. In this context, the research questions of this study are as follows:

- *RQ1* – When a natural disaster occurs, how should the location of the ELC, established to deliver aid to the region as quickly and accurately as possible, be selected?
- *RQ2* – What are the most essential criteria in this ELC selection?
- *RQ3* – In a natural disaster, how should the ELC be selected to employ a new, robust, and powerful tool?

The novelty of this study lies not in proposing an entirely new decision-making technique, but in systematically integrating and operationalizing existing advanced methods within a unified and uncertainty-aware framework tailored to emergency logistics center location problems. Unlike prior studies that apply weighting and ranking methods as independent or weakly connected procedures, this research explicitly models their interaction by coherently combining objective dispersion-based weighting (LOPCOW) and normalization-sensitive alternative ranking (MACONT) under a T2N structure. Moreover, the proposed framework enhances the practical applicability of these methods by incorporating expert heterogeneity and reputation into both the weighting and ranking stages, thereby better reflecting real-world decision-making conditions. To the best of the authors' knowledge, this is the first study to implement such an integrated T2N LOPCOW–MACONT framework for emergency logistics center location selection using real post-disaster data.

The contributions of this study can be summarized as follows:

(i) The study demonstrates how objective weighting (LOPCOW) and normalization-sensitive ranking (MACONT) can be coherently integrated within a T2N framework, addressing interaction effects that are often ignored in sequential fuzzy-MCDM applications.
(ii) Unlike many conceptual or hypothetical studies, the proposed framework is validated using real post-disaster data and expert judgments derived from the Kahramanmaraş earthquake, enhancing its empirical relevance.
(iii) The model explicitly incorporates expert reputation into the evaluation process, allowing decision-maker heterogeneity to be reflected in both weighting and ranking stages, which is rarely operationalized in existing emergency logistics studies.

The remaining parts of this paper are structured as follows: Section 2 investigates the relevant literature, while Section 3 focuses on the case study and the hierarchical structure. Section 4 outlines the research framework and methodologies used. Section 5 presents the application's results, findings, and sensitivity analysis. Finally, Section 6 concludes the paper with recommendations for future research.

2. Research background

Natural disasters have profound social, economic, and environmental impacts on communities worldwide. Researchers have employed MCDM methods to minimize these effects. In this section, the relevant literature was reviewed in three stages. The first subsection comprehensively reviews studies on natural disasters and MCDM. The second subsection examines the various approaches to warehouse site selection for HL activities. The third subsection examines the application of fuzzy MCDM methods within this context.

2.1. Natural disasters and MCDM

Studies on natural disasters have frequently employed MCDM methods. Some recent, vital studies are outlined below. Peker et al. [28] conducted a study to alleviate the influence of global epidemics, such as the 2022 pandemic. They applied the IF-ANP and the IF-VIKOR methods, identifying effective coordination and enhanced automation and programming as the most critical criteria. Fatrias et al. [29] focused on developing disaster resilience indicators for small and medium-sized corporations, utilizing the fuzzy BWM. Physical resistance was identified as the most crucial criterion. Ak & Acar [30] explored charitable supply chain storehouse site choice and management, integrating AHP and TOPSIS in their study.

Peng [31] analyzed the earthquake exposure of 31 cities in China employing MCDM frameworks. The cities were evaluated in four categories using the TOPSIS method, revealing that many were highly vulnerable to earthquakes. Celik et al. [32] employed a fuzzy MCDM approach to assess success factors in humanitarian aid logistics, applying the trapezoidal interval type-2 fuzzy AHP method. Critical criteria included personnel, inventory safety, and efficient human resource management. Malekmohammadi et al. [33] performed an MCDM analysis for emergency response planning in urban areas, focusing on post-disaster drinking water supply. AHP revealed that the most critical criteria were water quality, service delays, costs, and affected population.

Yilmaz & Kabak [34] applied AHP and TOPSIS with a fuzzy interval type-2 MCDM approach to select locations for humanitarian aid distribution and centers, identifying transportation, cost, infrastructure, and security as critical factors. Liu [35] studied the selection of sites for emergency medical supply centers following devastating earthquakes, applying AHP and TOPSIS methods. Critical criteria included safety, favorable terrain, available resources, and transportation. Budak et al. [36] developed a real-time positioning system for four alternative HL warehouses, employing DEMATEL, ANP, and TOPSIS.

Using a post-earthquake case study in Iran, Foroughi et al. [16] proposed a dual-purpose resilience recovery logistics model that considers operational and interruption threats. BWM identified flexible facilities as the most critical criterion. Sheu [37] applied clustering and MCDM methods in the context of large-scale natural disasters. Tuzkaya et al. [38] implemented an ELC location selection study using DEMATEL and ANP methods, identifying 11 criteria.

2.2. Warehouse site selection for humanitarian logistics

Regarding humanitarian aid logistics, selecting warehouse and facility locations is a critical decision-making problem. To address and solve this decision-making problem, researchers in the literature have tried different decision-making models and approaches [39–42]. While a significant part of the authors used the classical AHP approach [39–42], fuzzy forms of this method were preferred in a few studies [43,44]. In some studies, the authors used AHP only to calculate the criteria weights, generally preferring the classic fuzzy sets. In these studies, the authors preferred to integrate the AHP method with sequencing methods such as TOPSIS [45,46], MULTIMOORA [47], and WASPAS [48].

In terms of the approaches used in other studies, Wang et al. [49] investigated the selection of optimal warehouse locations for aid logistics using DEA, while He et al. [50] opted for ELECTRE. Additionally, investigators have employed methods such as MULTIMOORA [31], goal programming [32], and genetic algorithms [33] to handle this decision-making issue in the literature. Some studies have also developed optimization models to solve the issue of warehouse location selection in humanitarian aid logistics [19,51]. Finally, Korucuk et al. [52] introduced the LOPCOW and RAFSI methods with interval-valued Fermatean fuzzy clusters, identifying population density as the most significant factor in their study.

Overall, in most studies in the literature—specifically all but five—the authors did not conduct sensitivity or comparison analyses to test the robustness and consistency of their proposed models. It raises serious concerns about the reliability of the models presented in these studies. Furthermore, none of the researchers examined whether their proposed approaches and models were immune to the rank reversal problem, a fundamental limitation in decision-making methodologies. Lastly, despite the significant complexities and uncertainties associated with natural disasters, few studies have employed fuzzy clustering, which is more effective at addressing these uncertainties. Traditional fuzzy sets may fall short of adequately capturing and processing the intricate uncertainties in this field.

2.3. Fuzzy sets used in the relevant literature

The literature contains limited studies that integrate disaster logistics with fuzzy MCDM approaches. This section reviews relevant studies that have combined fuzzy MCDM methods with disaster management. For instance, Yılmaz & Kabak [34] identified critical factors for establishing a regional logistics distribution center in preparation for disasters. They combined type-2 fuzzy AHP and TOPSIS to identify the primary factors of transportation, pricing, infrastructure, and security. Edjossan-Sossou et al. [53] focused on identifying critical criteria for risk management strategies, utilizing fuzzy AHP and PROMETHEE in their analysis. Their main criteria included economic, environmental, and social sustainability. Otay & Jaller [54] employed a multi-expert MCDM framework to assess disaster risk management and response processes and capacities in Atlantico, Colombia, using a straightforward fuzzy TOPSIS approach.

Jiang et al. [55] applied fuzzy comprehensive assessment, fuzzy similarity methods, and primary fuzzy classification to evaluate the probability of flood disasters in Kelantan, Malaysia, leading to the identification of high-risk and low-risk flood zones. Guo et al. [56] outlined the processes and methods for evaluating flood hazards in Liaoning Province, China, employing variable fuzzy set theory to obtain their results. Yariyan et al. [57] conducted a seismic susceptibility analysis in densely populated areas of Iran, integrating fuzzy AHP and artificial neural network models in their application. Their study accurately identified regions with high earthquake susceptibility.

Yanilmaz et al. [58] performed an extensive catastrophe hazard assessment for Tunceli Province, examining likely alleviation measures using the Bayesian BWM method. Their findings ranked the top three disaster hazards in Tunceli as earthquakes, mass movements, and floods. Polat [59] investigated disaster logistics in Türkiye, applying AHP and TOPSIS to determine the locations of logistics distribution centers for disasters. The study found that Altınçevre and Buzlupınar received the highest values according to TOPSIS results. Simic et al. [60] implemented T2N MABAC and critical methods for determining public transport fare pricing, identifying 13 criteria for their analysis. This study is notable for its innovative application method. Finally, Abdel Basset et al. [61] applied T2N weighting and TOPSIS to the supplier selection problem, utilizing nine criteria and five alternative suppliers.

2.4. Research and theoretical gaps

The scarcity of studies on natural disasters in the literature is noteworthy. While these efforts often focus on disaster prediction or prevention, insufficient attention has been paid to strategies to minimize post-disaster deaths and to promptly seek public assistance in the early stages of the crisis. This research aims to contribute to such a body of knowledge. In cases where highways, airports, ports, and disaster centers are devastated, strategies for establishing an ELCLSP to sustain relief efforts will be examined. The study emphasizes the destructive effects of the Kahramanmaraş earthquake, and T2N MCDM techniques are applied in the study's application section. There is no example of literature that combines this strategy with disaster studies. While related studies have addressed disaster logistics using fuzzy or neutrosophic MCDM approaches, the combined use of T2N modeling with dispersion-sensitive objective weighting and normalization-robust ranking remains limited, particularly in real post-disaster emergency logistics center selection contexts. It shows a meaningful application study that makes exceptional contributions to the literature regarding subjects and methodology.

A closer examination of uncertainty modeling approaches further clarifies the methodological advantage of the proposed framework. Hesitant Fuzzy Sets are primarily designed to represent situations in which experts hesitate among several possible membership degrees; however, they do not allow for a clear separation between the degree of truth and the reliability or credibility of the provided information. As a result, while multiple opinions can be accommodated, the underlying uncertainty regarding whether these opinions are trustworthy or indeterminate cannot be explicitly captured.

Similarly, type-2 fuzzy systems improve upon type-1 fuzzy sets by modeling uncertainty in the membership functions themselves, thereby offering greater flexibility in handling vagueness. Nevertheless, these systems remain conceptually limited to a truth-oriented uncertainty structure and do not explicitly define or quantify indeterminacy as a distinct component. Consequently, situations in which experts are genuinely unsure, provide contradictory assessments, or lack sufficient confidence in their evaluations are not adequately represented.

In contrast, type-2 neutrosophic sets (T2NSs) decompose uncertainty into three independent components—truth, indeterminacy, and falsity—each modeled under a second-order uncertainty structure. This decomposition enables a more nuanced and realistic representation of expert judgments, particularly in disaster-related decision environments where incomplete information, conflicting opinions, and low confidence levels are prevalent. By explicitly capturing the "I am not sure" state of experts through the indeterminacy component, T2N modeling offers a higher representational capacity and decision robustness. This fundamental distinction explains why the proposed approach outperforms Hesitant Fuzzy Sets and classical Type-2 Fuzzy systems in emergency logistics and humanitarian decision-making contexts.

In addition, the use of MCDM methods in managing natural disasters is increasing. However, the studies in this area have some critical gaps and limitations. The limited use of fuzzy MCDM methods reduces the capacity to address uncertainties, and innovative approaches are needed in the field of research. For example, the study by Yilmaz & Kabak [34] used a combination of classical fuzzy sets based on AHP and TOPSIS, while other studies mainly focused on classical methods. Most studies have not conducted sensitivity and comparison analyses to assess the trustworthiness of the proposed models. It raises serious doubts about the models' robustness and casts their practical applicability into question. In addition, the resilience of the suggested approaches to the rank reversal problem has not been studied. It constitutes a significant limitation in decision-making processes, and more work is needed on how current approaches respond to such situations.

Thus, the existing literature has critical and significant research gaps and limitations. Addressing these gaps can help develop more effective decision-making processes in managing natural disasters. Integrating innovative methods, such as advanced fuzzy MCDM methods, multi-objective optimization approaches, and dynamic modeling techniques, will significantly advance research in this area.

2.5. Study objectives and motivations

After the Kahramanmaraş earthquake, new measures regarding future disasters, changes, and regulations for post-disaster interventions were given an important place on Turkey's agenda. One of the biggest problems posed by this disaster has been the difficulty in delivering emergency aid on time due to road damage. Therefore, the importance of logistics activities during and after the disaster was again emphasized, underscoring the criticality of effective logistics planning. Developing detailed, well-structured logistics plans for disasters is essential for effectively managing post-disaster situations.

This study aims to develop a robust and reliable mathematical tool for DMs in disaster management. Drawing on the Kahramanmaraş earthquake, this study aims to evaluate and select effective ELC locations. The selection of ELCs involves a complex evaluation process that requires rigorous criteria that reflect real-world conditions. These criteria were determined by a comprehensive literature review and field research. Interviews with disaster management professionals were conducted with logistics center managers to understand the importance of ELCs during the Kahramanmaraş earthquake. The central goal of this process is to define which criteria gained more importance during the earthquake crisis.

One motivation for this study is that DMs are not sufficiently adaptable to effectively address and solve complex decision-making problems that arise during a disaster. T2NSs used in the developed model are presented as an effective tool for dealing with uncertainty and tolerating possible misjudgments by practitioners. This study proposes a new method for evaluating and selecting ELCs in an earthquake zone. The decision-making model developed for T2NNs, which integrates two effective, practical, and robust methods, LOPCOW and MACONT, is used in ELCs to define effective criteria logically and rationally. As a result, this study aims to contribute to both theoretical and practical fields by offering innovative solutions to the problems experienced in disaster management. The development of post-disaster logistics planning has the potential to minimize the challenges faced by both DMs and practitioners. In that regard, the work outcomes will enable the creation and implementation of future disaster response strategies more effectively.

3. Suggested neutrosophic decision support model

This section presents the fundamental algorithm of the suggested model and the implementation steps of the integrated approach, which combine LOPCOW and MACONT procedures. Besides, it demonstrates the mathematical notions of the proposed model. Fig. 1 illustrates the fundamental procedure of the proposed model. To improve readability and avoid textbook-style repetition of well-established mathematical procedures, detailed algorithmic steps, mathematical expansions, and computational formulations are provided in Appendix C.

In the introduced neutrosophic decision support model for emergency logistics center selection during crises, T2NN has been employed, one of the most successful clustering methods for addressing disaster-related issues and resolving uncertainty. In addition, the relative weights of the criteria were determined using a combination of subjective and objective weighting methods. Finally, the rankings in the study were determined using the T2NN-based MACONT approach. The related preliminary information is given in Appendix C.

3.1. Finding expert reputation degrees

In collaborative decision-making environments, DMs often come from diverse professional backgrounds and have varying knowledge domains, attitudes, and levels of expertise. Acknowledging these

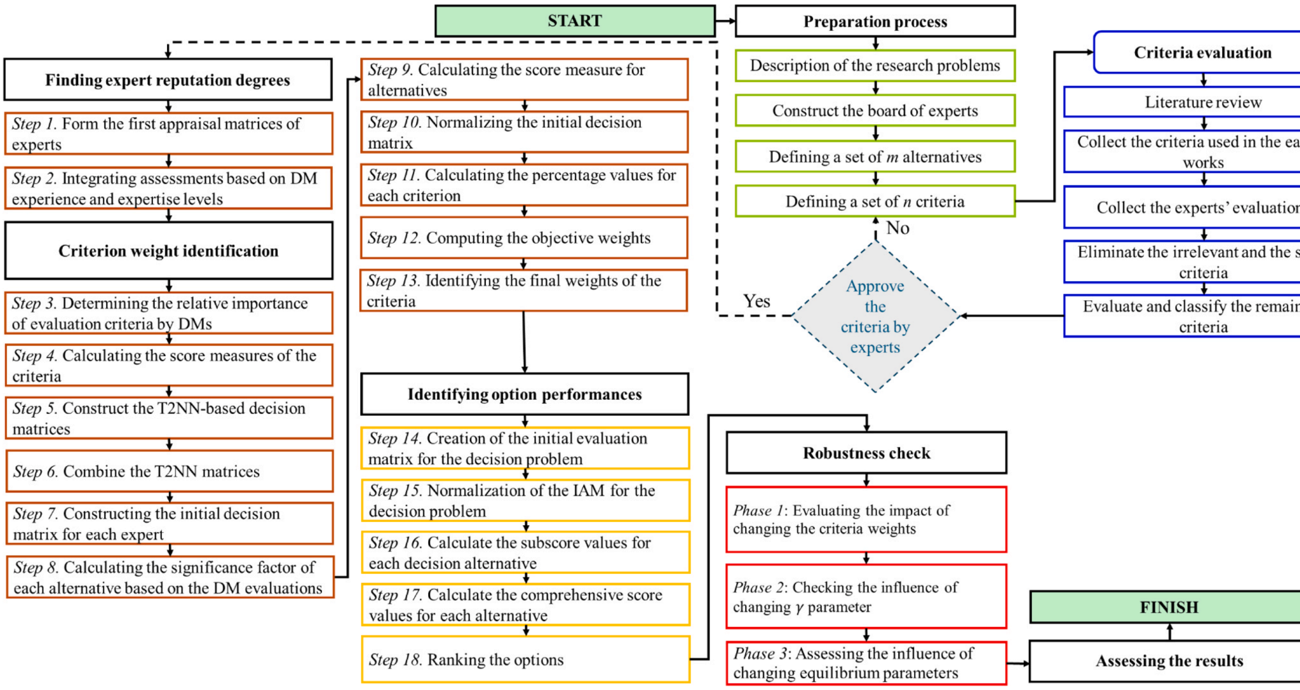

Fig. 1. Algorithm of the proposed neutrosophic decision support model.

Fig. 2. Wave of the Kahramanmaraş earthquake.

differences is essential for determining DM importance and integrating them into the analytical framework, ultimately improving the quality of decision-making outcomes [62]. To this end, the current study employs a methodological approach based on T2NNs, as suggested by Simic et al. [63], to assign weights to DMs. The procedural steps for this approach are outlined in Appendix C [63,64].

3.2. Criterion weight identification

Here, the fundamental procedure of the suggested model for identifying the subjective and objective weights of the criteria is presented. Detailed formulations for subjective and objective weighting procedures are provided in Appendix C.

3.2.1. Calculating subjective criterion weights

The basic procedure based on T2NSs is followed to calculate the subjective weights of the criteria. The basic procedure, involving four implementation steps, for identifying the subjective weights of the criteria is demonstrated in Appendix C.

3.2.2. Calculating objective criterion weights

The basic procedure of the LOPCOW approach was employed to identify the objective weights of the measures. Appendix C demonstrates the implementation steps for the method.

3.3. Identifying option performances

At this stage, MACONT was employed to assess and rank the alternatives, utilizing an approach that enhances and expands the T2NSs. The suggested T2N MACONT method is an innovative approach for ranking alternatives. It consists of five primary steps. The complete MACONT-based ranking algorithm and normalization procedures are shown in Appendix C.

4. Case study

The proposed MCDM model was applied following the Kahramanmaraş earthquake to assess the importance of ELCs. A four-step process was developed to implement and evaluate the hybrid model. In the first phase, we observed and analyzed how logistics operations were managed during and after the earthquake. In this study, we conducted face-to-face interviews with experts and authorities on humanitarian aid logistics and search and rescue related to earthquakes and natural disasters, and we took notes to structure the research questions to be addressed.

When the crisis was overcome and the situation was under control, search and rescue experts shifted their full attention to operations, and researchers formed a committee of experts on the subject. The group of experts comprised professionals with a high level of knowledge and extensive experience in the relevant field. One of the most essential tasks of the experts was to eliminate the gaps in the researchers' technical knowledge and observations. To serve on the panel of experts, the researchers conducted a comprehensive study and determined the appropriate candidates. As a result of the final negotiations, the professionals who would do it were determined by the expert committee. However, additional efforts were made to ensure that the research process did not disrupt the tasks of the selected specialists.

In addition to the small number of experts and authorized professionals in humanitarian aid logistics and search and rescue, three experts were included in the board of experts because some did not want to serve on the board due to their duties. In addition, three veterans were invited to participate in the study to calculate the weight of these experts and include them in the evaluation process. Numerous group meetings and face-to-face personal interviews were held with these experts. In these meetings, in addition to the criteria for the evaluation process, many technical issues related to alternatives and natural disasters were discussed and evaluated.

A thorough literature review was conducted to identify the key and supporting criteria for the ELCLSP using the keywords "location center selection", "emergency logistics center selection", and "MCDM" across databases such as Scopus, Web of Science, and Google Scholar. Following this, the criteria and alternatives were discussed with the experts.

The researchers reviewed the existing literature to identify criteria used in prior studies on ELC location selection (Table 1). Concurrently, they asked each expert to compile a list of criteria for selecting an appropriate location based on their prior experience. The experts' lists were then integrated with the criteria from the literature, and redundant items were removed. The final selection criteria were established through consensus among the experts.

4.1. Finding expert reputation degrees

The procedure proposed by Simic et al. [87] was followed to calculate the relative weights of the experts involved in the evaluation process and to incorporate them into an analysis to be carried out to evaluate ELCs. However, while the proposed model considers only the expertise and experience of the experts, in this study, in addition to the experts' characteristics, the experts' age and the duties they undertake were also included in the model.

Step 1: Each expert characteristic was evaluated in detail by three professionals identified as veterans. The veterans evaluated the characteristics of the experts using the linguistic terms on the linguistic scale presented in Table B.1. Table 2 presents the information obtained on the characteristics of experts and professionals defined as veterans, along with veterans' evaluations of the experts. The experts involved in the decision-making process were systematically evaluated rather than being treated as homogeneous contributors. Each expert was assessed based on multiple qualification dimensions, including educational background, years of professional experience, domain specialization, role in disaster-related logistics and emergency management, and overall field expertise. This structured expert evaluation procedure ensures that expert opinions incorporated into the model are grounded in demonstrable qualifications and relevant experience, using the linguistic terms listed in Table B.1.

The linguistic terms in matrices given in Table 2 were converted to the T2NNs corresponding to the linguistic appraisal scale presented in Table B.1.

It is well recognized in the decision-making literature that the inclusion of human judgment inevitably introduces a certain degree of subjectivity and bias. In this study, such bias is not overlooked; instead, it is explicitly addressed through multiple methodological mechanisms.

Table 1
Emergency logistics centers selection criteria.

Criteria	Sub-criteria	Description	Reference
Logistics assess (C_1)	Proximity to highway (C_{1-1})	Proximity to highways provides both public transportation and easier distribution of aid.	[65–68]
	Proximity to railway (C_{1-2})	Proximity to the railway means aid can be delivered via it and used in different ways.	[6,65,68]
	Proximity to seaport (C_{1-3})	It means that help can come by sea.	[67,68]
	Proximity to airport (C_{1-4})	It means aid can be accepted via air.	[65,68–70]
	Traffic condition (C_{1-5})	The traffic situation may make it easier or more difficult for aid to reach the ELC and to transport the collected aid to the disaster areas.	[6,71,72]
Cost (C_2)	Land (C_{2-1})	This cost represents the investment cost.	[73-75,77]
	Storage (C_{2-2})	This cost represents the logistics center's operating expenses.	[76]
Location (C_3)	Proximity to beneficiaries (C_{3-1})	To distribute faster and more accurately, it is necessary to be closer to the beneficiaries.	[77,80]
	Disaster-free location (the safe area not easily affected by disasters) (C_{3-2})	For the warehouse to be used appropriately, the relevant area must be unaffected or minimally affected by the disaster.	[79–81]
	Climate (C_{3-3})	It reflects the region's climate.	[77]
	Closeness to the warehouses (C_{3-4})	It refers to the distance from the logistics center to the warehouses.	Expert opinion
	Shortest starting time (C_{3-5})	It refers to the preparation time for the distribution center's opening, and this period should be kept to a minimum.	[83]
	Proximity to disaster-prone areas (C_{3-6})	It refers to the distance to the disaster area.	[78]
	Ease of access for auxiliary materials (C_{3-7})	It refers to the accessibility to supporting materials.	Expert opinion
Land structure (C_4)	Flora (C_{4-1})	The location where the ELC will be built must have a low vegetation density.	[65]
	Slope (C_{4-2})	Since transportation is more difficult in areas with steep slopes, the ELC is expected to have a low slope.	[79]
	Elevation (C_{4-3})	The expected elevation of the ELC to be opened is low.	[80]
	Distance of fault line (C_{4-4})	The newly opened ELC must be located sufficiently far from the fault line in case of a natural disaster.	[84,85]
	Landslide risk (C_{4-5})	The newly opened ELC must have a low risk of landslides due to potential natural disasters.	[65,68,85, 86]

Table 2
Boards of decision-makers, professionals, and experts and details of the members.

Code	Duty	Company	Experience	Number of disasters	Expertise
Board of professionals					
PR_1	Area Manager	AFAD	34	-	Emergence management
PR_2	Vice president	Blue crescent	32	-	Humanitarian aid
PR_3	Logistics manager	AFAD	25	-	Search and rescue
Board of decision-makers					
DM1	Logistics manager	-	32	10	Business
DM2	Logistics manager	-	26	7	Economy
DM3	Logistics manager	-	19	4	Industrial Engineer
Professional-I					
	Graduation	**Degree**		**Duty**	**Experience**
DM_1	VG	MG		G	M
DM_2	G	G		G	P
DM_3	MG	MG		G	MG
Professional-II					
DM_1	G	M		MG	M
DM_2	MG	MG		MG	P
DM_3	MG	M		MG	MG
Professional-III					
DM_1	M	M		G	M
DM_2	VG	MG		G	P
DM_3	MG	M		G	MG

First, the use of a heterogeneous panel of experts reduces individual dominance and personal bias by aggregating diverse perspectives. Second, the T2N representation enables experts to express not only their degree of agreement but also their uncertainty and hesitation via the indeterminacy component. By modeling truth, indeterminacy, and falsity as independent dimensions under a second-order uncertainty structure, the proposed framework effectively absorbs inconsistencies, conflicting opinions, and low-confidence assessments. Consequently, the influence of biased judgments is mitigated, and the reliability and robustness of the final decision outcomes are significantly enhanced.

Step 2: Afterwards, the graduation, degree, duty, and experience features of the experts were equally weighted, i.e. $\wp_1 = \wp_2 = \wp_3 = \wp_4 = 0.25$. These T2NNs were combined according to the T2NNWA operator with the help of Eq. (1). The matrix elements in the T2NN form obtained for the three professional evaluations were converted to score values with the help of Eq. (8.a) and normalized. The geometric average was taken in the last stage, and the weight values were calculated for each expert. Table 3 presents the calculations and expert weights at this process stage. Next, each expert's weight represents each specialist's reputation, which is determined by employing Eq. (2).

As given in Table 3, the geometric means of the score values were then calculated to determine the final score for each expert. These values were subsequently normalized to compute the final prestige of the experts.

4.2. Criterion weight identification

This subsection presents the calculation of the objective and subjective weight values for the criteria, along with the results obtained by combining these two sets of weights. First, the subjective weights of the criteria were determined using the recommended procedure outlined below.

4.2.1. Calculating subjective criterion weights

The basic procedure based on T2NSs was followed to calculate the subjective weights of the criteria. For this, the proposed approach, which consisted of four steps, was followed, as shown below.

Table 3
Experts' weight values.

	Aggregated T2NN values	Score value	Reputation
Professional-I			
Expert-1	$\langle (0.766, 0.705, 0.776), (0.222, 0.206, 0.281), (0.159, 0.193, 0.228)\rangle$	0.772	0.357
Expert-2	$\langle (0.636, 0.683, 0.709), (0.256, 0.402, 0.461), (0.223, 0.374, 0.349)\rangle$	0.656	0.303
Expert-3	$\langle (0.628, 0.548, 0.602), (0.188, 0.163, 0.250), (0.100, 0.226, 0.163)\rangle$	0.737	0.341
Professional-II			
Expert-1	$\langle (0.584, 0.548, 0.602), (0.297, 0.268, 0.388), (0.235, 0.252, 0.327)\rangle$	0.666	0.348
Expert-2	$\langle (0.548, 0.427, 0.421), (0.289, 0.374, 0.461), (0.223, 0.430, 0.319)\rangle$	0.577	0.301
Expert-3	$\langle (0.577, 0.450, 0.500), (0.256, 0.205, 0.322), (0.170, 0.263, 0.238)\rangle$	0.671	0.351
Professional-III			
Expert-1	$\langle (0.560, 0.548, 0.602), (0.345, 0.315, 0.447), (0.295, 0.265, 0.396) \rangle$	0.635	0.315
Expert-2	$\langle (0.750, 0.693, 0.741), (0.256, 0.375, 0.428), (0.212, 0.376, 0.310) \rangle$	0.681	0.338
Expert-3	$\langle (0.606, 0.548, 0.602), (0.244, 0.217, 0.322), (0.170, 0.239, 0.249) \rangle$	0.701	0.348

Score values			**Weights (reputations)**		
Expert-1	Expert-2	Expert-3	Expert-1	Expert-2	Expert-3
0.689	0.636	0.703	0.3397	0.3138	0.3465

Step 3: Based on the linguistic terms outlined in the assessment scale provided in Table B.2, experts evaluated the criteria for determining the optimal location for an emergency center to manage natural disasters effectively. Table S.1 (Supplementary Material) summarizes the linguistic evaluations of the criteria and sub-criteria as assessed by the three experts.

Step 4: The linguistic assessments for each criterion, based on DMs' expressed preferences, were then converted into T2NNs. Subsequently, the score values for the main criteria and sub-criteria were calculated separately. These scores were then normalized, allowing for the determination of the weight values for the criteria and sub-criteria.

Steps 5–6: In the final stage, the relative weight values of the criteria were multiplied by the sub-criteria's weight values within their respective categories, yielding the global weight coefficients for the sub-criteria. Table 4 presents the subjective weight values for all criteria and sub-criteria, as well as the criteria ranking based on their subjective importance.

4.2.2. Calculating objective criterion weights

In this part, the results obtained by following the T2N LOPCOW method to determine the objective weights of the criteria are summarized.

Steps 7 –8: The experts first evaluated each alternative linguistically against each criterion, as shown in Table S.2. The linguistic assessments were converted to T2NNs and combined. Table S.3 shows the integrated T2NN decision matrix for the alternatives.

Step 9: The combined T2NN decision matrix was transformed into the IDM (Table S.4) by employing Eq. (8a).

Step 10: Then, using Eq. (7), the elements in the IDM were normalized. Table S.5 shows the normalized IDM.

Steps 11 –12: With the help of Eq. (8), the mean square value of each criterion was calculated as a percentage of its standard deviation. This approach aims to eliminate differences (gaps) that may arise due to differences in data size. The objective weights of the criteria were calculated using Eq. (9) and provided in Table S.6.

Step 13: In the final step of the procedure, the final weight coefficients of the criteria were calculated using Eq. (10). The objective and subjective criteria weights were combined by giving equal value for the γ parameter. The final criteria weights are presented in Table 5.

It should be explicitly noted that the ranking of alternatives in this

Table 4
Score measures and subjective weights of the criteria.

Criteria	Sub-criteria	Aggregated T2NN values	Score value	Weights	Global weights	Rank
C_1		< (0.876, 0.912, 0.912), (0.124, 0.150, 0.141), (0.071, 0.062, 0.124)>	0.894	0.359		
C_2		< (0.493, 0.361, 0.361), (0.434, 0.516, 0.442), (0.416, 0.528, 0.477)>	0.477	0.191		
C_3		< (0.453, 0.357, 0.357), (0.473, 0.554, 0.554), (0.413, 0.561, 0.520)>	0.444	0.178		
C_4		< (0.712, 0.609, 0.609), (0.315, 0.308, 0.446), (0.261, 0.247, 0.288)>	0.677	0.272		
	C_{1-1}	< (0.873, 0.908, 0.908), (0.127, 0.150, 0.145), (0.073, 0.063, 0.127)>	0.892	0.209	0.07501	4
	C_{1-2}	< (0.900, 0.950, 0.950), (0.100, 0.150, 0.100), (0.050, 0.050, 0.100)>	0.917	0.215	0.07711	3
	C_{1-3}	< (0.839, 0.829, 0.829), (0.161, 0.150, 0.213), (0.106, 0.080, 0.161)>	0.852	0.200	0.07168	5
	C_{1-4}	< (0.805, 0.803, 0.803), (0.205, 0.220, 0.262), (0.143, 0.130, 0.195)>	0.809	0.190	0.06807	6
	C_{1-5}	< (0.800, 0.700, 0.700), (0.200, 0.150, 0.300), (0.150, 0.100, 0.200)>	0.796	0.187	0.06695	7
	C_{2-1}	< (0.773, 0.790, 0.790), (0.247, 0.308, 0.305), (0.178, 0.195, 0.227)>	0.765	0.508	0.09721	1
	C_{2-2}	< (0.728, 0.750, 0.750), (0.258, 0.329, 0.273), (0.194, 0.223, 0.264)>	0.740	0.492	0.09405	2
	C_{3-1}	< (0.651, 0.532, 0.532), (0.329, 0.332, 0.401), (0.286, 0.287, 0.338)>	0.638	0.131	0.02335	18
	C_{3-2}	< (0.711, 0.608, 0.608), (0.316, 0.310, 0.448), (0.262, 0.250, 0.289)>	0.675	0.139	0.02471	15
	C_{3-3}	< (0.646, 0.527, 0.527), (0.335, 0.342, 0.407), (0.293, 0.298, 0.343)>	0.631	0.129	0.02309	19
	C_{3-4}	< (0.706, 0.604, 0.604), (0.322, 0.319, 0.455), (0.268, 0.259, 0.294)>	0.669	0.137	0.02448	16
	C_{3-5}	< (0.800, 0.700, 0.700), (0.200, 0.150, 0.300), (0.150, 0.100, 0.200)>	0.796	0.163	0.02913	13
	C_{3-6}	< (0.706, 0.604, 0.604), (0.322, 0.319, 0.455), (0.268, 0.259, 0.294)>	0.669	0.137	0.02448	16
	C_{3-7}	< (0.800, 0.700, 0.700), (0.200, 0.150, 0.300), (0.150, 0.100, 0.200)>	0.796	0.163	0.02913	13
	C_{4-1}	< (0.876, 0.912, 0.912), (0.124, 0.150, 0.141), (0.071, 0.062, 0.124)>	0.894	0.206	0.05581	9
	C_{4-2}	< (0.900, 0.950, 0.950), (0.100, 0.150, 0.100), (0.050, 0.050, 0.100)>	0.917	0.211	0.05722	8
	C_{4-3}	< (0.839, 0.829, 0.829), (0.161, 0.150, 0.213), (0.106, 0.080, 0.161)>	0.852	0.196	0.05319	11
	C_{4-4}	< (0.873, 0.908, 0.908), (0.127, 0.150, 0.145), (0.073, 0.063, 0.127)>	0.892	0.205	0.05566	10
	C_{4-5}	< (0.800, 0.700, 0.700), (0.200, 0.150, 0.300), (0.150, 0.100, 0.200)>	0.796	0.183	0.04968	12

study is not performed based on objective or subjective criteria weights in isolation. Instead, the final ranking results are obtained using the integrated criteria weights derived through the γ-based combination of objective and subjective weighting schemes. Accordingly, all subsequent decision-making and ranking outcomes reflect the joint and balanced influence of both data-driven objectivity and expert-based subjectivity.

Table 5
Final weights of the criteria.

Criteria	w_j^{int}	w_j^{obj}	w_j^{subj}
Proximity to highway (C_{1-1})	0.075	0.032	0.054
Proximity to railway (C_{1-2})	0.077	0.045	0.061
Proximity to seaport (C_{1-3})	0.072	0.059	0.065
Proximity to airport (C_{1-4})	0.068	0.037	0.053
Traffic condition (C_{1-5})	0.067	0.064	0.066
Land (C_{2-1})	0.097	0.057	0.077
Storage (C_{2-2})	0.094	0.071	0.083
Proximity to beneficiaries (C_{3-1})	0.023	0.052	0.037
Disaster-free location (C_{3-2})	0.025	0.071	0.048
Climate (C_{3-3})	0.023	0.052	0.037
Closeness to the warehouses (C_{3-4})	0.024	0.071	0.048
Shortest starting time (C_{3-5})	0.029	0.052	0.040
Proximity to disaster-prone areas (C_{3-6})	0.024	0.027	0.026
Ease of access for auxiliary materials (C_{3-7})	0.029	0.071	0.050
Flora (C_{4-1})	0.056	0.050	0.053
Slope (C_{4-2})	0.057	0.018	0.038
Elevation (C_{4-3})	0.053	0.050	0.051
Distance of fault line (C_{4-4})	0.056	0.071	0.063
Landslide risk (C_{4-5})	0.050	0.050	0.050

4.3. Identifying option performances

In this stage, alternative ELCs were selected. Many emergency management experts and organizations recommend positioning logistics bases a few hundred kilometers from the disaster zone to ensure rapid access and effective operational coordination. However, the distance may vary depending on regional characteristics and specific factors. For example, the logistics base must be as close as possible to allow an immediate response in the event of sudden disasters such as earthquakes or tsunamis. By contrast, for prolonged disasters such as storms or floods, positioning the base slightly farther away can ensure the safety of areas within the affected region and facilitate more efficient logistics operations.

Accordingly, specialists who consider factors such as catastrophe type, geographical features, population density, and other relevant factors should select an emergency logistics foundation. In this work, a panel of specialists, including individuals directly influenced by the Kahramanmaraş earthquake, determined the suitable distances between calamity centers and potential ELC sites. For example, 50 kilometers were selected for the proposed ELCs, as illustrated in Fig. 3. The red lines mark alternative zones, suggesting that ELCs could be established along these boundaries. The closest circle to the disaster center represents the

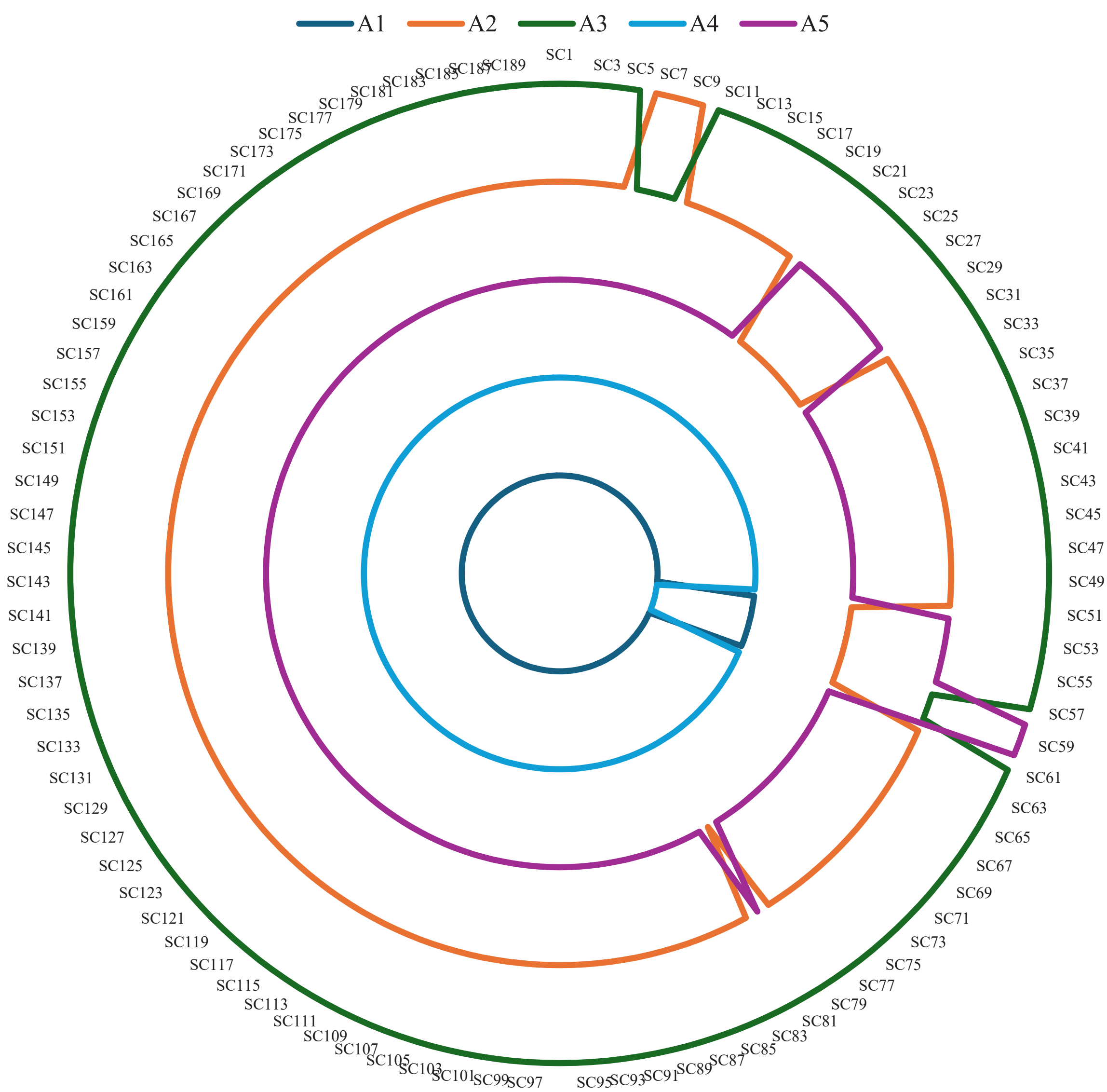

Fig. 3. Influences of changing the criteria weights on the ranking results.

first alternative, while the others represent the second, third, fourth, and fifth options.

The proposed T2N MACONT method was used to rank the identified alternatives. The weights determined in the previous phase were applied within the T2N MACONT method. A structured questionnaire, designed as a decision matrix, was distributed to the same decision-making committee for evaluation. It is important to note that all evaluation criteria were considered beneficial. The committee identified five centers based on their proximity to the earthquake's epicenter. The committee then assessed these centers. The experts evaluated the centers' locations using the linguistic values provided in Table B.3. The evaluations of all experts are presented in Table S.2.

Steps 14 –15: The IAM elements were normalized using three different normalization techniques (Table S.7). In this context, three different normalized decision matrices (NAM-I, NAM-II, and NAM-III) were created using Eq. (11)–(13). Afterward, these matrices were synthesized using equilibrium parameters Δ_1, Δ_2, and Δ_3 according to Eq. (14), and the C-NDM was constructed (Table S.8). The values of these equilibrium parameters were initially defined as $\Delta_1 = 0.45$, $\Delta_2 = 0.4$, and $\Delta_3 = 0.15$ based on expert opinions. Additionally, various trials with different parameter values are conducted during the sensitivity analysis phase.

In real-world MCDM problems, evaluation criteria often exhibit heterogeneous characteristics in terms of scale, orientation, and data distribution. Some criteria are benefit-oriented, where higher values indicate better performance, while others are cost-oriented, where lower values are preferred. Moreover, certain criteria are ratio-based and suitable for proportional comparison, whereas others are more sensitive to extreme values or dispersion. Applying a single normalization technique uniformly across all criteria may therefore lead to information distortion or loss of discriminatory power. For this reason, the MACONT method employs different normalization techniques tailored to the intrinsic nature of each criterion, thereby preserving the original preference structure and decision logic.

Steps 16 –18: After obtaining the normalized matrix, the two sub-score values $\mathbb{N}_i^{(1)}$ and $\mathbb{N}_i^{(2)}$ for each criterion were computed by employing Eq. (15) and Eq. (16), respectively, with the help of the arithmetic and geometric weighted addition operator. Next, the comprehensive score values ($\mathbb{Z}_{1i}$and $\mathbb{Z}_{2i}$) for each alternative were determined using Eq. (17)–(18). The final score value of each option is calculated using Eq. (19) and presented in Table 6.

5. Robustness check

Several tests were conducted to demonstrate the robustness and validity of the proposed neutrosophic decision support model. First, the criteria weights were changed, and the effects on the ranking results were reviewed. Secondly, the value of the γ parameter used to combine subjective and objective criterion weights was varied across scenarios, and the effects of these changes were evaluated. In the third stage, equilibrium parameter values (Δ_1, Δ_2, and Δ_3) were changed, and the final results were examined.

5.1. Evaluating the impact of changing the criteria weights

At this stage, the weighting of each criterion was changed, and the effects of these changes on the final ranking results were observed. For this, the procedure recommended by Görçün et al. [88] was followed, and a total of 190 scenarios were created, 10 for each criterion. Starting with the criterion with the highest weight, the criterion's weight was reduced by 10% in the first scenario, and the resulting difference was equally distributed among the other criteria to maintain the condition that the sum of the criteria's weights is 1. In subsequent scenarios, the criterion's weight is gradually reduced by 20%, 30%, …, and 100% until zero. The same procedures were applied for all criteria. Fig. 3 illustrates the effects of changes in the criterion weights on the overall ranking results.

As seen from Fig. 3, the most appropriate alternative (i.e., alternative A_1) was only sensitive to changes in the weight value of the C_{2-1} criterion among the criteria. When the weight of this criterion was increased by 20% or more, the A1 alternative lost its ranking position and fell to second place. Similarly, the second-best alternative (i.e., A4) was sensitive to the same criterion and was replaced by A1 when the weight of this criterion changed.

On the other hand, the third-best alternative (i.e., alternative A_3) showed sensitivity with the C_{1-3} and C_{2-1} criteria. The A_2 alternative, which ranked fourth, lost its place when the weight value of the C_{1-1} criterion changed by 70% or more. In addition, with each change in the C_{1-3} and C_{2-1} criteria, the ranking performance of the alternative changed. The A_3 alternative, which is in last place, changes its ranking when the weight values of the C_{1-1} and C_{2-1} criteria are changed by more than 70%.

Finally, when the correlation between the new ranking results resulting from changes made in 190 scenarios and the original ranking results is considered, it is observed that the average similarity rate reaches a very high value of 0.9274. It shows that the proposed approach is maximally resistant to changes in criterion weights while proving that the proposed model is valid, consistent, and reliable.

5.2. Checking the influence of changing γ parameter

In the second stage, we developed various scenarios to examine the impact of the γ parameter on overall ranking results, with values ranging from 0 to 1. For instance, when the γ parameter was set to 0.1, the $1 - \gamma$ parameter naturally took a value of 0.9 to ensure that the total value equals 1. Based on this approach, we developed 11 scenarios. Table 7 shows the ranking performance of the alternatives as the γ parameter is adjusted from 0 to 1.

It should be emphasized that the analysis conducted by varying the γ parameter is not limited to a conventional sensitivity assessment. Rather, this scenario-based examination is deliberately employed as a validation mechanism to evaluate the robustness and stability of the proposed decision-making framework. By systematically adjusting the relative contribution of objective and subjective criteria weights across the full range of γ values, the consistency of alternative rankings is thoroughly investigated. The preservation of ranking stability across different γ scenarios indicates that the proposed model yields reliable and trustworthy decision outcomes, thereby confirming its robustness in handling criterion uncertainty in real-world decision environments.

When the γ parameter, used to combine subjective and objective weights, is set to 0.9 or higher, subjective weights are prioritized, and objective weights are largely disregarded. In this case, the A_1 and A_4 alternatives switch places. However, no changes in the ranking performance of these alternatives were observed until the γ parameter reached 0.8. When γ was set to 0.7 or below, A_2 moved from fourth to third, while A_5 dropped from third to fourth. Finally, the average similarity between the ranking results from the scenarios and the original results was 0.8. These findings demonstrate the robustness and consistency of the proposed model.

It is important to note that this study does not presume a single predefined "optimal" value for the γ parameter. In real-life MCDM problems, the relative importance assigned to objective data and

Table 6
Ranking performance of the options.

Alternatives	$\mathbb{N}_i^{(1)}$	$\mathbb{N}_i^{(2)}$	$\mathbb{Z}_{1i}$	$\mathbb{Z}_{2i}$	$\mathbb{Z}_i$	Rank
A_1	0.0116	7.7977	0.5313	0.0021	0.4927	1
A_2	0.0018	2.4963	0.1558	-0.0036	-0.3201	5
A_3	-0.0534	1.0667	-0.3341	-0.0012	-0.2989	4
A_4	0.0397	2.2290	0.4213	0.0001	0.2237	2
A_5	0.0003	1.8606	0.1083	-0.0014	-0.0956	3

Table 7
Influence of changing γ parameter on overall ranking.

Alternatives	γ= 0	γ= 0.1	γ= 0.2	γ= 0.3	γ= 0.4	γ= 0.5	γ= 0.6	γ= 0.7	γ= 0.8	γ= 0.9	γ= 1
A_1	1	1	1	1	1	1	1	1	1	2	2
A_2	5	4	4	4	4	4	4	3	3	3	3
A_3	4	5	5	5	5	5	5	5	5	5	5
A_4	2	2	2	2	2	2	2	2	2	1	1
A_5	3	3	3	3	3	3	3	4	4	4	4

subjective expert judgments is highly context-dependent. It may vary according to decision-maker preferences, operational conditions, and environmental constraints. For this reason, γ is allowed to vary continuously over the interval [0,1], and a scenario-based validation strategy is adopted rather than enforcing a rigid optimal combination. This approach enables decision-makers to observe how ranking results behave under different weighting preferences. It ensures that the proposed framework remains flexible, transparent, and practically applicable across diverse decision contexts.

5.3. Assessing the influence of changing equilibrium parameter values

Finally, the equilibrium parameter (Δ_1, Δ_2, and Δ_3) values used in the three different normalization processes in the second step of the T2N MACONT method were adjusted, and the impact of these changes was analyzed. A total of 18 scenarios were created, with each parameter value gradually reduced from 0.85 to 0.0 (Table 8). The evaluation revealed that altering these parameters did not affect the ranking results of the alternatives.

5.4. Comparative analysis

One way to demonstrate the validity and soundness of the decision-making procedure used to address a decision-making problem is to provide an analysis in which the results are tested against other established and accepted methods. The T2NFN-Subjective & LOPCOW & MACONT integrated decision-making framework proposed in this study was subjected to a comprehensive comparison analysis using type-2 neutrosophic fuzzy (T2NFN)-based CoCoSo, MABAC, MAIRCA, MARCOS, PSI, TOPSIS, WASPAS, RAWEC, AROMAN, and RAM methods in terms of capacity to handle uncertainty, computational systematics, and decision-making precision (Fig. 4). The comparison analysis performed goes beyond validating the ranking results obtained by applying the proposed decision-making tool, objectively revealing the model's consistency across different algorithmic approaches and its stability in the decision-making process. In this context, a comprehensive analysis was carried out by comparing it with ten different ranking methods. As a result, despite comparisons with methods that employ different normalization methods and mathematical steps, the mean correlation between the results (0.712) strongly supports the consistency of the proposed model. Fig. 4 shows the results of comparisons with 10 different decision-making procedures.

Table 8
Impact of changing equilibrium parameter coefficients on overall ranking.

Scenario	Δ_1	Δ_2	Δ_3	Ranking of the alternatives				
				A_1	A_2	A_3	A_4	A_5
1	0.85	0.00	0.15	1	4	5	2	3
2	0.80	0.05	0.15	1	4	5	2	3
3	0.75	0.10	0.15	1	4	5	2	3
4	0.70	0.15	0.15	1	4	5	2	3
5	0.65	0.20	0.15	1	4	5	2	3
6	0.60	0.25	0.15	1	4	5	2	3
7	0.55	0.30	0.15	1	4	5	2	3
8	0.50	0.35	0.15	1	4	5	2	3
9	0.45	0.40	0.15	1	4	5	2	3
10	0.40	0.45	0.15	1	4	5	2	3
11	0.35	0.50	0.15	1	4	5	2	3
12	0.30	0.55	0.15	1	4	5	2	3
13	0.25	0.60	0.15	1	4	5	2	3
14	0.20	0.65	0.15	1	4	5	2	3
15	0.15	0.70	0.15	1	4	5	2	3
16	0.10	0.75	0.15	1	4	5	2	3
17	0.05	0.80	0.15	1	4	5	2	3
18	0.00	0.85	0.15	1	4	5	2	3

In general, when examining the results, there is notable consistency across rankings obtained with different decision-making procedures for the alternatives. In this context, the fact that the A1 alternative, which ranked first in the original results, was identified as the best alternative by the majority of the ten methods demonstrates consistency between the methods' application and the results obtained. This alternative CoCoSo ranked 3rd in the MABAC and AROMAN methods, while it ranked first in all other methods.

According to the proposed integrated model, the A4 alternative, which is the second-best, ranked second in the MAIRCA, MARCOS, PSI, TOPSIS, and WASPAS methods. CoCoSo ranked first according to the AROMAN and MABAC methods, while according to the RAWEC method, this alternative ranked fourth. Moreover, the ranking results obtained using the original decision-making tool ranked A1 first, A4 second, A5 third, A3 fourth, and A2 fifth. This sequencing method is identical to powerful methods such as MARCOS, PSI, TOPSIS, and WASPAS. There is a very high correlation of 0.900 between the results of these methods. This indicates that the T2NFN-Subjective & LOPCOW & MACONT integrated decision-making tool produces results that are almost identical to those of these widely accepted methods in the literature.

The mean correlation of 0.712 indicates that these T2NFN-based methods are highly positively correlated with one another. This confirms that the results obtained are not random and that the technique is correct—the lowest agreement is between MACONT and MABAC (0.139). The different approaches to the MABAC method in A3 and A5 rankings are the main reason for this low correlation.

In conclusion, the proposed integrated decision-making model produces stable, reliable results. Especially its high correlation with mainstream methods (TOPSIS, WASPAS) proves that the method can be used as an effective tool in decision-making processes. The A1 alternative can be safely recommended as a "top choice," as it comes out on top across most methods.

In the second stage, we observed changes in the ranking results across different weighting methods (Fig. 5). In this context, MEREC, CRITIC, Entropy, and PSI methods, which are frequently used in the literature, were integrated into the MACONT method based on T2NFN, and the weight values obtained using these methods were used in the T2NFN-MACONT application. Fig. 5 shows the new ranking results obtained.

As shown in Fig. 5, when the responses of the T2NFN-MACONT method to different weighting inputs (LOPCOW, MEREC, CRITIC, ENTROPY, PSI) are examined, it is seen that the A1 alternative ranks 1st in all weighting methods except CRITIC. This indicates that A1 is a dominant top choice and maintains its lead even as the criterion weights change. The A4 alternative has been a consistent performer, ranking 2nd in most scenarios, only rising to 1st place when using the CRITIC weighting. The most notable variability is seen in the A5 alternative. LOPCOW ranked 3rd with MEREC and ENTROPY, while PSI and CRITIC, which weighted it, dropped to 5th place. It indicates that the success of

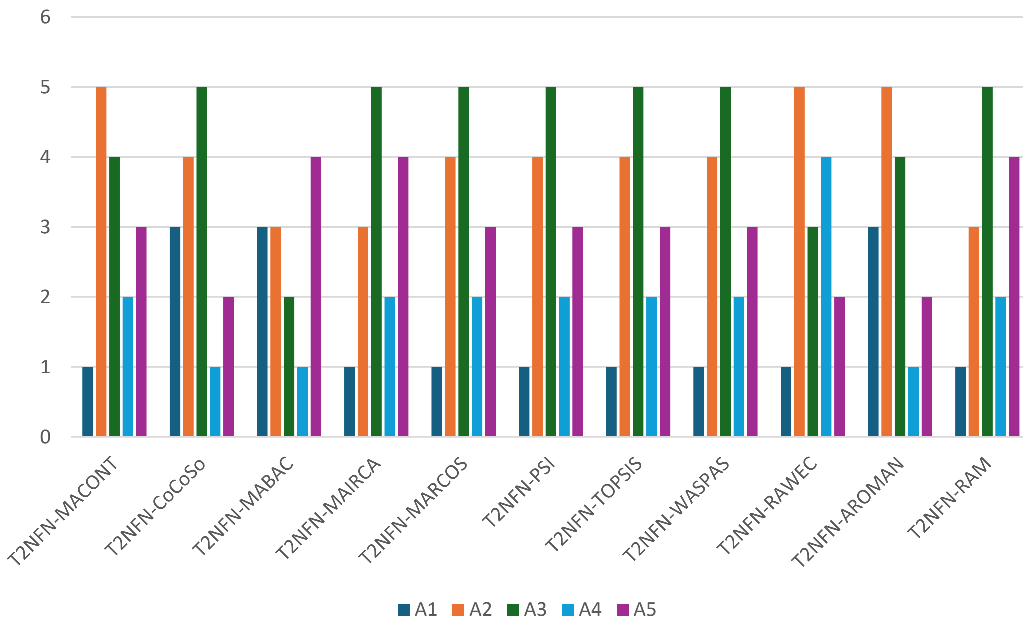

Fig. 4. Results of the comparative analysis.

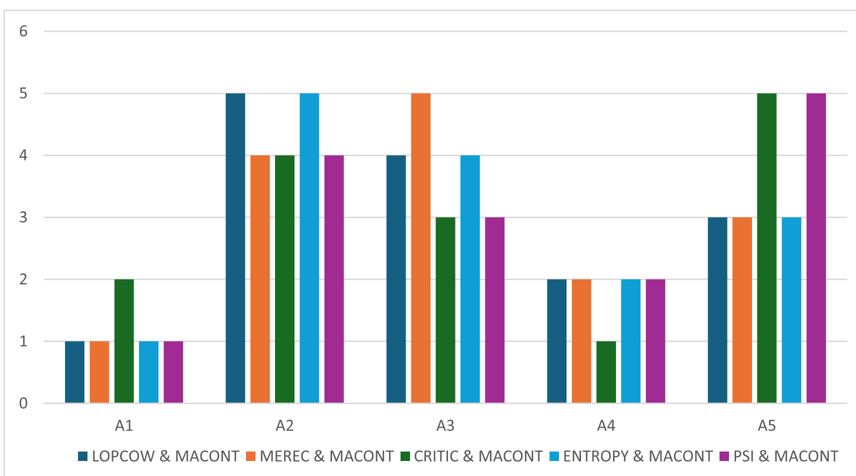

Fig. 5. Results of the comparative analysis employing various weighting methods.

A5 is hypersensitive to the weight of specific criteria (especially those that CRITIC and PSI attach high importance to).

In addition, the mean correlation value of 0.800, calculated in the context of the ranking results obtained, is a notable strength of the study. In this context, a value of 0.800 indicates a "very high" level of agreement between the methods. It demonstrates that the proposed integrated decision-making approach maintains the overall ranking trend regardless of the weighting method employed. Moreover, there are 1000 (exact agreement) correlations between LOPCOW & MACONT and ENTROPY & MACONT combinations. It indicates that these two different weighting methods produce identical sorting results on the MACONT algorithm. The lowest correlation is between MEREC and CRITIC at 0.500. The CRITIC method presented a different weight distribution than the others because it was based on the correlation and contrast between the criteria, which was reflected in the ranking (especially on A4 and A5).

At this stage of the study, a comparative analysis was conducted to assess the sensitivity of the T2NFN-MACONT model to various objective weighting methods. The findings reveal that the model exhibits a highly resistant and consistent structure against weight changes.

In tests conducted under five different weighting scenarios, the A1 alternative maintained its first place at a rate of 80%. The mean correlation coefficient between the methods was as high as 0.800. Notably, the LOPCOW and ENTROPY-based weightings produced identical results with exact agreement (1000) on MACONT, reinforcing the model's reliability. Partial differences obtained with the CRITIC method show that the model can give sensitive responses in cases where the interaction between the criteria is intense. In conclusion, the T2NFN-MACONT method supports stable decision-making regardless of the weighting mechanism used.

5.5. *Resistance to the rank reversal problem*

The rank reversal (RR) problem is one of the most significant challenges in MCDM methods. It occurs when the relative ranking of alternatives changes unexpectedly when a non-optimal alternative is added to or removed from the decision set. Ideally, a robust decision-making model should maintain the internal order of the remaining alternatives; for instance, if A1 is preferred over A4, it should remain preferred even if A2 (the worst-performing alternative) is excluded. Significant rank reversals can lead to inconsistent decisions and undermine the mathematical reliability of the applied methodology.

To test the resilience of the proposed T2NFN-LOPCOW & MACONT model against this phenomenon, a systematic elimination procedure was conducted (Table 9). In each successive scenario, the alternative ranked at the bottom was removed, and the calculations were repeated until only one alternative remained. The results demonstrate an exceptional level of stability. In the initial full set, the ranking was determined as A1 > A4 > A5 > A3 > A2. Upon the removal of A2, the order of the remaining four alternatives (A1, A4, A5, A3) remained perfectly preserved.

The analysis continued with the sequential removal of the new bottom-ranked alternatives. When A3 was excluded, the top three (A1 > A4 > A5) maintained their exact positions, and even at the final comparison stage between A1 and A4, the hierarchy remained unchanged. This consistent behavior across all iterations proves that the T2NFN-MACONT model is highly resistant to the rank reversal problem. It confirms that the scores generated by the model are not merely relative to the presence of inferior options but are based on a stable evaluation of each alternative's intrinsic performance.

In conclusion, these findings provide strong evidence for the mathematical validity and reliability of the proposed model. The zero-reversal outcome indicates that the decision-maker can trust the ranking of top-tier alternatives regardless of the changes in the broader alternative pool. This robustness makes the T2NFN-LOPCOW & MACONT approach particularly suitable for dynamic real-world environments where the number of available options may change over time.

6. Findings

The Kahramanmaraş-centered earthquake, distinct from other disasters in scale and scope, caused widespread devastation across 11 provinces. In such catastrophic events, the effectiveness of the HL is evaluated based on the ability to deliver the right supplies to the right place at the right time.

The success of emergency response efforts during a disaster heavily depends on the efficiency of logistics operations. The findings of this study indicate that the most critical and influential criterion for selecting ELC locations is the "storage cost" (C_{2-2}), which ranked first with a significance score of 0.083. Upon examining the underlying reasons, it becomes clear that there are many logical and rational justifications for why storage cost is the most critical factor in site selection for ELCs. After natural disasters, a swift and efficient response with limited resources is crucial. Storage costs constitute a significant portion of the total logistics expenses. By minimizing these costs, more supplies can be stockpiled with the same resources, enabling more widely distributed aid. Consequently, this allows for budget reallocation to other critical areas, promoting more effective resource utilization in disaster management.

The long-term sustainability of storage costs plays a decisive role in emergency logistics center location decisions, as disaster response activities extend beyond immediate relief to prolonged recovery and reconstruction phases. High storage costs can undermine the financial viability of logistics operations over time, whereas cost-efficient and strategically located warehouses enhance operational sustainability and enable faster resource mobilization during critical response periods. Moreover, storage costs are closely associated with inventory capacity and availability. Lower-cost warehouses allow larger quantities of essential supplies to be pre-positioned, ensuring preparedness for emergency interventions and reducing the risk of shortages during disasters. In contrast, high-cost storage facilities may constrain inventory levels and delay response operations. Therefore, minimizing storage costs directly supports efficient resource utilization, rapid response capability, and the long-term effectiveness of disaster logistics systems.

This finding is consistent with previous studies in humanitarian logistics and disaster management literature, which emphasize that warehousing and inventory-related costs represent a dominant share of total emergency response expenditures. Prior research has similarly underlined that minimizing storage-related expenses enhances the capacity to pre-position relief supplies and improves overall responsiveness under budget constraints. However, unlike studies that primarily focus on accessibility or proximity-based criteria, this study demonstrates that, in the context of large-scale and geographically widespread disasters such as the Kahramanmaraş earthquake, cost-based criteria may outweigh purely spatial considerations. This result contributes to the literature by empirically highlighting the pivotal role of storage cost within a complex, multi-criteria emergency logistics decision-making framework.

In this study, the "land cost" (C_{2-1}) was identified as the second most important and influential criterion for selecting the location of ELCs. The emphasis on land cost as a critical factor is grounded in logical and rational considerations related to cost-effectiveness and long-term sustainability. Land costs tend to be elevated in areas close to disaster zones; therefore, effectively managing these expenses is essential for the financial sustainability of logistics operations over time. Lower land costs make establishing ELCs more economical, leading to more efficient budget utilization. Consequently, the resources allocated for establishing the response center can be redirected to other critical areas, such as relief supplies or equipment.

Maintaining low land costs also enables ELCs to be strategically situated in optimal locations. Investing in high-cost land too close to disaster areas or hazardous regions can compromise logistics operations. Particularly in the aftermath of a disaster, the variability associated with land use and restructuring costs makes establishing centers in more cost-effective and safer areas advantageous, thereby enhancing operational flexibility. Furthermore, lower land costs facilitate the establishment of multiple logistics centers, thereby expanding the capacity to deliver aid across a broader geographic area.

The low land cost also positively influences ELC growth and expansion potential. Centers established on lower-cost land are more advantageous regarding additional expenses if expansion is desired in the future. Additionally, these centers play a crucial role in post-disaster reconstruction efforts. In contrast, logistics centers built on high-cost land may incur substantial maintenance and operational expenses over time, diminishing overall efficiency. Therefore, maintaining low land costs is a critical factor that enhances the effectiveness, flexibility, and sustainability of ELCs. Following storage costs, the careful management of land costs significantly contributes to success and financial efficiency in disaster response operations. For these reasons, land cost is the second most important criterion in the site selection.

The specific contextual characteristics of the Kahramanmaraş-centered earthquakes can also explain the prominence of land cost. The extensive spatial impact across multiple provinces significantly increased land-use uncertainty and reconstruction pressure, particularly in zones close to heavily damaged urban areas. In such contexts, establishing emergency logistics centers on high-value or redevelopment-prone land may lead to long-term financial and operational constraints. Therefore, prioritizing lower land-cost locations not only enhances economic sustainability but also increases flexibility for post-disaster adaptation, relocation, or expansion, which is critical in prolonged recovery phases.

Table 9
Results of rank reversal problem.

Scenario	Ranking	Removed alternative
Original	A1 > A4 > A5 > A3 > A2	-
1	A1 > A4 > A5 > A3	A2
2	A1 > A4 > A5	A3
3	A1 > A4	A5
4	A1	A4

Another significant finding of this study regarding the effectiveness and importance of the criteria is that the criterion "traffic condition" (C_{1-5}) was identified as the third most compelling factor. The prioritization of traffic conditions in selecting ELC locations is crucial for the speed and efficiency of logistics operations. The traffic situation directly influences the timely delivery of post-disaster relief materials to those in need. The state of transportation infrastructure and traffic density can pose significant obstacles, particularly during emergency response processes when time is of the essence. Therefore, situating intervention centers in areas with high traffic accessibility is a vital strategy to enhance operational success.

Areas with favorable traffic conditions enhance the effectiveness of rescue teams by accelerating the distribution of relief supplies. Heavy traffic, road closures, or congestion can lead to delays in these time-sensitive operations, preventing relief supplies from reaching those in need. It is particularly critical during large-scale disasters, as damaged infrastructure may limit the availability of alternative routes. Locations with good traffic conditions ensure that vehicles carrying essential materials arrive at their destinations promptly, minimizing disruptions in logistics processes. Moreover, establishing ELCs in areas with favorable traffic conditions provides a significant advantage not only for the timely delivery of relief materials but also for the rapid acceptance of aid and supplies from external sources. Positioning logistics centers away from heavy traffic yet close to major arteries and connecting roads ensures the continuity of the supply chain and reduces operational interruptions.

Another important aspect of traffic conditions is their impact on post-disaster reconstruction and recovery processes. A regular and rapid supply of materials to disaster areas ensures that rescue and recovery operations proceed efficiently. Centers established in areas with poor traffic conditions can significantly impact the distribution of relief supplies and hinder long-term reconstruction efforts. Consequently, prioritizing traffic conditions as the third most crucial criterion for ELCs is a critical factor that directly influences the speed, reliability, and efficiency of disaster response operations.

This outcome reflects the critical role of transportation network resilience during large-scale disasters. The Kahramanmaraş earthquakes caused severe disruptions to road infrastructure, traffic flow, and alternative route availability, thereby amplifying the importance of traffic conditions in emergency logistics planning. While proximity-based criteria are often emphasized in the literature, the present findings indicate that network functionality and congestion resilience may be more decisive than mere distance under crisis conditions. This insight reinforces the need to integrate dynamic traffic considerations into emergency logistics center location models.

The remaining criteria were ranked as "proximity to seaport" (C_{1-3}) > "distance of fault line" (C_{4-4}) > "proximity to railway" (C_{1-2}) > "proximity to highway" (C_{1-1}) > "flora" (C_{4-1}) > "proximity to airport" (C_{1-4}) > "elevation" (C_{4-3}) > "ease of access for auxiliary materials" (C_{3-7}) > "landslide risk" (C_{4-5}) > "disaster free location" (C_{3-2}) > "closeness to the warehouses" (C_{3-4}) > "shortest starting time" (C_{3-5}) > "slope" (C_{4-2}) > "proximity to beneficiaries" (C_{3-1}) > "climate" (C_{3-3}) > "proximity to disaster-prone area" (C_{3-6}).

Although criteria such as proximity to the airport, climate, and slope ranked relatively low, this does not imply that they are insignificant in all disaster scenarios. Instead, their lower priority reflects the urgent and cost-sensitive nature of the immediate emergency response phase addressed in this study. These criteria may become increasingly important in long-term recovery or reconstruction-oriented logistics planning. Therefore, the relative ranking of criteria should be interpreted as context-dependent, varying according to the disaster scale, response phase, and available infrastructure.

Beyond these findings' significant managerial and policy implications, there are also noteworthy insights. The effectiveness of emergency response processes is closely tied to the efficiency of logistics operations following natural disasters. The results of this study highlight that the most critical criterion in selecting locations for ELCs is the cost of storage. Considering that storage costs constitute a significant part of the total costs related to humanitarian aid logistics and emergency response processes, reducing storage costs to the lowest possible level is critical regarding the optimal, effective, and efficient use of resources. Reducing storage costs allows more humanitarian and rescue supplies to be stockpiled, allowing humanitarian aid to be distributed on a larger scale. In addition, lower storage costs allow the limited budget to be reallocated to other critical areas under more appropriate and optimal conditions. Accordingly, it allows the existing resources to be used more effectively and efficiently in disaster and humanitarian aid logistics processes.

In addition, increasing the sustainability of storage costs can be considered an essential factor in ensuring operational and financial sustainability in humanitarian aid logistics. Relatively high storage costs can adversely affect the continuity of humanitarian and emergency response operations. In this respect, the strategic positioning of humanitarian aid logistics warehouses with reduced storage costs in humanitarian aid logistics dramatically increases the efficiency of emergency response operations. In this respect, optimizing and reducing warehouse costs has a decisive role in increasing the long-term sustainability performance of the HL operations, which is a critical criterion. In this context, the land costs related to the locations where emergency centers will be established allow these centers to be structured more economically and to use a more effective budget. In addition, prioritizing the more affordable land cost criterion facilitates the establishment of more ELCs with the available budget. At the same time, humanitarian aid activities enable humanitarian aid activities to reach a wider geographical area and a more significant number of earthquake victims.

Another important finding of the study is that the third most crucial criterion for the location selection of ELCs is the traffic conditions criterion. The existing transportation infrastructure, especially in times of crisis when time is very critical and vital, can lead to severe problems and obstacles in traffic density emergency response processes. For this reason, establishing emergency centers in locations with relatively better traffic conditions can reduce possible disruptions to the HL operations in the rapid delivery of aid to the points where it is needed. At the same time, locations with these advantages allow foreign aid to reach more easily and quickly. For this reason, choosing the locations where emergency centers will be established at the points with the most suitable traffic conditions emerges as a critical strategy for increasing the effectiveness and efficiency of emergency and humanitarian aid activities.

The key takeaways and findings of this study provide insights into how identifying practical and critical criteria for determining the most suitable locations for emergency centers and effectively evaluating these criteria can improve response to natural disasters and the HL activities when they occur. In this context, stakeholders related to natural disasters and humanitarian aid logistics can manage the processes related to disaster logistics more effectively and efficiently by considering the most effective and essential criteria. The inferences and insights obtained in this study can be considered an extremely valuable roadmap for developing managerial strategies and improving and accelerating search and rescue activities after disasters.

The research conclusion revealed that option A_1 was the most suitable variant for the ELC, while the sorting for the other variants was A_4 > A_5 > A_2 > A_3. This ranking is associated with the advantages and drawbacks associated with each site. Specifically, the superior performance of alternative A1 can be attributed to its balanced structure in terms of storage cost efficiency, land affordability, and favourable traffic conditions, which collectively enhance both rapid response capability and long-term operational sustainability. In contrast, the lower-ranked alternatives exhibit trade-offs between cost, accessibility, and infrastructural resilience, which negatively affect their overall suitability as emergency logistics centers. This finding demonstrates the effectiveness of the proposed model in distinguishing optimal locations under multiple, and often conflicting, criteria.

In addition to this study's critical perceptions and administrative implications, the suggested decision-making procedure provides substantial theoretical contributions and advantages for both DMs and practitioners. First, this investigation promotes the generation of more optimal, sensible, and reasonable outcomes by integrating the diverse features of DMs and their influences into the decision-making process. Second, this study differentiates itself from current literature by combining subjective and objective appraisals, combining both types of information into the evaluation process. This procedure exploits the effectiveness of information usage within the decision-making environment. Moreover, by leveraging the structural advantages of T2NSs, this framework efficiently integrates the evaluations and judgments of experts into the overall appraisal process.

The T2NN-based LOPCOW and MACONT incorporated decision-making model offers critical theoretical contributions to managing vague and intricacy in decision-making processes. Integrating these methods establishes an innovative framework for effectively addressing multidimensional and uncertain data sets. Primarily, the superiorities provided by T2NNs encompass a more in-depth analysis of ambiguity and vagueness. Unlike conventional fuzzy logic systems, T2NN offers a more extensive depiction of decision-making processes by accounting for first- and second-level ambiguities. When integrated with approaches such as LOPCOW and MACONT, this approach facilitates DMs to make more informed and trustworthy evaluations of variants. This flexibility is especially beneficial in intricate systems with many criteria, as it efficiently manages uncertainties.

The LOPCOW procedure is a highly effective, practical, and powerful weighting approach for objectively determining the weight coefficients of the criteria. It allows the criteria weights to be calculated easily, practically, and accurately at the maximum level. A more accurate and logical weighting of the criteria also provides a more effective and accurate reflection of the relative importance of the alternatives and a more balanced evaluation process. In addition, the MACONT approach normalizes and integrates data and information from different sources. It makes it possible to use the existing information most effectively.

The proposed integrated model also offers a significant advantage due to its high capacity and ability to increase the transparency of the decision-making process. The proposed T2NN-based model manages uncertainties more effectively and successfully, facilitating a better understanding of the options available to DMs. The transparency and ease of implementation provided by the method make it easier for a more significant number of DMs and stakeholders to participate in the decision-making process while allowing the decisions taken to be evaluated with a more accurate approach.

The proposed integrated decision-making model provides significant contributions and inferences to the literature, theories, and fields related to handling and managing uncertainties. The model expands the two powerful approaches with a competent fuzzy set, increasing their applicability and capabilities of applications. Therefore, the proposed model makes it possible to address extremely complex decision-making problems, which are highly affected by uncertainties, more effectively and to produce practical solutions. In addition, the model can be used in many different areas. From this perspective, the proposed model is expected to be used effectively in various disciplines, including logistics, healthcare, and finance.

In summary, the T2NN-based LOPCOW and MACONT integrated decision-making approach provides several advantages, including enhanced management of ambiguities and intricacy, efficient data integration, and enhanced clearness, trustworthiness, and correctness. While its theoretical contributions significantly enhance the quality of decision-making processes, its potential for practical applications further underscores the model's significance. Thus, integrated frameworks like this emerge as critical tools for navigating intricate and uncertain decision-making environments.

7. Conclusions

The results obtained from the study demonstrate that the proposed framework successfully identifies the most suitable emergency logistics center location by jointly considering infrastructural adequacy, accessibility, operational resilience, and expert-driven uncertainty. The findings reveal that the top-ranked alternative consistently outperforms other candidate sites across multiple criteria, highlighting the effectiveness of the integrated weighting and ranking structure. Sensitivity analysis further confirms that the final ranking remains stable under different weighting scenarios, indicating robustness against normalization and data dispersion effects.

From a methodological perspective, this study demonstrates that integrating LOPCOW and MACONT within a T2N framework provides a more reliable decision-support structure than conventional sequential fuzzy-MCDM approaches. While LOPCOW ensures objective and scale-insensitive criterion weighting, MACONT effectively mitigates ranking instability caused by normalization dependence. The use of T2NNs further enhances the framework by explicitly modeling indeterminacy, inconsistency, and expert heterogeneity, which are inherent in post-disaster decision environments.

In this study, the critical issue of determining the location of an ELC, particularly for post-earthquake aid delivery (at the inventory level), is addressed whenever an earthquake occurs. The importance of this matter came to the forefront through a case analysis following two major earthquake disasters centered around Kahramanmaraş in Türkiye in 2023.

The empirical findings of this study clearly reveal that cost-oriented criteria dominate the ELC location decision under large-scale earthquake scenarios. Storage cost emerged as the most influential criterion, followed by land cost and traffic conditions, indicating that financial sustainability and rapid accessibility play a decisive role in post-disaster humanitarian logistics. The ranking of alternatives (A1 > A4 > A5 > A2 > A3) further demonstrates that locations balancing low operational costs with high accessibility provide superior performance in emergency response operations. These results underline that economic efficiency and logistical responsiveness are critical determinants of effective emergency logistics center deployment.

Studies in the literature concerning the selection of ELC locations typically overlook the post-disaster period, instead concentrating on mitigating and preventing disaster risks. Notably, no prior study has endeavored to pinpoint the precise location of ELCs following a disaster using MCDM methods. This gap underscores the uniqueness of the present study within the literature. Moreover, incorporating insights from experts with firsthand experience with earthquakes in Türkiye, particularly in ELC operations post-disaster, adds significant value to this research. Additionally, introducing the neutrosophic decision support model for ELC selection during crises in this study represents a novel approach. The proposed T2NN-based LOPCOW–MACONT integrated decision-making framework plays a critical role in achieving these results by effectively capturing uncertainty, ambiguity, and expert subjectivity inherent in post-disaster decision environments. The integration of objective (LOPCOW) and subjective weighting schemes within a T2N structure ensures a more balanced, reliable, and realistic evaluation of criteria and alternatives. Compared to traditional fuzzy or deterministic approaches, the proposed methodology provides a more robust and transparent mechanism for handling complex and uncertain humanitarian logistics problems. Furthermore, it seeks to provide practical assistance by addressing real-world needs.

The practical significance of the proposed framework lies in its ability to support disaster management authorities and policy-makers in making timely, robust, and transparent location decisions under extreme uncertainty. By providing a systematic and adaptable decision-support tool, the framework can be effectively utilized by institutions such as AFAD to improve emergency preparedness and response planning. Moreover, the proposed approach is not limited to emergency logistics center location problems and can be extended to other disaster-related strategic decision-making contexts, such as shelter location, medical facility allocation, and relief distribution planning.

Overall, this study makes significant theoretical, methodological, and practical contributions to the field of humanitarian logistics and disaster management. From a theoretical perspective, it extends the literature on emergency logistics center location by explicitly addressing post-disaster decision-making conditions. Methodologically, the integration of T2NNs with LOPCOW and MACONT offers an innovative and powerful framework for managing multidimensional uncertainty and expert-driven evaluations. From a practical standpoint, the findings provide decision-makers and policymakers with a structured, data-driven tool to enhance rapid response capability, resource efficiency, and operational sustainability in large-scale disaster scenarios. Therefore, the proposed approach not only advances academic knowledge but also delivers actionable insights for real-world emergency logistics planning.

7.1. Study limitations

Despite its contributions, this study is subject to several limitations that should be acknowledged. First, the experts consulted in the application were those who directly experienced the Kahramanmaraş earthquake. Consequently, expert judgments may reflect context-specific operational priorities associated with large-scale seismic events, potentially influencing the relative importance assigned to certain criteria. Therefore, it can be considered that the application results are oriented towards an earthquake. Second, due to the limited availability of logistics experts with direct post-disaster operational experience in the Kahramanmaraş earthquake, the empirical evaluation relied on the judgments of three experts, which may limit the generalizability of the weighting and ranking results. Third, the study has applied to an inland region that does not border the sea.

Third, the case study was conducted in an inland region without coastal exposure. As a result, disaster-specific risks such as tsunamis or coastal flooding were not incorporated into the evaluation framework, limiting the direct applicability of the findings to coastal earthquake scenarios. In addition, the proposed framework assumes static criterion weights and expert evaluations, whereas disaster environments are highly dynamic. Finally, while the proposed T2NN-based MACONT–LOPCOW framework is methodologically flexible, its performance was validated through a single real-world case study. Broader empirical validation across different disaster types and regions is required to further confirm its robustness and transferability. Temporal changes in infrastructure conditions, accessibility, and demand patterns were not explicitly modelled, which may affect decision outcomes under rapidly evolving crisis conditions.

7.2. Future research directions

Future studies may extend the proposed framework by integrating alternative advanced fuzzy environments (e.g., interval-valued Fermatean or q-rung orthopair fuzzy sets) with the MACONT–LOPCOW structure to examine their comparative performance in emergency logistics center selection problems. Furthermore, this study establishes a framework for all applications associated with ELC and disaster-related keywords. Therefore, it is anticipated that both the application section and the methodologies presented in the paper will serve as crucial research resources. This study also offers researchers valuable guidelines for future research. Future investigations may explore various methods to manage uncertainties and enhance decision-making processes in disaster logistics. For instance, the T2NSs and MACONT-LOPCOW methods utilized in this study could be compared with alternative models. Future research may conduct systematic comparative analyses between the proposed model and widely used ranking methods such as MARCOS, TOPSIS, and VIKOR under identical data sets to evaluate ranking stability, sensitivity to normalization, and robustness under varying uncertainty levels.

Future studies may further assess the robustness of the proposed model through scenario-based analyses incorporating different disaster magnitudes, infrastructure damage levels, and logistics capacity constraints. Sensitivity analyses focusing on expert weight variation and criterion importance shifts would also provide deeper insights into the model's stability under extreme decision-making conditions.

In addition, real-time data analytics and advanced technologies, which have developed in the Industry 4.0 process and started to be used in the broader framework, are promising developments for innovative applications in humanitarian aid logistics and emergency response. In this respect, technological applications such as big data analytics, the Internet of Things, geographic information systems, and artificial intelligence applications can be included in the evaluation processes for the selection of ELCs and the management of logistics operations related to humanitarian aid activities, and they can enable better management of these processes. Future research may explicitly integrate real-time IoT data and GIS-based spatial analytics into the MACONT normalization stage to dynamically update alternative rankings during ongoing disaster response operations.

Future applications of the proposed framework in different countries and disaster-prone regions would allow cross-regional validation of the model and facilitate benchmarking analyses to assess its transferability across diverse institutional, geographical, and socio-economic contexts. These comparative analyses can provide unique inferences and insights into how HL and emergency response operations can differ across countries and different geographic conditions, cultures, and attitudes of people and institutions. In this respect, examining the practices of different countries and regions can provide important implications about the robustness and validity of the proposed model and its generalizability, and it can also help to identify areas related to improvement policies and practices related to various areas in different regions.

In addition, integrating economic, social, and environmental sustainability approaches into disaster management and HL activities can be a beneficial and vital focus and research area for future studies. Accordingly, green logistics practices and environmentally friendly transportation and transportation systems in humanitarian aid logistics and emergency response operations can reduce environmental impacts and create a more sustainable environment. Integrating sustainability-related practices and approaches into HL activities can significantly contribute to economic viability, social acceptance, and environmental protection. In this context, future studies may incorporate explicit sustainability indicators and evaluate trade-offs between response speed, cost efficiency, and environmental impact within a multi-objective decision-making framework.

Increasing the involvement of social factors and local communities in disaster management can enhance the effectiveness of disaster logistics. Future research should focus on aligning logistics operations in disaster-affected areas with residents' needs and social dynamics. This approach can significantly improve crisis management by ensuring that humanitarian aid is distributed more swiftly and effectively. Finally, emerging technologies such as blockchain, drones, and intelligent logistics systems can potentially drive innovation in disaster logistics. Integrating these technologies will enable more efficient resource utilization, real-time aid distribution monitoring, and rapid assistance deployment. These technology-driven innovations can enhance disaster management efforts' speed and efficiency. Future research may explore hybrid decision-support systems that integrate the proposed T2NN-based framework with emerging technologies such as blockchain-enabled transparency mechanisms or drone-assisted last-mile logistics to enhance responsiveness and coordination in disaster environments.

CRediT authorship contribution statement

Vladimir Simic: Writing – review & editing, Writing – original draft, Validation, Resources, Project administration, Formal analysis. **Ahmet Çalık:** Writing – review & editing, Writing – original draft, Validation, Investigation. **Esra Boz:** Writing – review & editing, Writing – original draft, Validation, Formal analysis, Data curation. **Sinan Çizmecioğlu:** Writing – review & editing, Writing – original draft, Validation, Investigation, Formal analysis, Data curation, Conceptualization. **Ömer Faruk Görçün:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix-A. Preliminary Information on T2NS

Definition 1. [61]: Let $\varXi$ represent a finite universe of discourse, and let K be the interval [0,1], encompassing all triangular neutrosophic numbers. A set of T2NNs, denoted by $\widetilde{L}$, can be expressed within the universe $\varXi$ as shown in Eq. (1.a):

$$\widetilde{L} = (\langle y, \widetilde{T}_{\widetilde{L}}(y), \widetilde{I}_{\widetilde{L}}(y), \widetilde{F}_{\widetilde{L}}(y) | y \in \varXi \rangle), \tag{1.a}$$

where $\widetilde{T}_{\widetilde{L}}(y)$ is the degree of truth, $\widetilde{I}_{\widetilde{L}}(y)$ is the degree of indeterminacy, and $\widetilde{F}_{\widetilde{L}}(y)$ is the falsity degree, with $\widetilde{T}_{\widetilde{L}}(y) : \varXi \rightarrow K[0,1], \widetilde{I}_{\widetilde{L}}(y) : \varXi \rightarrow K[0,1]$, and $\widetilde{F}_{\widetilde{L}}(y) : \varXi \rightarrow K[0,1]$. Further, the sum of the membership functions must satisfy the condition given in Eq. (2.a) below:

$$0 \leq \widetilde{T}_{\widetilde{L}}(y)^3 + \widetilde{I}_{\widetilde{L}}(y)^3 + \widetilde{F}_{\widetilde{L}}(y)^3 \leq 3, \quad \forall y \in \varXi. \tag{2.a}$$

Remark 1. For the subsequent definitions, a T2NN is represented as $\widetilde{L} = \langle (T_{T_{\widetilde{L}}}(y), T_{I_{\widetilde{L}}}(y), T_{F_{\widetilde{L}}}(y)), \; (I_{T_{\widetilde{L}}}(y), I_{I_{\widetilde{L}}}(y), I_{F_{\widetilde{L}}}(y)), \; (F_{T_{\widetilde{L}}}(y), F_{I_{\widetilde{L}}}(y), F_{F_{\widetilde{L}}}(y)) \rangle$ to facilitate a quicker and more straightforward understanding of the representations.

Definition 2. [61]: Let $\widetilde{L}_k (k = 1, 2, \ldots, p)$ be represented as a set of T2NNs, with their corresponding weights denoted by $\delta = (\delta_1, \delta_2, \ldots, \delta_p)^T$ with $\sum_{k=1}^{p} \delta_k = 1$. Accordingly, the T2NNWA can be defined as given in Eq. (3.a) [87]:

$$\begin{aligned}
&T2NNWA_{\delta}(\widetilde{L}_1, \widetilde{L}_2, .., \widetilde{L}_P) = \delta_1 \widetilde{L}_1 \oplus \delta_2 \widetilde{L}_2 + \ldots + \delta_p \widetilde{L}_p \\
&= \left\langle \left(1 - \prod_{k=1}^{p} \left(1 - T_{T_{\widetilde{L}_k}}(y) \right) \delta_k, 1 - \prod_{k=1}^{p} \left(1 - T_{I_{\widetilde{L}_k}}(y) \right)^{\delta_k}, 1 - \prod_{k=1}^{p} \left(1 - T_{F_{\widetilde{L}_k}}(y) \right)^{\delta_k} \right), \right. \\
&\left(\prod_{k=1}^{p} \left(I_{T_{\widetilde{L}_k}}(y) \right)^{\delta_k}, \prod_{k=1}^{p} \left(I_{I_{\widetilde{L}_k}}(y) \right)^{\delta_k}, \prod_{k=1}^{p} \left(I_{F_{\widetilde{L}_k}}(y) \right)^{\delta_k} \right), \\
&\left. \left(\prod_{k=1}^{p} \left(F_{T_{\widetilde{L}_k}}(y) \right)^{\delta_k}, \prod_{k=1}^{p} \left(F_{I_{\widetilde{L}_k}}(y) \right)^{\delta_k}, \prod_{k=1}^{p} \left(F_{F_{\widetilde{L}_k}}(y) \right)^{\delta_k} \right) \right\rangle.
\end{aligned} \tag{3.a}$$

Definition 3. [61]: Let us suppose $\widetilde{L}_1$ and $\widetilde{L}_2$ are two T2NNs. In this context, the following algebraic equations can be expressed:

(1) Addition "$\oplus$"

$$\widetilde{L}_1 \oplus \widetilde{L}_2 = \left\langle \begin{array}{l}
\left(\left(T_{T_{\widetilde{L}_1}}(y) \oplus T_{T_{\widetilde{L}_2}}(y) \right) - \left(T_{T_{\widetilde{L}_1}}(y) \otimes T_{T_{\widetilde{L}_2}}(y) \right) \right), \left(\left(T_{I_{\widetilde{L}_1}}(y) \oplus T_{I_{\widetilde{L}_2}}(y) \right) - \left(T_{I_{\widetilde{L}_1}}(y) \otimes T_{I_{\widetilde{L}_2}}(y) \right) \right), \\
\left(\left(T_{F_{\widetilde{L}_1}}(y) \oplus T_{F\widetilde{L}_2}(y) \right) - \left(T_{F_{\widetilde{L}_1}}(y) \otimes T_{F\widetilde{L}_2}(y) \right) \right), \\
\left(\left(I_{T_{\widetilde{L}_1}}(y) \otimes I_{T_{\widetilde{L}_2}}(y) \right) \right), \left(\left(I_{I_{\widetilde{L}_1}}(y) \otimes I_{I_{\widetilde{L}_2}}(y) \right) \right), \left(\left(I_{F_{\widetilde{L}_1}}(y) \otimes I_{F\widetilde{L}_2}(y) \right) \right), \\
\left(\left(F_{T_{\widetilde{L}_1}}(y) \otimes T_{T_{\widetilde{L}_2}}(y) \right) \right), \left(\left(F_{I_{\widetilde{L}_1}}(y) \otimes F_{I_{\widetilde{L}_2}}(y) \right) \right), \left(\left(F_{F_{\widetilde{L}_1}}(y) \otimes F_{F\widetilde{L}_2}(y) \right) \right),
\end{array} \right\rangle, \tag{4.a}$$

(2) Multiplication "$\otimes$"

$$\widetilde{L}_1 \otimes \widetilde{L}_2 = \left\langle \begin{array}{l}
\left(T_{T_{\widetilde{L}_1}}(y) \otimes T_{T_{\widetilde{L}_2}}(y) \right), \left(T_{I_{\widetilde{L}_1}}(y) \otimes T_{I_{\widetilde{L}_2}}(y) \right), \left(T_{F_{\widetilde{L}_1}}(y) \otimes T_{F_{\widetilde{L}_2}}(y) \right), \\
\left(\left(I_{T_{\widetilde{L}_1}}(y) \oplus I_{T_{\widetilde{L}_2}}(y) \right) - \left(I_{T_{\widetilde{L}_1}}(y) \otimes I_{T_{\widetilde{L}_2}}(y) \right) \right), \left(\left(I_{I_{\widetilde{L}_1}}(y) \oplus I_{I_{\widetilde{L}_2}}(y) \right) - \left(I_{I_{\widetilde{L}_1}}(y) \otimes I_{I_{\widetilde{L}_2}}(y) \right) \right), \\
\left(\left(I_{F_{\widetilde{L}_1}}(y) \oplus I_{F\widetilde{L}_2}(y) \right) - \left(I_{F_{\widetilde{L}_1}}(y) \otimes I_{F\widetilde{L}_2}(y) \right) \right), \\
\left(\left(F_{T_{\widetilde{L}_1}}(y) \oplus F_{T_{\widetilde{L}_2}}(y) \right) - \left(F_{T_{\widetilde{L}_1}}(y) \otimes F_{T_{\widetilde{L}_2}}(y) \right) \right), \left(\left(F_{I_{\widetilde{L}_1}}(y) \oplus F_{I_{\widetilde{L}_2}}(y) \right) - \left(F_{I_{\widetilde{L}_1}}(y) \otimes F_{I_{\widetilde{L}_2}}(y) \right) \right), \\
\left(\left(F_{F_{\widetilde{L}_1}}(y) \oplus F_{F\widetilde{L}_2}(y) \right) - \left(F_{F_{\widetilde{L}_1}}(y) \otimes F_{F\widetilde{L}_2}(y) \right) \right)
\end{array} \right\rangle, \tag{5.a}$$

(3) Scalar multiplication

$$\lambda \widetilde{L} = \left\langle \begin{array}{l}
(1 - (1 - T_{T_{\widetilde{L}}}(y))^{\lambda}), (1 - (1 - T_{I_{\widetilde{L}}}(y))^{\lambda}), (1 - (1 - T_{F_{\widetilde{L}}}(y))^{\lambda}), \\
(I_{T_{\widetilde{L}}}(y))^{\lambda}, (I_{I_{\widetilde{L}}}(y))^{\lambda}, (I_{F_{\widetilde{L}}}(y))^{\lambda}, \\
(F_{T_{\widetilde{L}}}(y))^{\lambda}, (F_{I_{\widetilde{L}}}(y))^{\lambda}, (F_{F_{\widetilde{L}}}(y))^{\lambda}
\end{array} \right\rangle, \tag{6.a}$$

(4) Power

$$\widetilde{L}^{\lambda} = \left\langle \begin{array}{l} ((T_{T_{\widetilde{L}}}(y))^{\lambda}), (T_{I_{\widetilde{L}}}(y)^{\lambda}), (T_{F_{\widetilde{L}}}(y)^{\lambda}), \\ (1-(1-I_{T_{\widetilde{L}}}(y))^{\lambda}), (1-(1-I_{I_{\widetilde{L}}}(y))^{\lambda}), (1-(1-I_{F_{\widetilde{L}}}(y))^{\lambda}) \\ (1-(1-F_{T_{\widetilde{L}}}(y))^{\lambda}), (1-(1-F_{I_{\widetilde{L}}}(y))^{\lambda}), (1-(1-F_{F_{\widetilde{L}}}(y))^{\lambda}) \end{array} \right\rangle. \tag{7.a}$$

Definition 4. [61]: The score function $[Score(\widetilde{L})]$ can be calculated with the aid of Eq. (8.a) for T2NN $\widetilde{L}$ as:

$$Score(\widetilde{L}) = \frac{8 + T_{T_{\widetilde{L}}}(y) + 2(T_{I_{\widetilde{L}}}(y)) + T_{F_{\widetilde{L}}}(y) - I_{T_{\widetilde{L}}}(y) - 2\,I_{I_{\widetilde{L}}}(y) - I_{F_{\widetilde{L}}}(y) - F_{T_{\widetilde{L}}}(y) + 2\,F_{I_{\widetilde{L}}}(y) + F_{F_{\widetilde{L}}}(y)}{12}. \tag{8.a}$$

Appendix-B

Table B.1
T2NN-based scale for experts' experience and expertise levels [87]

Experience (years)	Expertise	T2NN
< 5	Very-poor (VP)	< (0.2, 0.2, 0.1), (0.65, 0.8, 0.85), (0.45, 0.8, 0.7)>
[5,10)	Poor (P)	< (0.35, 0.35, 0.1), (0.5, 0.75, 0.8), (0.5, 0.75, 0.65)>
[10,15)	Medium-poor (MP)	< (0.4, 0.3, 0.35), (0.5, 0.45, 0.6), (0.45, 0.4, 0.6)>
[15,20)	Medium (M)	< (0.5, 0.45, 0.5), (0.4, 0.35, 0.5), (0.35, 0.3, 0.45)>
[20,25)	Medium-good (MG)	< (0.6, 0.45, 0.5), (0.2, 0.15, 0.25), (0.1, 0.25, 0.15)>
[25,30)	Good (G)	< (0.7, 0.75, 0.8), (0.15, 0.2, 0.25), (0.1, 0.15, 0.2)>
> =30	Very-good (VG)	< (0.95, 0.9, 0.95), (0.1, 0.1, 0.05), (0.05, 0.05, 0.05)>

Table B.2
T2NN rating scale of criteria [45]

Linguistic terms	T_T	T_t	T_F	I_T	I_t	I_F	F_T	F_t	F_F	Score value
Weakly-important (WI)	0.20	0.30	0.20	0.60	0.70	0.80	0.45	0.75	0.75	0.292
Equal-important (EI)	0.40	0.30	0.25	0.45	0.55	0.40	0.45	0.60	0.55	0.425
Strong-important (SI)	0.65	0.55	0.55	0.40	0.45	0.55	0.35	0.40	0.35	0.579
Very-strongly-important (VSI)	0.80	0.75	0.70	0.20	0.15	0.30	0.15	0.10	0.20	0.804
Absolutely-important (AI)	0.90	0.85	0.95	0.10	0.15	0.10	0.05	0.05	0.10	0.900

Table B.3
Linguistic appraisal scale of options [48]

Linguistic terms	T_T	T_t	T_F	I_T	I_t	I_F	F_T	F_t	F_F
Extremely-low (EL)	0.05	0.10	0.05	0.80	0.95	0.95	0.80	0.90	0.80
Very-low (VL)	0.15	0.20	0.10	0.70	0.85	0.85	0.60	0.80	0.70
Low (L)	0.35	0.30	0.25	0.60	0.70	0.80	0.50	0.75	0.65
Medium-low (ML)	0.45	0.35	0.35	0.50	0.65	0.55	0.40	0.65	0.55
Medium (M)	0.50	0.45	0.50	0.35	0.55	0.50	0.35	0.55	0.45
Medium-high (MH)	0.60	0.55	0.55	0.25	0.40	0.45	0.25	0.45	0.35
High (H)	0.70	0.65	0.65	0.20	0.30	0.40	0.20	0.25	0.30
Very-high (VH)	0.80	0.75	0.80	0.15	0.15	0.25	0.10	0.15	0.20
Extremely-high (EH)	0.95	0.90	0.95	0.10	0.10	0.05	0.05	0.05	0.10

Appendix-C

Initially, describing the principles and some mathematical notions of the T2NSs is proper and necessary to understand better and internalize the T2NSs [81]. This section clarifies the fundamental concepts of T2NNs [81]. Neutrosophic sets have gained significant attention and application in academic research due to their effectiveness in addressing various uncertainties, including ambiguity and inconsistency [87,91]. Their prominence arises from their ability to represent multiple dimensions, encompassing "truth", "indeterminacy", and "degree of falsity". Building upon this framework, Abdel-Basset et al. [61] have enhanced the applicability of neutrosophic sets by integrating fuzzy triangular numbers, leading to the development of T2NNs.

Finding expert reputation degrees

Step 1. Form the first appraisal matrices of experts: Suppose that the options to our decision problem are ascertained as $\mathbb{Z} = \{\mathbb{Z}_1, \mathbb{Z}_2, \ldots, \mathbb{Z}_i, \ldots, \mathbb{Z}_m\}$, $(m \geq 2)$ and the criteria as $\beth = \{\beth_1, \beth_2, \ldots, \beth_j, \ldots, \beth_n\}$, $(n \geq 2)$. Besides, let us symbolize our analysts who engaged in the execution of the group evaluation process as $\daleth = \{\daleth_1, \daleth_2, \ldots, \daleth_d, \ldots, \daleth_t\}$, $(t \geq 2)$. Consequently, the specialists are evaluated using linguistic assessments based on the scale presented in Table B.1 (Appendix-B), taking into account their levels of expertise and experience. By transforming the linguistic terms into the T2NN format, the initial T2NN-based evaluation matrix $\widetilde{\wp} = \left[\widetilde{\wp}_d^{(l)}\right]_{4xt}$, $\quad d = (1, 2, \ldots, t)$ for DMs is constructed. At this stage of the algorithm, the consensus of the professional group was solicited to assess the levels of both properties of DMs.

Step 2. Integrating assessments based on DM experience and expertise levels: At this stage, the T2NN-based evaluations of the experience and expertise of each DM are combined using the type-2 neutrosophic number weighted averaging (T2NNWA) operator, as described in Eq. (1). This integration aims to derive the reputation ratings for each DM, which will be utilized in the modeling phase [92].

$$\widetilde{\mathfrak{H}}_d = T2NNWA_{\mathscr{g}}\left(\widetilde{\wp}_d^{(1)}, \widetilde{\wp}_d^{(2)}\right) = \mathscr{g}_1\widetilde{\wp}_d^{(1)} \oplus \mathscr{g}_2\widetilde{\wp}_d^{(2)} = \oplus_{l=1}^{2}\mathscr{g}_l\widetilde{\wp}_d^{(l)} =$$

$$\left[\begin{array}{c}\left(1-\prod_{l=1}^{2}\left(1-T_{T_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}, 1-\prod_{l=1}^{2}\left(1-T_{I_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}, 1-\prod_{l=1}^{2}\left(1-T_{F_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}\right),\\ \left(\prod_{l=1}^{2}\left(I_{T_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}, \prod_{l=1}^{2}\left(I_{I_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}, \prod_{l=1}^{2}\left(I_{F_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}\right),\\ \left(\prod_{l=1}^{2}\left(F_{T_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}, \prod_{l=1}^{2}\left(F_{I_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}, \prod_{l=1}^{2}\left(F_{F_{\tilde{\wp}_d^{(l)}}}(y)\right)^{\mathscr{g}_l}\right)\end{array}\right], \quad d = 1, 2, \ldots, t, \tag{1}$$

where $\widetilde{\mathfrak{H}}_d = \left\langle \left(T_{T_{\tilde{\mathfrak{H}}_d}}(y), T_{I_{\tilde{\mathfrak{H}}_d}}(y), T_{F_{\tilde{\mathfrak{H}}_d}}(y)\right), \left(I_{T_{\tilde{\mathfrak{H}}_d}}(y), I_{I_{\tilde{\mathfrak{H}}_d}}(y), I_{F_{\tilde{\mathfrak{H}}_d}}(y)\right), \left(F_{T_{\tilde{\mathfrak{H}}_d}}(y), F_{I_{\tilde{\mathfrak{H}}_d}}(y), F_{F_{\tilde{\mathfrak{H}}_d}}(y)\right) \right\rangle$ is the T2NN aggregated reputation of the specialists $\mathscr{H}_d$, with $\mathscr{g}_1\mathscr{g}_2\varepsilon[0,1]$ and $\mathscr{g}_{1,} + \mathscr{g}_2 = 1$. Subsequently, the weight of each expert, representing their reputation, is determined using Eq. (2):

$$\mathscr{e}_d = \frac{Score(\widetilde{\mathfrak{H}}_d)}{\sum_{l=1}^{t} Score(\widetilde{\mathfrak{H}}_l)}, d = 1, 2, \ldots, t, \tag{2}$$

here, $\mathscr{e} = [\mathscr{e}_1, \ldots, \mathscr{e}_e, \ldots, \mathscr{e}_t]^T$ indicates the order of specialists' weights, while $Score(\widetilde{\mathfrak{H}}_d)$ illustrates the score function. Further, $\mathscr{e}_d\varepsilon[0,1](d = 1, \ldots, t)$ and $\sum_{d=1}^{t} \mathscr{e}_d = 1$.

Calculating subjective criterion weights

Step 3. Determining the relative importance of evaluation criteria by DMs: In this step, the weight coefficients for the evaluation criteria are calculated. A panel of experts $\xi = \{\xi_1, \xi_2, \ldots, \xi_e\}$ first assesses the criteria $C_j = \{C_1, C_2, \ldots, C_n\}$ using the T2NN linguistic scale from Table B.2 (Appendix-B). Following this assessment, matrices that incorporate the evaluations provided by the experts are created, where $\mathfrak{I} = \left[\gamma_{jb}\right]_{n \times e}$ $(j = 1,.,n;\ b=1,2,\ldots,e)$ depicts the initial matrix for the measures and γ_{jb} implies the elements of the matrix.

Step 4. Calculating the score measures of the criteria: The impact of each criterion is determined according to the inclinations expressed by DMs. This impact is computed for each dimension of the T2NN, establishing a T2NN for each criterion. The significance factor for each criterion is then calculated using Eq. (3):

$$SF_j = \left[\begin{array}{c}\left(\frac{\sum_{k=1}^{e}\gamma_{kj}^{T_T} - \prod_{k=1}^{e}\gamma_{kj}^{T_T}}{e}, \frac{\sum_{k=1}^{e}\gamma_{kj}^{T_I} - \prod_{k=1}^{e}\gamma_{kj}^{T_I}}{e}, \frac{\sum_{k=1}^{e}\gamma_{kj}^{T_F} - \prod_{k=1}^{e}\gamma_{kj}^{T_F}}{e}\right),\\ \left(\frac{\sum_{k=1}^{e}\gamma_{kj}^{I_T} - \prod_{k=1}^{e}\gamma_{kj}^{I_T}}{e}, \frac{\sum_{k=1}^{e}\gamma_{kj}^{I_I} - \prod_{k=1}^{e}\gamma_{kj}^{I_I}}{e}, \frac{\sum_{k=1}^{e}\gamma_{kj}^{I_F} - \prod_{k=1}^{e}\gamma_{kj}^{I_F}}{e}\right),\\ \left(\frac{\sum_{k=1}^{e}\gamma_{kj}^{F_T} - \prod_{k=1}^{e}\gamma_{kj}^{F_T}}{e}, \frac{\sum_{k=1}^{e}\gamma_{kj}^{F_I} - \prod_{k=1}^{e}\gamma_{kj}^{F_I}}{e}, \frac{\sum_{k=1}^{e}\gamma_{kj}^{F_F} - \prod_{k=1}^{e}\gamma_{kj}^{F_F}}{e}\right)\end{array}\right], \tag{3}$$

where e signifies the number of specialists while γ_j illustrates the value appointed by the professionals to criterion j.

Steps 5 –6. Additive normalization of the score measures of the criteria: The score measures are established following this step. Subsequently, $1xn$ vector is subjected to further standardization using Eq. (4) to obtain the weights for each criterion.

$$w_j^{(subj)} = \frac{S(SF_j)}{\sum_{j=1}^{n} S(SF_j)}, \tag{4}$$

here $S(SF_j)$ signifies the score measure calculated according to Eq. (8.a), and 'n' stands for the total number of criteria. Consequently, the vector $w_j^{(subj)}$

$= (w_1, w_2, ..., w_n)^T$ containing the weight coefficients of the criteria is then utilized to figure out the weighted order of options.

Calculating objective criterion weights

Step 7. Constructing the initial decision matrix for each expert: In this step, specialists execute a linguistic appraisal for the decision alternatives using the linguistic scale given in Table B.3 (Appendix-B). According to the scale, these assessments are then transformed into T2NNs. Following this process, each expert is assigned a foundational decision matrix $\aleph^b = \left[\overrightarrow{\theta}_{ij}^b\right]_{m\times n}$. Each pair $\overrightarrow{\theta}_{ij}^b$ $(1 \le b \le e;\ i = 1,\ldots,m;\ j = 1,\ldots,n)$ takes a value from the predefined scale.

Step 8. Calculating the significance factor of each alternative based on the evaluations of DMs: The relative importance of each alternative is assessed according to the evaluations provided by DMs. Eq. (5) is employed to form the T2NN matrix of alternatives regarding criteria:

$$\aleph = \begin{bmatrix} \theta_{11}^{SF} & \theta_{12}^{SF} & \theta_{13}^{SF} & \cdots & \theta_{1n}^{SF} \\ \theta_{21}^{SF} & \theta_{22}^{SF} & \theta_{23}^{SF} & \cdots & \theta_{2n}^{SF} \\ \theta_{31}^{SF} & \theta_{32}^{SF} & \theta_{33}^{SF} & \cdots & \theta_{3n}^{SF} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \theta_{m1}^{SF} & \theta_{m2}^{SF} & \theta_{m3}^{SF} & \cdots & \theta_{mn}^{SF} \end{bmatrix}. \tag{5}$$

Step 9. Calculating the score measure for alternatives: A matrix of score measures for the criteria is generated, as outlined in Eq. (6), and the initial decision matrix (IDM) is generated.

$$\overline{\aleph} = \begin{bmatrix} \aleph_{11} & \aleph_{12} & \aleph_{13} & \cdots & \aleph_{1n} \\ \aleph_{21} & \aleph_{22} & \aleph_{23} & \cdots & \aleph_{2n} \\ \aleph_{31} & \aleph_{32} & \aleph_{33} & \cdots & \aleph_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \aleph_{m1} & \aleph_{m2} & \aleph_{m3} & \cdots & \aleph_{mn} \end{bmatrix}, \tag{6}$$

where $\aleph_{ij}$ $(i = 1,\ldots,m;\ j = 1,.,n)$ is obtained by Eq. (8.a).

Step 10. Normalizing the initial decision matrix (IDM): The linear max-min normalization technique is employed to derive the normalized values of the IDM elements:

$$\aleph_{ij}^{*} = \begin{cases} \dfrac{\aleph_{\max} - \aleph_{ij}}{\aleph_{\max} - \aleph_{\min}} & j \in B \\ \dfrac{\aleph_{\max} - \aleph_{ij}}{\aleph_{\max} - \aleph_{\min}} & j \in C \end{cases}. \tag{7}$$

Step 11. Calculating the percentage values for each criterion: In this step, the mean square value of each criterion is calculated as a percentage of its standard deviation. This approach aims to eliminate differences (gaps) that may arise due to variations in data size.

$$PV_{ij} = \left| \ln\left(\frac{\sqrt{\frac{\sum_{i=1}^{m} \aleph_{ij}^{*2}}{m}}}{\sigma} \right).100 \right|, \tag{8}$$

where σ denotes the standard deviation.

Step 12. Computing the objective weights: Each objective weight is determined using Eq. (9).

$$w_j^{obj} = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}}. \tag{9}$$

Step 13. Identifying the final weights of the criteria: Integrated criterion weights are obtained according to Eq. (10).

$$w_j^{\text{int}} = (1 - \gamma)\, w_j^{obj} + (\gamma)\, w_j^{subj}. \tag{10}$$

Identifying option performances

Step 14. Creation of the initial evaluation matrix (IAM) for the decision problem: This matrix is not given here because it is given in Eq. (6).

Step 15. Normalization of the IAM for the decision problem: The MACONT technique employs three distinct normalization methods during the normalization process. Accordingly, benefit-type and cost-type criteria are normalized using different formulations to maintain their inherent directional meanings. The selected normalization techniques ensure that all normalized values are transformed onto a comparable scale without altering the relative dominance relationships among alternatives. This criterion-specific normalization strategy enhances the robustness and interpretability of the decision results, particularly when heterogeneous criteria are simultaneously considered. The first method is the "linear sum-based normalization technique", as outlined in Eq. (11):

$$\Theta_{ij}^{(1)} = \begin{cases} \dfrac{\wp_{ij}}{\sum_{i=1}^{m} \wp_{ij}} j \in B \\ \dfrac{1/\wp_{ij}}{\sum_{i=1}^{m} 1/\wp_{ij}} j \in C \end{cases}, \tag{11}$$

The second is the "linear ratio-based normalization technique" presented in Eq. (12):

$$\Theta_{ij}^{(2)} = \begin{cases} \dfrac{\wp_{ij}}{\max_i \wp_{ij}} j \in B \\ \dfrac{\min_i \wp_{ij}}{\wp_{ij}} j \in C \end{cases}, \tag{12}$$

The third is the "linear max-min normalization technique" specified in Eq. (13):

$$\Theta_{ij}^{(3)} = \begin{cases} \dfrac{\wp_{ij} - \min_i \wp_{ij}}{\max_i \wp_{ij} - \min_i \wp_{ij}} j \in B \\ \dfrac{\wp_{ij} - \max_i \wp_{ij}}{\min_i \wp_{ij} - \max_i \wp_{ij}} j \in C \end{cases}, \tag{13}$$

Using these three techniques, the IAM is normalized, resulting in the matrices NAM-I, NAM-II, and NAM-III. Subsequently, these matrices are synthesized using Δ_1, Δ_2, and $\Delta_3$equilibrium parameters according to Eq. (14) to produce a comprehensive normalized decision matrix (C-NDM):

$$\Theta_{ij} = (\Delta_1)\Theta_{ij}^{(1)} + (\Delta_2)\Theta_{ij}^{(2)} + (\Delta_3)\Theta_{ij}^{(3)}, \tag{14}$$

where the symbols $\Theta_{ij}^{(1)}$, $\Theta_{ij}^{(2)}$, and $\Theta_{ij}^{(3)}$ represent the normalized values calculated according to those mentioned above three different normalization techniques, while $\Delta_1 + \Delta_2 + \Delta_3 = 1$ with $\Delta_1, \Delta_2, \Delta_3 \in [0, 1]$. Various trials incorporating different values for these parameters should be conducted during the sensitivity analysis phase.

Step 16. Calculate the subscore values for each decision alternative. After obtaining the normalized matrix, the two sub-score values based on the arithmetic $\mathbb{N}_i^{(1)}$ and geometrically weighted addition $\mathbb{N}_i^{(2)}$ operators for each criterion are calculated according to Eq. (15) and Eq. (16), respectively:

$$\mathbb{N}_i^{(1)} = \sum_{j=1}^{n} \omega_j^{\text{int}} \left(\Theta_{ij} - \overline{\Theta}_{ij}\right), \tag{15}$$

$$\mathbb{N}_i^{(2)} = \frac{\prod_{\theta=1}^{n} \left(\overline{\Theta}_{ij} - \Theta_{ij}\right)^{\omega_j^{\text{int}}}}{\prod_{\alpha=1}^{n} \left(\Theta_{ij} - \overline{\Theta}_{ij}\right)^{\omega_j^{\text{int}}}}, \tag{16}$$

where ω_j^{int} represents the integrated weight value of the j-th criterion, $\overline{\Theta}_{ij}$ is the average of the performance values of the alternatives under each criterion, θ is the part provided the condition that $\Theta_{ij} < \overline{\Theta}_{ij}$, and α denotes the part provided the condition that $\overline{\Theta}_{ij} \le \Theta_{ij}$ in Eq. (16).

Step 17. Calculate the comprehensive score values for each alternative with the help of two mixed aggregation operators: Each option's comprehensive score value is computed using the preference parameters λ and Φ based on $\mathbb{N}_i^{(1)}$and $\mathbb{N}_i^{(2)}$ as well as by implementing Eq. (17) and Eq. (18):

$$\mathbb{Z}_{1i} = \lambda \frac{\mathbb{N}_i^{(1)}}{\sqrt{\sum_{i=1}^{m} \left(\mathbb{N}_i^{(1)}\right)^2}} + (1-\lambda) \frac{\mathbb{N}_i^{(2)}}{\sqrt{\sum_{i=1}^{m} \left(\mathbb{N}_i^{(2)}\right)^2}}, \tag{17}$$

$$\mathbb{Z}_{2i} = \Phi \max_j \left(\omega_j^{\text{int}} \left(\Theta_{ij} - \overline{\Theta}_{ij}\right)\right) + (1-\Phi) \min_j \left(\omega_j^{\text{int}} \left(\Theta_{ij} - \overline{\Theta}_{ij}\right)\right), \tag{18}$$

here, the preference parameters were taken equally (i.e. $\lambda = \Phi = 0.5$) during the first solution.

Step 18. Ranking the options: The final score value of each option is computed with the help of Eq. (19). The alternatives are sorted by considering the alternatives' score values.

$$\mathbb{Z}_i = \frac{1}{2} \left(\mathbb{Z}_{i1} + \frac{\mathbb{Z}_{i2}}{\sqrt{\sum_{i=1}^{m} \left(\mathbb{Z}_{i2}\right)^2}} \right), \tag{19}$$

here, $\mathbb{Z}_i$denotes the final score value computed for the i-th alternative.

Appendix-D

Table D.1
Assessments for the features of the experts

Professional	Expert	Graduation	Degree	Duty	Experience
	DM1	VG	MG	G	M
E1	DM2	G	G	G	P
	DM3	MG	MG	G	MG
	DM1	G	M	MG	M
E2	DM2	MG	MG	MG	P
	DM3	MG	M	MG	MG
	DM1	M	M	G	M
E3	DM2	VG	MG	G	P
	DM3	MG	M	G	MG

Table D.2
Linguistic aassessments of the experts for the alternatives

	C11	C12	C13	C14	C15	C21	C22	C31	C32	C33	C34	C35	C36	C37	C41	C42	C43	C44	C45
A1	MH	H	VH	MH	L	VH	EL	VH	EL	VH	EL	VH	VH	EL	VH	EL	VH	EL	VH
A1	EL	VH	H	L	MH	H	H	H	H	H	H	H	H	H	H	H	H	H	H
A1	MH	MH	MH	M	L	MH	H	MH	H	MH	H	MH	MH	H	MH	H	MH	H	MH
A2	H	ML	VH	MH	VH	VH	MH	VH	MH	VH	MH	VH	VH	MH	VH	MH	VH	MH	VH
A2	EL	L	L	VH	EL	MH	MH	M	MH	M	MH	M	MH	MH	M	MH	M	MH	M
A2	H	ML	ML	VH	VH	VH	MH	H	MH	H	MH	H	VH	MH	H	MH	H	MH	H
A3	ML	EL	H	M	M	H	EL	MH	EL	MH	EL	MH	H	EL	MH	EL	MH	EL	MH
A3	VH	MH	VH	MH	EL	MH	H	VH	H	VH	H	VH	MH	H	VH	H	VH	H	VH
A3	VH	EL	VH	VH	ML	EL	ML	VH	ML	VH	ML	VH	EL	ML	VH	ML	VH	ML	VH
A4	ML	L	VH	VH	EL	VH	ML	M	ML	M	ML	M	VH	ML	M	ML	M	ML	M
A4	VH	L	VH	VH	H	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH	VH
A4	M	VH	ML	ML	MH	M	M	M	M	M	M	M	M	M	M	M	M	M	M
A5	H	L	MH	MH	EL	L	MH	H	MH	H	MH	H	L	MH	H	MH	H	MH	H
A5	L	ML	VH	ML	MH	M	H	VH	H	VH	H	VH	M	H	VH	H	VH	H	VH
A5	ML	VH	M	ML	MH	VH	ML	ML	ML	ML	ML	ML	VH	ML	ML	ML	ML	ML	ML

Table D.3
Linguistic aassessments of the experts for the criteria and sub-criteria

Criteria	Code	DM1	DM2	DM3
Logistics Assess	C1	AI	VSI	AI
Proximity to Highway	C11	VSI	AI	AI
Proximity to Railway	C12	AI	AI	AI
Proximity to Seaport	C13	VSI	AI	VSI
Proximity to Airport	C14	VSI	AI	SI
Traffic condition	C15	VSI	VSI	VSI
Cost	C2	EI	SI	EI
Land	C21	SI	SI	AI
Storage	C22	EI	SI	AI
Location	C3	SI	WI	EI
Proximity to beneficiaries	C31	VSI	SI	EI
Disaster free location	C32	VSI	SI	SI
Climate	C33	SI	VSI	EI
Closeness to the warehouses	C34	SI	VSI	SI
Shortest starting time	C35	VSI	VSI	VSI
Proximity to disaster prone area	C36	SI	VSI	SI
Ease of access for auxiliary materials	C37	VSI	VSI	VSI
Land Structure	C4	SI	SI	VSI
Flora	C41	AI	VSI	AI
Slope	C42	AI	AI	AI
Elevation	C43	VSI	AI	VSI
Distance of Fault line	C44	VSI	AI	AI
Landslide risk	C45	VSI	VSI	VSI

Appendix E. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.asoc.2026.115404.

Data availability

Data will be made available on request.

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