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Holistic Decision-Making for Optimal Siting of Urban Earthquake Emergency Shelters: An Integrated Ontology and Fuzzy-AHP Approach

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Abstract Earthquakes are amongst the most destructive natural hazards, posing substantial risks to urban populations and infrastructure. As cities grow and modernise, identifying optimal locations for Urban Earthquake Emergency Shelters (UEES) becomes key for ensuring public safety. However, this process involves complex, multi-faceted criteria that must be carefully evaluated. This paper introduces a multi-criteria decision-making (MCDM) framework thatffiga integrates ontology with the fuzzy analytic hierarchy process (FAHP) to prioritise potential locations. A key contribution is the use of an ontology to model and interconnect the diverse criteria necessary for UEES site selection, providing a structured perspective that enhances both the theoretical understanding and practical decision-making in urban emergency management. The designed ontology structures and analyses the selection criteria, which are then processed using the FAHP to prioritise potential sites. This framework was validated through a case study in Beijing, where the Shijingshan and Haidian districts were identified as the most suitable locations due to high safety levels, economic benefits, and infrastructure interactions. The results also highlight key challenges in planning and construction across different sites. By combining ontology with FAHP, this framework optimises UEES location selection and supports the digital transformation of urban emergency management systems, offering a holistic, data-driven approach to disaster preparedness.

Keywords Urban disaster preparedness · Semantic web · Fuzzy analytic hierarchy process · Ontology-based evaluation · Multi-criteria decision analysis · Urban emergency management

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Abbreviations

AEE	Adaptive evacuation efficiency
AHP	Analytic hierarchy process
CI	Consistency index
CR	Consistency ratio
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DSS	Decision Support System
DL	Description logic
EDMs	Expert decision-makers
FAHP	Fuzzy analytic hierarchy process
FTOPSIS	Fuzzy Technique for Order Preference by Similarity to Ideal Solution
GIS	Geographical Information System
IT2FSs	Interval type-2 fuzzy sets
MCDM	Multi-criteria decision-making
PC	Proportional change
RF	Random Forest
SQWRL	Semantic Query-Enhanced Web Rule Language
SWRL	Semantic Web Rule Language
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TFNs	Triangular fuzzy numbers
UEES	Urban Earthquake Emergency Shelters
VGAE	Variational graph autoencoder
OWL	Web Ontology Language

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1 Introduction

Urban expansion has been a cornerstone of modern development, resulting in increased building density and higher floor area ratios in cities. Whilst this growth signals economic progress, it also introduces significant challenges for disaster management, particularly in earthquake-prone areas. Earthquakes, as one of the most destructive and unpredictable natural phenomena, present substantial risks to urban safety. In China, for instance, the 5.12 Wenchuan and 4.14 Yushu earthquakes caused significant fatalities and economic losses. Many of these losses were due to the absence of timely evacuation measures and effective decision support systems [1–3]. With millions of earthquakes recorded globally each year, the rapid pace of urbanisation necessitates the adoption of modern technologies to enhance resilience, as traditional earthquake-resistant methods alone are no longer sufficient [4].

Disaster management focuses on implementing policies and strategies to reduce disaster risks, manage residual risks, and enhance preparedness [5]. Earthquake emergency shelters play a critical role in this process, providing refuge and essential services during the aftermath of an earthquake [6]. However, many cities lack well-planned shelters, leaving civilians vulnerable to secondary hazards such as aftershocks and resource shortages. This highlights the urgent need for effective earthquake evacuation strategies, particularly in optimising the siting of shelters, defining service areas, and stratifying shelter tiers. Therefore, it is necessary to develop methods for selecting suitable shelter locations to enhance civilian safety and mitigate the impact of secondary disasters [7].

Given the complexity of shelter siting, several studies have attempted to address these challenges. For instance, Xu et al. [8] developed a multi-objective mathematical model to optimise evacuation paths and shelter selection, considering constraints such as hazard paths, shelter layout, and evacuation times. He and Xie [9] proposed a bi-level multi-objective location-allocation model that balances long-term economic sustainability with evacuee preferences for shelter proximity and scale. The study acknowledges the limitation that evacuees may not always make rational choices based on shelter size and proximity in real emergencies. Madanchian and Taherdoost [10] applied the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method, supported by the analytic hierarchy process (AHP), to select shelters based on multiple criteria for urban evacuation. Whilst this method is a valuable tool for decision-making, the study highlighted challenges in the weighting process. Meanwhile, Wang et al. [11] integrated machine learning models, such as Variational Graph Autoencoders (VGAE) and Random Forests (RF), to enhance shelter site selection by analysing spatial topological data. The authors recommend incorporating additional factors to enhance the model's predictive accuracy and exploring multi-model fusion to increase adaptability in data-limited environments.

Despite these advancements, current multi-objective approaches often fail to fully integrate diverse and relevant criteria into a holistic framework due to inconsistencies in data representation and the integration of heterogeneous hazard-related data [12,13]. Moreover, there is limited research that comprehensively identifies and evaluates the criteria for shelter site selection under multi-faceted urban conditions [14]. This gap becomes even more pronounced in the context of rapid urban expansion, which complicates emergency response due to increased data complexity [15] and the absence of a holistic decision-making framework. Therefore, disaster management should be viewed as a continuous and cyclical process, covering the pre-disaster, disaster, and post-disaster phases [5,15], as illustrated in Fig. 1. The pre-disaster phase emphasises risk knowledge and monitoring to identify potential hazards, whilst the disaster phase focuses on immediate response, where the effectiveness of communication and response capabilities determines the success of evacuation and sheltering efforts. Finally, the post-disaster phase centres on recovery and learning from the event, feeding back into risk knowledge to refine future monitoring and preparedness strategies.

In recent years, ontology-based Semantic Web technologies have emerged as a promising solution for overcoming data inconsistencies by providing machine-readable data and standardised terminologies [15]. This structured approach enhances decision-making processes by allowing for more efficient disaster management. Given the increasing complexity of modern urban environments, integrating ontology with decision-making methods like the FAHP provides a powerful framework for optimising UEES site selection. Thus, this paper aims to develop a holistic framework for UEES site selection, utilising FAHP to define and prioritise site selection criteria and employing ontology to facilitate the identification of optimal shelter locations. This integrated approach not only enhances decision-making efficiency but also supports the digital transformation of urban emergency management systems. The paper is structured as follows: Sect. 2 reviews the classification of UEES and key principles for site selection, discusses the interconnections between MCDM, AHP, and FAHP, and explores ontology applications in UEES. Whilst the literature review is not exhaustive, it highlights the most relevant research. Section 3 presents the research methodology, whilst Sect. 4 establishes the evaluation criteria for UEES site selection based on hierarchical theory and FAHP. Section 5 discusses the development of an ontology-based system using Protégé 5.5, offering systematic insights into key ontological concepts. In Sect. 6, a case study in Beijing applied the proposed approach to determine

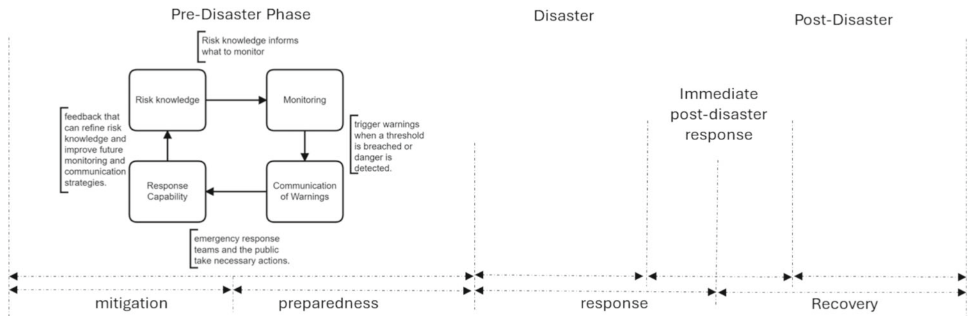

Fig. 1 Phases of disaster management

optimal shelter locations. Finally, Sect. 8 provides the conclusion.

2 Literature Review

2.1 Classification of UEES and Site Selection Principles

A UEES is a designated structure or area that provides essential protection, livelihood support, and rescue coordination for community residents following major natural disasters, especially earthquakes. These shelters are typically located in public spaces such as urban parks, stadiums, green areas, and city squares [14]. UEES are critical components of a city's disaster response infrastructure, which are designed to offer protection against aftershocks and secondary hazards, ensuring the safety and well-being of affected individuals [1].

UEES are classified into three categories: temporary shelters, short-term shelters, and long-term shelters [16]. This classification helps urban planners organise shelters based on their capacity and the duration they are intended to serve evacuees, as outlined in Table 1. Temporary shelters are established immediately after an earthquake, providing refuge for up to 10 days. They are typically located in accessible urban areas, such as parks and sports grounds, with a minimum area of 2000 m^2 and a Comprehensive Score (CS) of 3 or less. If evacuation extends beyond 10 days, evacuees are transferred to short-term shelters, which provide more comprehensive facilities for extended stays. These shelters cover areas larger than 10,000 m^2 and have a CS between 3 and 4. For evacuations lasting more than 30 days, long-term shelters are required. These shelters provide essential services for prolonged evacuations, requiring areas greater than 100,000 m^2 and having a CS of 4 or higher. This hierarchical classification ensures that each shelter type is capable of meeting the specific needs of evacuees depending on the duration of their stay. Moreover, higher-level shelters incorporate the functions of lower-level shelters. For instance, long-term shelters also offer the functions of short-term shelters and temporary shelters, and short-term shelters provide the functions of temporary shelters.

After classification, the next step is selecting optimal locations based on site selection principles. Site selection for UEES must follow principles that ensure safety, accessibility, and functionality during disasters [16]. These principles guide decision-makers to optimise shelter locations in preparation for earthquake emergencies. The Safety Principle requires that shelters be located away from seismic faults and geologically hazardous areas on flat and open land with access routes to ensure quick and safe accessibility. Moreover, shelters should have easy access to essential infrastructure and services to support the livelihood of the sheltered population. The Traffic Principle dictates that UEES should have multiple evacuation routes, with each shelter site having at least two accessible routes leading in and out of the area. This ensures that evacuees can reach the shelter without restricted access and provides alternative paths in case any primary route becomes obstructed or unusable due to earthquake damage. The Life Support Capacity principle emphasises that chosen sites should have the infrastructure to offer basic living necessities, medical care, and recreational facilities for disaster civilians. Personnel Capacity is another critical factor in site selection, requiring effective space distribution to avoid overcrowding and ensure comfort for sheltered individuals. For general shelters, the available space per person should be no less than 1.5 square metres [16]. For long-term shelters, where evacuees may stay for extended periods, a minimum of 2 square metres per person is recommended to provide adequate living conditions [16].

In the aftermath of an earthquake, individuals often instinctively evacuate to the nearest UEES or open areas within the city. However, due to the uneven distribution of shelters and their varying capacities, disorganised evacuations often occur, driven by panic and based solely on life experiences. This can result in some UEES being overcrowded, exceeding their design capacity, whilst others are underutilised. Therefore, effective distribution and zoning of UEES are critical for managing evacuation and optimising resource use. To ensure an organised evacuation and equitable shelter distribution, certain zoning principles must be followed [16]: the Proximity Principle, which ensures that each UEES is easily accessible to its service area popula-

Table 1 Classification of UEES by site type, size, and comprehensive score [16]

Name	Site type	Site size	Comprehensive Score (CS)
Temporary shelters	Green spaces, parks, squares, sports grounds	Area $\geq 2000\,\mathrm{m}^2$	CS ≤ 3
Short-term shelters	Green spaces, parks, squares, sports grounds	Area $> 10{,}000\,\mathrm{m}^2$	$3 <$ CS < 4
Long-term shelters	Green spaces, parks, squares, sports grounds	Area $> 100{,}000\,\mathrm{m}^2$	CS ≥ 4

tion, reducing travel distance during emergencies; the Spatial Continuity Principle, which ensures that service areas should be contiguous, avoiding fragmented zones that complicate evacuation and access; the Full Coverage Principle, which ensures that every high-density population area is within the service area of at least one UEES, ensuring no one is left without access to a safe shelter. By adhering to these principles, urban planners can ensure that UEES are not only equitably distributed but also efficiently utilised. Hence, the effectiveness of the UEES depends on precise planning, site selection, and zoning based on principles of safety, accessibility, and capacity. When properly implemented, UEES advance urban resilience and secure reasonable access to essential services during emergencies.

2.2 Enhancing MCDM with FAHP

MCDM is a framework that refers to the evaluation of decision-making based on multiple, often conflicting criteria. It requires a systematic approach to assess various alternatives against a set of predetermined criteria, assigning weights to each criterion based on its relative importance in the overall decision [17]. A key requirement in this evaluation process is that the sum of the weights for all criteria must equal 1, as shown in Eq. (1).

$$W\,(pc) = \sum_{i=1}^{n} W\,(c_i,\, pc) = 1 \tag{1}$$

$W(c_i, pc)$ is the weight of the ith criterion at a given proportional change (PC); n is the total number of criteria.

The MCDM approach is widely applied for site selection, where expert decision-makers (EDMs) assess the most suitable alternative from a limited set of options based on predefined criteria. To effectively apply MCDM to site selection, it is crucial to establish a comprehensive evaluation index system that covers all relevant criteria that affect the decision. In the context of earthquake shelter site selection, four main categories of criteria are typically considered: Safety Criteria, which include factors related to the protection of occupants from aftershocks and other hazards; Planning Criteria, concerning the accessibility, capacity, and layout of the shelter, Economic Criteria, which is associated with construction, operation, and maintenance of the shelter, and Construction Criteria, aspects related to the feasibility and speed of building the shelter. Each of these main criteria can be broken down into sub-criteria to capture more specific aspects of the decision.

Several studies have leveraged the MCDM approach, Table 2. One of the most widely used methods under the MCDM umbrella is the AHP, which is particularly effective for planning, prioritisation, and alternative selection problems [18]. AHP decomposes complex decision problems into their constituent factors and then synthesises the results. The process begins by organising the problem into a hierarchical structure, breaking it down into component factors that are clustered into various levels based on their interrelationships, forming a multi-layer analytical structure. At the lowest level, the alternatives are assessed with respect to the overall objective at the top level. For example, Omidvar et al. [19] developed a systematic approach for pre-earthquake temporary shelter site selection by combining a geographical information system (GIS) with MCDM techniques, notably the AHP. AHP was employed to assess and rank 14 potential zones in Tehran, Iran, based on 13 criteria, helping to determine the most appropriate shelter sites. Similarly, Roh et al. [20] used AHP to prioritise key factors influencing warehouse location decisions in humanitarian relief logistics, with criteria such as accessibility, proximity to transportation hubs, and local resource availability. The study also recommended integrating other mathematical models, such as TOPSIS, to enhance decision-making accuracy.

Pang et al. [21] focused on optimising emergency material reserve locations using an evaluation model based on TOPSIS, combining subjective and objective weighting methods to reduce bias in decision-making. However, the study acknowledged limitations, such as the exclusion of important factors like logistics and transportation and a lack of consideration for the correlation between alternatives. Demir et al. [22] proposed an approach to revising the initial AHP matrix in solar PV site selection, improving accuracy and reliability by adjusting weights based on known ratios between criteria. Another study by Zhang et al. [23] developed a multi-objective optimisation model that not only optimises evacuation efficiency and minimises costs but also seeks to maximise vulnerability coverage across the city. By incorporating constraints related to population coverage and evacuation capacity, the model enhances the scientific basis

Table 2 Studies of AHP and FAHP on site selection for disaster management

Authors	Problem area	Approach	Criteria
Omidvar et al. [19]	Temporary shelter site selection	AHP, TOPSIS	Accessibility, culture, public opinion, water resources
Roh et al. [20]	Warehouse location in humanitarian logistics	AHP	Proximity to transport, local resources, disaster impact
Pang et al. [21]	Material storage site selection	TOPSIS	Geographic proximity, logistics, capacity, response time
Demir et al. [22]	Solar PV site selection	AHP	Transmission costs, road costs, construction phase costs
Zhang et al. [23]	Traditional evacuation site selection and social vulnerability in disaster management	AHP	Social vulnerability, population coverage, evacuation capacity
Arca and Keskin Çıtıroğlu [24]	Disaster assembly area selection	GIS, AHP	Slope, population, distance to roads, rivers
Xu et al. [25]	Urban evacuation shelter site selection	AHP	Safety, accessibility, shelter facilities, demand matching
Çetinkaya et al. [27]	Refugee camp location selection	GIS, Fuzzy-AHP, TOPSIS	Geographic, social, infrastructural risk factors (slope, population, distance)
Celik [28]	Cause-effect relationships for shelter locations	DEMATEL, IT2FS	Logistics technology, financial support, optimal distribution, infrastructure
Celik [6]	Critical factors in shelter site selection	DEMATEL, IT2FS	Proximity, transport, distribution capacity, logistics, accessibility
Boonmee and Thoenburin [29]	Temporary safety zones during haze crises	FAHP, FTOPSIS	Proximity to community, air quality, budget, capacity, emergency preparedness
Lam and Cruz [30]	Evacuation shelter site suitability assessment	Fuzzy AHP, topological networks	Network metrics (density, centrality), accessibility, reachability, hazard maps

for evacuation site planning, ensuring that strategies are both efficient and equitable. Arca and Keskin Çıtıroğlu [24] combined GIS and AHP to generate a sensitivity map for site selection. Using AHP, weights for key factors such as slope, population, distance to roads, geology, and land use were calculated, with slope identified as the most critical parameter. Xu et al. [25] proposed an evaluation index system for assessing the emergency response capability of urban shelters using AHP within an MCDM framework. This study identified factors such as site safety, spatial accessibility, demand matching, and public awareness as key criteria.

AHP further refines MCDM by structuring criteria into a hierarchical model, which allows for pairwise comparisons and the derivation of priority scales that quantify decision-makers preferences. Whilst AHP is effective in many decision-making scenarios, it relies on precise numerical judgments, which can be challenging to provide in environments characterised by uncertainty or subjectivity. To address the limitation, FAHP extends the traditional AHP by incorporating fuzzy logic. Fuzzy logic is based on fuzzy set theory, which allows for degrees of membership and helps handle uncertainty in human judgment [26]. FAHP uses Triangular Fuzzy Numbers (TFNs), represented by triplets (l, m, u), to model uncertainty. In fuzzy sets, elements have degrees of membership ranging continuously between 0 and 1, indicating their level of association with a given set. For instance, in Eq. (2), a membership degree of 0 indicates that the element does not belong to the fuzzy set, a degree of 1 signifies full membership and any value between 0 and 1 reflects partial membership.

$$\mu_{\mathrm{A}}(x) = \begin{cases} 0, & \text{if } x \leq a \text{ or } x \geq c \\ \dfrac{x-a}{b-a}, & \text{if } a < x < b \\ \dfrac{c-x}{c-b}, & \text{if } b \leq x < b \\ 1, & \text{if } x = b \end{cases} \tag{2}$$

Fuzzy set A: The membership degree of x in A is defined by the triangular membership function; a, b, and c represent the lower, middle, and upper bounds of the triangular fuzzy number, respectively.

By adopting TFNs and a linguistic scale of corresponding importance, EDMs can express their judgments in a manner that more accurately reflects the inherent fuzziness of human perception. FAHP has been successfully applied in various site selection studies. For instance, Çetinkaya et al. [27] proposed a GIS-based fuzzy MCDM framework for identifying suitable refugee camp locations, incorporating Fuzzy AHP to prioritise geographic, social, infrastructural, and risk-related indicators and TOPSIS to rank potential sites. The use of FAHP allowed for the incorporation of uncertainty in EDMs' opinions, enhancing the reliability of the indicator weighting process. Celik [28] presented a decision-making framework that combines the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method with interval type-2 fuzzy sets (IT2FSs) to evaluate cause-and-effect relationships amongst 14 critical criteria for shelter location. Key factors identified include logistics technology, financial support, and optimal distribution. Another study by Celik [6] focused on identifying critical factors for shelter site selection to support humanitarian relief efforts after disasters. Amongst the most important criteria identified were proximity and transport–distribution capacity. Sub-criteria such as distribution centre capacity, logistics personnel, available electricity, and accessibility were also highlighted.

Boonmee and Thoenburin [29] proposed an integrated approach for selecting temporary safety zones during haze pollution crises, combining FAHP, the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS), and a fuzzy multi-objective mathematical model. The methodology provides EDMs with a comprehensive framework to prioritise and evaluate criteria, optimise resource allocation, and select suitable locations. However, the approach has limitations, such as computational complexity and reliance on expert input, which may introduce bias. Lam and Cruz [30] introduced a modelling framework that integrates a topological network and FAHP to assess potential evacuation shelters, focusing on accessibility, reachability, and other critical criteria. By modelling shelters and their interdependencies as nodes and links in an evacuation network, the study evaluates shelter suitability using network metrics like density, degree centrality, and closeness centrality. These studies demonstrate the effectiveness of FAHP in handling uncertainty and refining decision-making processes for site selection in disaster management. Hence, FAHP enhances traditional AHP by addressing the inherent uncertainty in human judgments, offering a more flexible approach to complex decision-making scenarios, such as earthquake shelter site selection. By incorporating fuzzy logic, FAHP allows decision-makers to express their preferences with greater accuracy, leading to more robust and reliable outcomes. Further details about this approach are given in Sect. 4.

2.3 Ontologies and Their Role in UEES

Ontologies play a critical role in organising and managing knowledge in the field of UEES. They provide structured frameworks for capturing, representing, and reasoning about complex information, which is particularly useful in disaster management. The construction of ontologies is guided by foundational principles that ensure clarity, consistency, and adaptability. These principles, first established by Gruber [31] and further developed by Arpirez et al. [32], include clarity, consistency, extensibility, minimal encoding errors, and minimal ontological commitment. First, clarity states that ontologies must clearly and effectively define concepts in a way that is easily understood. Second, consistency involves these definitions remaining uniform across the ontology to ensure that subsequent reasoning and knowledge representation are reliable. Third, extensibility is the principle that ontologies should be designed with the anticipation of future extension. Fourth, the minimal coding error focuses on the importance of producing ontologies that can be easily transformed into different programming languages without losing information. Finally, minimal ontological commitment means that ontologies should be built with the most basic and general concepts possible, avoiding unnecessary complexity and making fewer assumptions to prevent limiting their applicability. These principles are essential in dynamic fields such as UEES, where adaptability to different crisis scenarios is important. By adhering to these principles, ontologies can support the development of flexible systems capable of adapting to various disaster management contexts.

Ontologies are composed of several key elements that provide a structured framework for representing knowledge [33]. The most fundamental element is the Class, which is a formatted description of a domain concept. Below the class level, there can be individuals (also referred to as instances) or subclasses, which represent narrower divisions of the class. Attributes describe the characteristics of the class and typically include object attributes, data attributes, and annotation attributes. An instance is a real existence under the concept of a class, which is an abstract generalisation of a feature.

An individual belongs to a class, and it is an instance of the class.

Moreover, relationships are used to describe the interactions between classes, both as a detailed description of properties and as a logical qualification of reasoning. There are four basic types of relationships in ontology development: 'part-of' for component relationships, 'kind-of' for inheritance, 'instance-of' for membership, and 'attribute-of' for characteristics, each providing a different perspective on the links between classes [34]. A function is a special form of ontology expression that involves the mapping between classes, often used to complete reasoning within the ontology. For example, functions can be used to calculate the scores and weights of each criterion for alternative sites in a UEES. Additionally, axioms are used to constrain interactions between classes, attributes, and instances, ensuring logical consistency and supporting more sophisticated reasoning.

Several studies have explored the application of ontologies in disaster management, highlighting their potential to improve decision-making, interoperability, and response strategies. Table 3 summarises key studies that have applied ontology-based frameworks to disaster management, with a focus on site selection and decision-making. Liu et al. [35] conducted a review of 26 existing ontologies, identifying 11 essential subject areas relevant to crisis management. They concluded that whilst there is a high degree of semantic interoperability, gaps remain in the integration of ontologies for crisis response. The review emphasised the need for more formal and standardised ontologies to enhance interoperability across systems. Malizia et al. [36] developed an ontology called SEMA4A, which integrates concepts from accessibility, emergency scenarios, and communication technologies. This ontology was designed to adapt emergency notifications based on users' profiles, abilities, and the available communication media. Onorati et al. [37] extended SEMA4A by adding a domain focused on evacuation routes. This extension allows for the automatic adaptation of evacuation routes based on user profiles, the type of emergency, and the available infrastructure. The study identified a significant gap in existing systems, which lack interoperability and the ability to automatically adapt evacuation routes to different users and scenarios. Jain et al. [38] developed a recommendation system for emergencies, such as earthquakes, using a combination of ontology-supported rule-based reasoning and case-based reasoning. The system provides immediate actions based on past cases and predefined rules, helping to mitigate damage to life and property.

In the context of urban flood disaster management, Wu et al. [13] developed an ontology-based framework that integrates, shares and manages data from various sources such as the Internet, social media, and sensors. However, the data input process was done manually, which was time-consuming. Yahya and Ramli [39] proposed a standard ontology to improve information sharing amongst Malaysian agencies during floods, addressing issues related to inaccurate or unavailable data on flood victims. The system enables faster access to important data, such as victim information, flood locations, evacuation centres, and aid distribution, enhancing the overall efficiency of emergency responses. Shukla et al. [40] proposed an ontology-based Decision Support System (DSS) for disaster management, integrating a knowledge base with Semantic Web Rule Language (SWRL) to generate logic-based solutions. The SWRL rules form the core of the system, providing valuable assistance to decision-makers. Liu et al. [41] developed a framework using knowledge graphs and community discovery algorithms to match disaster methods and data, particularly focusing on rainstorm and flood disaster risk assessment. Finally, Zhong et al. [15] suggested an ontology-based crisis simulation system for population sheltering management, incorporating features like resource allocation and scenario simulation. As was shown in recent studies, ontologies have great promise for enhancing disaster management strategies and improving the resilience of urban areas to natural disasters.

Through an extensive review of the existing literature, it becomes clear that both AHP and FAHP have been widely applied to various disaster management challenges, particularly in shelter site selection. Whilst these methods have advanced MCDM frameworks by incorporating fuzzy logic to handle uncertainty, a significant research gap remains. Current studies largely focus on the standalone application of these methods without fully exploring their integration with other advanced technologies. FAHP enhances traditional AHP by leveraging fuzzy set theory to manage the inherent uncertainty in human judgment, yet its application is limited by a lack of interoperability with diverse data sources and semantic systems. Similarly, ontologies have demonstrated their ability to enhance interoperability, data integration, and decision support systems in UEES. However, the full potential of combining ontologies with MCDM frameworks, particularly FAHP, has yet to be realised. The existing research does not address how FAHP and ontologies can be integrated to form a comprehensive, interoperable decision-making framework for shelter site selection.

Thus, the problem statement arises from the lack of a unified MCDM framework that integrates ontology with FAHP for optimal decision-making in shelter site selection. Selecting locations for UEES involves complex, multi-faceted criteria that require a decision-making system capable of handling both qualitative and quantitative data whilst ensuring semantic interoperability across diverse data sources. By integrating ontology with FAHP, the decision-making process can be significantly enhanced to address both the technical and practical challenges of shelter site selection

Table 3 Studies of ontologies in site selection for disaster management

Authors	Problem area	Approach	Criteria
Malizia et al. [36]	Accessible emergency notifications for diverse users	SEMA4A ontology for adaptive notifications based on user profiles	Accessibility, user profiles, emergency scenarios, communication technologies
Onorati et al. [37]	Adaptable evacuation routes for diverse users	Extended SEMA4A ontology for adaptive evacuation routes	User profiles, emergency type, route adaptability, infrastructure
Jain et al. [38]	Adaptive recommendations during earthquakes	Ontology-supported rule-based and case-based reasoning systems for recommendations	Seismic activity, population density, response time, operator verification
Wu et al. [13]	Integrated data management for urban flood disasters	Ontology-based framework to manage urban flood data	Rainfall intensity, topographical factors, data integration, impact indices
Yahya and Ramli [39]	Lack of shared data during flood emergencies	Ontology to standardise terms and improve data sharing	Interoperability, standardised terminology, access to flood information
Shukla et al. [40]	Inefficient decision-making in disaster management	Ontology-based decision support system	SWRL rules, disaster phases, knowledge flow, disaster recovery assistance
Liu et al. [41]	Effective evacuation management	Framework using knowledge graphs and simulations	Knowledge graphs, evacuation scenarios, disaster management strategies
Zhong et al. [15]	Ack of an efficient resource allocation system for population sheltering during crises	Ontology-based crisis simulation system with decision support and recommendations	Key components: ontology, resource allocation, four-layer simulation system, tested in disaster scenarios

whilst also advancing the digital transformation of urban emergency management systems.

3 Methodology

This section presents the overall research methodology used in this study, which integrates the FAHP, ontology-based modelling, and GIS data to develop a comprehensive approach for UEES site selection. The methodology leverages the Web Ontology Language (OWL) and the SWRL in combination with the FAHP to develop a robust framework for UEES site selection. By moving beyond traditional site selection methods, this approach enhances decision-making processes, ensuring more effective and informed choices for UEES site selection. The overall research methodology is illustrated in Fig. 2:

- **Pre-selected site selection** The first step involves filtering potential shelter sites based on the appropriate land uses and collecting GIS data to support spatial analysis. This process includes evaluating factors such as accessibility, hazard vulnerability, and proximity to essential services. These criteria are crucial for incorporating geographical considerations into the shelter evaluation. After this filtering process, a set of shelter site alternatives are identified for further evaluation.
- **FAHP for criteria weighting** In this step, the FAHP is employed to assign weights to the criteria involved in selecting shelter sites. The process begins with a thorough review of relevant literature and standards, particularly from the Chinese national guidelines for EES sites [16], to systematically identify the main criteria for UEES. A hierarchical structure model is then established to organise these criteria and the decision-making process. Following this, the criteria weights are calculated using TFNs, which are applied in fuzzy pairwise comparison matrices to compare the relative importance of the criteria. The fuzzy weights are then defuzzified to produce crisp values. Finally, the Consistency Index (CI) and Consistency Ratio (CR) are calculated to validate the consistency of the pairwise comparisons, ensuring that the criteria weighting is reliable.
- **Ontology-based modelling for UEES** This step focuses on developing an ontological framework to support the assessment of UEES site alternatives. The process includes three main parts: conceptualisation, reorganisation of terms, and the creation of ontology instances. This framework compiles all relevant data, criteria, and indicators related to UEES, representing them hierarchically and in a machine-readable format. The open-source Protégé 5.5 ontology editor, along with the SWRL rule editor and the Semantic Query-Enhanced Web Rule Language

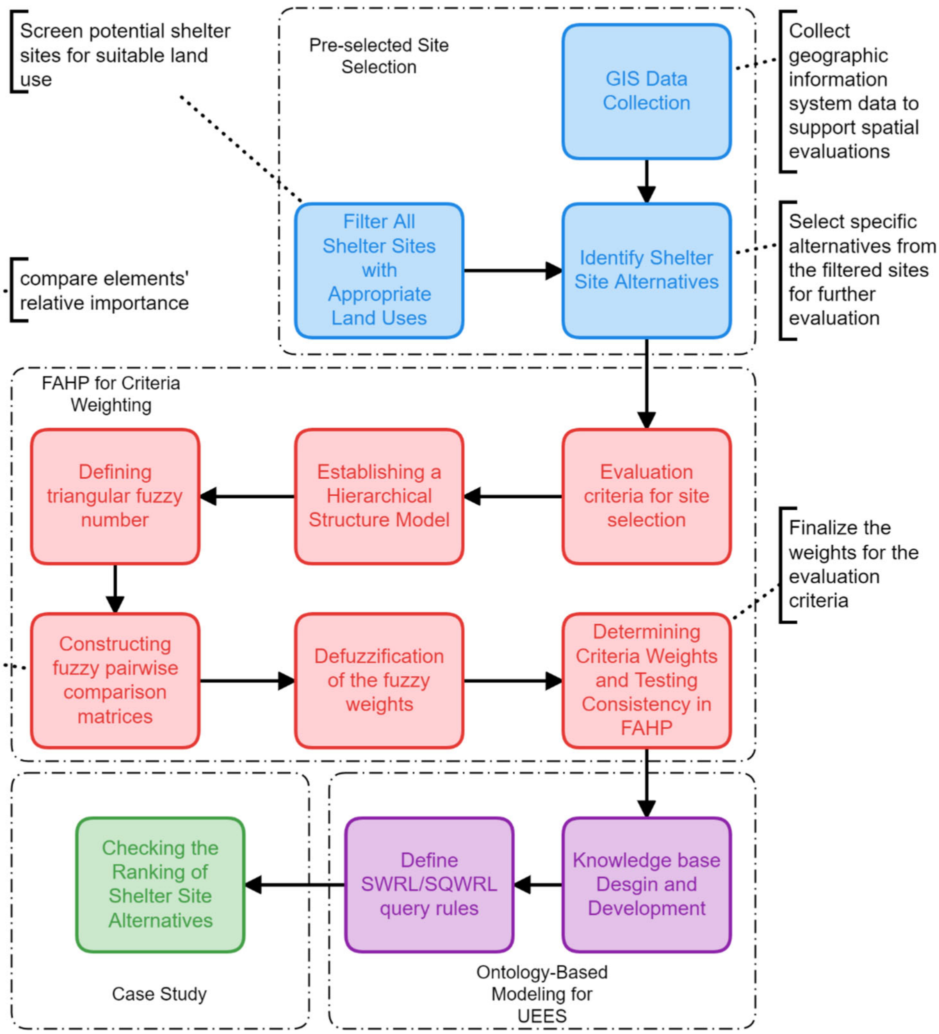

Fig. 2 Research methodology

(SQWRL) data query plugin, is utilised to develop this ontology, enabling advanced data querying and analysis.

- **Case study and discussion** The developed methodology is then applied in a case study focused on Beijing to demonstrate the approach's effectiveness in ranking potential UEES locations. After the evaluation process, the rankings of the shelter site alternatives are reviewed to ensure consistency with the established methodology. Any inconsistencies identified during this review are addressed before making the final selection of shelter sites.

4 FAHP for Criteria Weighting

4.1 Evaluation Criteria for Site Selection

The selection of appropriate evaluation criteria and sub-criteria is crucial for the site selection of UEES. An in-depth review of relevant literature, along with standards from the Chinese national guidelines for EES sites [16], has led to the systematic identification of four main criteria that are essential for the assessment process (illustrated in Fig. 3): Safety criteria, Planning criteria, Economic criteria, Construction criteria.

4.1.1 Safety Criteria (S1)

Safety is the primary consideration when selecting a site for UEES. The location must be inherently safe from earthquake impacts (C11) and ideally situated far from seismic rupture zones to minimise risks during an earthquake [42]. Additionally, the site should not be vulnerable to secondary hazards, such as landslides, that earthquakes might trigger. Proximity to residential areas is also critical (C12), as the shelter should be accessible for the swift evacuation of victims [43]. Lastly, in urban environments with high-rise buildings, the site should maintain a safe distance from these structures

(C13) to avoid risks associated with the potential collapse of buildings during an earthquake.

4.1.2 Planning Criteria (S2)

Population density in the surrounding area, where the preparation site is located (C21), is a key factor. A higher population density increases the value of the UEES, as more people can be served in the event of an emergency. This is directly related to the plans of the local government. Traffic accessibility (C22) is another vital aspect for ensuring that evacuees and rescue teams can reach the site quickly; this includes evaluating the number of major roads and intersections that facilitate access. The distance from other emergency shelters (C23) is also considered to avoid overlap in services and ensure efficient decision-making for evacuees. Additionally, proximity to critical infrastructure (C24), such as hospitals, fire stations, and transport hubs, is equally important as it enhances the shelter's operational effectiveness.

4.1.3 Economic Criteria (S3)

Economic criteria focus on the costs associated with establishing and operating the UEES. These expenses vary regionally and are influenced by the local economic development level. In Beijing, for example, land costs are amongst the highest in China, followed by construction costs, whilst maintenance costs are comparatively consistent across regions. Land cost (C31) typically accounts for the largest portion (around 60%) of the total cost, followed by construction cost (C32) at 30% and maintenance cost (C33) at roughly 10%.

4.1.4 Construction Criteria (S4)

The available area of the site (C41) is critical for determining the shelter's capacity and the scope of services it can offer. The presence of complete hydropower facilities (C42) is important for larger sites, allowing for the development of essential infrastructure, such as water and electricity supplies, which can support medical services and supply stations.

4.2 Establishing a Hierarchical Structure Model

A structured three-tiered hierarchical model was developed to facilitate the selection of optimal sites for UEES, as illustrated in Fig. 3. At the highest level, the Objective Layer (G) represents the overarching goal of identifying the optimal most suitable locations for emergency shelters. The middle level comprises the Criteria (S) and Sub-Criteria Layers (C), which encompass key evaluation factors such as safety, accessibility, and capacity. The sub-criteria further refine these broader categories, creating a comprehensive framework designed to support informed decision-making. The Alternatives Layer (A), at the lowest level, contains the potential shelter sites. These sites are evaluated based on the criteria and sub-criteria defined in the middle tier, ensuring that the most appropriate locations are selected for emergency sheltering in the event of an earthquake. The relationships between the layers and elements are depicted through connecting lines, illustrating the flow of evaluation from objectives to alternatives.

The selection process involves determining the relative weights of each main criterion (S) with respect to the overall objective (G) and the weights of each sub-criterion (C) relative to its associated criterion (S). These two sets of weights are then aggregated to compute the global weight of each sub-criterion (C) in relation to the objective (G). It is essential that the elements within the hierarchy are clearly defined and that the relationships between them are logically sound. Inadequate definitions or incorrect relationships could compromise the quality of the site selection process, potentially leading to suboptimal outcomes or the failure of the AHP. The weighting of these elements is a critical step in the decision-making process, requiring pairwise comparisons to establish their relative importance within the context of UEES site selection. This ensures that the model accurately reflects the priorities and considerations necessary for the effective identification of optimal emergency shelter locations.

4.3 Criteria Weights Calculation Process

4.3.1 Definition of Triangular Fuzzy Numbers (TFNs)

Determining the weights of both the main criteria and sub-criteria is critical, especially since the four primary criteria and twelve sub-criteria do not share uniform weight distribution. Traditionally, the AHP has been employed for this purpose. However, AHP's reliance on subjective judgments during the matrix construction phase makes it prone to bias, which may result in outcomes that are not universally accepted by decision-makers [44]. To address this issue, this study integrates fuzzy logic, which allows decision-makers to express preferences using TFNs, enabling more precise expression of judgments and capturing the inherent uncertainty in human perception. Table 4 presents the linguistic scale of importance, the corresponding TFNs, and their reverse semantic ranges with inverse TFNs.

The linguistic scale of importance allows decision-makers to express their subjective judgments in terms of predefined categories such as "Equally important" or "Strongly important". Each of these linguistic terms is quantified using a TFN, represented by three values: l (lower bound), m (middle value), and u (upper bound). These values capture the uncertainty and imprecision inherent in human judgments.

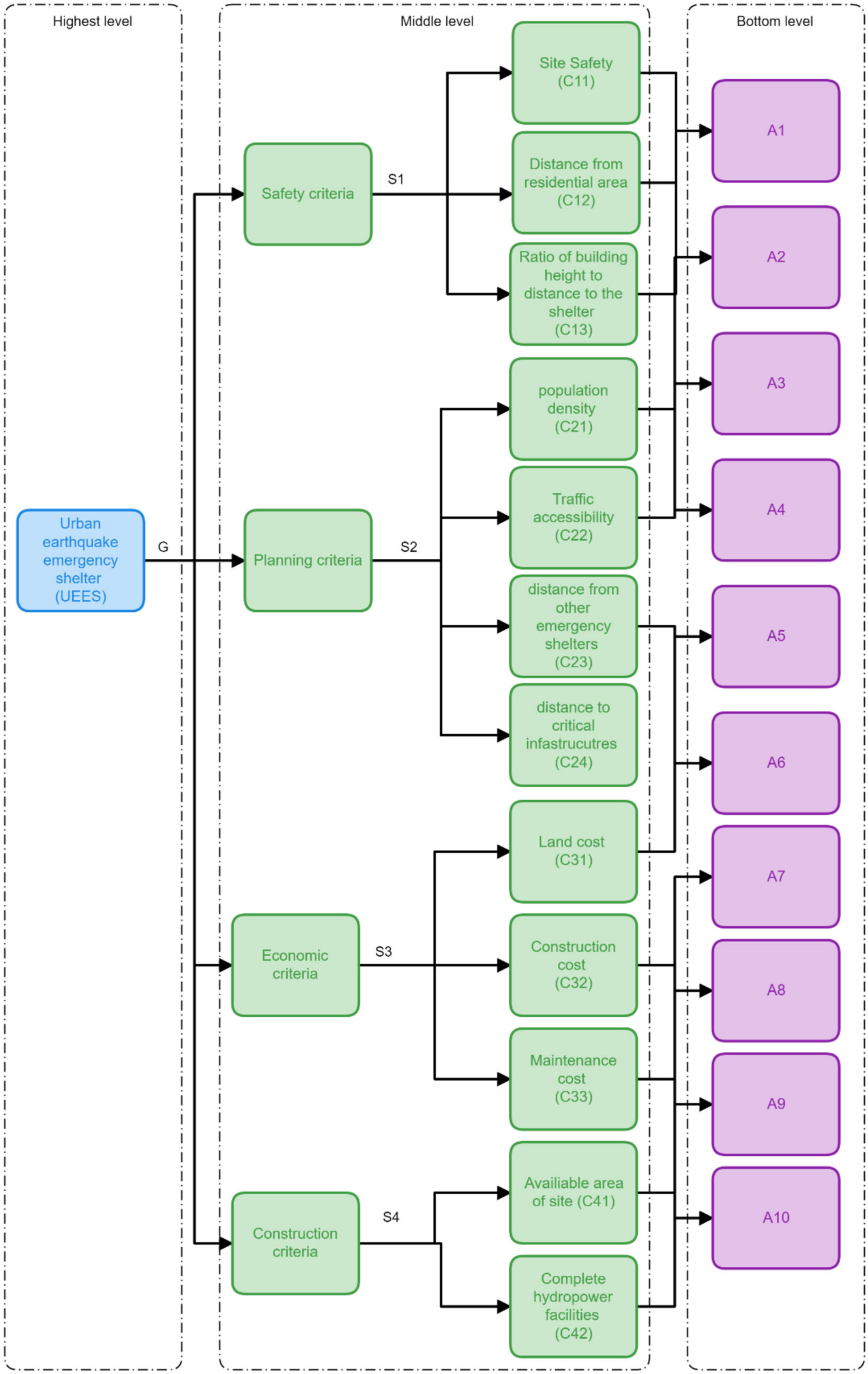

Fig. 3 Hierarchical structure model of UEES

Table 4 Linguistic scale of importance, the corresponding TFNs, and their reverse semantic ranges with inverse TFNs

Semantic range	TFNs (l, m, n)	Reverse semantic range	Inverse TFNs (1/n,1/m,1/l)
Equally important	(1,1,1)	Equally weak	(1,1,1)
Slightly important	(1,1,3/2)	Slightly weak	(2/3,1,1)
Significantly important	(1,3/2,2)	Significantly weak	(1/2,2/3,1)
Strongly important	(3/2,2,5/2)	Strongly weak	(2/5,1/2,2/3)
Extremely important	(2,5/2,3)	Extremely weak	(1/3,2/5,1/2)

For example, a judgment that is considered "Slightly important" is represented by the TFN (1,1,3/2), meaning that the importance lies somewhere between 1 (equally important) and 1.5 (more important), with 1 as the most likely value. Additionally, the reverse semantic ranges and their corresponding inverse TFNs are used to account for pairwise comparisons in the opposite direction. For example, if Criterion A is "Slightly more important" than Criterion B, then Criterion B is "Slightly less important" than Criterion A, and the corresponding inverse TFN (2/3,1,1) is used.

4.3.2 Constructing Fuzzy Pairwise Comparison Matrices and Defuzzification of the Fuzzy Weights

For each layer of the hierarchical structure, a fuzzy pairwise comparison matrix is constructed. This matrix compares each criterion or sub-criterion with every other element at the same level, assessing their relative importance. The comparison matrix assists in structuring the decision-making process, starting from high-level objectives to more specific factors. Decision-makers utilise the linguistic scale of importance to evaluate and compare both the main criteria (denoted as S) and the sub-criteria (denoted as C).

Each expert's judgment is represented as matrix elements W_{ij}^E, where i refers to the row criterion and j refers to the column criterion. Each element expresses the relative importance of one criterion over another, using TFNs to capture the uncertainties in these judgments. To synthesise the individual judgments of multiple experts into a collective decision, the arithmetic means of the pairwise comparison values provided by all experts is computed for each pair of criteria i and j. This process results a consensus on the relative importance of each pair of criteria or sub-criteria. The fuzzy pairwise comparison matrix for an expert group can be expressed as shown in Eq. (3).

$$W_E = \begin{bmatrix} 1 & W_{12}^E & \cdots & W_{1n}^E \\ W_{21}^E & 1 & \cdots & W_{2n}^E \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1}^E & W_{n2}^E & \cdots & 1 \end{bmatrix} \tag{3}$$

where W_{ij}^E represents the fuzzy comparison value between criteria i and j as provided by expert E.

Each matrix element W_{ij}^E is a TFN (l, m, u), where l, m, and u represent the lower, middle, and upper bounds of the fuzzy judgment, respectively. The aggregation of these judgments across all experts is weighted by their respective importance μ_E, where $\Sigma_{E=1}^{E}, \mu_E = 1, \mu_E > 0$. The aggregated fuzzy pairwise comparison matrix W_{ij} is represented in Eq. (4).

$$\begin{aligned} \bar{W}_{ij} &= \sum_{E=1}^{E} \mu_E w_{ij}^E = \left(\sum_{E=1}^{E} \mu_E l_{ij}^E, \sum_{E=1}^{E} \mu_E m_{ij}^E, \sum_{E=1}^{E} \mu_E u_{ij}^E \right) \\ &= \left(l_{ij}, m_{ij} u_{ij} \right) \end{aligned} \tag{4}$$

where μ_E represents the weight assigned to the judgment of expert E; The summation $\Sigma_{E=1}^{E}$ accounts for the aggregation of all experts' opinions; l_{ij}^E, m_{ij}^E, and u_{ij}^E are the lower, middle, and upper bounds of the fuzzy comparison value W_{ij}^E for the pairwise comparison between criteria i and j.

Once the fuzzy pairwise comparison matrix is constructed, the next step is to defuzzify the fuzzy weights for each criterion. Defuzzification is the process of converting fuzzy numbers into crisp values, thus simplifying the comparison of criteria. These defuzzified weights for the ith criterion, denoted as W_{ci}, is calculated according to Eq. (5). The TFN (l, m, u) is then defuzzified using Eq. (6), converting the fuzzy weights into crisp scalar values, which can be more easily interpreted and applied in the decision-making process.

$$W_{C_i} = \frac{\sum_{j=1}^{n} W_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}, \quad i = 1, 2, \cdots, n \tag{5}$$

where W_{C_i} is the defuzzified weight for the ith criterion, derived from the aggregated fuzzy comparison matrix; n is the number of criteria.

$$\text{Crisp number} = \frac{l + 2m + u}{4} \tag{6}$$

Finally, the local weights are normalised to ensure that the sum of weights equals 1. This normalisation is done by dividing each crisp number by the sum of all crisp numbers. The same steps are applied to construct fuzzy pairwise comparison matrices for the sub-criteria and to defuzzify their respective fuzzy weights.

4.3.3 Fuzzy Pairwise Comparison Matrix Consistency Check

The consistency of pairwise comparison matrices is crucial for achieving consensus amongst experts and validating the logical consistency of their judgments. In this paper, pairwise comparison matrices were constructed for different experts, where each element represents the relative importance of one criterion over another, as judged by the expert. These matrices are then normalised to compute the relative weights, and the normalised weights are averaged to determine the priority of each criterion for each expert.

To assess the consistency of each expert's judgments, the sum of the products of the elements in the weight column with the sum of the corresponding columns of the original pairwise comparison matrix, denoted as $\sum AW$, was calculated. Subsequently, $\sum AW$ was divided by the corresponding weight W, yielding $\sum \frac{AW}{W}$. This process helps ensure that the matrix reasonably represents the experts' opinions without significant logical contradictions. A key aspect of the consistency test is the calculation of the principal eigenvalue, which provides the relative weights of the criteria. The principal eigenvalue $\lambda_{\max}$ is obtained by summing the entries of $\frac{AW}{W}$ across each row and dividing by the number of criteria n, as expressed in Eq. (7):

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_i} \tag{7}$$

where n is the number of criteria; AW_i represents the sum of the products of the elements in th ith row of the original pairwise comparison matrix and the corresponding weights W_i; W_i is the weight of the ith criterion.

If the Consistency Ratio (CR) is within an acceptable range, the weights derived from the principal eigenvector are used as the relative weights of the criteria. However, if the CR exceeds the acceptable threshold, the pairwise comparison process may need to be revisited and revised to improve consistency, thereby ensuring more reliable and robust decision-making outcomes. Following the determination of the principal eigenvalue, the Consistency Index (CI) is calculated using Eq. (8):

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{8}$$

where $\lambda_{\max}$ is the principal eigenvalue, as calculated in Eq. 7; n is the number of criteria.

A CI of zero indicates perfect consistency, though perfect consistency is rarely achieved; thus, a measure of acceptability is required. Saaty [45] has provided Average Random Consistency Index (RI) values for matrices of sizes 1 to 9, which serve as a benchmark (Table 5). The CR is then calculated by dividing the CI by the corresponding RI, as shown in Eq. (9). A CR value of less than 0.10 generally indicates that the consistency of the matrix judgments is acceptable. Otherwise, the judgment matrix should be appropriately revised.

Table 5 Average random consistency index (RI)

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.89	1.12	1.24	1.32	1.41	1.45

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{9}$$

where CI is the Consistency Index, as calculated in Eq. 9; RI is the Random Consistency Index, which depends on the number of criteria (n) and serves as a benchmark for comparison; CR is a measure of how consistent the judgments are in the pairwise comparison matrix relative to a randomly generated matrix.

5 Ontology-Based Modelling for UEES

5.1 Knowledge Base Design and Development

This section focuses on developing an ontological framework for the holistic assessment of alternative sites for UEES. The construction process is divided into three main stages. The first is conceptualisation, which defines the purpose and scope of the ontology. It involves identifying the domain-specific knowledge and the goals the ontology should achieve. The second stage focuses on organising the key terms within the domain by defining classes, establishing hierarchical relationships between these classes, and identifying the properties of each class. The connections between properties are also defined at this stage. The third stage involves the practical application of the newly created ontology by generating instances based on real-world data. This step ensures the ontology's validity and applicability to the domain.

The construction process of the UEES ontology is centred on a hierarchical representation of the domain's knowledge. The goal is to represent this knowledge in a scientific, hierarchical, and machine-readable manner. Various methods can be used for ontology development. In this study, ontology 101 [46] was utilised due to its top-down approach. The tool Protégé 5.5 was employed for its Description Logic (DL) query reasoning, which facilitates hierarchical restrictions and logical checks. Protégé performs automatic checks for hierarchical consistency and logical correctness, improving the proposed ontology's accuracy and validity.

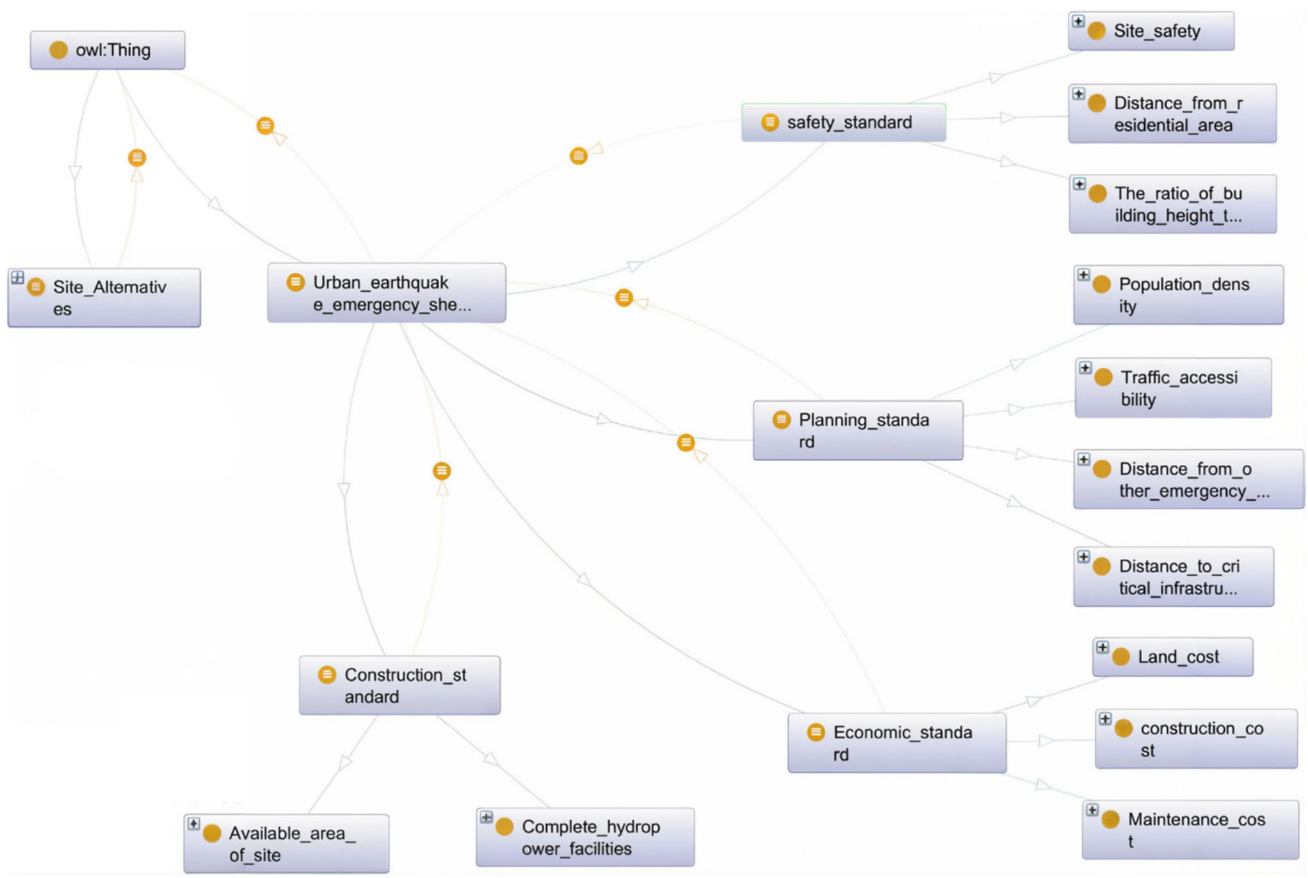

Fig. 4 The class hierarchy of the UEES ontology

5.1.1 Defining Classes and Class Hierarchies

A clear definition of terms related to the domain is a crucial first step. Once the terms are identified, they are organised into a hierarchy structure, also known as a taxonomy. A taxonomy provides a pyramid structure that organises key information logically. According to Ontology 101 [46], the process of developing an ontology includes several key tasks: defining classes by identifying the main concepts within the domain, organising these classes into a hierarchical taxonomy (with more general concepts at the top and more specific ones as subclasses), and defining properties (slots) for each class, along with possible values for these properties.

In this study, the ontology was developed using a top-down approach, where each class represents a general concept within the domain and may include several subclasses or instances representing more specific cases. For example, the class hierarchy of the UEES ontology is shown in Fig. 4; the top class, named "Thing," is automatically generated when creating the ontology in protégé. In the context of UEES, the main class is "Urban_earthquake_emergency_shelter," which contains four subclasses that are further broken down into more subclasses:

- "Safety_standard" includes "Site_safety", "Distance_from_residential_area", and "The_ratio_of_ building_height_to_the_ distance_to_the_shelter".
- "Planning_standard" encompasses "Population_density", "Traffic_accessibility", "Distance_from_ other_ emergency_shelters", and "Distance_to_critical_infrastructure"
- "Economic_standard" consists of "Land_cost" "Construction_cost," and "Maintenance_cost"
- "Construction_standard" comprises "Available_ area_of_site" and "Complete_hydropower facilities".

5.1.2 Defining the Properties of a Class

Attributes in an ontology describe the internal structural connections between concepts. There are three primary types of attributes: object attributes, data attributes, and annotation attributes.

- **Object attributes** describe relationships between two concepts, specifically between different classes. They not only define these relationships but also impose constraints that guide reasoning processes. For example, the "Is_Subcriteria_of" attribute indicates a sub-criteria rela-

Table 6 Data attribute description

Data property	Description	Corresponding class or instance
District	Alternate address name	–
Latitude	Address longitude	–
Longitude	Address latitude	–
Final Score	Final score of address	–
GS_C11	Substandard final score	Site_safety
GS_C12		Distance_from_residential_area
GS_C13		The_ratio_of_building_height_to_the_distance_to_the_shelter
GS_C21		Population_density
GS_C22		Traffic_accessibility
GS_C23		Distance_from_other_emergency_shelters
GS_C24		Distance_to_critical_infrastructure
GS_C31		Land_cost
GS_C32		construction_cost
GS_C33		Maintenance_cost
GS_C41		Available_area_of_site
GS_C42		Complete_hydropower_facilities
S_C11	Substandard subjective and objective score	Site_safety
S_C12		Distance_from_residential_area
S_C13		The_ratio_of_building_height_to_the_distance_to_the_shelter
S_C21		Population_density
S_C22		Traffic_accessibility
S_C23		Distance_from_other_emergency_shelters
S_C24		Distance_to_critical_infrastructure
S_C31		Land_cost
S_C32		construction_cost
S_C33		Maintenance_cost
S_C41		Available_area_of_site
S_C42		Complete_hydropower_facilities
Score_Sa	Final score of main standard	Safety_standard
Score_Pn		Planning_standard
Score_Ec		Economic_standard
Score_Cn		Construction_standard
W_C11	Substandard global weight	Site_safety
W_C12		Distance_from_residential_area
W_C13		The_ratio_of_building_height_to_the_distance_to_the_shelter
W_C21		Population_density
W_C22		Traffic_accessibility
W_C23		Distance_from_other_emergency_shelters
W_C24		Distance_to_critical_infrastructure
W_C31		Land_cost
W_C32		construction_cost
W_C33		Maintenance_cost
W_C41		Available_area_of_site
W_C42		Complete_hydropower_facilities

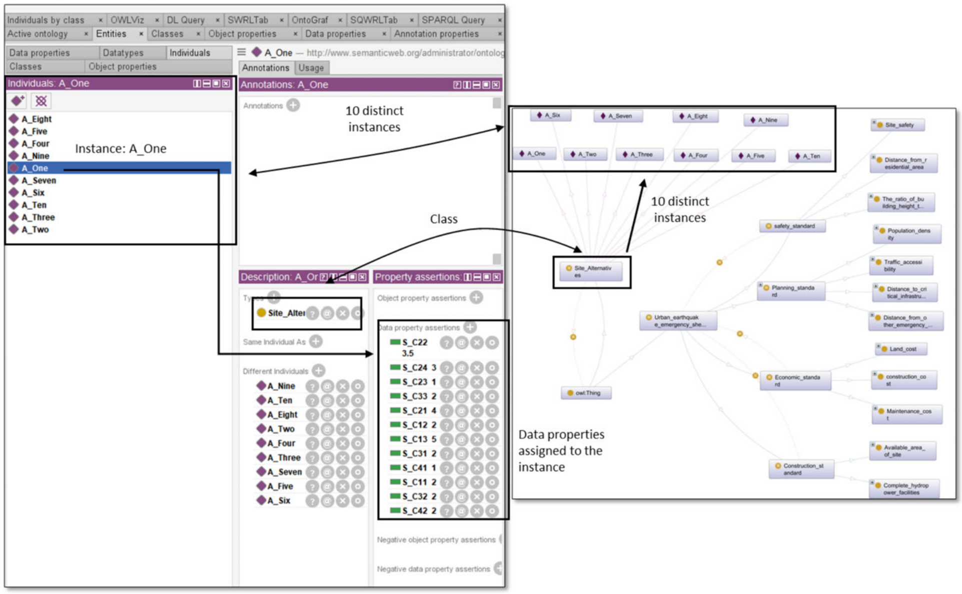

Fig. 5 Example of an alternative address instance definition

tionship, and "Is_Supercriteria_of" represents a main criterion relationship.

- **Data attributes** link instances to specific data, defining how data are associated with each instance. Table 6 shows various data attributes, their descriptions, and the classes or instances they correspond to. For example, "GS_C11" represents the substandard final score for Site_safety, whilst "W_C11" represents the global weight for the same criterion.
- **Annotation attributes** provide additional descriptions of classes, instances, and attributes but do not participate in inferential reasoning. They are primarily used for documentation and clarification within the ontology.

5.1.3 Create Pre-selected Site Instances

In an ontology, instances serve as specific expressions of their respective classes, each characterised by unique properties and values. In the context of this ontology, the "Site_Alternatives" class includes a set of 10 distinct instances, each representing a viable alternative site for evaluation. These instances are not merely abstract representations; they are accompanied by detailed attributes defined within their data properties. These attributes play a crucial role in the reasoning process used to rank the sites based on predefined criteria, ensuring a structured and data-driven approach to site selection.

The ontology management interface, Protégé, offers a clear visualisation of how these instances are structured and managed. As shown in Fig. 5, the instances represent a series of alternative site addresses, each assessed based on a set of defined criteria. On the left panel of the Protégé interface, a collection of individuals is displayed, with each individual being an instance of the "Site_Alternatives" class. The instances are labelled from "A_One" to "A_Ten", each corresponding to a distinct site. The Description pane provides a classification of the selected instance, indicating, for example, that "A_One" is categorised under "Site_Alternative".

Moreover, the Data Property Assertions section of the interface lists the individual properties associated with each instance, along with their corresponding quantified values. These values represent specific evaluative metrics that contribute to the ranking process. For example, properties such as "S_C22" and "S_C24" capture key evaluative scores relevant to the site alternative "A_One". The value of "S_C22" represents the "Traffic_accessibility" score, whilst "S_C24" reflects the "Distance_to_critical_infrastructure" score. These quantified attributes are integral to the inferential mechanism employed to establish a ranking hierarchy amongst the site alternatives. By assigning specific values to these properties, the ontology enables a structured and transparent evaluation process, ensuring that each alternative site is assessed based on consistent and predefined criteria.

5.2 Defining SWRL Rules and SQWRL Queries

SWRL allows for the generation of new facts by applying rules to existing information within an ontology. Several rules were defined in the proposed ontology based on the requirements specified in this research. The complexity of those rules varies, from rules that consider only one condition to rules that account for multiple conditions, creating a multi-objective knowledge base. SWRL includes several types of atoms: class atoms, individual property atoms, and data-valued property atoms, each playing a unique role in rule formation. A detailed examination of these atom types can be found in Ren, Ding, and Li [47]. In SWRL, the symbol '^' is used to connect class atoms and individual atoms, the question mark '?' represents a variable in each atom, and the symbol "→" is used to connect antecedents and consequents of a rule, as shown in Tables 7 and 8.

Within the Protégé 5.5 ontology editor, extensions such as SWRLTap and SQWRLTap integrate seamlessly with the OWL framework. SWRLTab is used to define rules, whereas SQWRLTab is used to query inferred data. For example, a class expression might look like Site_Alternatives(A_One), where "A_One" is a variable representing a site. Data attributes could be represented as Score_Sa(A_One, ?x), where "?x" is a variable for safety scores at the site "A_One". These rules leverage SWRL built-in functions such as swrlb:multiply() and swrlb:add() for performing arithmetic. Moreover, to query the ontology after applying SWRL rules, the syntax sqwrl:select and sqwrl:orderByDescending is used, as shown in Table 9.

6 Case Study: Application in Beijing

Beijing's distinct geographical and demographic challenges, combined with its proactive disaster management strategies, offer valuable insights for urban earthquake preparedness. Given its historical experience with earthquakes, Beijing was chosen to demonstrate the proposed UEES site selection framework. For this study, only potential UEES sites with an area exceeding 2000 square metres were considered, Table 10. The evaluation of these sites was based on four main criteria: safety, planning, economy, and construction, further divided into 12 sub-criteria. The data used for analysis included both subjective (expert assessments) and objective (GIS-based) information for each of the pre-selected sites (Table 11). The decision-making team consists of 5 industry experts: economic experts (E1), construction experts (E2), transportation experts (E3), earthquake experts (E4), and safety experts (E5).

Table 12 provides the quantitative evaluation data necessary for performing pairwise comparisons in the site selection process. It organises the scores for each site across multiple criteria. In constructing the pairwise comparison matrices, the EDM team uses the scores from Table 12. The process began by calculating the arithmetic means of the pairwise comparisons for each criterion and sub-criterion, considering their lower (l), middle (m), and upper (u) values separately. Next, the means for each comparison were summed to provide an overall score for each criterion. These sums were then normalised by dividing each value by the total sum of the respective column, resulting in the initial fuzzy weights. This normalisation ensures that the weights for all criteria add up to 1, making them comparable.

To simplify the decision process, the fuzzy weights were defuzzified, converting each fuzzy value into a crisp number. This was done by calculating the weighted average of the lower, middle, and upper values. The resulting crisp values represent the final importance of each criterion without the uncertainty inherent in the fuzzy numbers. Finally, the local weights were derived from the crisp values, which reflect each sub-criterion's relative importance to its main criterion. Table 13 shows the relative importance of the main criteria. The results indicate that Site Safety (S1) is the most significant criterion, with a weight of 0.333. Similarly, Table 14 shows that within the safety sub-criteria, Site Safety (C11) is the most important, with a weight of 0.445. The bold formatting in Tables 13 and 14 is used to highlight the most significant criterion or sub-criterion based on their calculated weights. The global weight for each sub-criterion was calculated by multiplying its local weight by the global weight of its immediate parent sub-criterion. These global weights are summarised in Table 15.

The analysis reveals three sub-criteria with a weight greater than 0.1: site safety (C11), area of the site (C41), and distance from residential areas (C12). Amongst these, site safety (C11) is the most important, followed by the area of the site (C41) and the distance from residential areas (C12). The least weighted sub-criterion is construction cost (C32), which has a weight of 0.04. Finally, the consistency of the pairwise comparison matrices is checked to ensure the reliability of the expert judgments.

Finally, the consistency of the pairwise comparison matrices is checked to ensure the reliability of the expert judgments. Table 16 shows the detailed consistency calculation for Expert E1, including the evaluation matrix, normalisation process, weight determination, and consistency check (CI and CR). To determine the largest characteristic root $\lambda_{\max}$, the following steps are taken: the matrix E1 Evaluation Matrix is multiplied by the weight vector W to obtain AW for each row, and this is followed by dividing each entry of AW by the corresponding entry of W to get $\frac{AW}{W}$ for each row. In this case, there are four criteria (C1, C2, C3, C4), hence, n is equal to 4. To check the consistency, the average of the $\frac{AW}{W}$ values is calculated, which gives the largest eigenvalue $\lambda_{\max}$. This value $\lambda_{\max}$ is then used to calculate the CI, as shown in Table 16. The CR is then calculated by dividing the CI by the corresponding RI. The RI is a value that depends on the number of criteria n. For a matrix of size 4, the RI is typically 0.89, as previously mentioned in Table 5. A CR value of 0.017 indicates that the consistency ratio is less than 0.1, which is the commonly accepted threshold for consistency. A CR below 0.1 signifies that the expert's judgments are consistent and reliable.

Table 7 Example of SWRL substandard definition (for A_One)

Rule 1: Score for site sub-criterion C11

Site_Alternatives(A_One) ^Site_safety(W_C11) ^W_C11(W_C11, ?x) ^S_C11(A_One, ?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C11(A_One, ?y)

Rule 2: Score for site sub-criterion C12

Site_Alternatives(A_One) ^Distance_from_residential_area(W_C12) ^W_C12(W_C12, ?x) S_C12(A_One, ?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C12(A_One, ?y)

Rule 3: Score for site sub-criterion C13

Site_Alternatives(A_One) ^The_ratio_of_building_height_to_the_distance_to_the_shelter(W_C13) ^W_C13(W_C13. ?x) ^S_C13(A_One, ?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C13(A_One, ?y)

Rule 4: Score for site sub-criterion C21

Site_Alternatives(A_One) ^Population_density(W_C21) ^W_C21(W_C21, ?x) ^S_C21(A_One, ?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C21(A_One, ?y)

Rule 5: Score for site sub-criterion C22

Site_Alternatives(A_One) ^Traffic_accessibility(W_C22) ^W_C22(W_C22, ?x) ^S_C22(A_One, ?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C22(A_One, ?y)

Rule 6: Score for site sub-criterion C23

Site_Alternatives(A_One) ^Distance_from_other_emergency_shelters(W_C23) ^W_C23(W_C23, ?x) S_C23(A_One,?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C23(A_One, ?y)

Rule 7: Score for site sub-criterion C24

Site_Alternatives(A_One) ^Distance_to_critical_infrastructure(W_C24) ^C24(W_C24, ?x) ^S_C24(A_One, ?s)^swrlb:multiply(?y, ?x, ?s) → GS_C24(A_One, ?y)

Rule 8: Score for site sub-criterion C31

Site_Alternatives(A_One) ^Land_cost(W_C31) ^W_C31(W_C31, ?x) ^S_C31(A_One, ?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C31(A_One, ?y)

Rule 9: Score for site sub-criterion C32

Site_Alternatives(A_One) ^Construction_cost(W_C32) ^W_C32(W_C32, ?x) ^S_C32(A_One, ?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C32(A_One, ?y)

Rule 10: Score for site sub-criterion C33

Site_Alternatives(A_One) ^Maintenance_cost(W_C33) ^W_C33(W_C33 ?x) ^S_C33(A_One, swrlb:multiply(?y, ?x, ?s) → GS_C33(A_One, ?y)

Rule 11: Score for site sub-criterion C41

Site_Alternatives(A_One) ^Available_area_of_site(W_C41) ^W_C41(W_C41, ?x) ^S_C41(A_One, ?s) ^swrlb:multiply(?y, ?x, ?s) → GS_C41(A_One, ?y)

Rule 12: Score for site sub-criterion C42

Site_Alternatives(A_One) ^Complete_hydropower_facilities(W_C42) ^W_C42(W_C42, ?x) ^swrlb:multiply(?y, ?x, ?s) → GS_C42(A_One, ?y)

Table 8 SWRL main standard definition example (for A_One)

Rule 1: Score of main criteria S1 for site 1
GS_C11(A_One, ?a) ^GS_C12(A_One, ?b) ^GS_C13(A_One, ?c) ^swrlb:add(?s, ?a, ?b, ?c) → Score_Sa(A_One, ?s)
Rule 2: Score of sub-criteria S2 for site 1
GS_C21(A_One, ?a) ^GS_C22(A_One, ?b) ^GS_C23(A_One, ?c) ^GS_C24(A_One, ?d) ^swrlb:add(?s, ?a, ?b, ?c, ?d) → Score_Pl(A_One, ?s)
Rule 3: Score of sub-criteria S3 for site 1
GS_C31(A_One, ?a) ^GS_C32(A_One, ?b) ^GS_C33(A_One, ?c) ^swrlb:add(?s, ?a, ?b, ?c) → Score_Ec(A_One, ?s)
Rule 4: Score of sub-criteria S4 for site 1
GS_C41(A_One, ?a) ^GS_C42(A_One, ?b) ^swrlb:add(?s, ?a, ?b) → Score_Co(A_One, ?s)
Rule 5: Score for Site 1
Score_Sa(A_One, ?a) ^Score_Pl(A_One, ?b) ^Score_Ec(A_One, ?c) ^Score_Co(A_One, ?d) ^swrlb:add(?s, ?a, ?b, ?c, ?d) → Final_Score(A_One, ?s)

Table 9 SQWRL ranking query of alternative sites

Query 1: Descending reasoning substandard ranking
Site_Alternatives(?x) ^GS_C11(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C12(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C12(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C21(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C22(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C23(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C24(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C31(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C32(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C33(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C41(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^GS_C42(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Query 2: Descending reasoning Main standard ranking
Site_Alternatives(?x) ^Score_Sa(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^Score_Pn(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^Score_Ec(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Site_Alternatives(?x) ^Score_Cn(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)
Query 3: Descending reasoning for final ranking
Site_Alternatives(?x) ^Final_Score(?x, ?a) → sqwrl:select(?x, ?a) ^sqwrl:orderByDescending(?a)

Table 10 Basic information of alternative sites

Site alternative no	Type	Area (m^2)	Longitude	Latitude	District
A1	Park	37,000	39.878469	116.424628	Dongcheng
A2	Park	400,000	39.99242	116.302269	Haidian
A3	Park	270,000	39.953313	116.288869	Haidian
A4	Park	54,000	39.959903	116.421358	Dongcheng
A5	Park	3,357,000	40.025231	116.396797	Chaoyang
A6	Park	47,000	39.885845	116.37434	Xicheng
A7	Park	20,000	39.841377	116.378608	Fengtai
A8	Park	434,000	39.919156	116.540303	Chaoyang
A9	Urban green space	280,000	39.975005	116.506423	Chaoyang
A10	Park	400,000	39.912449	116.244861	Shijingshan

Table 11 Data sources for subjective and objective criteria

Sub-criteria	Data name	Data source
Site_safety	S_C11	DMT
Distance_from_residential_area	S_C12	GIS
The_ratio_of_building_height_to_the_distance_to_the_shelter	S_C13	GIS
Population_density	S_C21	GIS
Traffic_accessibility	S_C22	GIS
Distance_from_other_emergency_shelters	S_C23	GIS
Distance_to_critical_infrastructure	S_C24	GIS
Land_cost	S_C31	DMT
Construction_cost	S_C32	DMT
Maintenance_cost	S_C33	DMT
Available_area_of_site	S_C41	GIS
Complete_hydropower_facilities	S_C42	GIS

Table 12 Standard evaluation data and scores

Criterion	Sub-criterion	Pre-selected sites									
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10
C11: site safety	Distance to earthquake rupture zone (km)	1.6	2.2	1.3	1.8	3.6	2.1	2.5	1.4	4.0	6.8
	Score	2	2	1	2	3	2	3	1	4	5
C12: residential areas	Distance from residential areas (km)	0.93	1.2	0.41	0.17	0.99	0.24	0.19	1.2	1.6	0.5
	Score	2	5	4	5	2	4	5	1	1	3
C13: building height	Ratio of building height to distance	0.24	0.53	0.61	0.52	1.58	1.92	2.52	0.85	0.48	1.18
	Score	5	4	3	4	1	1	1	3	4	2
C21: population density	Population density (People per square km)	18,977	7274	7274	18,977	7333	22,400	6628	7333	7333	6628
	Score	4	2	2	4	3	5	1	3	3	1
C22: transport accessibility	Main roads	4	7	4	5	14	2	3	6	3	5
	Score (50%)	3	4	3	4	5	1	2	4	2	4
	Main road junctions	20	26	17	19	30	7	10	15	13	11
	Score (50%)	4	5	3	4	5	1	2	3	2	2
	Final score	3.5	4.5	3	4	5	1	2	3.5	2	3
C23: adjacent emergency shelter	Distance to other emergency shelters (km)	1.8	2.4	2.7	2.0	2.1	2.9	4.0	3.0	2.7	1.2
	Score	1	3	3	2	2	4	5	4	3	1
C24: neighbouring urban infrastructure	Distance to critical infrastructure (km)	1.3	2.9	0.86	2.6	2.8	0.91	1.9	0.6	0.84	0.29
	Score	3	1	4	1	1	3	2	4	4	5
C31: cost of land	Land cost (CNY/m^2)	82,000	58,000	58,000	82,000	61,000	82,000	39,000	61,000	61,000	36,000
	Score	2	4	4	2	3	2	5	3	3	5
C32: cost of construction	Construction cost (CNY/m^2)	1800	1200	1400	1400	1200	1400	2000	1600	2000	1200
	Score	2	5	4	4	5	4	1	3	1	5
C33: cost of maintenance	Maintenance cost (CNY/m^2)	260	200	240	220	200	220	280	240	280	200
	Score	2	5	3	4	5	4	1	3	1	5
C41: area available on site	Usable area (m^2)	3700	400,000	270,000	54,000	40,000	47,000	20,000	434,000	280,000	400,000
	Score	1	4	3	2	2	2	1	5	3	4
C42: emergency shelter equipment	Completeness of equipment	–	–	–	–	–	–	–	–	–	–
	Score	2	5	4	1	3	4	1	3	1	5

Table 13 Main standard weight and pairwise comparison matrix

Criteria	S1	S2	S3	S4	Weight
S1	(1,1,1)	(1,1.1,1.4)	(1.6,2.1,2.6)	(1.1,1.5,2)	**0.333**
S2	(0.767,0.933,1)	(1,1,1)	(1.2,1.6,2.1)	(1,1.2,1.6)	0.276
S3	(0.392,0.45,0.667)	(0.493,0.667,0.867)	(1,1,1)	(0.7,0.933,1)	0.176
S4	(1,1,1)	(0.667,0.867,1)	(1,1.1,1.5)	(1,1,1)	0.215

The "Weight" column shows the normalised importance of each criterion, calculated using the FAHP based on expert pairwise comparisons

Table 14 Safety standard local weight and pairwise comparison matrix

Criteria	C11	C12	C13	Weight
C11	(1,1,1)	(1,1.3,1.7)	(1.6,2.1,2.6)	**0.445**
C12	(0.633,0.8,1)	(1,1,1)	(1.1,1.4,1.9)	0.327
C13	(0.392,0.493,0.667)	(0.583,0.767,0.933)	(1,1,1)	0.228

The "Weight" column shows the normalised importance of each criterion, calculated using the FAHP based on expert pairwise comparisons

Table 15 Global sub-criteria weights

Sub-criteria	C11	C12	C13	C21	C22	C23	C24	C31	C32	C33	C41	C42
Global weights	0.148	0.11	0.076	0.095	0.078	0.045	0.057	0.058	0.04	0.077	0.129	0.087

Table 17 summarises the consistency calculations for all experts (E1 to E5), providing a broader view of the reliability of the judgments across multiple experts. For each expert, the $\lambda_{\max}$ CI and CR were calculated using the same procedure outlined for Expert E1. The results indicate that all experts have CR values below the threshold of 0.1. Specifically, Expert E1 has a CR of 0.017, Expert E2 has a CR of 0.031, and Expert E4 and Expert E5 have CR values of 0.011 and 0.006, respectively, all suggesting highly consistent judgments. Expert E3, with a CR of 0.091, has the highest CR value amongst the group, though still within the acceptable threshold. These results confirm that the judgments provided by all experts are consistent and reliable. The same procedure applies to other experts and criteria matrices to ensure that all pairwise comparison judgments are consistent.

Following the previous calculation, the derived data was integrated into the ontology via a rule-based query operation. This process involved developing several rules and queries to enable the generation of various alternative address rankings, as shown in Tables 7, 8 and 9. These queries can be classified as follows:

Table 16 Expert E1 evaluation consistency calculation

E1 evaluation matrix	C1	C2	C3	C4
C1	1.000	2.000	3.000	4.000
C2	0.500	1.000	3.000	3.000
C3	0.333	0.333	1.000	1.000
C4	0.250	0.333	1.000	1.000
Sum	2.083	3.666	8	9

Normalisation	C1	C2	C3	C4	Weight (W)	$\sum AW$	$\sum AW/W$
C1	0.480	0.546	0.375	0.444	0.461	1.884	4.084
C2	0.240	0.273	0.375	0.333	0.305	1.236	4.049
C3	0.160	0.091	0.125	0.111	0.122	0.489	4.016
C4	0.120	0.091	0.125	0.111	0.112	0.450	4.031

λ	n	RI	CI	CR
4.045	4	0.890	0.015	0.017

Table 17 Expert evaluation consistency calculation

Expert (E)	λ	*n*	RI	CI	CR
E1	4.045	4	0.890	0.015	0.017
E2	4.082	4.000	0.890	0.027	0.031
E3	4.244	4.000	0.890	0.081	0.091
E4	4.031	4.000	0.890	0.010	0.011
E5	4.015	4.000	0.890	0.005	0.006

- **Sub-criteria rankings** A query was executed to produce ten alternative address rankings based on sub-criteria scores, resulting in twelve rankings.
- **Main criteria ranking** Another query was conducted to determine the ranking of ten alternative addresses based on the main criteria score, resulting in four rankings.
- **Comprehensive ranking** Query to obtain ten alternative address rankings based on the total score, resulting in one overall ranking.

The results are given in Tables 18 and 19. The final analysis showed that alternative address A10 was ranked first in the overall score. It is ranked first in both the main criteria of safety and economy and second in the main criterion of construction, Table 19. Thus, alternative site A10 is identified as the optimal site for the UEES construction. This site, which is located in Beijing's Shijingshan District, benefits from its large area and the ability to supply a large population, making it remarkably appropriate for large-scale UEES. In a close contest, alternative site A2 was ranked second in the overall ranking. It leads in the construction criterion, places second in the economic criterion, and third in safety. It is located in Beijing's Haidian District, which is the location of a concentration of universities and high-tech companies, pointing out its suitability for UEES deployment. On the contrary, alternative site A7 ranks lowest overall, primarily due to its weak performance in the planning and construction criteria and its lower ranking in economic efficiency, although it scores well in safety.

In the actual decision-making process, the views of the individual in the EDM team may vary due to a variety of reasons, such as experience, learning, and differences in opinion. Hence, sensitivity analysis is necessary to determine how changes in decision information may affect the ranking results. Tables 20 and 21 show a sensitivity analysis to verify the effect of slight changes in the main criteria weights on the ranking, allowing the rationality and stability of the model's design to be evaluated. The main criterion, S1, is the most heavily weighted. Hence, the change in the main criterion S1 weight is used as an example to provide insights into the fluctuation of scores for each alternative address. The weight of S1 is adjusted to see how changes in this weight affect the final scores and rankings of the alternatives. Typically, the weight is both increased and decreased by a certain percentage. For instance, ±5% (Table 20) and ±15% (Table 21). This adjustment is done whilst ensuring that the total sum of all criteria weights remains 1 (or 100%). After adjusting the weights, the scores for each alternative site are recalculated by multiplying each criterion's adjusted weight by the site's score on that criterion, and summing these products to obtain a new total score for each site.

The final scores, Table 22, show that sites A2 and A10 are close in condition. The final score is higher in the ontology score only because of the higher safety score due to the distance from the earthquake centre. When the main criterion S1 weighting changed slightly, A2 scored more than A10, but both remained in the top two positions. Conversely, sites A1 and A7 consistently rank lowest, suggesting that shifts in S1's weight impact their evaluations. This could indicate that other criteria where they score poorly are more influential in their ranking or that other sites across most criteria significantly outperform them. Other sites like A3, A4, A5, A6, A8, and A9 experience some shifts in rankings with changes to S1 weight, but these shifts are not significant, and these sites maintain a middle-tier position. This indicates a moderate sensitivity to the changes in the weight of S1 but overall stability in their rankings.

The sensitivity analysis, therefore, confirms that the decision model is well-designed, with the rankings showing rational behaviour in response to changes in criterion weightings. It indicates that the ontology's design is capable of producing a rational and stable ranking of alternative sites, even when accounting for the natural variability in the views and opinions of the individual decision-makers within the decision-making team.

7 Managerial Implications

This study aims to highlight the critical importance of strategically placing UEES within rapidly modernising urban areas as a vital component of urban disaster preparedness. The proposed framework, which integrates the FAHP with ontology-based modelling, effectively addresses significant challenges in UEES site selection, such as inconsistencies in data representation and the integration of diverse hazard-related data. By providing a structured and standardised approach to managing the complexities of urban environments, this framework enhances decision-making by better handling uncertainties in expert judgments. It enables disaster management professionals to conduct a more comprehensive evaluation of potential shelter sites, prioritising them based on a robust set of criteria, including safety, planning, economic benefits, and infrastructure interactions.

Table 18 SQWRLTab substandard query ranking

C11		C12		C13		C21		C22		C23		C24		C31		C32		C33		C41		C42	
Add	S	Add	S	Add	S	Add	S	Add	S	Add	S	Add	S	Add	S	Add	S	Add	S	Add	S	Add	S
A10	0.740	A2	0.55	A2	0.55	A6	0.475	A5	0.390	A7	0.225	A10	0.285	A10	0.29	A2	0.2	A2	0.385	A8	0.645	A2	0.435
A9	0.592	A7	0.55	A7	0.55	A1	0.380	A2	0.351	A6	0.18	A3	0.228	A7	0.29	A10	0.2	A10	0.385	A2	0.516	A10	0.435
A7	0.444	A4A4	0.55	A4	0.55	A4	0.380	A4	0.312	A8	0.18	A9	0.228	A2	0.232	A5	0.2	A5	0.385	A10	0.516	A3	0.348
A5	0.444	A3	0.44	A3	0.44	A9	0.285	A1	0.273	A2	0.135	A8	0.228	A3	0.232	A3	0.16	A6	0.308	A3	0.387	A6	0.348
A2	0.296	A6	0.44	A6	0.44	A5	0.285	A8	0.273	A3	0.135	A6	0.171	A9	0.174	A6	0.16	A4	0.308	A9	0.387	A5	0.261
A6	0.296	A10	0.33	A10	0.33	A8	0.285	A3	0.234	A9	0.135	A1	0.171	A5	0.174	A4	0.16	A3	0.231	A6	0.258	A8	0.261
A1	0.296	A1	0.22	A1	0.22	A2	0.190	A10	0.234	A4	0.09	A7	0.114	A8	0.174	A8	0.12	A8	0.231	A4	0.258	A1	0.174
A4	0.296	A5	0.22	A5	0.22	A3	0.190	A7	0.156	A5	0.09	A2	0.057	A6	0.116	A1	0.08	A1	0.154	A5	0.258	A7	0.087
A3	0.148	A9	0.11	A9	0.11	A10	0.095	A9	0.156	A10	0.045	A4	0.057	A1	0.116	A7	0.04	A7	0.077	A7	0.129	A9	0.087
A8	0.148	A8	0.11	A8	0.11	A7	0.095	A6	0.078	A1	0.045	A5	0.057	A4	0.116	A9	0.04	A9	0.077	A1	0.129	A4	0.087

Address (Add)
Score (S)

Table 19 Final ranking of alternative addresses

Final Score		S1 Score_Sa		S2 Score_Pn		S3 Score_Ec		S4 Score_Cn	
Address	Score	Address	Score	Address	Score	Address	Score	Address	Score
A10	3.707	A10	1.222	A8	0.966	A10	0.875	A2	0.951
A2	3.575	A4	1.15	A6	0.904	A2	0.817	A10	0.951
A3	2.961	A2	1.074	A1	0.869	A5	0.759	A8	0.906
A4	2.918	A7	1.07	A4	0.839	A3	0.623	A3	0.735
A6	2.906	A9	1.006	A5	0.822	A6	0.584	A6	0.606
A8	2.883	A1	0.896	A9	0.804	A4	0.584	A5	0.519
A5	2.84	A3	0.816	A3	0.787	A8	0.525	A9	0.474
A9	2.575	A6	0.812	A2	0.733	A7	0.407	A4	0.345
A1	2.418	A5	0.74	A10	0.659	A1	0.35	A1	0.303
A7	2.283	A8	0.486	A7	0.69	A9	0.291	A7	0.216

Table 20 Weight and score of main standard S1 after adding and reducing 5%

Original weight of main criteria and global sub-criteria weight												
Main standards	S1:0.333			S2:0.276				S3:0.176			S4:0.215	
Sub-criteria	C11	C12	C13	C21	C22	C23	C24	C31	C32	C33	C41	C42
Global weights	0.148	0.11	0.076	0.095	0.078	0.045	0.057	0.058	0.04	0.077	0.129	0.087
Weight and score after adding 5% to main standard S1												
Main standards	S1:0.350			S2:0.269				S3:0.172			S4:0.210	
Sub-criteria	C11	C12	C13	C21	C22	C23	C24	C31	C32	C33	C41	C42
Global weights	0.156	0.114	0.080	0.093	0.076	0.044	0.056	0.057	0.039	0.075	0.125	0.085
Alternative sites	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10		
Score	2.451	3.787	2.974	2.956	2.857	2.925	2.323	2.878	2.611	3.738		
Weight and score after reduced 5% to main standard S1												
Main standards	S1:0.316			S2:0.283				S3:0.180			S4:0.220	
Sub-criteria	C11	C12	C13	C21	C22	C23	C24	C31	C32	C33	C41	C42
Global weights	0.141	0.103	0.072	0.098	0.080	0.046	0.059	0.060	0.041	0.079	0.131	0.089
Alternative sites	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10		
Score	2.413	3.771	2.973	2.903	2.858	2.920	2.258	2.919	2.565	3.709		

The ontology framework, in particular, facilitates the structuring and analysis of selection criteria, thereby improving information exchange and reusability, which is an essential capability in disaster-prone urban areas where quick and informed decision-making is crucial. The successful application of this framework in Beijing illustrates its practical utility in optimising UEES placement, contributing to the development of more resilient urban emergency management systems. This approach supports local governments in effective disaster preparedness by providing a data-driven, holistic decision-making tool. Moreover, by addressing the inherent complexities of UEES site selection, this framework also supports the digital transformation of urban emergency management systems, paving the way for more responsive and adaptive disaster management strategies.

8 Conclusion

This paper presented a novel approach that integrates the FAHP with ontology-based modelling to enhance the selection of UEES. The FAHP method effectively addresses inherent uncertainties and subjective elements in expert judgments, whilst the ontology framework structures and captures domain knowledge, enhancing information exchange and reusability. Applied to a case study in Beijing, the approach successfully evaluated potential shelter locations and identified the Shijingshan and Haidian districts as the most suitable sites based on safety, economic benefits, and infrastructure interactions. This research not only demonstrates the practical utility of the integrated decision-making model but also contributes to the theoretical foundations for optimising

Table 21 Weight and score of main standard S1 after adding and reducing 15%

Original weight of main criteria and global sub-criteria weight												
Main standards	S1:0.333			S2:0.276				S3:0.176			S4:0.215	
Sub-criteria	C11	C12	C13	C21	C22	C23	C24	C31	C32	C33	C41	C42
Global weights	0.148	0.11	0.076	0.095	0.078	0.045	0.057	0.058	0.04	0.077	0.129	0.087
Weight and score table after adding 15% to main standard S1												
Main standards	S1:0.383			S2:0.255				S3:0.163			S4:0.199	
Sub-criteria	C11	C12	C13	C21	C22	C23	C24	C31	C32	C33	C41	C42
Global weights	0.170	0.125	0.087	0.088	0.072	0.042	0.053	0.054	0.037	0.071	0.118	0.081
Alternative sites	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10		
Score	2.440	3.738	2.921	2.955	2.796	2.872	2.350	2.776	2.609	3.704		
Weight and score table after reduced 15% to main standard S1												
Main standards	S1:0.283			S2:0.297				S3:0.189			S4:0.231	
Sub-criteria	C11	C12	C13	C21	C22	C23	C24	C31	C32	C33	C41	C42
Global weights	0.126	0.093	0.065	0.103	0.084	0.049	0.062	0.063	0.044	0.083	0.138	0.094
Alternative sites	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10		
Score	2.400	3.787	2.999	2.877	2.889	2.944	2.213	2.990	2.543	3.711		

Table 22 Change of S1 weight of main standard and ranking of address

Final Score		S1 Score_Sa		S2 Score_Pn		S3 Score_Ec		S4 Score_Cn	
Address	Score	Address	Score	Address	Score	Address	Score	Address	Score
A10	3.707	A2	3.787	A2	3.771	A2	3.738	A2	3.787
A2	3.575	A10	3.738	A10	3.709	A10	3.704	A10	3.711
A3	2.961	A3	2.974	A3	2.973	A4	2.955	A3	2.999
A4	2.918	A4	2.956	A6	2.92	A3	2.921	A8	2.99
A6	2.906	A6	2.925	A8	2.919	A6	2.872	A6	2.944
A8	2.883	A8	2.878	A4	2.903	A5	2.796	A5	2.889
A5	2.84	A5	2.857	A5	2.858	A8	2.776	A4	2.877
A9	2.575	A9	2.611	A9	2.565	A9	2.609	A9	2.543
A1	2.418	A1	2.451	A1	2.413	A1	2.44	A1	2.4
A7	2.283	A7	2.323	A7	2.258	A7	2.35	A7	2.213

UEES site selection within urban emergency management systems. The findings underscore the value of a holistic, data-driven approach to urban disaster preparedness and the potential for digital transformation in emergency management.

Despite the promising results, the proposed approach has several limitations. One limitation is the reliance on expert judgments for criteria weighting, which can introduce subjectivity and bias. Exploring more objective weighting methods or leveraging machine learning to enhance the robustness of the decision-making process is important. Additionally, the case study was conducted in a specific urban context (Beijing), which may limit the generalizability of the findings to other cities with different geographic, demographic, or infrastructural characteristics. The complexity of the multi-criteria decision-making model also presents challenges, particularly in terms of computational requirements and data availability. Furthermore, whilst the ontology framework enhances the structuring and analysis of criteria, it may not fully capture the dynamic and evolving nature of urban environments, necessitating frequent updates and refinements.

Future research should concentrate on refining the complexities inherent in multi-criteria decision-making, improving weighting procedures, and collecting more accurate data to enhance the model's accuracy. This could involve the development of more advanced techniques for handling uncertainty and subjectivity in expert judgments, as well as the incorporation of real-time data to enhance the model's responsiveness to changing conditions. Additionally, expanding the scope of case studies to include diverse urban contexts would improve the generalisability of the findings and provide insights into the model's adaptability across different environments. Further exploration of both the theoretical and empirical boundaries of FAHP is also recommended, particularly in managing the complex and dynamic relationship amongst site selection criteria. Finally, integrating this approach with other emerging technologies, such as machine learning, could further enhance its applicability and effectiveness in urban emergency management. By providing a data-driven, structured approach to decision-making, this research contributes to the ongoing efforts to develop smarter, more resilient cities, ultimately aiding local governments with tools for earthquake disaster prevention planning and improving the overall safety and preparedness of urban populations.

Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests 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.

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