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A novel data–intelligence–driven three–stage dynamic model for resilience assessment in an emergency material support system

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ABSTRACT

Resilience is a crucial benchmark in characterizing the comprehensive capability of the emergency material support system (EMSS) to respond to major risk events. Given the involvement of multiple stakeholders, multiple stages and dynamic evolution, EMSS resilience assessment remains a challenge. Therefore, we attempt to develop a novel data–intelligence–driven three–stage dynamic model based on multi–source text data and multi–expert knowledge. In Stage 1, a large language models–enhanced named entity recognition model is proposed to extract and analyze EMSS risk events, providing a foundational dataset for scenario construction. In Stage 2, an ontology–based scenario construction model is proposed to abstract risk events into ontological concepts, providing a feature reference for the hierarchical system of assessment criteria. In Stage 3, a feature–matching assessment model is proposed to quantify the profile of EMSS resilience, where the uncertainty and variability in experts' perceptions of resilience feature are addressed. Subsequently, the model effectiveness is demonstrated in a case study, in which the key criteria and improvement paths for EMSS resilience are identified. This study provides a holistic solution and efficient methodology for EMSS resilience assessment, offering significant insights into a multifaceted recognition of EMSS resilience to risk scenarios.

1. Introduction

An emergency material support system (EMSS) is an essential part of the national emergency management system in China, which aims to ensure the successful execution of rescue operations and minimize losses and negative impacts when dealing with major risk events [1]. In recent years, with the increased frequency of major risk events at both global and local regional levels, such as the *COVID–19 pandemic* and *Hurricane Hilary* in the United States, the lives and safety of humanity have been threatened significantly [2]. These unprecedented severe challenges presented higher requirements for the current EMSS to cope with increasingly complex risk scenarios, meet the demand for diverse emergency supplies, improve emergency response timeliness, and alleviate pressure on emergency resource allocation [3].

Resilience is a multidisciplinary concept that can describe the degree to which a system can adapt to change by absorbing recurring perturbations and dealing with risks while maintaining its key properties [4]. Many countries have consistently underscored the significance of resilience in managing major risks, asserting its applicability in various aspects, including the EMSS [5,6]. In China, resilience serves as a crucial benchmark in characterizing the comprehensive capacity of the EMSS to withstand the impact of risk outbreaks, maintain its normal functioning during the risk diffusion process, and adapt to uncertain environmental changes following dissipation of the immediate risk [7,8]. Therefore, an EMSS resilience assessment is particularly important to clarify the resilience profile and identify weaknesses and thereby support resilience improvement. This not only relates to the basic survival needs of disaster–affected populations but also impacts the safety of entire countries at large.

However, studies on EMSS resilience, especially the quantitative ones, remain relatively sparse, predominantly centered on discussing its necessity and significance qualitatively [9]. In contrast, resilience assessment studies in other fields have garnered more areas of focus, such as urban resilience [10] and supply chain resilience [11]. These

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studies contribute to clarifying resilience concepts, refining the assessment criteria, and developing assessment methods, which can provide valuable theoretical and methodological insights for the current study. It is crucial to highlight that EMSS resilience assessment faces significant challenges due to the following three inherent features.

(1) *Multiple stakeholders*. The EMSS is a complex system involving government departments, enterprises, social organizations, and community residents. There are significant differences among different stakeholders as to the claims of EMSS resilience [12]. For government departments, the emphasis is on strengthening the capacity building of EMSS resilience to cope with major risk events through top–level design and institutional arrangements, such as formulating emergency response plans and establishing joint–action mechanisms [13]. For enterprises, leveraging their industrial chain advantages and optimizing the capacity layout of key materials are their primary concerns in terms of EMSS resilience [14]. For social organizations, such as the Red Cross, the focus is on developing volunteer networks and engaging in emergency response training to build EMSS resilience [15]. For community residents, increasing the stockpile of emergency supplies in homes, participating in emergency drills, and enhancing mutual aid to support EMSS resilience are essential aspects [16]. Due to differences in the understanding of resilience among different stakeholders, their opinions on EMSS resilience may, therefore, show some uncertainty [17]. Unfortunately, the fuzzy set (FS) theory used to quantify the uncertainty in existing studies struggles to deal with multi–source fuzzy information [18]. Especially when the EMSS is required to cope with major risk events, the inadequacy of risk information and incomplete emergency supply–demand information can cause different stakeholders to hesitate in their resilience assessment [19]. As a new extension of FS theory, the hesitant fuzzy set (HFS) theory can capture a broader range of information from different decision–makers more effectively [20]. Therefore, developing an HFS–based method to reduce the uncertainty caused by stakeholders' hesitation, thereby forming a comprehensive assessment of EMSS resilience, is a significant challenge that needs to be addressed.

(2) *Multiple stages*. The operation of the EMSS involves various interconnected stages, such as demand estimation, material procurement, warehouse management, logistics, and distribution. For instance, the results of demand estimation influence procurement decisions directly, while warehouse layout determines the choice of distribution routes. Focusing disproportionately on or neglecting certain stages may distort the resilience assessment results, impacting the specificity and effectiveness of resilience improvement efforts. Therefore, an effective assessment of EMSS resilience must synthesize the various stages and cover the entire process of risk response. Existing EMSS studies mainly focus on certain stages of major risk events, including analyzing distribution mechanisms for emergency materials [21], selecting storage sites for emergency materials [22], and optimizing emergency procurement cost and inventory [23]. While these studies address specific operational challenges, the scholars involved often treat stages in isolation rather than examining their dynamic interrelationships. This fragmented mode fails to capture the holistic nature of EMSS operations and may lead to suboptimal resilience strategies.

(3) *Dynamic evolution*. The multi–stage feature of EMSS operations is further complicated by its dynamic evolution across different risk scenarios and timeframes. EMSS resilience is manifested not only in its immediate response to risk events but also in its capacity for recovery and adaptation in the face of continually changing risk scenarios [24]. The inherent dynamic evolution of EMSS resilience arises primarily from the uncertainty and variety inherent in these risk scenarios [25]. For example, in a natural disaster risk scenario such as an earthquake, rapid deployment of materials and restoration of transportation are critical [26]. Conversely, in a public health emergency like an epidemic, the capabilities for warning of risks and forecasting demand become crucial [27]. In various risk scenarios, an EMSS must reallocate resources adaptively to meet the specific needs of each scenario [28]. This dynamic adaptation occurs not only across different risk scenarios but also evolves through time within a single event, from pre–event prevention to mid–event response and post–event recovery. While the dynamic evolution of an EMSS across various risk scenarios is recognized, most existing studies tend to focus on specific or simplified risk scenarios and quantify resilience based on static analyses or data from a single point in time [29]. The assessment criteria systems are often developed on fixed analytical logic and frameworks, such as "wuli–shili–renli" [30] and "pressure–state–response" [31]. These methods may struggle to capture the dynamic interplay between stages and the evolving feature of resilience across different phases of risk events.

Therefore, the limitations of current studies become particularly evident when considering both the multi–stage feature and dynamic evolution of EMSS resilience. Existing studies mainly focus on the static analysis framework of "task–response" in major risk events [32], which addresses isolated operational challenges but fails to capture the complex mechanisms of risk generation, development, and response across the entire EMSS lifecycle. This fragmented perspective hinders an in–depth understanding of how scenario–specific demands translate into governance tasks and how system capabilities must be dynamically aligned to meet these demands. Consequently, there is a critical need for a more comprehensive analytical framework that can simultaneously address the interconnected stages of EMSS operations and their dynamic evolution across diverse risk scenarios. The "scenario–task–capability" framework offers such a perspective by establishing clear relationships between scenario elements, task requirements, and capability responses, thereby providing a more holistic and dynamic mode to EMSS resilience assessment.

To address these challenges, a novel data–intelligence–driven three–stage dynamic model for EMSS resilience assessment was developed. In Stage 1, a large language models (LLMs)–enhanced named entity recognition model was proposed for risk event extraction. The proposed model can process multi–source text data and integrate domain–specific expert knowledge to extract and analyze risk events. This stage lays the groundwork for understanding and constructing dynamic risk scenarios. In Stage 2, a $\langle$I–N–C–A$\rangle$ ontology representation–based model was proposed for risk scenario construction to transform risk events into structured scenario elements. This model captures the interrelations between issues, nodes, constraints, and annotations within risk scenarios, enabling the depiction of dynamic interactions in EMSS. Based on these structured scenarios, resilience features were identified through a "scenario–task–capability" analysis framework, which clarified the alignment between risk scenarios, governance tasks, and the system capabilities. This provides a construction foundation for a hierarchical system of assessment criteria. In Stage 3, a dynamic hesitant fuzzy matter–element extension (DHF–MEE) model was proposed to conduct a feature–matching quantitative assessment for the profile of EMSS resilience by measuring and aggregating the performance of each criterion at each time point, which was obtained from multi–expert knowledge. The classic MEE model was extended to a dynamic hesitant fuzzy environment, aiming to more accurately reflect the experts' differences of opinions and hesitant attitudes in the resilience assessment process. The developed data–intelligence–driven three–stage dynamic model enabled us to conduct EMSS resilience assessment based on multitime–point features, multidimensional criteria, and multi–source heterogeneous data, effectively catering for the involvement of multiple stakeholders, multiple stages, and dynamic evolution. It overcomes limitations in existing frameworks by enabling robust and dynamic assessment, addressing decision–making uncertainties and providing actionable insights for resilience improvement.

The remainder of this paper is organized as follows. Section 2 reviews the existing studies, reveals the research gaps, and sets out our contribution. Section 3 details the framework of the developed data–intelligence–driven three–stage dynamic model, including the processes of risk event extraction, resilience feature recognition, and resilience quantitative assessment. Section 4 elaborates on the developed model for EMSS resilience assessment. Section 5 demonstrates the applicability of the developed model through a case study. Section 6 summarizes the conclusions and presents a roadmap for future work.

2. Literature review

In this section, existing studies on resilience assessment methods and risk scenario construction are reviewed. Subsequently, the research gaps are discussed, and our contribution is set out.

2.1. Resilience assessment methods

Current studies on resilience assessment focus primarily on system performance, emphasizing the assessment of how resilient a given system is. Resilience assessment methods mentioned in these studies can be classified into four categories.

(1) *Deterministic methods* assume the known or fixed states and parameters of a system. These methods are appropriate for situations where the effects of major risk events are well–defined, and resilience is quantified by changes in system performance before and after major risk events. Zobel [33] quantified resilience by calculating the ratio of the total loss within a certain interval after a disaster to the system's performance under normal conditions. Henry and Ramirez–Marquez [34] described the system's progression through three states: stable initial state, disrupted state, and stable recovery state, and quantified the system's resilience by calculating the ratio of recovery to loss. However, the deterministic methods fail to consider the uncertainties inherent in systems [35], thereby rendering them less effective for analyzing complex real–world scenarios.

(2) *Probabilistic methods* account for the inherent uncertainties in systems. These methods are particularly effective for systems whose states and parameters are indeterminate or prone to substantial variation, and probability distributions are often used to model and quantify system resilience against major risk events. Chen et al. [36] analyzed the uncertainties during the disruption and mitigation phases and applied the Monte Carlo method to assess the resilience of chemical plants. Tong and Gernay [37] examined the uncertainty associated with cascading events and used dynamic Bayesian networks to conduct resilience assessments in the facilities industry. Although probabilistic methods are adept at addressing system uncertainties, they depend extensively on comprehensive historical data and statistical analyses [38]. In addition, they confront challenges such as data scarcity, inconsistency, or inadequacy, and the difficulty of identifying appropriate probabilistic models and parameters persists [39].

(3) *Simulation–optimization methods* can address the complexity of system structures and behaviors alongside various potential disturbances and corresponding response strategies. Herein, agent–based modeling (ABM) and robust optimization techniques are often used, enabling the simulation of system responses to diverse risk scenarios and providing a flexible model for a resilience assessment of complex systems. Sun et al. [40] applied ABM to project the functional trajectory of road networks during recovery phases after major risk events and analyzed system resilience using different restoration methods. Parast et al. [41] developed a multi–objective three–stage robust stochastic optimization model, in which deep learning is leveraged to simulate social behaviors and conduct a resilience assessment of microgrids and distribution systems. While simulation–optimization methods have significant advantages in assessing system resilience, they require substantial computational resources, especially for large–scale or highly complex systems [42]. Inadequate agent behavioral parameters and rules can lead to models that fail to reflect real–world dynamics accurately, particularly when facing new types of previously unencountered risk events [43].

(4) *Criterion–based methods* concentrate on the attributes or functions of a system and emphasize how to make a system more resilient. In these studies, resilience is often assessed by establishing a set of specific criteria, making the assessment process more concrete and actionable. Huang et al. [44] identified the key criteria of urban resilience through a literature review and the Delphi method and analyzed their influence mechanisms using the decision–making trial and evaluation laboratory (DEMATEL) and interpretive structural modeling (ISM) with criteria data sourced from surveys of industry experts. Liu et al. [45] developed a criterion system for urban resilience assessment incorporating aspects such as social and ecological perspectives and employed night lights data to analyze the weighted average of each criterion empirically through four historical earthquake cases. Jaafari et al. [18] categorized social resilience into five facets: social recovery, economic recovery, institutional recovery, and infrastructure recovery, and identified 31 resilience criteria. Wang et al. [46] established a multicriteria resilience assessment model for urban power systems based on the physical–network–human model.

While these criterion–based methods provide a structured and practical framework for resilience assessment, they face a significant challenge when applied to complex systems like the EMSS: the inherent uncertainty and hesitation in expert judgments. In real–world scenarios involving multiple stakeholders and dynamic risks, decision–makers often struggle to assign a single, precise value to a criterion due to incomplete information, diverse perspectives, or conflicting evidence [47]. This subjectivity can undermine the accuracy and reliability of the assessment results. To address this limitation, scholars have increasingly turned to fuzzy set (FS) theory, proposed by Zadeh [48], which allows for the representation of vague or imprecise information. However, traditional FS theory, which assigns a single membership degree, is insufficient for capturing the full spectrum of expert opinion in group decision–making. Recognizing this, Torra [49] introduced Hesitant Fuzzy Set (HFS) theory as a powerful extension. HFS theory permits decision–makers to express their assessment using a set of possible membership values for a single criterion, thereby directly modeling their hesitation and capturing multiple potential viewpoints [50,51].

The HFS theory provides a robust solution for addressing resilience assessment challenges in complex decision–making environments. For example, Luo et al. [52] combined HFS theory with prospect theory to evaluate flood resilience plans, effectively mitigating uncertainties from subjective biases. Alimohammadlou and Khoshsepehr [53] employed HFS theory in a multicriteria model for resilient supplier selection, allowing experts to provide multiple potential assessments and reducing model oversimplification errors. Bu et al. [54] refined the DEMATEL model using HFS theory to more precisely identify critical features in subway system resilience, thereby improving the analysis of complex interactions and reducing biases from expert subjectivity. These studies affirm the adaptability of HFS theory for resilience assessment in complex decision–making environments, highlighting its effectiveness in managing decision uncertainty and elevating the quality of the decision–making process.

Table 1 provides a comparative summary of representative studies

Table 1
Comparisons of resilience assessment methods.

Method Category	Specific Methods	Data Type	Dynamic Support	Uncertainty Handling
Deterministic methods	Parameter–adjusted resilience function [33]	Expert judgment data	No	No
	Time–dependent resilience function with recovery ratio calculation [34]	System performance data	Yes	No
Probabilistic methods	Dynamic Monte Carlo [36]	Industrial facility data	Yes	Time-dependent conditional probabilities
	Dynamic Bayesian networks [37]	Industrial facility data	Yes	Monte Carlo simulation
Simulation–optimization methods	Agent–based modeling [40]	Infrastructure network data	Yes	Monte Carlo simulation
	Hybrid robust–stochastic optimization [41]	Power system operational data, social behavior data	Yes	Two-stage stochastic optimization
Criterion–based methods	DEMATEL–ISM [44]	Expert judgment data	No	No
	Entropy weight method [45]	Socio-economic, remote sensing data	No	No
	Fuzzy AHP [18]	Socio-economic data	No	Fuzzy AHP for expert assessment uncertainty
	Hesitant Fuzzy TOPSIS [46]	Power system data, expert judgment data	No	HFSs for expert assessment uncertainty

across the four categories of resilience assessment methods, highlighting key aspects such as data type, dynamic support, and uncertainty handling. This comparison reveals that while existing methods offer valuable frameworks, the complexity of an EMSS resilience assessment stems not only from its multiple stakeholders and multiple interconnected stages but also from the diverse and dynamically changing risk events to which it is exposed. The diversity and dynamics of risk events, the magnitude of their impacts, and their evolutionary paths make it difficult for traditional resilience assessment methods to address the challenges that an EMSS faces in practice.

2.2. Risk scenario construction

Risk response plays a crucial role in advancing the modernization of national security systems and capabilities [55]. In the policy document released by the China State Council [8], major risk response is divided into three stages: pre–event, in–event, and post–event. When major risk events occur, decision–makers in the previously mentioned stakeholders must swiftly enact measures to mitigate the adverse effects of major risk events and reinstate the functionality of the EMSS. Nowadays, some models have been developed by scholars to address the risk response problem in major risk events from different perspectives, such as the three–stage risk–averse and risk–neutral stochastic optimization model [56], and the adaptive robust optimization model [57]. These models are typically built on specific assumptions and have high computational complexity [58]. In practice, the outbreak of risk events might be more complex or undefined, potentially limiting these models' ability to fully capture all the features of risk events. Furthermore, the high computational complexity may hinder the application of these models in risk scenarios that require a rapid response. To address the time–sensitivity issue, some scholars have applied the case–based reasoning (CBR) model [59]. The CBR model offers rapid decision support by leveraging historical data and actual cases. Nevertheless, given the unpredictability and relative rarity of major risk events, applying the CBR model faces challenges due to the extremely limited extant repository of historical experiences and reliable cases.

The dynamic nature of major risk events makes the risk responses meet the requirements of high adaptability and flexibility. The conventional "task–response" process, constrained by a scarcity of decision–making data, suffers from an overreliance on historical experiences and actual cases, making it difficult to adapt dynamically to the complexity and variability of major risk events [60]. Scenario construction is a common method in risk management, which is beneficial to understanding the complexity and uncertainty of major risk events as well as depicting and assessing their evolution. Existing research has explored various methods for scenario construction, which can be broadly categorized into qualitative and quantitative approaches. Qualitative methods, such as expert judgment and narrative–based techniques, are particularly effective in scenarios with high uncertainty or limited data. Expert judgment, often combined with brainstorming, leverages collective expertise to generate diverse risk scenarios by identifying key drivers and uncertainties. For instance, Deep and Dani [61] demonstrated how expert–driven scenario construction can uncover potential disruptions and inform strategic responses. Similarly, narrative methods, such as storytelling, enhance the visualization and comprehension of risk scenarios. Ringland [62] emphasized that storytelling constructs detailed narratives that depict potential risk events, enabling stakeholders to intuitively grasp the implications of complex scenarios. Rodgers et al. [63] employed storytelling to construct earthquake scenarios, helping people intuitively understand earthquake risks and preparedness techniques to reduce the destruction and consequences caused by earthquakes.

In contrast, quantitative methods rely on mathematical models and data–driven analyses to construct and evaluate risk scenarios, offering precision in predictive and optimization tasks. Stochastic programming–based scenario analysis is a widely adopted approach in supply chain resilience research. This method constructs multiple risk scenarios and optimizes decisions to enhance system robustness. Roshani et al. [64] employed a two–stage stochastic programming model to design resilient supply chain networks, where initial decisions are made under uncertainty, followed by scenario–specific adjustments. While effective for proactive and reactive strategies, this approach faces challenges due to high computational complexity, which escalates with the number of scenarios, as noted by Sabbaghtorkan et al. [32]. Another promising quantitative method is ontology–based scenario construction, particularly suited for emergency management. Qian and Liu [66] proposed a framework that structures disaster knowledge into ontological elements, using an element–object–consequence (EOC) model to quantify scenario severity. By normalizing attributes and calculating weighted impacts, this method provides a structured and reusable representation of complex risk scenarios, as demonstrated in a case study on low–temperature freezing rain disasters affecting highways.

Despite these advances, existing studies on EMSS mostly focus on specific task solutions and response measures. This research paradigm lacks comprehensive consideration and may fail to provide a deeper understanding of the demands, constraints, and objectives of EMSS resilience in different risk scenarios and at different risk response stages. For example, Ye et al. [65] and Xing et al. [23] contributed to the task of emergency procurement costs and inventory optimization before risk event outbreaks with risk scenarios of natural disasters and supply chain risk management, respectively. However, the applicability and flexibility of these optimization strategies may be limited when facing different risk scenarios or other risk response stages. Broadening the research framework to scenario–task–capability is beneficial to identify and strengthen the key capabilities of EMSS in dealing with complex and constantly changing major risk events. Meanwhile, a holistic perspective based on the whole process of risk response also provides strong support for the identification of EMSS resilience weaknesses and key improvement elements.

2.3. Research gaps and our contribution

As previously mentioned, resilience is deemed an intuitive presentation of EMSS's comprehensive capacity in response to major risk events, which helps stakeholders clarify the overall situation of system efficacy. Although existing studies provide a preliminary framework and methodology for EMSS resilience assessment, they still show some limitations in the following aspects.

(1) Regarding the construction of criterion systems, existing studies often construct criterion systems through a static "task–response" logic, relying on predefined resilience criteria derived from expert intuition or generic frameworks. This priori mode lacks traceable linkage to the dynamic, heterogeneous, and evolving nature of real–world risk scenarios, failing to capture the full process of EMSS risk response and undermining the adaptability and contextual relevance of resilience assessment.
(2) Regarding the information depiction of criterion performance, existing studies have not mentioned or sufficiently depicted EMSS demand for resilience development when confronted with complex risk scenarios, and it is difficult to effectively manage uncertain information and hesitancy in complex decision–making environments. This restricts an in–depth understanding of EMSS resilience features and reduces the accuracy and reliability of resilience assessment.
(3) Regarding the temporal representation of criterion performance, existing studies often model resilience based on static or single––time–point data, failing to construct the profile of EMSS resilience. These studies struggle to depict the resilience profile as it adapts through distinct phases, lacking the ability for tracking and retrospective analysis of the resilience profile, which makes it difficult to identify weaknesses in specific stages of the EMSS.

To overcome these limitations, this paper proposes a data––intelligence–driven three–stage dynamic model for EMSS resilience assessment, which can address and reflect more accurately the complexity and dynamic changes in the decision–making environment. The main contributions are summarized as follows.

(1) More intelligent risk event extraction for EMSS resilience. A risk event extraction model is developed using advanced methods like BERT–BiLSTM–CRF, enhanced by LLMs. This model integrates a closed–loop annotation mechanism involving LLM–generated annotations, cross–validation with alternative models, and expert reviews. This iterative process significantly enhances annotation accuracy, improves the reliability of risk data while accelerating the extraction process, and ensures robust extraction of risk events from multi–source text data. This will provide a robust foundation for constructing realistic and dynamic risk scenarios.
(2) More scientific scenario construction for EMSS resilience. Using the proposed ontology–based model, multi–source text data on major risk events are organized and abstracted into ontological hierarchies and relationships to construct a risk scenario library of EMSS based on multi–expert knowledge. This will provide a clear description and analysis of the risk scenarios faced by EMSS resilience.
(3) More accurate feature quantification for EMSS resilience. A scenario–driven approach is adopted to extract resilience features from systemic analyses of diverse real–world risk scenarios, with inputs from multi–expert knowledge. Subsequently, a hierarchical criterion system matching the extracted features is constructed to characterize and quantify EMSS resilience. This will provide comprehensive guidance for an EMSS resilience assessment and be beneficial in ensuring the accuracy of assessment results.
(4) More multifaceted result presentation for EMSS resilience. Using the proposed DHF–MEE model, the profile of EMSS resilience is constructed by synthesizing multi–expert knowledge data across multiple critical time points. Meanwhile, the uncertainty in the process of EMSS resilience assessment is also overcome effectively. This will provide an important basis for stakeholders to recognize EMSS resilience and improve the problem–solving effectiveness of EMSS resilience assessment.

3. Framework

In this section, a three–stage framework is constructed to support EMSS resilience assessment (see Fig. 1). A brief description of each stage is presented below.

(1) Stage 1: Risk event extraction

The main work of stage 1 is to extract and analyze risk events to support the subsequent scenario construction. Specifically, this stage involves the preprocessing of multi–source text data, the annotation and extraction of risk events, and the analysis of causal relationships between events.

First, data sources are determined, and multi–source text data are collected to construct a corpus. During data preprocessing, the text undergoes cleaning and normalization, including removing irrelevant content, tokenization, synonym replacement, and stop–word filtering. These steps ensure that the data is structured and suitable for subsequent analysis.

Second, a risk event annotation module enhanced by LLMs is constructed. Professionalized prompts are designed to leverage the capabilities of the models to understand risk text data and automatically annotate entities within the text. To ensure the reliability of the annotations, cross–validation is performed using another LLM to verify whether the annotated segments match the original text and identify any potential inconsistencies. The annotated results are reviewed by domain experts, whose feedback is used to refine the prompts and annotation rules, further enhancing the accuracy and reliability of the annotation process. A closed–loop annotation mechanism is established, consisting of LLM–generated annotations, validation, expert revision, and iterative optimization of annotation rules. This creates an efficient annotation system. After multiple rounds of validation, a high–quality training dataset suitable for named entity recognition (NER) tasks is generated to train the BERT–BiLSTM–CRF model.

Furthermore, the BERT–BiLSTM–CRF model is used to extract event entities from the corpus and construct an event library. Dependency syntax analysis is applied to identify causal relationships between events, constructing event linkage graphs (ELGs) to validate the connections between entities. It can reveal the mutual influences and causal chains among different risk events, providing robust data support for the construction of risk scenarios.

(2) Stage 2: Resilience feature recognition

The main work involved in this stage is to construct EMSS risk scenarios, identify key features of EMSS resilience, and develop a hierarchical multidimensional criterion system for EMSS resilience assessment.

First, to provide a comprehensive understanding of EMSS risk response capabilities under different risk scenarios, as well as to provide insights into the characterization of EMSS resilience, scenario construction methods are employed to capture and analyze the dynamic

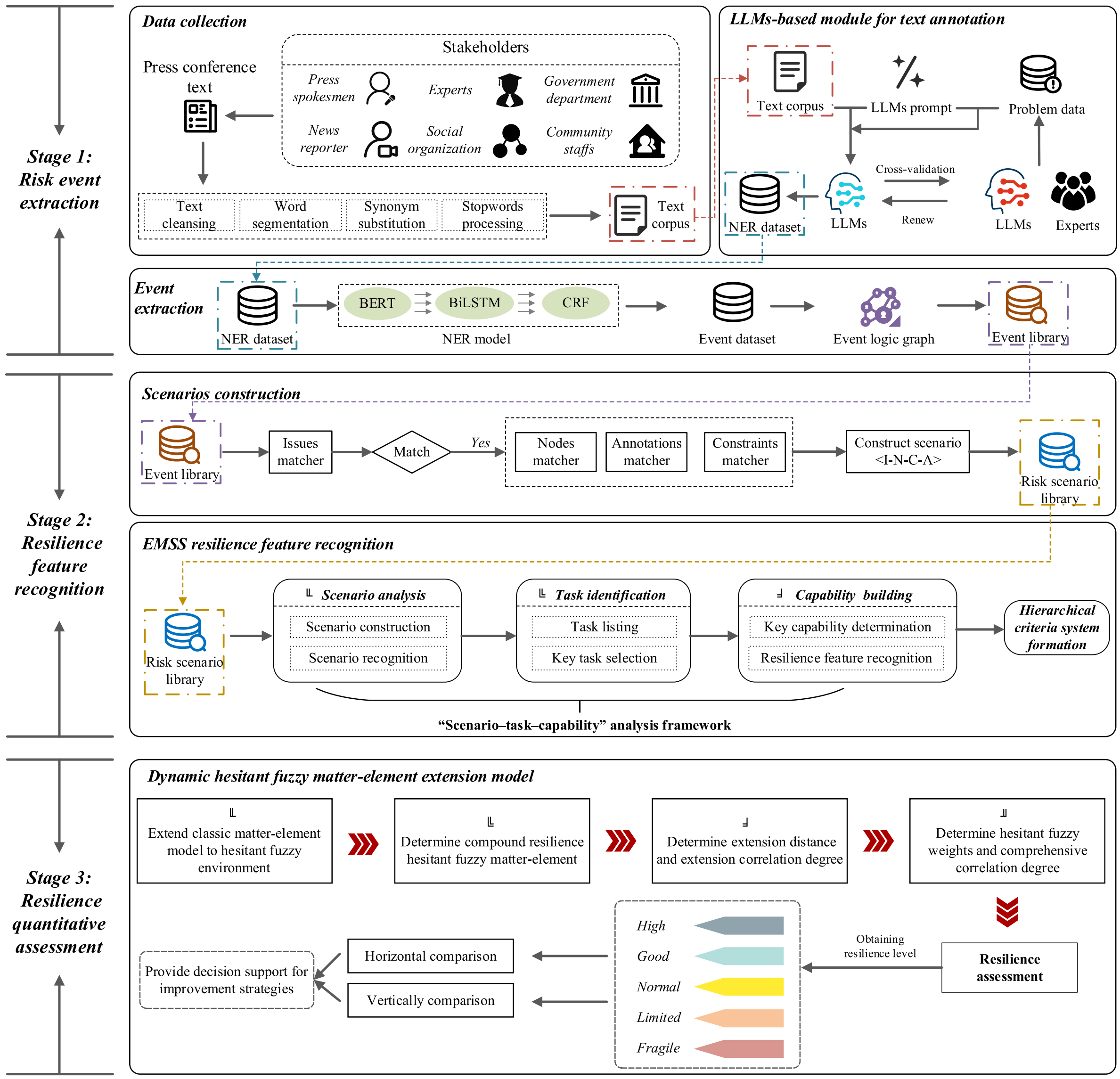

Fig. 1. Three–stage framework for EMSS resilience assessment.

changes and complexities of EMSS risk scenarios. Ontology representation provides rich semantic support for in–depth analysis of complex risk scenarios [66], showing higher flexibility and scalability in handling multi–source information. Therefore, the ⟨I–N–C–A⟩ ontology representation is used to construct a risk scenario library. Based on the event library constructed in Stage 1, the ontology model abstracts risk events into ontological concepts, transforming them into structured scenario elements to construct the risk scenario library. This library abstracts and organizes multiple risk events into dynamic scenarios, illustrating their evolution and associations with response strategies, while providing a structured and systematic basis for resilience assessment.

Second, based on the constructed risk scenario library, core scenarios related to EMSS risk response are extracted from the risk scenario library. Thus, the key nodes and response mechanisms in EMSS risk scenarios are captured. The set of scenario elements in the risk scenario library that are consistent with the characteristics of EMSS risk response objectives is located, and the scenario element representation to compose EMSS risk scenarios with certain causal and temporal relationships are extracted.

Then, the EMSS risk scenarios are systematically analyzed to understand the EMSS risk response modes and strategies under different risk scenarios from the analysis framework of "scenario–task–capability". Combining case studies and expert insights, we identify features of EMSS resilience, determine the key dimensions and criteria required for EMSS resilience assessment, and form a hierarchical multidimensional criterion system to characterize and quantify EMSS resilience.

(3) Stage 3: Resilience quantitative assessment

The main work involved in this stage is to develop the DHF–MEE model, which can perform dynamic assessments of EMSS resilience at multiple time points in an uncertain decision–making environment. Also, the model aims to reveal potential weaknesses in EMSS resilience and identify key features for resilience improvement.

First, the model incorporates the HFS theory to address the uncertainty and hesitation in the resilience assessment process. This theory allows experts to provide multiple possible assessment values for the same criterion, thereby quantifying their hesitant opinions. By integrating the hesitant fuzzy assessment of various criteria within the hierarchical criterion system of EMSS resilience assessment from different experts, a data foundation is provided for the quantitative assessment of EMSS resilience.

Second, the classic MEE model is extended to a hesitant fuzzy environment, thus proposing the DHF–MEE model suitable for EMSS resilience assessment. The proposed model aggregates multiple time points of hesitant fuzzy assessment information by constructing hesitant fuzzy matter–elements and dynamically assesses the EMSS resilience by calculating the extension correlation between these elements and predefined resilience levels.

Finally, based on the output of the DHF–MEE model, EMSS resilience can be classified into corresponding resilience levels. By comparing the correlation between various criteria and the ideal state of resilience, the model can be used to precisely identify key features for EMSS resilience improvement and the current weakness. This analysis not only reveals the current level of EMSS resilience but also provides decision support for formulating specific improvement strategies.

4. Methodology

In this section, a data–intelligence–driven three–stage dynamic model for EMSS resilience assessment is developed, in which the three stages involved are risk event extraction (Stage 1), resilience feature recognition (Stage 2) and resilience quantitative assessment (Stage 3). The details of the proposed model are elaborated to support the main work of each stage.

4.1. LLMs–enhanced NER model for risk event extraction

To enable efficient extraction of risk events from multi–source text data, a BERT–BiLSTM–CRF model and an LLMs–based annotation module are developed. This subsection outlines the design and application of these methods.

4.1.1. BERT–BiLSTM–CRF model for the NER task

NER is an important task in information extraction, aiming at identifying entity information (e.g., names of people, places, organizations, etc.) with specific meaning from unstructured data [67]. In NER tasks, the BERT–BiLSTM–CRF model integrates contextual semantic modeling, sequence dependency capture, and global optimization strategies, enabling efficient extraction of contextual information and annotation of sequence features. In this study, the BERT–BiLSTM–CRF model is employed for extracting risk events, incorporating the following three core components.

(1) BERT embedding layer: Deep contextual representation

To fully capture the contextual information of the text input, the model utilized BERT (Bidirectional Encoder Representations from Transformers) to generate contextualized word embeddings. Given an input sequence $\mathbf{x} = \{x_1, x_2, ..., x_n\}$, BERT produces a sequence of word embeddings $\mathbf{E} = \{\mathbf{e}_1, \mathbf{e}_2, ..., \mathbf{e}_n\}$, where $\mathbf{e}_i \in \mathbb{R}^d$ represents the embedding of the i th word in a D-dimensional space:

$$\mathbf{E} = \mathrm{BERT}(\mathbf{x}). \tag{1}$$

The bidirectional encoding mechanism of BERT enables it to capture deep semantic features and contextual dependencies, providing a rich feature representation for downstream sequence modeling.

(2) BiLSTM layer: Precise sequential dependency modeling

Following BERT embeddings, the model employs a BiLSTM (Bidirectional Long Short–Term Memory) network to further model sequential dependencies and long–range relationships within the input sequence. BiLSTM extracts sequential features in both forward and backward directions. The forward hidden state $\overrightarrow{h}_i$ and the backward hidden state $\overleftarrow{h}_i$ are concatenated to form the final feature representation $\mathbf{h}_i$ at each time step.

$$\mathbf{h}_i = \left[\overrightarrow{h}_i; \overleftarrow{h}_i\right], \mathbf{H} = \{\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_n\}, \tag{2}$$

where $[\cdot;\cdot]$ denotes the concatenation operation. By capturing both local and global sequential dependencies, BiLSTM complements BERT's ability to model patterns across long–range contexts.

(3) CRF layer: Global optimization for label dependencies

To ensure global consistency in the predicted label sequence, the model integrates a conditional random field (CRF) layer at the output. The CRF layer models the interdependencies between adjacent labels to optimize the sequence–level predictions. For a given label sequence $\mathbf{y} = \{y_1, y_2, ..., y_n\}$, the CRF layer assigns a score $s(\mathbf{y}, \mathbf{H})$ based on:

$$s(\mathbf{y}, \mathbf{H}) = \sum\nolimits_{i=1}^{n} \mathbf{W}_{y_{i-1}, y_i} + \sum\nolimits_{i=1}^{n} \mathbf{h}_i^T \mathbf{W}_{y_i}. \tag{3}$$

Here, W_{y_{i-1}, y_i} represents the transition score between labels y_{i-1} and y_i, while $\mathbf{h}_i^T \mathbf{W}_{y_i}$ denotes the emission score from BiLSTM outputs to the labels. For the first position ($i = 1$), y_0 is a predefined start label. The optimal label sequence is determined by maximizing the conditional probability:

$$\mathbf{y}^* = \mathrm{arg}\max_{\mathbf{y}} P(\mathbf{y}|\mathbf{x}) = \mathrm{arg}\max_{\mathbf{y}} \frac{\exp(s(\mathbf{y}, \mathbf{H}))}{\sum_{\mathbf{y}'} \exp(s(\mathbf{y}', \mathbf{H}))}. \tag{4}$$

The entire model is trained end–to–end by minimizing the negative log–likelihood (NLL) loss:

$$\mathscr{L} = -\log P(\mathbf{y}|\mathbf{x}). \tag{5}$$

This training framework not only leverages the pre–trained contextual knowledge of BERT but also captures task–specific sequential patterns through BiLSTM and optimizes global label distribution using the CRF layer. By integrating these three components, the BERT–BiLSTM–CRF model effectively captures complex patterns in risk text corpora, enabling robust extraction of relevant risk events. In event analysis, this study employs the dependency syntax analysis method proposed by Chen and Manning [68] to construct ELGs, which visualize and validate the intrinsic connections and interactions among risk events. This method facilitates understanding the evolution of different risk scenarios and their impact on EMSS, providing solid data support for constructing future EMSS risk scenarios.

4.1.2. LLMs–based module for text annotation

In the early stages of NER tasks, scholars primarily relied on traditional rule–based and template–based methods. However, these methods were often limited to specific domains and required extensive expert labor, making them increasingly obsolete. With the rise of deep learning technologies, neural network–based NER methods have significantly improved model performance. These methods leverage the powerful computational capabilities of neural networks to automatically learn high–dimensional latent semantic information, thereby reducing dependence on manual feature engineering. In recent years, the development of LLMs, such as ChatGPT, has further advanced progress in NER tasks. With larger parameter sizes, LLMs have demonstrated great performance in NER tasks [69]. However, LLMs are essentially generative models with hallucination problems and limited adaptability to domain tasks, and their performance on NER tasks is still much lower than supervised baselines [70]. Therefore, it is difficult to achieve the desired results by directly using LLMs for risk event extraction.

Although LLMs cannot directly replace supervised learning models for NER tasks, they possess powerful natural language understanding, generation, and information extraction capabilities, and coalesce a rich knowledge base based on large–scale corpora, providing new possibilities for efficiently generating labeled data. In NER tasks, the quality and scale of annotated data are crucial to the performance of the model, while the traditional manual annotation approach is time–consuming and laborious, and the annotation cost is more significant, especially in tasks with high domain knowledge requirements. Meanwhile, prompt is the bridge connecting the LLMs and application, and the good or bad use of prompt directly affects the final performance of the big model [71]. To address these challenges, this study expands the application of LLMs–based systems and proposes a simple and effective module for text annotation based on LLMs (see Fig. 1) to support risk event extraction tasks. The integration of LLMs is primarily motivated by their pre-training on large–scale corpora, which enables them to comprehend complex contextual semantics and infer potential entity categories within the text [72]. By designing refined prompts, the framework guides the model to understand and annotate target entities in the text.

(1) Label list

The label list specifies the core entity categories to be identified in risk events and their detailed definitions. The design of each label aligns with the specific characteristics and objectives of the task, ensuring coverage of critical elements such as causes of the event, affected objects, environmental conditions, and time and location. This provides a clear categorical framework for the annotation task.

(2) Annotation rules

Annotation rules standardize the annotation behavior of LLMs, including criteria for selecting entity fragments, handling of multiple fragments, and output formats in cases of no content. These rules are tailored to task requirements, ensuring accuracy, consistency, and formatted outputs for annotated results, thereby providing high–quality input data for subsequent NER model training.

Compared to traditional methods that rely entirely on manual annotation, the use of LLMs for generating annotated data significantly improves efficiency. It not only captures explicit information in the text but also extracts implicit semantic relationships through prompt guidance. Considering the potential "hallucination" issues that may arise during the annotation process, this study introduces a human–machine collaborative annotation mechanism, integrating LLMs' automated annotations with expert review to establish a closed–loop annotation optimization process. Specifically, the initial annotations generated by LLMs are first cross–validated using another large model to detect inconsistencies and potential errors. Subsequently, domain experts review and refine the annotations, with the revised results used to optimize prompt design. This closed–loop mechanism enables effective synergy between machine intelligence and domain expertise, thereby improving both the efficiency and accuracy of text annotation. Notably, it plays a critical role in addressing terminology ambiguity—a common challenge in the emergency management domain. When the LLM produces ambiguous or contextually incorrect annotations (e.g., interpreting "封锁" as a traffic control measure rather than a supply chain disruption), such instances are systematically identified and corrected during the expert review phase. The corrected annotations, along with the experts' contextual justifications, are then fed back into the system to iteratively refine the prompting strategies and annotation rules. Through this iterative process, domain–specific knowledge is progressively integrated, enabling the framework to adapt to the nuanced use of technical terms. As a result, the mechanism functions not only as an annotation optimizer but also as a structured approach for active terminology disambiguation and knowledge incorporation.

Furthermore, the high–quality annotated data is used to train a BERT–BiLSTM–CRF model. This model, combining the knowledge augmentation capabilities of LLMs with the strengths of supervised learning, not only addresses the challenges of annotation efficiency and accuracy but also substantially improves the performance of NER in risk event extraction tasks. This provides an efficient and reliable solution for data annotation in complex domain–specific tasks.

4.2. Ontology–based scenario construction model for resilience feature recognition

To systematically capture and analyze dynamic risk scenarios, an ontology–based model is proposed to construct a structured risk scenario library and identify resilience features. This subsection details the scenario construction process and resilience feature recognition framework.

4.2.1. Risk scenario construction

To provide a comprehensive understanding of EMSS response capabilities in different risk scenarios, and to provide insights into the characterization of EMSS resilience, scenario construction methods need to be used to capture and analyze the dynamic changes and complexities of EMSS risk scenarios based on multi–source text data and multi–expert knowledge. With the advantage of supporting the construction of semantically dense and highly expressive risk scenarios, the issues, nodes, constraints, and annotations ($<I–N–C–A>$) ontology representation model [73,74] is developed to extract the risk scenario elements and construct a risk scenario library. By utilizing the model, core issues and key elements within risk scenarios can be systematically identified and organized. It allows for a precise expression of the interrelationships and constraints among various elements, thus facilitating the construction of a risk scenario library. This structured scenario data support is essential for the subsequent extraction of resilience features, offering a systematic and detailed representation of the risk scenarios.

By employing the ⟨I–N–C–A⟩ ontology representation model, the complex risk scenarios faced by the EMSS are distilled into four fundamental elements, namely, *Issues, Nodes, Constraints*, and *Annotations*. The formulation of each element is detailed as follows.

(1) Issues

These represent the meta–level characterization of risk events, functioning as the contextual framework that defines the scope and parameters of the entire scenario. The *Issues* element specifies the fundamental attributes of the risk scenarios—including its typological classification, spatiotemporal coordinates, and application domain—without detailing the internal structural components. It serves as the essential reference point that answers the questions of 'what general type of event has occurred', 'when and where it took place', and 'in what operational context it is situated'. This meta–perspective ensures consistent framing of diverse risk scenarios, enabling systematic comparison while maintaining conceptual separation from the intra–scenario entities analyzed at subsequent stages. The formal expression is

$$\begin{aligned}\text{Issues}\{<\ & id : I0001,\\ & name : XXX,\\ & type\_dis : COVID-19,\\ & time : \text{'2020.1.6'},\\ & address : \text{'}SCity\text{'},\\ & application : \text{'}Decision\text{'}\\ & > ((attribute\ items\,[attribute-qualifiers]), value)\},\end{aligned} \tag{6}$$

where "id" refers to the unique identifier of the issue; "name" denotes the designation of the risk scenario; "type_dis" specifies the risk event type; "time" records the timing of the occurrence of the risk event; "address" is the geographic location where the risk event occurs; and "application" indicates the domain of case applicability, which, in this instance, pertains to the safeguarding of emergency supplies.

(2) Nodes

These represent the constituent entities operating within the contextual framework established by the Issues element, constituting the interactive components that drive dynamic scenarios. Nodes are categorized into two distinct ontological types based on disaster theory: hazard agents and vulnerable receptors. Crucially, Nodes represent the concrete entities within the event context, rather than the overarching event category itself. The formal expression is

$$\begin{aligned}\text{Nodes}\{<\quad & \text{id}: N0001,\\ & \text{name}: XXX,\\ & \text{type}: (\text{‘}\textit{hazardagents}\text{’}, \text{‘}\textit{vulnerablereceptors}\text{’}),\\ & >((\text{attribute items}[\text{attribute - qualifiers}]), \text{value})\},\end{aligned} \tag{7}$$

where “id” is the number assigned to the node; “name” is the name of the node; and “type” indicates the role of the entity in the scenario.

(3) Constraints

These represent the normative scenario constraint elements that affect the selection of evolutionary paths for nodes during the development of the major risk events. These include rule constraints, response constraints, and time constraints, where time constraints are included in rule constraints and response constraints. The formal expression is

$$\begin{aligned}\text{Constraints}\{<\quad & \text{id}: C0001,\\ & \text{name}: XXX,\\ & \text{rule constraints}: [\textit{type}, \textit{elements}, \textit{time}],\\ & \text{response constraints}: [\textit{peoplenumber}, \textit{materialresources}, \textit{transportation}, \textit{time}]\},\end{aligned} \tag{8}$$

where “id” is the constraint number; “name” is the constraint name; “rule constraints” are the constraints imposed by rules; “type” is the type of rule constraint; “elements” are the pairs of scenario elements that are affected by the rule constraints; “time” is the period that the rule constraints apply to; “response constraints” are the constraints imposed by responses, mainly referring to the emergency measures taken during the occurrence of the risk event; “people number” is the number of people involved in the response; “material resources” are the resources used in the response; “transportation” is the means of transportation used in the response; and “time” is the period to which the response constraints applies.

(4) Annotations

These represent the scenario attribute elements of the nodes in the risk scenario, i.e., the collection of different performance carriers presented by nodes under constraints. Let h (h_1, h_2, …, h_m) be the attribute list of hazard agents; for example, regarding an epidemic, these include the susceptible population, the infected population, and the incubation population. Let a (a_1, a_2, …, a_n) be the attribute list of vulnerable receptors; for example, regarding the material support infrastructure, these include physical elements, informational elements, and management elements. Each attribute is described by a tuple (*values, timestamp*), where *values* represents the specific values of the attribute and *timestamp* represents the effective date of the identified attribute.

Taking the public health emergency as an example, the scenario covers a series of complex processes from the prediction of demand for emergency materials at the early stage of the outbreak of an infectious disease to the deployment and distribution of materials at later stages. In this scenario, “Issues” refer to the overarching description of the risk event itself, specifying the fundamental characteristics such as the event type (e.g., public health crisis), temporal and spatial parameters, and application domain; “Nodes” represent the specific entities that interact within the context defined by the *Issues*, including hospitals and emergency response teams as vulnerable receptors and material stockpiles as hazard agents; “Constraints” cover the operational limitations such as material variety, quantities, and distribution timelines; and “Annotations” denote the specific behaviors of these nodes and constraints within given spatial and temporal contexts. It is important to note that while the initial identification of these elements from textual data involves expert judgment, the structured ⟨I–N–C–A⟩ framework provides clear classification criteria that minimize subjective interpretation by distinguishing between the event’s defining characteristics (*Issues*) and the constituent entities within the events (*Nodes*). Through comprehensive modeling and analysis of the risk scenario, the resilience features of the EMSS against unforeseen public health emergencies are explored thoroughly to lay a scientific foundation for improving emergency material support strategies. The formal expression of the above four elements can be adjusted by adding or removing items as needed, while preserving the conceptual distinction between the scenario’s defining framework and its internal components, to ensure both flexibility and analytical consistency in risk scenario representation.

4.2.2. *“Scenario–task–capability” analysis framework*

The construction of the “scenario–task–capability” analysis framework is essential for addressing the dynamic interplay between risk scenarios, governance tasks, and system capabilities, particularly within the context of complex, multiple stakeholder systems like EMSS. As shown in Fig. 1, this analysis framework provides a systematic approach to understanding how risk scenarios lead to governance demands and how these demands are met through the alignment of tasks and capabilities.

The starting point of the framework is the risk scenario, which serves as the foundation for understanding potential losses and governance needs. Risk scenarios emerge from the interaction of hazard agents, hazard–prone environments, and vulnerable receptors, as depicted in Fig. 2. These elements collectively determine the type and scale of risk events faced by the EMSS. By systematically analyzing these scenarios, stakeholders can identify critical challenges and their implications, forming the basis for defining governance tasks.

Subsequently, the task identification process bridges the gap between risk scenarios and the responses required to address them. Governance tasks are developed to mitigate potential losses and meet the demands arising from the identified scenarios. These tasks must be precisely defined and tailored to the characteristics of risk scenario, ensuring a targeted and effective response. Given that EMSS operates within a multiple stakeholder context, including government departments, enterprises, social organizations, and community residents, the framework for resilience feature recognition focuses on systematically identifying and organizing resilience–related criteria by analyzing the diverse objectives and requirements of these stakeholders. This is achieved by abstracting dynamic risk scenarios into structured scenario elements and aligning them with governance tasks and system capabilities, ensuring that the final criterion system comprehensively reflects the multifaceted nature of EMSS resilience.

Furthermore, the framework emphasizes the critical role of capability building in ensuring that the system can fulfill the identified

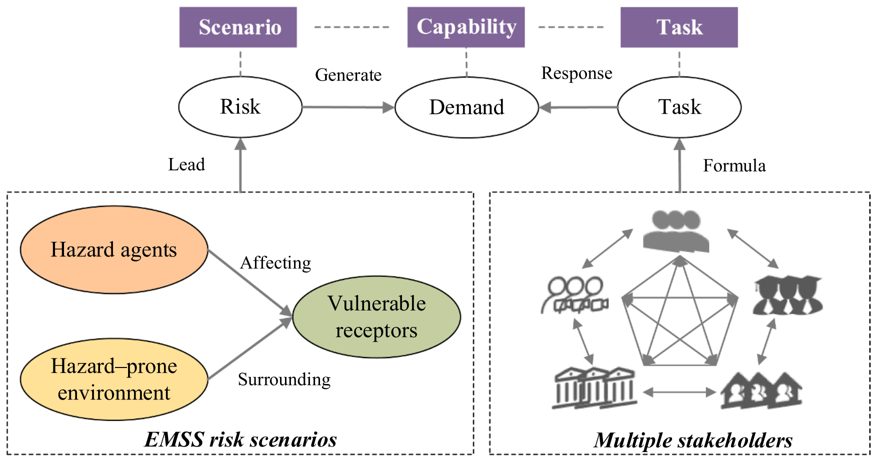

Fig. 2. "Scenario–task–capability" analysis process.

governance tasks. The successful implementation of tasks depends on whether the system capabilities are aligned with the demands posed by risk scenarios. The framework thus guides the inductive identification of key system capabilities through the analysis of multiple, diverse risk scenarios. By synthesizing and comparing the tasks and required capabilities in different scenarios, the core resilience features of EMSS are extracted and constructed into a hierarchical criterion system for resilience assessment. Moreover, capability building is not only reactive but also forward–looking, as it underpins the system resilience by equipping it to handle future uncertainties and dynamic risks effectively.

4.3. Feature–matching DHF–MEE model for resilience quantitative assessment

To support the quantitative assessment for EMSS resilience in a dynamic uncertain decision–making environment, a feature–matching DHF–MEE model is developed. This model leverages the resilience features extracted in the previous stages to build a robust and adaptable quantitative assessment framework. This subsection demonstrates the details of the DHF–MEE model and illustrates its application.

4.3.1. Definition of hesitant fuzzy matter element

The MEE model combines matter element and extension theories enabling the combination of complex criteria for comprehensive assessment, in which an ordered triad of "matter, feature, and value" is used to construct a "matter element" that describes the object to be assessed. Suppose that the EMSS resilience is N, the criterion set for EMSS resilience assessment is X, and the values of the criteria are V, then the basic matter–element R of the EMSS resilience can be expressed by the ordered triad:

$$R = [N, X, V]. \tag{9}$$

As described previously, given the uncertainty that usually exists at the boundaries and levels of the criteria for an EMSS resilience assessment, traditional methods may not be enough to capture the dynamic uncertainty. To describe this uncertainty more completely, HFS theory is applied to extend the classic MEE model. Xia and Xu [50] provided a mathematical expression for HFS and introduced the concept of hesitant fuzzy elements (HFEs) to express the HFS more precisely. Let $X = \{x_1, x_2, ..., x_p\}$ be a reference set, i.e., the criterion set for EMSS resilience assessment. A hesitant fuzzy set on X, denoted by A, is characterized by a function $g_A : X \to \mathscr{P}([0,1])$, which returns a set of possible values for each element $x_i \in X$. This HFS can be written in the following form:

$$A = \{ < x_i, g_A(x_i) > | x_i \in X, i = 1, 2, \ldots, p\}, \tag{10}$$

where $g_A(x_i)$ is called a HFE, representing the possible degrees to which x_i belongs to the set A. When each HFE contains only one value, the HFS degenerates into a classical fuzzy set.

In the context of EMSS resilience assessment, assuming that the HFS of criterion set X is M, and the corresponding HFE of each criterion x_i is denoted as $m(x_i)$, $i = 1, 2, ..., p$, the hesitant fuzzy matter element (HF–ME) of EMSS resilience can be expressed as follows:

$$R = [N, X, M] = \begin{bmatrix} N & x_1 & m(x_1) \\ & x_2 & m(x_2) \\ & \vdots & \vdots \\ & x_p & m(x_p) \end{bmatrix}. \tag{11}$$

The HF–ME allows the mapping of each assessment criterion to a collection of possible values rather than just a single value. By dealing with the uncertainty and hesitancy of information, the uncertainty and bias of experts can be reduced, thus improving the reliability and validity of the EMSS resilience assessment results.

4.3.2. Main procedures of the proposed DHF–MEE model

The main procedures of the proposed DHF–MEE model are illustrated step by step.

Step 1: Determine compound resilience DHF–ME.

Let the resilience level of EMSS at time t be N_t, $t = 1, 2, \ldots, k$, the HFE of each criterion x_i at time t is $m_t(x_i)$, $i = 1, 2, \ldots, p$, then the compound DHF–ME R_{pk} of EMSS resilience is defined as

$$R_{pk} = \begin{bmatrix} & N \\ X & M \end{bmatrix} = \begin{bmatrix} & N_1 & N_2 & \cdots & N_k \\ x_1 & m_1(x_1) & m_2(x_1) & \ldots & m_k(x_1) \\ x_2 & m_1(x_2) & m_2(x_2) & \cdots & m_k(x_2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_p & m_1(x_p) & m_2(x_p) & \cdots & m_k(x_p) \end{bmatrix}. \tag{12}$$

Step 2: Determine the matter element to be assessed and the extension domain.

The ME of the EMSS resilience N_t at the time t to be assessed is defined as R_t.

$$R_t = \begin{bmatrix} & N_t \\ x_1 & m_t(x_1) \\ x_2 & m_t(x_2) \\ \vdots & \vdots \\ x_p & m_t(x_p) \end{bmatrix}, \quad t = 1, 2, \ldots, k. \tag{13}$$

The proposed DHF–MEE model categorizes the assessment results of EMSS resilience into l levels, such as "excellent," "good," "medium," "qualified," and "poor." In the model, the extension domain is used to represent the ideal membership for each criterion in the set X at different resilience levels. Specifically, let $< a_i, b_i >$ be the ideal membership interval of the criterion x_i for the resilience level j, $i = 1,2,...,p$, $j = 1,2,...,l$. Then, the extension domain is defined as R_j.

$$R_j = \begin{bmatrix} & N_t \\ x_1 & < a_{1j}, b_{1j} > \\ x_2 & < a_{2j}, b_{2j} > \\ \vdots & \vdots \\ x_p & < a_{pj}, b_{pj} > \end{bmatrix}, \quad j = 1, 2, ..., l. \tag{14}$$

Following the principles in extension theory, the notation $< a_i, b_i >$ may denote an open interval, a closed interval, or a half–open, half–closed interval, $i = 1, 2, ..., p$.

Step 3: Determine the extension distance and the degree of extension correlation.

The extension distance is a concept in extension theory designed to describe the difference between objects within a class. Considering the multivalued nature and uncertainty of the HFE $m_t(x_i)$, the modified Hausdorff distance (MHD) base was chosen to define the extension distance function. The MHD can capture the overall differences between sets comprehensively, not just the distances of single elements, and is highly robust to outliers. According to the MHD definition of Dubuisson and Jain [75], the extension distance function is defined as follows:

$$D_t(\Gamma, \Theta) = \max[d(\Gamma, \Theta), d(\Theta, \Gamma)], t = 1, 2, \dots, k, \tag{15}$$

where Γ is the HFE of the criterion x_i at time t and is a finite set of discrete points, $i = 1,2,...,p$, $t = 1,2,\dots,k$; Θ is the set that contains the upper and lower bounds of the ideal membership interval of x_i at the resilience level j, $i = 1,2,...,p$, $j = 1,2,...,l$; $d(A,B)$ and $d(B,A)$ are forward MHD and backward MHD. The directed distance of the MHD is calculated as follows:

$$d(\Gamma, \Theta) = \frac{1}{N_A} \sum_{a \in \Gamma} \min_{b \in \Theta} \| a - b \|_z, \tag{16}$$

$$\| \mathbf{x} \| = \left(\sum_{i=1}^{p} |x_i|^z \right)^{1/z}, \tag{17}$$

where $\| \cdot \|_z$ is the vector norm, z is the order of the norm. The norm method can accommodate different needs by varying the order of the norm. For instance, the Euclidean norm corresponds to $z = 2$. The distance between two sets of points, $d(\Gamma, \Theta)$, is obtained by averaging the distances from each point a in Γ to its closest point b in Θ.

In extension theory, extension relevance helps to determine the degree of match between an element and a predefined set of ideals or criteria. $K_t^j(x_i)$ is the extension correlation degree of the assessment criterion x_i for the resilience level j at time t, which is calculated as

$$K_t^j(x_i) = 1 - D_t(\Gamma, \Theta), i = 1, 2, ..., p, j = 1, 2, ..., l, t = 1, 2, \dots, k. \tag{18}$$

The extension correlation degree is negatively correlated with the extension distance: the shorter the distance, the higher the correlation degree, indicating that the actual situation is closer to the ideal criteria.

Step 4: Determine the comprehensive degree of correlation and the resilience level.

The comprehensive correlation degree refers to the extension correlation degree between objects and different resilience levels.

$$K_t^j(N_t) = \sum_{i=1}^{p} w_i K_t^j(x_i), i = 1, 2, ..., p, j = 1, 2, ..., l, t = 1, 2, \dots, k, \tag{19}$$

where $K_t^j(N_t)$ represents the comprehensive correlation degree of the object N_t to be assessed for the resilience level j at time t; $K_t^j(x_i)$ represents the extension correlation degree of the assessment criterion x_i for the resilience level j at time t; w_i represents the weight of each criterion and satisfies $\sum_{i=1}^{p} w_i = 1$, which was calculated by hesitant analytic hierarchy analysis (HAHP). This not only accepts the structured decision–making framework of traditional AHP but also allows the inclusion of hesitancy in the assessment process, which can improve the accuracy of weight calculation. The specific calculation process of HAHP can be referred to in the study by Zhu et al. [76].

In the proposed DHF–MEE model, the principle of maximum correlation degree is used. If $K_t^\beta(x_\alpha) = \max\left(K_t^j(x_i)\right)$, this means that the criterion x_α of the EMSS reaches the resilience level β; if $K_t^\beta(N_t) = \max\left(K_t^j(N_t)\right)$, which means that the matter–element N_t to be assessed reaches the resilience level β at time t, $\alpha, i = 1,2,...,p$, $\beta, j = 1,2,...,l$, $t = 1, 2, \dots, k$. Following the above principle, the scientific and reasonable assessment results of the EMSS resilience level can then be finalized.

5. Case study

In this section, a case study was conducted to demonstrate how the developed data–intelligence–driven three–stage dynamic model for EMSS resilience assessment can be applied to real–world EMSS risk scenarios, to analyze the resilience assessment results, to validate the performance and robustness of the proposed model by method comparative analysis, and provide corresponding suggestions for resilience improvement.

5.1. Scenario construction

Major risk events are characterized by high uncertainty, significant social harm, and wide–ranging impacts, which impose stricter requirements for policy precision in risk responses. Considering the timeliness, completeness, and authority of data, this study selects data from press conferences in China for case analysis. Press conference data balances official narratives and public concerns, providing a more reliable foundation for systematically analyzing EMSS resilience features. Furthermore, the diversity of press conference stakeholders allows this study to classify them into six categories: press spokespeople, government departments, experts, social organizations, news reporters, and community staff. It is important to note that while direct representatives from private enterprises are not typically present as formal speakers at official government press conferences, their operational roles and contributions are often reflected through the statements of government departments and industry experts who are frequently affiliated with or represent enterprise perspectives. For risk event extraction, this study employs Alibaba's Qwen2.5 LLMs, which is known for its superior ability to understand Chinese language and process structured data [77].

In this case study, two typical risk scenarios were considered: natural disasters and public health emergencies. Regarding the natural disaster scenario, the *720 Henan rainstorm*, which occurred in Henan Province of China in July 2021 was taken as an example. The storm caused great economic losses and human casualties, especially in Zhengzhou City. In this scenario, EMSS resilience, particularly in terms of early warnings, rescue material stockpiling, and rapid response, was put to a severe test. This scenario uses the verbatim transcripts of press conferences held by the People's Government of Henan Province and its prefecture–level cities between July 21, 2021 and August 4, 2021 as the source of risk text data.

For the public health emergency scenario, the range of responses since the *COVID–19 pandemic* outbreak was reviewed. Taking Wuhan (the initial outbreak site) as an example, the decision–makers in municipal government adopted unprecedented measures to seal off the city, which slowed down the spread of the pandemic effectively. This measure also posed an unprecedented challenge for the EMSS, especially in ensuring the provision of medical supplies and daily necessities. This scenario uses the verbatim transcripts of press conferences held by China's State Council Joint Prevention and Control Mechanism between January 22, 2020 and November 5, 2022 as the source of risk text data.

By extracting risk events and constructing scenarios for these two typical risk scenarios, an EMSS risk scenario library that contains natural disasters and public health emergencies was constructed based on multi–source text data and multi–expert knowledge. Each scenario involved different risk factors, response tasks, and response measures, which imply different requirements for EMSS resilience. Based on a detailed analysis of these scenarios, a deeper understanding of EMSS resilience features in different risk scenarios can be gained. As shown in Fig. 3, in an ELG for risk scenario of *720 Henan rainstorm*, the main transmission nodes of hazard agents to the vulnerable receptors include urban transportation system, electricity supply network, and communication network. Specifically, each line segment and its accompanying arrow in Fig. 3 label the directionality of the causal relationship, where the arrow points from "cause" to "effect." The risk scenario elements of EMSS are expressed in Table 2.

As shown in Fig. 4, in the risk scenario of the *COVID–19 pandemic*, the main transmission nodes of hazard agents to the vulnerable receptors include rice, frozen meat, and vegetables. The risk scenario elements of the EMSS are expressed in Table 3.

5.2. Criterion system construction

The criterion system for EMSS resilience assessment is constructed based on resilience feature extraction, and the details of the analysis process and finalized criteria are elaborated as follows.

5.2.1. Demonstration of criterion determination

As mentioned previously, complex EMSS risk scenarios were abstracted into a set of scenario elements with a hierarchical structure, which included a wealth of information. In response to the demands for improved storage for emergency supplies, rational resource allocation, and effective quality management, a comprehensive risk response process including pre–event prevention, mid–event response, and post–event recovery was designed. Based on a systematic literature review and two rounds of expert interviews, three dimensions of resilience were finalized, namely, *Withstanding capacity* (B_1), *Recovery capacity* (B_2), and

Table 2
EMSS risk scenario elements in the *720 Henan rainstorm*.

Element	Expression
Issues	<id: *I01*, name: *Example scenario*, type_dis: *Rainstorm*, time: *2021.7.20*, address: *Henan*, application: *Emergency material security*>
Nodes	<id: *N01*, name: *Example scenario*, type: (*Hazard agents, Vulnerable receptors*) > (attribute items [*Rainstorm – Farmland and crops / Urban transportation system / Electricity supply network / Communication network / Social public order*])
Constraints	<id: *C01*, name: *Example scenario*, rule constraints: [*Rainstorm, Inadequate urban drainage, 2021.7.20*], respond constraints: [*14.786 million people, Resident safety / Farmland and crops / Urban commuters / Business activities / Urban transportation system / Social public order*]>
Annotation	(*Drainage difficulty, Heavy precipitation, 2021.07.20*)

Adaptation capacity (B_3). Following the analysis framework of "scenario–task–capability", a criterion system for EMSS resilience assessment was constructed with a hierarchical structure consisting of a "goal layer, dimension layer, and criterion layer."

Taking the criterion involved in the dimension of *Withstanding capacity* (B_1), i.e., *Emergency supply sufficiency* (X_1), as an example, the process of criterion determination is described as follows. As shown in Fig. 5, an analysis was conducted on two specific risk scenarios: one was the *720 Henan rainstorm*, involving the stock levels of critical supplies such as water, food, and medical supplies; the other was the *COVID–19 pandemic* in Wuhan, focusing on the inventory management of medical and protective supplies.

In these scenarios, two major risk factors—supply chain disruptions and surges in demand—were identified, and detailed scenario element representations were constructed. In the task identification session, various tasks related to these scenarios were listed, including management of critical supplies inventory, inventory audit, and supply chain diversification. Among these tasks, the management of critical supplies inventory and inventory audit were specifically selected as key tasks based on the feedback of expert interviews, as they form the basis for ensuring that critical supplies meet demand during emergencies.

Once the key tasks were determined, the key capabilities required to execute these tasks were identified in the capability–building session. The inventory management capability allows for the real–time tracking and updating of the inventory status of critical materials, ensuring the accuracy and timeliness of inventory data. This includes continuous monitoring of essential supplies such as water, food, and medical products. Rapid replenishment capability is a system's ability to act

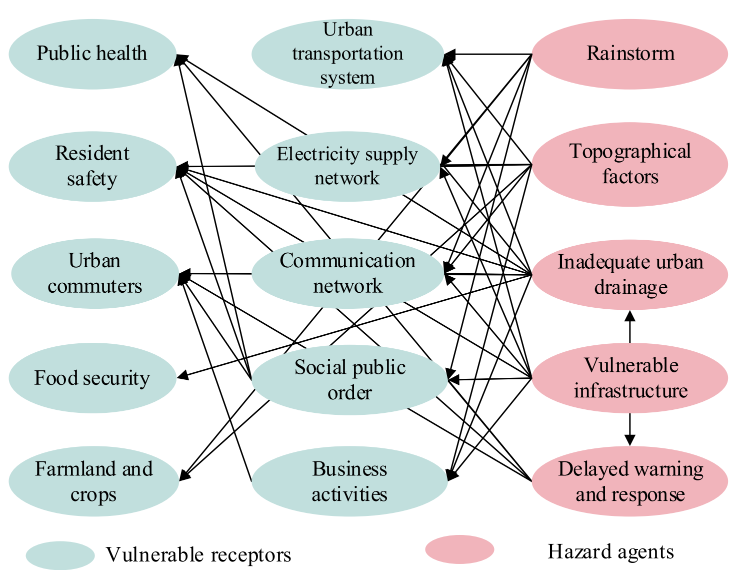

Fig. 3. Node relationship in the risk scenario of the *720 Henan rainstorm*.

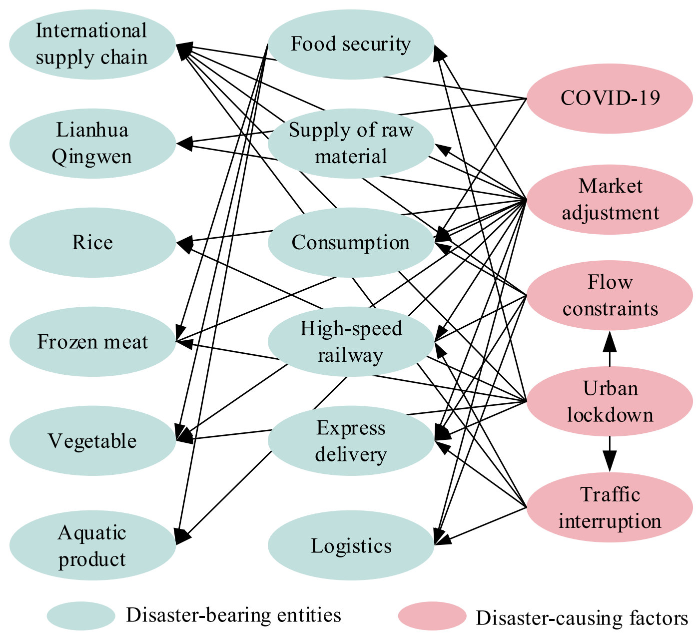

Fig. 4. Node relationship in the risk scenario of the *COVID–19 pandemic*.

Table 3
EMSS risk scenario elements in the *COVID–19 pandemic*.

Element	Expression
Issues	<id: *I02*, name: *Example scenario*, type_dis: *COVID–19 pandemic*, time: *2020.2.5*, address: *Wuhan*, application: *Emergency supplies security*>
Node	<id: *N02*, name: *Example scenario*, type: (*Hazard agents, Vulnerable receptors*) > (attribute items [*Urban lockdown – Rice / Frozen meat / Vegetables / Food security / International supply chain / Express Delivery*])
Constraints	<id: *C02*, name: *Example scenario*, rule constraints: [*COVID–19 pandemic, Urban lockdown – Rice, 2020.1.23 to 2020.4.8*], respond constraints: [*13.73 million people, Rice / Frozen meat / Vegetables / Aquatic products, Express delivery / High–speed railway*]>
Annotation	(*Physical element, Information element, Management element, 2020.2.5*)

quickly to restock when inventory levels fall below predetermined safety thresholds, which requires close collaboration with suppliers and effective logistical support. Establishing these capabilities ensures the effective provision of critical emergency materials. Subsequently, a key feature for EMSS resilience was extracted: inventory persistence. This feature measures the ability of the EMSS inventory system to supply necessary materials continuously in the face of demand fluctuations or supply interruptions. It reflects the adaptability and efficiency of the EMSS in addressing both sudden and sustained demands. Finally, this resilience feature, i.e., inventory persistence, translates directly into a specific assessment criterion: *Emergency supply sufficiency* (X_1). This criterion is measured by the effective implementation of real–time inventory monitoring and rapid replenishment responses, assessing whether critical emergency supplies can meet continuous and emergent needs.

5.2.2. Finalized criterion system

The "scenario–task–capability" analysis process ensures that the transition from scenario element representations to criteria is not only systematic but also highly specific, allowing for precise assessment and improvement suggestions for EMSS resilience. Following the aforementioned demonstration, a hierarchical criterion system for EMSS resilience assessment was finalized (Table 4), comprising three dimensions and twelve criteria X_i, $i = 1, 2, \ldots, 12$. Tables A.1–A.3, which are presented in Appendix A, show the criteria for an EMSS resilience assessment under different dimension layers derived from the transformation of scenario element representations. This structured approach facilitates a thorough EMSS resilience assessment across various scenarios, ensuring that all relevant features are considered and addressed effectively.

5.3. Assessment data collection

In this case study, EMSS resilience assessment on six sample cities in J Province of China denoted as Cities A, B, C, D, E, and F, was conducted based on data from 2019 to 2024. To ensure the reliability and multidisciplinary validity of the assessment, seven domain experts (denoted as I, II, …, VII) were systematically selected according to the following criteria: (1) professional expertise in emergency management, disaster response, supply chain logistics, or risk assessment; (2) a minimum of 10 years of practical or research experience in related fields; and (3) possession of advanced academic qualifications (e.g., master's or doctoral degrees) and senior professional positions. As detailed in Table 5, the experts possess 10 to 22 years of professional experience, hold advanced degrees in relevant fields, and occupy key positions such as directors, senior engineers, and professors. These experts provided their assessments in the form of hesitant fuzzy numbers on a percentage scale, allowing for a set of possible values to reflect their uncertainty and hesitation regarding various resilience criteria of EMSS.

By systematically integrating and normalizing the knowledge data from the seven experts, the hesitant fuzzy assessment information for the EMSS resilience assessment of each city was determined across different periods. Taking the multi–expert knowledge collected from expert I in 2019 and 2024 as an example, the hesitant fuzzy assessment information for City A is shown in Table 6.

In the constructed criterion system for EMSS resilience assessment, each criterion plays a vital role and holds significant importance. To accommodate the experts' potential hesitation or uncertainty in their assessments, their relative importance judgments for these criteria were collected using a hesitant fuzzy judgment matrix. The weights for each criterion were then calculated using the HAHP method. For instance, the hesitant fuzzy judgment for criterion weights from expert I is displayed in Table 7. Additionally, referring to the design concept of the urban disaster resilience scorecard developed by the United Nations [78], EMSS resilience is divided into five levels (ranking from high to low): "High", "Good", "Normal", "Limited", and "Fragile", and the scoring for

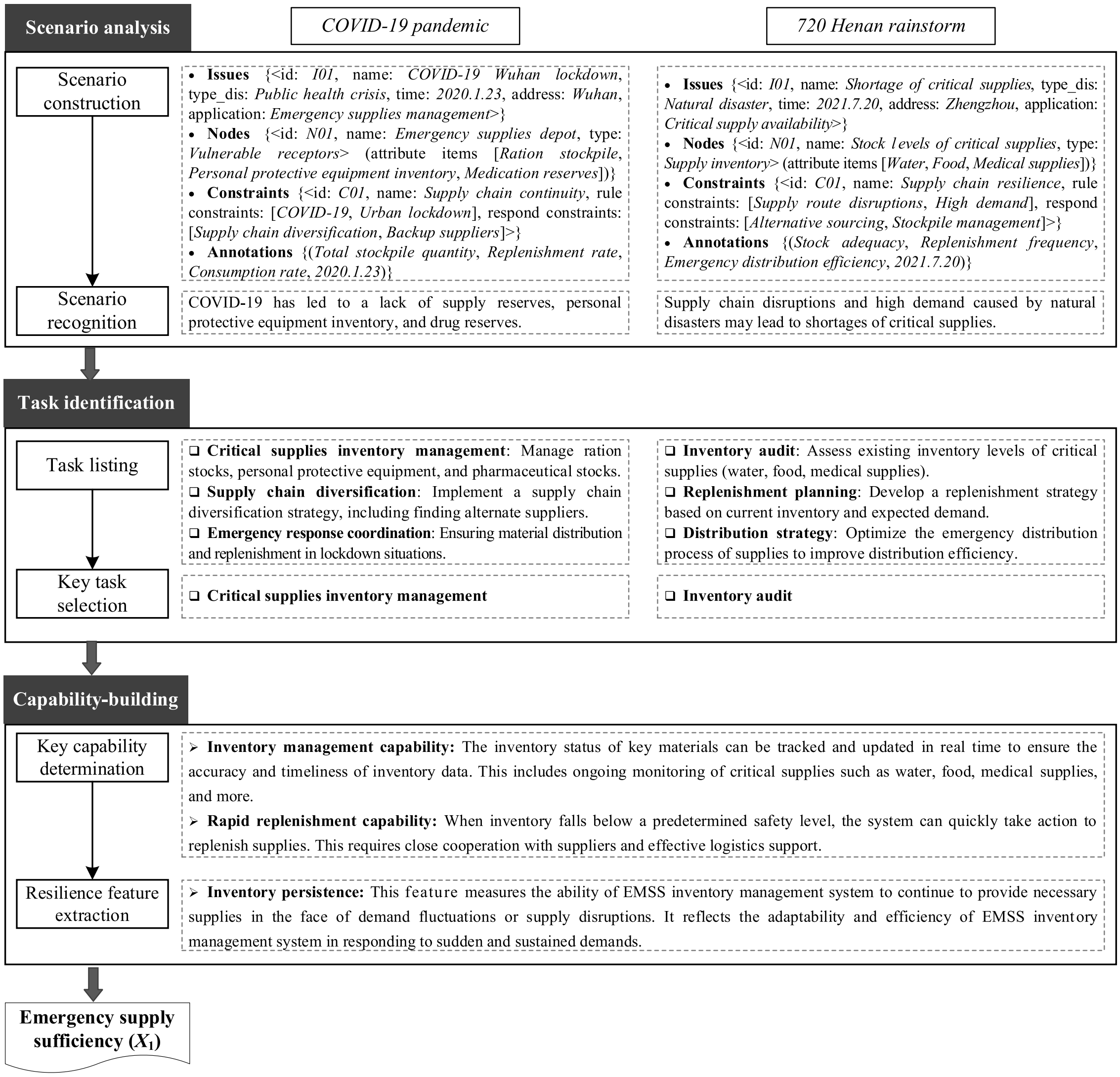

Fig. 5. "Scenario–task–capability" analysis process of the criterion emergency supply sufficiency (X_1).

Table 4
Hierarchical criterion system for EMSS resilience assessment.

Dimensions	Criteria
Withstanding capacity (B_1)	Emergency supply sufficiency (X_1)
	Supply category allocation (X_2)
	Warehouse infrastructure quality (X_3)
	Warehouse efficiency (X_4)
Recovering capacity (B_2)	Emergency response timeliness (X_5)
	Supply–demand forecasting (X_6)
	Safety information sharing (X_7)
	Staff reliability (X_8)
Adaptive capacity (B_3)	Inventory cost reduction (X_9)
	Vendor risk sharing (X_{10})
	Risk review capability (X_{11})
	Interdepartmental collaboration (X_{12})

each resilience level is shown in Table 8.

5.4. Resilience assessment results

The results of the EMSS resilience assessment for the six sample cities in J Province from 2019 to 2024 are shown in Table 9. The weights of the assessment criteria were 0.0827, 0.077, 0.076, 0.098, 0.082, 0.089, 0.079, 0.082, 0.085, 0.079, 0.083, and 0.083. As shown in Fig. 6, the overall profile of EMSS resilience is upward, i.e., the EMSS resilience of the six sample cities has improved or at least remained the same, but there are some differences. This suggests that the EMSS construction efforts in J Province are effective in improving the cities' capability for emergency supplies security.

From a horizontal comparison perspective, the EMSS construction of Cities C and E was almost complete in 2019, which meant it could respond better to risk events, and resilience level was at "Normal". However, the EMSS construction of City F was still in its initial stage. In 2021, the resilience level of the six sample cities rose to "Good". This indicates that in that year, the EMSS construction of the six cities had improved significantly. This might be due to some major risk events that occurred in 2021, such as the *COVID–19 pandemic*, which forced these cities to strengthen their work in the reserve, allocation, dispatch, and transportation of emergency supplies, thus improving their EMSS resilience.

From a vertically comparison perspective, although the EMSS resilience of City F was the weakest in 2019, with resilience at "Fragile", the resilience level quickly improved to "Good" in 2021. After 2021, the resilience level remained unchanged, but those at "High" increased steadily every year, which indicates that the EMSS resilience of City F was still improving continuously, that is, the consistency between the resilience level and the actual resilience was high. Similarly, the resilience level of City B jumped from "Limited" in 2019 to "Good" in 2020

Table 5
Profiles of the selected experts in the EMSS resilience assessment.

Expert ID	Affiliation	Position/Title	Years of experience	Educational background	Professional Field
I	Provincial Emergency Management Department	Senior Officer	15	Master of Public Administration	Emergency Response & Planning
II	Provincial Emergency Management Department	Safety Assessment Engineer	12	Master of Safety Engineering	Risk Assessment & Mitigation
III	Provincial Logistics Association	Technical Consultant	20	PhD in Logistics Management	Emergency Logistics
IV	Provincial Disease Control Center	Emergency Response Specialist	18	Master of Epidemiology	Public Health Emergency
V	Provincial Transportation Department	Transport Planning Engineer	16	PhD in Transportation Engineering	Emergency Transport
VI	J University, School of Management	Professor	22	PhD in Management Science	Emergency Management
VII	J University, School of Civil Engineering	Assistant Professor	10	PhD in Civil Engineering	Infrastructure Resilience

Table 6
Hesitant fuzzy assessment information for City A in 2019 and 2024 for example.

Years Criteria	2019	2024
X_1	0.43, 0.44, 0.45	0.9, 0.92
X_2	0.31, 0.3	0.86, 0.88
X_3	0.5, 0.48	0.88
X_4	0.4, 0.42	0.8, 0.75
X_5	0.54, 0.53	0.92, 0.9
X_6	0.3, 0.32, 0.34	0.8
X_7	0.45, 0.46	0.9
X_8	0.68, 0.7	0.97, 0.95
X_9	0.32, 0.35	0.8, 0.78, 0.75
X_{10}	0.15	0.78, 0.8, 0.82
X_{11}	0.43, 0.45	0.95
X_{12}	0.34, 0.32	0.78, 0.77

and then reached “High” in 2024. Cities A, C, D, and E also showed steady resilience improvements over the period. Notably, all four reached “High” in 2024, with comprehensive correlation of 0.8468 (City A), 0.8419 (City C), 0.8479 (City D), and 0.9043 (City E), reflecting robust resilience across the province.

5.5. Comparative analysis

To validate the performance and robustness of the proposed DHF–MEE model, a comparative analysis was conducted against three established multi–criteria decision–making methodologies: the classic MEE model, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, and the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method. This comparison aims to benchmark the proposed model and demonstrate its added value in handling the specific challenges of EMSS resilience assessment.

To ensure a fair and objective comparison, all four methods were applied to the same dataset: the expert judgment data for City A spanning the years from 2019 to 2024. A challenge arose because the classic MEE model, TOPSIS method, and VIKOR method require crisp numerical inputs, whereas the original data in this study are represented as HFSs to capture expert uncertainty and hesitation. To resolve this, we adopted a standard and widely accepted practice: the hesitant fuzzy numbers for each criterion were converted into deterministic values by calculating their arithmetic mean values. This allowed for a direct comparison while preserving the core information from the original assessments.

Taking City A as an example, Table 10 shows the exemplary results of

Table 8
EMSS resilience level and scoring standard.

Resilience level	High	Good	Normal	Limited	Fragile
Score	0.8~1	0.6~0.8	0.4~0.6	0.2~0.4	0~0.2

Table 7
Hesitant fuzzy judgment matrix for criterion weights from expert I.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
X_1	1	2,3	4	1/3, 1/4	3,4,5	1/6,1/7	1/5,1/6	6,7,8	1/4	1/8	1/2,1/3	1/3,1/4
X_2	1/2,1/3	1	1/7,1/8	1/4,1/5	5,6,7	7,8,9	1/5,1/3,1/4	6,7	5	8,9	1/3,1/4,1/5	1/7,1/8
X_3	1/4	7,8	1	7,8	1/8,1/9	1/3,1/4,1/5	2	1/7, 1/8	1/8	3	1/2, 1/3,1/4	1/7
X_4	3,4	4,5	1/7,1/8	1	2,3	5,6	1,1/2,1/3	3,4,5	5,6,7	3,4	1/3,1/4	1/9
X_5	1/3,1/4,1/5	1/5,1/6,1/7	8,9	1/2,1/3	1	3,4	1/4,1/5,1/6	8	1/7,1/8,1/9	4,5	1,1/2	1/4,1/5
X_6	6,7	1/7, 1/8,1/9	3,4,5	1/5,1/6	1/3,1/5	1	6,7,8	1/3,1/4,1/5	1/2,1/3,1/4	5,6	1,1/2,1/3	1/3,1/4
X_7	5,6	2,3,4	1/2	1,2,3	4,5,6	1/6,1/7,1/8	1	2	3,4	1/5,1/7,1/8	1/6	2,3
X_8	1/6,1/7,1/8	1/6,1/7	7,8	1/3,1/4,1/5	1/8	3,4,5	1/2	1	1/4	1,2,3	1/4,1/5,1/6	1/2,1/3
X_9	4	1/5	8	1/5,1/6,1/7	7,8,9	2,3,4	1/3,1/4	4	1	9	1/6,1/7,1/8	5,6,7
X_{10}	8	1/8,1/9	1/3	1/3,1/4	1/4,1/5	1/5,1/6	5,6,7	1,1/2,1/3	1/9	1	1/5	1/7
X_{11}	2,3	3,4,5	2,3,4	3,4	1,2	1,2,3	6	4,5,6	6,7,8	5	1	1/4,1/5
X_{12}	3,4	7,8	7	9	4,5	3,4	1/2,1/3	2,3	1/5,1/6,1/7	7	4,5	1

Table 9
Comprehensive correlation and the resilience assessment results.

City	Year	Fragile	Limited	Normal	Good	High	Resilience level
City A	2019	0.6275	0.7976	**0.8269**	0.6658	0.4675	Normal
	2020	0.5308	0.7309	**0.8446**	0.7485	0.5633	Normal
	2021	0.4168	0.6168	0.8142	**0.8386**	0.6757	Good
	2022	0.3243	0.5243	0.7243	**0.8769**	0.7956	Good
	2023	0.2096	0.4096	0.6096	0.8088	**0.8530**	High
	2024	0.1904	0.3904	0.5905	0.7905	**0.8602**	High
City B	2019	0.6739	**0.8317**	0.7780	0.5879	0.3878	Limited
	2020	0.4244	0.6245	0.8245	**0.8535**	0.6535	Good
	2021	0.3756	0.5757	0.7757	**0.8825**	0.7045	Good
	2022	0.3046	0.5046	0.7046	**0.8930**	0.8060	Good
	2023	0.1845	0.3845	0.5845	0.7845	**0.8977**	High
	2024	0.1645	0.3645	0.5645	0.7646	**0.9026**	High
City C	2019	0.5563	0.7564	**0.8794**	0.7109	0.5108	Normal
	2020	0.4050	0.6050	0.8011	**0.8501**	0.6517	Good
	2021	0.3468	0.5468	0.7468	**0.8968**	0.7156	Good
	2022	0.3074	0.5074	0.7075	**0.8976**	0.7627	Good
	2023	0.2578	0.4578	0.6578	**0.8578**	0.8094	Good
	2024	0.2423	0.4423	0.6423	0.8423	**0.8468**	High
City D	2019	0.7414	**0.8934**	0.7517	0.5517	0.3517	Limited
	2020	0.4909	0.6909	**0.8717**	0.7855	0.5855	Normal
	2021	0.3750	0.5750	0.7750	**0.8864**	0.6965	Good
	2022	0.3242	0.5242	0.7242	**0.9000**	0.7525	Good
	2023	0.2603	0.4603	0.6603	**0.8604**	0.8154	Good
	2024	0.2418	0.4418	0.6418	0.8419	**0.8479**	High
City E	2019	0.5485	0.7486	**0.8993**	0.7689	0.5688	Normal
	2020	0.3782	0.57825	0.7782	**0.8742**	0.6852	Good
	2021	0.3045	0.5046	0.7046	**0.8937**	0.7727	Good
	2022	0.2119	0.4119	0.6119	0.8119	**0.8781**	High
	2023	0.1372	0.3372	0.5373	0.7373	**0.9017**	High
	2024	0.1188	0.3189	0.5189	0.7189	**0.9043**	High
City	Year	Fragile	Limited	Normal	Good	High	Resilience level
City F	2019	**0.8801**	0.7904	0.5903	0.3903	0.1903	Fragile
	2020	0.5522	0.7522	**0.8986**	0.7600	0.5600	Normal
	2021	0.4021	0.6021	0.8021	**0.8712**	0.6712	Good
	2022	0.3359	0.5359	0.7360	**0.9002**	0.7542	Good
	2023	0.2631	0.4631	0.6631	**0.8632**	0.8104	Good
	2024	0.2510	0.4510	0.6510	**0.8510**	0.8496	Good

Note: Bolded values are the maximum comprehensive correlation for the current years, and the corresponding resilience level is the assessment result.

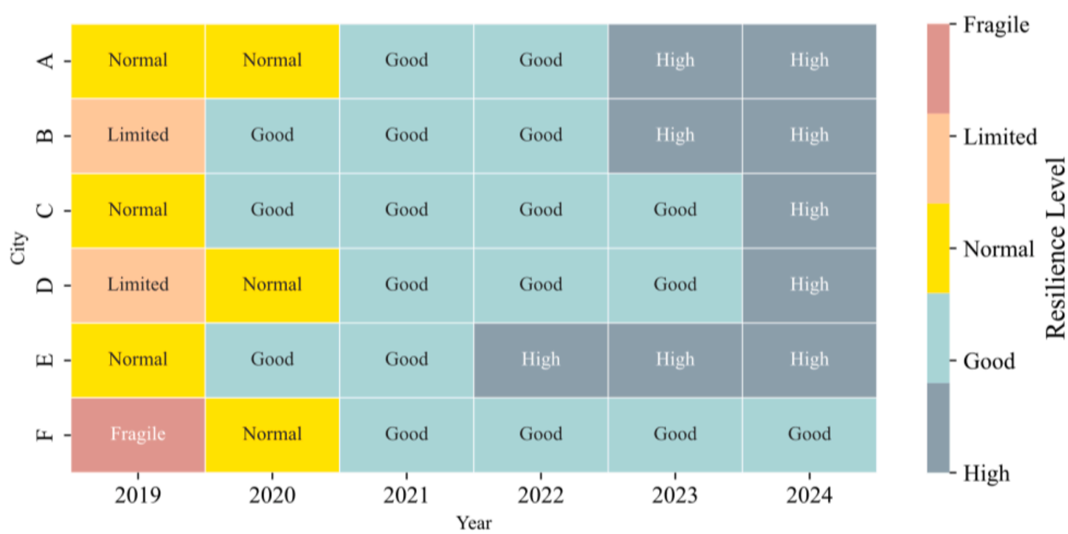

Fig. 6. Resilience levels of J Province from 2019 to 2024.

the four methods for assessing its resilience over the six years. All four methods produce outputs that exhibit a consistent trend over time, strongly validating the conclusion that the EMSS resilience of City A has been steadily improving. For TOPSIS method, the values represent the relative closeness coefficient (C^*), which also ranges from 0 to 1, with a higher value indicating better resilience. For VIKOR method, the values represent the compromise ranking index (Q), where a lower value indicates better resilience. Consequently, the monotonically increasing trend of K and C^* values, coupled with the monotonically decreasing trend of Q values, collectively confirm the improvement of EMSS resilience.

The primary advantage of the proposed DHF–MEE model lies in its ability to handle uncertainty and provide more abundant diagnostic information. By operating in a hesitant fuzzy environment, the

Table 10
Comparative results of EMSS resilience assessment for City A.

Year	DHF–MEE model	MEE model	TOPSIS method	VIKOR method
2019	Normal	Normal	0.45	0.82
2020	Normal	Normal	0.58	0.71
2021	Good	Good	0.72	0.54
2022	Good	Good	0.85	0.38
2023	High	High	0.91	0.19
2024	High	High	0.94	0.12

DHF–MEE model directly incorporates the inherent uncertainty and hesitation in expert judgments, which are simply averaged out in the comparison with the classic MEE model, TOPSIS method, and VIKOR method. While all methods can identify the overall trend, the DHF–MEE model offers a unique diagnostic feature. It can provide the correlation degrees of each individual criterion with each resilience level, allowing decision–makers to pinpoint specific strengths and weaknesses. This provides far more actionable insights for targeted improvements than the single aggregated scores from the other methods.

5.6. Resilience improvement strategies

This subsection provides some general strategies for EMSS resilience improvement, using City A as an example. The extension correlation degrees of City A's resilience assessment criteria with each resilience level in 2024 are shown in Table 11.

The resilience levels of City A's resilience assessment criteria from 2019 to 2024 are shown in Table 12. We note (see Fig. 7) an overall upward trend in City A's resilience between 2019 and 2024, with notable improvements in *Withstanding capacity* (B_1) and *Recovering capacity* (B_2) in particular, but still much room for improvement in *Adaptive capacity* (B_3).

Specifically, *Emergency supply sufficiency* (X_1) can meet emergency needs, and *Supply category allocation* (X_2) has been configured scientifically and effectively. However, the operational efficiency of emergency material storage warehouses still needs to be improved, with only one level of improvement in 2024 compared to 2019. This may be because storage improvement includes input from various aspects such as equipment, systems, personnel, and maintenance, and the input cost becomes a constraint. Given this constraint, the following specific withstanding capacity improvement strategies were proposed.

- Introducing intelligent warehousing and logistics management systems to improve the efficiency of material entry and exit, inventory and scheduling through intelligence technology [79].
- Implementing lean warehousing management using lean manufacturing tools such as Value Stream Mapping and 5S management. Eliminating the seven wastes of overproduction, waiting time, transportation, over–processing, inventory, motion, and defects will improve the operational efficiency of the warehouse [80].

Table 11
Extension correlation degrees for City A's resilience assessment criteria in 2024.

Criteria	Fragile	Limited	Normal	Good	High	Resilience level
X_1	0.11	0.31	0.51	0.71	**0.90**	High
X_2	0.14	0.34	0.54	0.74	**0.90**	High
X_3	0.18	0.38	0.58	0.78	**0.90**	High
X_4	0.25	0.45	0.65	**0.85**	0.82	Good
X_5	0.12	0.32	0.52	0.72	**0.90**	High
X_6	0.3	0.5	0.7	**0.90**	0.8	Good
X_7	0.18	0.38	0.58	0.78	**0.90**	High
X_8	0.05	0.25	0.45	0.65	**0.85**	High
X_9	0.28	0.48	0.68	**0.88**	0.85	Good
X_{10}	0.25	0.45	0.65	**0.85**	0.82	Good
X_{11}	0.14	0.34	0.54	0.74	**0.90**	High
X_{12}	0.26	0.46	0.66	**0.86**	0.80	Good

Table 12
Resilience level comparison for City A's resilience assessment criteria from 2019 to 2024.

Years Criteria	2019	2020	2021	2022	2023	2024
X_1	Normal	Normal	Normal	Good	High	High
X_2	Limited	Normal	Good	Good	High	High
X_3	Normal	Normal	Normal	Good	High	High
X_4	Normal	Normal	Good	Good	Good	Good
X_5	Normal	Good	Good	High	High	High
X_6	Limited	Limited	Normal	Good	Good	High
X_7	Normal	Normal	Good	Good	High	High
X_8	Good	Good	High	High	High	High
X_9	Limited	Normal	Normal	Good	Good	High
X_{10}	Fragile	Limited	Normal	Good	Good	Good
X_{11}	Normal	Normal	Good	High	High	High
X_{12}	Limited	Limited	Normal	Good	Good	High

In terms of *Recovery capacity* (B_2), City A has shown significant progress in its ability to recover from emergencies, with improved *Emergency response timeliness* (X_5) and improved *Supply–demand forecasting* (X_6). However, the need is identified to further improve precision in demand forecasting and streamline the response process for an even faster recovery during emergencies. Considering these aspects, the following specific strategies for improving recovery capacity were proposed.

- Developing a more efficient demand forecasting model that incorporates real–time data analytics and machine learning techniques to predict emergency supply needs with higher accuracy. By leveraging historical data and integrating predictive analytics, City A can anticipate and prepare better for the surge in demand for emergency supplies during various crises [81].
- Establishing a centralized emergency response command center equipped with modern communication and coordination tools. This center would serve as the hub for information flow and decision–making during emergencies, enabling swift and coordinated responses across different departments and agencies [82].

In terms of *Adaptive capacity* (B_3), although City A has improved its EMSS adaptability to changing circumstances, further measures can be taken to ensure long–term resilience. This includes improving the system's ability to adjust to new challenges and ensuring sustainability in the provision of emergency supplies. To this end, the following specific adaptive capacity improvement strategies were proposed.

- Implementing a flexible supply chain management approach that allows for rapid adjustment to supply chain disruptions. This can be achieved by diversifying supply sources, developing risk–sharing agreements with suppliers, and incorporating contingency planning into supply chain operations [83].
- Investing in technology–driven solutions for emergency supply management, such as blockchain for transparent and secure tracking of supplies. These technologies can significantly improve the adaptability of the EMSS by providing accurate and timely information for decision–making [84].

These strategies aim to bolster City A's EMSS resilience in recovering swiftly from emergencies and adapting to new challenges, ensuring that its EMSS remains robust and responsive in the face of future crises.

6. Conclusions

To address the challenges of EMSS resilience assessment with the involvement of multiple stakeholders, multiple stages and dynamic evolution, a novel data–intelligence–driven three–stage dynamic model is developed in this study. In Stage 1, a LLMs–enhanced NER model is

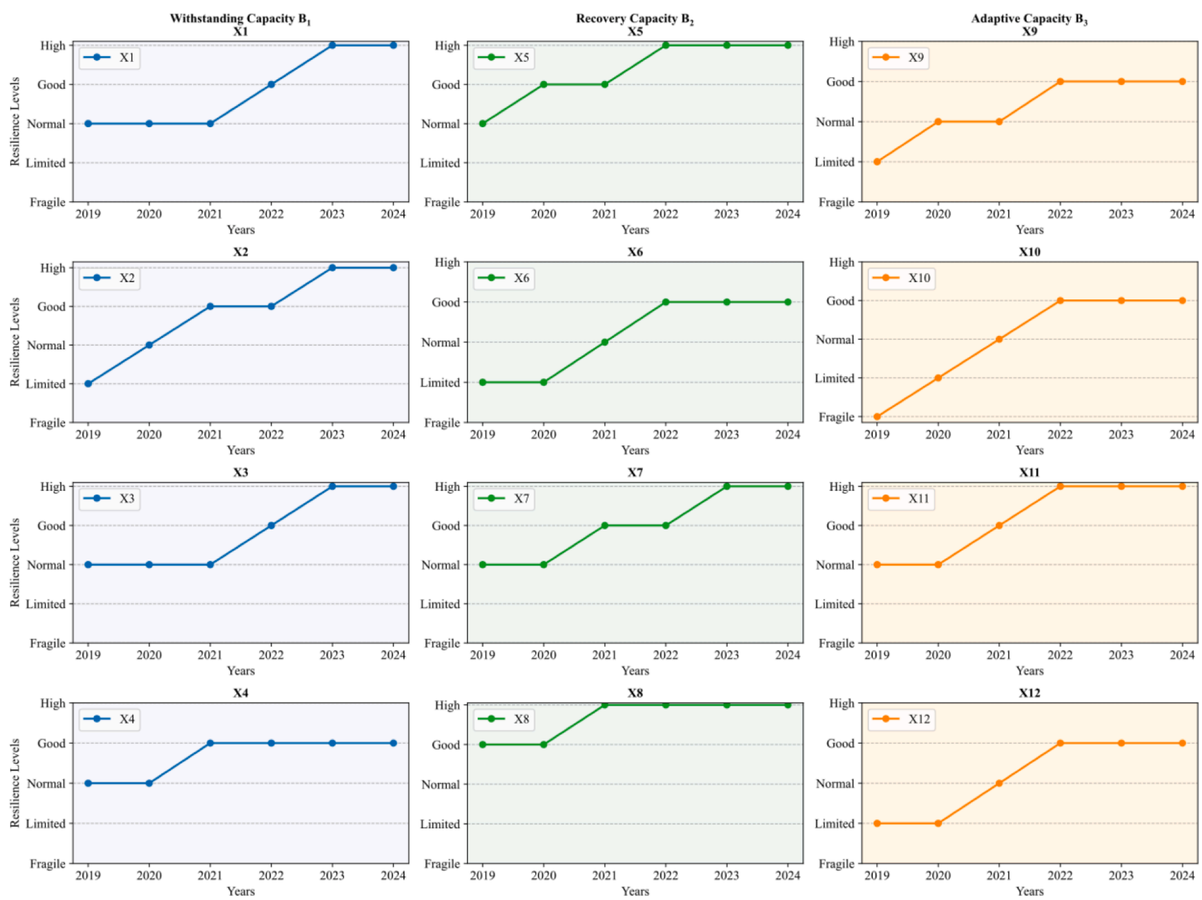

Fig. 7. Resilience level comparison for City A's resilience assessment criteria.

proposed to process multi–source text data and multi–expert knowledge for risk event extraction, constructing a foundational dataset for dynamic scenario modeling. In Stage 2, an ontology–based scenario construction model is proposed, leveraging the ⟨I–N–C–A⟩ representation framework to transform risk events into structured elements and construct a comprehensive risk scenario library. This allows for systematic recognition of resilience features by linking scenario elements, governance tasks, and system capabilities. In Stage 3, based on multi–expert knowledge and extension of the classic MEE model, a DHF–MEE model is proposed to conduct a feature–matching quantitative assessment for the profile of EMSS resilience. Through the model, we have navigated the inherent uncertainties in multi–expert perception for EMSS resilience features effectively, thereby providing a nuanced depiction of EMSS resilience across various risk scenarios. A scientific and efficient assessment of EMSS resilience is realized from the perspectives of multitime–point features, multidimensional criteria, and multi–source heterogeneous data, effectively catering for the aforementioned challenges.

Taking the EMSS resilience assessment of six sample cities in J Province as a case study, the effectiveness and applicability of the developed data–intelligence–driven three–stage dynamic model are verified. Through horizontal comparison, vertical self–examination, key criteria identification, etc., the assessment results are analyzed in depth, providing a new idea for EMSS resilience improvement. Our findings indicate that EMSS resilience has improved significantly over time, demonstrating the system's enhanced ability to adapt to and recover from disruptive events. To further this progress, we recommend focusing on improving these areas through strategic planning and policy adjustments. Moreover, our study underscores the importance of a multifaceted perspective on resilience assessment, which not only judges the current profile but also guides improvements in the system capacity to withstand and respond to emergencies. The DHF–MEE model's flexibility and depth in handling multidimensional criteria and hesitations have proven essential in refining the resilience assessment process, thus offering a valuable framework for other sectors to seek strategies for improving their resilience.

In conclusion, this study provides a holistic solution and efficient methodology for EMSS resilience assessment, not only offering significant insights into a multifaceted recognition of EMSS resilience to risk scenarios, but also ensuring that the system remains robust in the face of evolving global risk challenges. In the future, study on expanding the developed model to incorporate real–time data analytics is worth exploring to further improve the accuracy and operational effectiveness of EMSS resilience assessment.

CRediT authorship contribution statement

Weilan Suo: Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Wenjie Xu:** Writing – original draft, Validation, Methodology, Formal analysis, Data curation. **Longfei**

Li: Writing – original draft, Investigation, Data curation. **Xiaolei Sun:** Writing – review & editing, Supervision, Methodology, Funding acquisition.

Declaration of competing interest

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

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Appendix A. Scenario element representations supporting the construction of assessment criteria.

Table A.1
Exemplary scenario element representations used to identify criteria under the withstanding capacity dimension B_1.

Case	Scenario Element Representation	Identified Criterion
COVID–19 pandemic	Issues {<id: *I01*, name: *COVID–19 Wuhan lockdown*, type_dis: *Public health crisis*, time: *2020.1.23*, address: *Wuhan*, application: *Emergency supplies management*>} Nodes {<id: *N01*, name: *Emergency supplies depot*, type: *Vulnerable Receptors*> (attribute items [*Ration stockpile, Personal protective equipment inventory, Medication reserves*])} Constraints {<id: *C01*, name: *Supply chain continuity*, rule constraints: [*COVID–19, Urban lockdown*], respond constraints: [*Supply chain diversification, Backup suppliers*]>} Annotations {(*Total stockpile quantity, Replenishment rate, Consumption rate, 2020.1.23*)}	Emergency supply sufficiency (X_1)
720 Henan rainstorm	Issues {<id: *I01*, name: *Shortage of critical supplies*, type_dis: *Natural disaster*, time: *2021.7.20*, address: *Zhengzhou*, application: *Critical supply availability*>} Nodes {<id: *N01*, name: *Stock levels of critical supplies*, type: *Supply inventory*> (attribute items [*Water, Food, Medical supplies*])} Constraints {<id: *C01*, name: *Supply chain resilience*, rule constraints: [*Supply route disruptions, High demand*], respond constraints: [*Alternative sourcing, Stockpile management*]>} Annotations {(*Stock adequacy, Replenishment frequency, Emergency distribution efficiency, 2021.7.20*)}	
COVID–19 pandemic	Issues {<id: *I02*, name: *Omicron variant spread*, type_dis: *Public health crisis*, time: *2021.11.15*, address: *Wuhan*, application: *Strategic supplies allocation*>} Nodes {<id: *N02*, name: *Strategic supplies allocation*, type: *Vulnerable Receptors*> (attribute items [*Critical medical equipment, Essential commodities, Personal care items*])} Constraints {<id: *C02*, name: *Supply category management*, rule constraints: [*Public health emergency, Government intervention*], respond constraints: [*Supply prioritization, Redistribution policies*]>} Annotations {(*Allocation efficiency, Response to demand changes, Coverage completeness, 2021.11.15*)}	Supply category allocation (X_2)
720 Henan rainstorm	Issues {<id: *I02*, name: *Resource allocation failure*, type_dis: *Natural disaster*, time: *2021.7.20*, address: *Zhengzhou*, application: *Resource allocation*>} Nodes {<id: *N02*, name: *Supply distribution centers*, type: *Vulnerable Receptors*> (attribute items [*Medicines, Sanitation supplies, Shelter materials*])} Constraints {<id: *C02*, name: *Allocation strategy*, rule constraints: [*Demand surge, Supply chain interruptions*], respond constraints: [*Priority allocation, Equitable distribution*]>} Annotations {(*Resource utilization efficiency, Response speed, Coverage completeness, 2021.7.20*)}	
COVID–19 pandemic	Issues {<id: *I03*, name: *Infrastructure failure*, type_dis: *Operational interruption*, time: *2020.2.5*, address: *Wuhan*, application: *Infrastructure quality*>} Node: {<id: *N03*, name: *Central warehouse*, type: *Vulnerable receptors*> (attribute items [*Structural integrity, Climate control, Fire safety, IT systems*])} Constraints {<id: *C03*, name: *Infrastructure maintenance*, rule constraints: [*Regular inspections, Disaster resilience standards*], respond constraints: [*Upgrade schedule, Maintenance crew readiness*]>} Annotations {(*Facility condition, Accessibility, Safety compliance, 2020.2.5*)}	Warehouse infrastructure quality (X_3)
720 Henan rainstorm	Issues {<id: *I03*, name: *Warehouse damage*, type_dis: *Infrastructure impact*, time: *2021.7.21*, address: *Zhengzhou*, application: *Disaster impact*>} Nodes {<id: *N03*, name: *Affected storage facilities*, type: *Infrastructure*> (attribute items [*Structural damage, Water intrusion, Electrical failure*])} Constraints {<id: *C03*, name: *Preventive and responsive measures*, rule constraints: [*Construction standards, Flood zone regulations*, respond constraints: [*Emergency repairs, Waterproofing enhancements*]>} Annotations {(*Damage assessment, Recovery progress, Compliance with safety standards, 2021.7.21*)}	
COVID–19 pandemic	Issues {<id: *I04*, name: *Logistics deployment*, type_dis: *Operational interruption*, time: *2020.4.15*, address: *Wuhan*, application: *Material handling*>} Nodes {<id: *N04*, name: *Logistics management center*, type: *Vulnerable Receptors*> (attribute items [*Logistics coordination, Staff allocation, Resource management*])} Constraint: <id: *C04*, name: *Operational protocols*, rule constraints: [*Pandemic measures, Personnel safety*], respond constraints: [*Shift scheduling, Task automation*]>} Annotations {(*Order processing time, Delivery turnaround, Inventory accuracy, 2020.4.14*)}	Warehouse efficiency (X_4)
720 Henan rainstorm	Issues {<id: I04, name: Warehouse operational disruptions, type_dis: Operational interruption, time: 2021.7.20, address: Zhengzhou, application: Operational continuity>} Nodes {<id: N04, name: Warehouse operational capacity, type: Operational management> (attribute items [Staff accessibility, System functionality, Process continuity])} Constraints {<id: C04, name: Operational continuity plans, rule constraints: [Staff unavailability, Equipment malfunction], respond constraints: [Backup staff plans, Equipment maintenance]>} Annotations {(Process efficiency, System downtime, Operational recovery, 2021.7.20)}	

Table A.2
Exemplary scenario element representations used to identify criteria under the recovering capacity dimension B_2.

Case	Scenario Element Representation	Identified Criterion
COVID–19 pandemic	Issues <id: *I05*, name: *COVID–19 Delta variant*, type_dis: *Public health crisis*, time: *2021.7.15*, address: *Nanjing*, application: *Emergency response*>} Nodes ⟨id: *N05*, name: *Rapid response team*, type: *Disaster–response entities*⟩ (attribute items [*Response time, Decision speed, coordination*])} Constraints <id: *C05*, name: *Response protocol*, rule constraints: [*Delta variant, First cases detection*], respond constraints: [*Activation latency, Deployment speed*]>} Annotations {(*Response time, Response adequacy, Operational readiness, 2021.7.15*)}	Emergency response timeliness (X_5)
720 Henan rainstorm	Issues {<id: *I05*, name: *Delayed rescue operations*, type_dis: *Natural disaster*, time: *2021.7.20*, address: *Zhengzhou*, application: *Rescue response*>} Nodes {<id: *N05*, name: *Response team activation*, type: *Response management*> (attribute items [*Team mobilization, Equipment readiness*])} Constraints {<id: *C05*, name: *Response acceleration measures*, rule constraints: [*Communication delays, Access route blockages*], respond constraints: [*Enhanced communication systems, Clearing access routes*]>} Annotations {(*Time to mobilization, Response effectiveness, Impact of delays, 2021.7.20*)}	
COVID–19 pandemic	Issues {<id: *I06*, name: *Material shortage*, type_dis: *Supply chain disruption*, time: *2020.2.23*, address: *Wuhan*, application: *Supply demand*>} Nodes {<id: *N06*, name: *Supply planning*, type: *Supply management*> (attribute items [*Resource allocation, Supply adjustment*])} Constraints {<id: *C06*, name: *Resource adjustment strategies*, rule constraints: [*Fluctuating supply and demand, Logistical challenges*], respond constraints: [*Strategic stockpiling, Expedited distribution*]>} Annotations {(*Planning accuracy, Supply response speed, Effectiveness of adjustments, 2020.2.23*)}	Supply–demand forecasting (X_6)
720 Henan rainstorm	Issues {<id: *I06*, name: *Unanticipated demand surges*, type_dis: *Supply chain disruption*, time: *2021.7.22*, address: *Zhengzhou*, application: *Supplies demand*>} Nodes {<id: *N06*, name: *Supplies operations*, type: *Operational management*> (attribute items [*Resource allocation, Stock level adjustments*])} Constraints {<id: *C06*, name: *Resource management*, rule constraints: [*Sudden increase in demand, Logistical disruptions*], respond constraints: [*Resource reallocation, Emergency procurement*]>} Annotations {(*Allocation efficiency, Stock adjustment speed, Adequacy of response measures, 2021.7.22*)}	
COVID–19 pandemic	Issues {<id: *I07*, name: *Health tracking*, type_dis: *Data privacy*, time: *2020.5.15*, address: *Wuhan*, application: *Health information sharing*>} Nodes {<id: *N07*, name: *Health data management*, type: *Data security*> (attribute items [*Data collection, Data sharing, Privacy protections*])} Constraints {<id: *C07*, name: *Privacy–secure information systems*, rule constraints: [*Legal privacy requirements, Public trust*], respond constraints: [*Enhanced data encryption, Transparent data usage policies*]>} Annotations {(*Data security level, Public trust in data handling, Compliance with privacy laws, 2020.5.15*)}	Safety information sharing (X_7)
720 Henan rainstorm	Issues {<id: *I07*, name: *Communication breakdown in disaster*, type_dis: *Natural disaster*, time: *2021.7.23*, address: *Zhengzhou*, application: *Emergency communication*>} Nodes {<id: *N07*, name: *Critical communication channels*, type: *Communication systems*> (attribute items [*Rescue coordination, Public alerts, Information verification*])} Constraints {<id: *C07*, name: *Communication reliability and security*, rule constraints: [*Infrastructure vulnerability, Power failures*], respond constraints: [*Redundant communication systems, Emergency power solutions*]>} Annotations {(*Communication reliability, Information dissemination speed, Data security, 2021.7.23*)}	
COVID–19 pandemic	Issues {<id: *I08*, name: *Rapid mobilization*, type_dis: *Workforce management*, time: *2021.7.15*, address: *Nanjing*, application: *Emergency response*>} Nodes {<id: *N08*, name: *Emergency response team*, type: *Human resources*> (attribute items [*Rapid deployment, Staff training, Response readiness*])} Constraints {<id: *C08*, name: *Staffing and training*, rule constraints: [*Skilled personnel, Quick turnaround*], respond constraints: [*Training programs, Staff reallocation*]>} Annotations {(*Deployment speed, Training effectiveness, Overall response effectiveness, 2021.7.15*)}	Staff reliability (X_8)
720 Henan rainstorm	Issues {<id: *I08*, name: *Emergency workforce shortage*, type_dis: *Workforce management*, time: *2021.7.21*, address: *Zhengzhou*, application: *Emergency response staffing*>} Nodes {<id: N08, name: *Emergency workforce*, type: *Human resources*> (attribute items [*Staff availability, Staff condition*])} Constraints {<id: *C08*, name: *Workforce management strategies*, rule constraints: [*High demand, Staff fatigue*], respond constraints: [*Additional Hiring, Shift rotations*]>} Annotations {(*Staff readiness, Efficiency under pressure, Adaptability to extended hours, 2021.7.21*)}	

Table A.3
Exemplary scenario element representations used to identify criteria under the adaptive capacity dimension B_3.

Case	Scenario Element Representation	Identified Criterion
COVID–19 pandemic	Issues {<id: *I09*, name: *Supply chain disruptions*, type_dis: *Economic impact*, time: *2020.1.23*, address: *Wuhan*, application: *Supply chain management*>} Nodes {<id: *N09*, name: *Cost management strategies*, type: *Supply chain optimization*> (attribute items [*Supplier negotiation, Inventory management*])} Constraints {<id: *C09*, name: *Economic and operational constraints*, rule constraints: [*Increased supply costs, Reduced workforce availability*], respond constraints: [*Strategic sourcing, Automation*]>} Annotations {(*Cost reduction effectiveness, Supply chain resilience, Economic efficiency, 2020.1.23*)}	Inventory cost reduction (X_9)
720 Henan rainstorm	Issues {<id: *I09*, name: *Resource scarcity cost impact*, type_dis: *Economic impact*, time: *2021.8.2*, address: *Zhengzhou*, application: *Supply chain*>} Nodes {<id: *N09*, name: *Cost management*, type: *Economic management*> (attribute items [*Price tracking, Cost analysis, Negotiation*])} Constraints {<id: C09, name: *Cost control*, rule constraints: [*Market fluctuations, Supply disruptions*], respond constraints:	

(*continued on next page*)

Table A.3 (*continued*)

Case	Scenario Element Representation	Identified Criterion
	[*Stockpiling, Long–term contracts*]>}	
	Annotations {(*Cost efficiency, Budget adherence, Supplier relationship, 2021.8.02*)}	
COVID–19 pandemic	Issues <id: *I10*, name: *Material supply interruption*, type_dis: *Supply chain disruption*, time: *2020.3.1*, address: *Wuhan*, application: *Vendor collaboration*>}	Vendor risk sharing (X_{10})
	Nodes ⟨id: *N10*, name: *Supplier network*, type: *Disaster–prevention entities*⟩ (attribute items [*Supplier diversification, Contract terms, Contingency planning*])}	
	Constraints <id: *C10*, name: *Risk sharing policy*, rule constraints: ["*Global pandemic effects*", "*Supply chain disruptions*"], respond constraints: [*Multi–sourcing, Mutual support agreements*]>}	
	Annotations {(*Risk mitigation, Supplier reliability, Contract compliance, 2020.3.1*)}	
720 Henan rainstorm	Issues {<id: *I10*, name: *Supplier risk*, type_dis: *Supply chain disruption*, time: *2021.7.29*, address: *Zhengzhou*, application: *Vendor management*>}	
	Nodes {<id: *N10*, name: *Vendor management*, type: *Supply management*> (attribute items [*Risk assessment, Contract adjustments*])}	
	Constraints {<id: *C10*, name: *Risk mitigation*, rule constraints: [*Single–source dependency, Contract rigidity*], respond constraints: [*Diversification, Flexible contracts*]>}	
	Annotations {(*Risk management effectiveness, Contract flexibility, Diversification success, 2021.7.29*)}	
COVID–19 pandemic	Issues <id: *I11*, name: *Delta variant*, type_dis: *Post–event analysis*, time: *2021.7.15*, address: *Nanjing*, application: *Risk assessment and mitigation*>}	Risk review capacity (X_{11})
	Nodes {<id: *N11*, name: *Risk assessment team*, type: *Disaster–prevention entities*} (attribute items [*Epidemiological expertise, Risk analysis tools, Decision support systems*])}	
	Constraints {<id: *C11*, name: *Review procedures*, rule constraints: [*Delta variant transmission dynamics, Public health guidelines*], respond constraints: [*Rapid assessment turnaround, Adaptation to new evidence*]}	
	Annotations {(*Risk awareness, Response efficacy, Policy influence, 2021.7.15*)}	
720 Henan rainstorm	Issues {<id: *I11*, name: *Disaster investigation*, type_dis: *Post–event analysis*, time: *2022.1.27*, address: *Zhengzhou*, application: *Risk evaluation*>}	
	Nodes {<id: *N11*, name: *Investigation team*, type: *Evaluation*> (attribute items [*Report findings, Recommendations*])}	
	Constraints {<id: *C11*, name: *Recommendation implementation*, rule constraints: [*Resource allocation, Policy adoption*], respond constraints: [*Policy revisions, Resource redistribution*]>}	
	Annotations {(*Recommendation effectiveness, Policy change impact, Resource utilization, 2021.7.30*)}	
COVID–19 pandemic	Issues {<id: *I12*, name: *Operational efficiency*, type_dis: *Operational interruption*, time: *2021.7.15*, address: *Nanjing*, application: *Crisis management*>}	Interdepartmental collaboration (X_{12})
	Nodes: {<id: *N12*, name: *Crisis management team*, type: *Emergency operations*> (attribute items [*Strategic planning, Resource allocation, Unified command*])}	
	Constraints: {<id: *C12*, name: *Operational challenges*, rule constraints: [*Resource constraints, Information flow*], respond constraints: [*Resource optimization, Communication enhancement*]>}	
	Annotations: {(*Operational efficiency, Command effectiveness, Communication clarity, 2021.7.15*)}	
720 Henan rainstorm	Issues {<id: *I12*, name: *Coordination failures*, type_dis: *Operational interruption*, time: *2022.1.27*, address: *Zhengzhou*, application: *Disaster response coordination*>}	
	Nodes {<id: *N12*, name: *Response coordination*, type: *Emergency operations*> (attribute items [*Emergency command, Operational integration*])}	
	Constraints {<id: *C12*, name: *Operational coordination*, rule constraints: [*Fragmented response efforts, Communication barriers*], respond constraints: [*Unified response framework, Enhanced communication systems*]>}	
	Annotations {(*Coordination effectiveness, Response time reduction, Stakeholder engagement, 2022.1.27*)}	

Data availability

Data will be made available on request.

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