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Towards Intelligent Emergency Management: A Scenario–Learning–Decision Framework Enabled by Large Language Models

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Abstract

To address the governance challenges of "delayed response, fragmented strategies, and cognitive disconnection" in traditional emergency management, this paper proposes an intelligent framework—Scenario–Learning–Decision (SLD)—powered by Large Language Models (LLMs). The framework integrates Multi-Agent Systems (MAS) and prospect theory-based parameter modeling to build an emergency simulation platform featuring scenario perception, human–AI learning, and collective decision-making. Using the 2022 wildfire in City C as a case study, the research verifies the effectiveness of the SLD model in complex emergency contexts and provides theoretical support and practical pathways for developing human-centered intelligent emergency decision-making systems.

Keywords: emergency management; Scenario–Learning–Decision; large language models

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1. Introduction

Traditional emergency management has long relied on expert judgment in information collection, situational awareness, and cross-departmental coordination, leading to structural deficiencies such as delayed responses, information silos, and low collaboration efficiency. In recent years, Intelligent Emergency Decision-Making Systems (IEDMS) have emerged, integrating big data analytics, multi-agent systems (MAS), knowledge graphs, and generative AI into comprehensive decision platforms, thereby significantly enhancing the systemic and intelligent levels of disaster response [1]. Particularly under highly complex and rapidly evolving emergencies, decision-making requires responses within seconds, while traditional experience-driven modes are no longer sufficient to meet the demands of resource coordination and strategy integration. Consequently, building a new generation of intelligent emergency decision-making systems—characterized by data-driven, model-guided, and human–machine collaborative approaches—has become a shared consensus among academia and practice. This paper systematically reviews key research progress on MAS, Large Language Models (LLMs) [2], knowledge graphs, digital twins, and behavioral decision theories. Based on the evolution of emergency management systems summarized by Zhong (2020) [3] and the development of information systems reviewed by Chen et al. (2022) [4], this study outlines the paradigm shift from expert experience-driven emergency

decision-making to artificial intelligence-empowered emergency decision-making. The specific evolution process is illustrated in Figure 1.

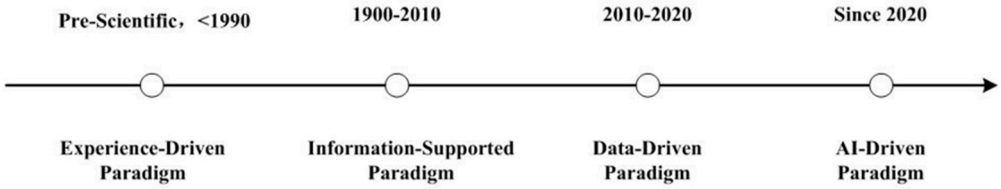


Figure 1. The Evolution of Paradigms in Emergency Management Decision-Making.

Phase I: Experience-Driven Stage (Pre-Scientific, <1990)

Before the late 20th century, emergency management systems primarily relied on experiential judgment, without systematic information analysis architectures or decision-model support mechanisms. During this stage, emergency response was largely based on the subjective judgment of individual experts and commanders. Information was mostly collected through manual reporting and telephone communication, resulting in fragmented and delayed data. While this mode retained limited adaptability in handling small-scale and familiar incidents, its limitations became evident in large-scale or complex cascading disasters: delayed response, imbalanced resource allocation, frequent judgment errors, and a lack of transparency and replicability in the overall decision-making process [5]. At the institutional level, the establishment of the Federal Emergency Management Agency (FEMA) in 1979 marked the initial formation of a national institutionalized emergency response mechanism [6]. The enactment of the Stafford Act in 1988 further standardized federal responsibilities and coordination mechanisms in major disasters, thereby laying the foundation for a systematic federal disaster response framework [7]. However, despite continuous institutional improvements, by the early 21st century, most countries and regions still lacked sufficient integration of modern information technologies, data modeling, and intelligent approaches in emergency management practices. As a result, overall systems remained experience-dominated and fragmented, proving inadequate in coping with increasingly complex, cross-sector, and multi-hazard emergencies.

Phase II: Informatization and System Integration (1990–2010)

With the advent of the 21st century, the introduction of Geographic Information Systems (GIS) and Multi-Criteria Decision Analysis (MCDA) into emergency management significantly enhanced capabilities in spatial disaster risk processing and multi-standard integrated evaluation [8]. GIS was first applied in watershed flood prevention and urban disaster mitigation, enabling visualization of disaster distribution, database construction for historical cases and infrastructure information, and partial simulation of expert judgment within expert systems to support command decisions. Meanwhile, Perry and Lindell (2003) [9] proposed a disaster response process model that emphasized the shift from static planning to dynamic coordination, representing a milestone in the networking and process-oriented transformation of emergency management. As system modeling capabilities improved, mathematical optimization and scheduling algorithms gradually became the backbone of emergency simulation modeling, leading to the development of model-based systems covering disaster evolution simulation, logistics scheduling, and traffic evacuation optimization [10]. Nevertheless, systems in this stage were constrained by model rigidity and limited scalability, restricting their capacity to respond in real time to rapidly changing disaster conditions.

Phase III: Data-Driven Stage (2010–2020)

After 2010, global emergency management entered a data-driven stage. In 2012, the United Nations Global Pulse launched the “Big Data for Disaster Response” initiative, marking the establishment of a data-centered paradigm [11]. This stage was characterized by the

deep integration of artificial intelligence (AI), the Internet of Things (IoT), remote sensing, and social media, which together formed a multi-source, heterogeneous big data ecosystem that significantly improved real-time disaster perception, dynamic early warning, and rapid response capabilities. In practice, data-fusion-driven intelligent modeling made important advances. For example, Guan and Chen (2014) [12] developed a disaster-related ratio (DRR) indicator to measure disaster-related Twitter usage, greatly improving the accuracy and timeliness of emergency responses. Chang et al. (2021) [13] further proposed a spatiotemporal modeling framework that integrates mobile device location, social media content, and case data for epidemic spread prediction and resource allocation optimization, offering valuable data support for public health emergencies. These systems widely employed deep neural networks (DNNs), reinforcement learning (RL), sentiment analysis, and clustering algorithms, demonstrating AI's strong potential in disaster modeling and decision support.

Despite these advancements, several challenges persisted. First, the "black-box" nature of deep models limited interpretability, undermining trust in high-risk emergency contexts. Second, heterogeneous data sources with fluctuating quality constrained system robustness and generalization in the face of complex disaster evolution. Furthermore, the reliance on high-performance computing resources-imposed deployment barriers, making it difficult to balance real-time performance with cost considerations.

Phase IV: AI-Driven Stage (2020–Present)

Entering the 2020s, the United Nations released a series of reports emphasizing that artificial intelligence (AI) in disaster management must ensure ethics, fairness, privacy protection, and robust design to mitigate technological risks and foster social trust [14]. In parallel, China promoted intelligent emergency management at the national level: the 14th Five-Year Plan for National Informatization (2021) [15] explicitly highlighted smart emergency systems as a key pillar for improving emergency governance capacity. Between 2022 and 2023, several countries advanced "smart and resilient" emergency management systems, incorporating cutting-edge technologies such as large models, federated learning, and digital twins into collaborative systems and real-world simulations [16,17]. In the decision-making domain, Ghaffarian et al. (2023) [18] examined applications of explainable AI in disaster risk management, noting that transparency can significantly enhance trust and reliability in natural disaster early warning and decision-making. In August 2024, China's Ministry of Emergency Management released the "Jiu'an" AI large model for emergency management, aimed at advancing reform and innovation while empowering new productive forces to strengthen emergency management capabilities [19]. Such initiatives highlight the growing application of large-model technology in emergency management, with the potential to enhance efficiency and accuracy through data integration, sharing, and analytics. As a new generation of AI technology, large models exhibit remarkable advantages and potential in generalization, universality, and emergent capabilities across recognition, understanding, decision-making, and generation tasks, offering new perspectives and methodologies for emergency management.

Although Geographic Information Systems (GIS), big data, and AI technologies have been continuously integrated into emergency management over the past three decades, greatly enhancing information acquisition and decision support, the paradigm shift from experience-based judgment to AI-driven autonomous decision-making still faces several theoretical and technical challenges.

First, existing intelligent emergency decision-making approaches often focus on isolated stages, lacking a systematic methodology that organically integrates scenario modeling, machine learning, and human–machine collaborative decision-making. Particularly in the context of complex disaster chains and cross-agency coordination, there is still an absence of comprehensive models that balance both generalizability and adaptability.

Second, the application of large language models (LLMs) in emergency management remains at an early stage. Although some studies have attempted to employ models such as GPT [20] and ERNIE Bot for event summarization and intelligent question answering, in-depth research on their integration into strategy generation, expert game-theoretic modeling, and emergency response workflows is still limited [21].

Third, there is a lack of dynamic learning mechanisms capable of handling cross-scale, multi-source heterogeneous data fusion.

Based on these gaps, the research questions of this study are formulated as follows:

RQ1: For different types of disasters and governance scenarios, how can scenario modeling, knowledge reasoning, machine learning, and group decision-making be rapidly integrated into a scalable and transferable intelligent emergency management framework?

RQ2: In developing an innovative intelligent framework for emergency management, how can LLM-based agents be effectively integrated with traditional simulation models to form new simulation approaches?

RQ3: How can human–AI interactive learning mechanisms be designed to enable closed-loop collaboration between AI systems and human experts, while adapting to the rapid evolution of disaster dynamics?

To address these questions, this study makes original contributions in terms of theoretical construction, model integration, and methodological innovation. First, it proposes an LLM-empowered Scenario–Learning–Decision framework for emergency management. Then, it develops a multi-agent simulation system that integrates LLM-based reasoning with prospect theory-inspired cognitive modeling. Finally, it introduces a multi-source heterogeneous data-driven human–AI collaborative learning and adaptive coordination method.

This study centers on the theme of "LLM-empowered emergency management" and is organized as follows: Section 1 introduces the research background and motivation, reviews relevant literature at home and abroad, and identifies research gaps and significance. Section 2 elaborates on the research methods and theoretical foundations, including prospect theory, multi-agent modeling, and LLM-based reasoning mechanisms, and constructs the proposed simulation and decision-making framework. Section 3 presents the design of the Scenario–Learning–Decision framework and explains its internal operating mechanisms. Section 4 reports the simulation experiments, comparing the performance of AI-driven strategies and expert-optimized strategies across multiple indicators, analyzing the contribution of human–AI collaboration to improving response quality and resource allocation efficiency, and exploring the impact of psychological parameter evolution on decision-making behaviors. Section 5 discusses and extends the study by examining the applicability boundaries and policy implications of the framework, analyzing its transferability to other emergency scenarios, and proposing a technical roadmap for platform-based visualization and integration. Section 6 concludes the paper by summarizing the main findings and theoretical innovations, acknowledging the limitations of the current study, and outlining future research directions for AI- and LLM-driven intelligent emergency management.

2. Theoretical Foundations and Research Methods

2.1. Prospect Theory

Traditional emergency decision-making models are largely grounded in expected utility theory, which assumes that decision-makers are fully rational and free from behavioral biases such as loss aversion. However, in reality, individuals often exhibit non-rational behaviors such as reference dependence, loss aversion, and asymmetric sensitivity to gains and losses. To more accurately capture the psychological decision-making processes of experts under uncertain emergency scenarios, this study adopts Prospect Theory proposed by [22] as the behavioral modeling foundation. Prospect theory has been widely applied in

emergency decision analysis, including risk decision-making methods based on prospect theory [23] and group emergency decision models incorporating prospect theory [24]. The core components of Prospect Theory can be summarized as follows:

(1) Value Function

$$v(x) = \begin{cases} x^{\alpha} & Gain\ domain\ (x \geq 0) \\ -\lambda(-x)^{\beta} & Loss\ domain\ (x < 0) \end{cases} \quad (1)$$

where the value function is characterized by three key parameters: First, the curvature parameter in the gain domain, denoted as α, captures the degree of risk aversion in gains, where $\alpha < 1$ indicates diminishing sensitivity and thus risk aversion. Second, the curvature parameter in the loss domain, denoted as β, reflects the risk attitude toward losses, where $\beta < 1$ suggests a tendency toward risk seeking. Finally, the loss aversion coefficient, denoted as λ, represents the relative psychological weight of losses compared to gains, with $\lambda > 1$ implying that losses are perceived more heavily than equivalent gains.

(2) Probability Weighting Function

The probability weighting function describes the phenomenon of subjective probability distortion, reflecting how decision-makers tend to overweight small probabilities and underweight large probabilities. The function can be formally expressed as follows:

$$w(p) = \frac{p^r}{\left(p^r + (1-p)^r\right)^{\frac{1}{r}}} \quad (2)$$

where r is the probability sensitivity parameter, with $r < 1$ indicating that decision-makers tend to overweight low-probability events while underweighting high-probability events.

(3) Integrated Decision Model

The overall prospect value, V, is calculated as follows:

Single-outcome prospect:

$$V = w(p)v(x) \quad (3)$$

Multi-outcome prospect:

$$V = \sum w(p_i)v(\Delta_{x_i}) \quad (4)$$

where $w(p_i)$ represents the decision weight assigned to outcome i.

In this study, each expert agent sets a unique reference point and psychological parameters based on their professional background and risk preferences, and then re-evaluates and adjusts the AI-generated response plans to produce a second-round collective intelligence decision. This modeling approach significantly enhances the simulation system's ability to replicate actual expert behavior, capturing the cognitive biases that are irrational yet explainable in complex scenarios and providing an important theoretical foundation for human and AI collaborative emergency modeling.

2.2. Numerical Simulation and Modeling Methods

Real-world decision-making problems in emergency management often involve complex characteristics such as multiple agents, nonlinearity, dynamic games, and incomplete information. Traditional static optimization models are insufficient to fully capture the evolutionary processes of such systems. In recent years, Agent-Based Modeling (ABM) has emerged as an effective tool for simulating the behavior of complex adaptive systems and has gradually been applied in emergency management research [25]. ABM can capture interactions among individual agents, feedback mechanisms, and emergent macro-level behaviors, making it particularly suitable for addressing dynamic coordination and resource allocation issues in disaster response [26].

2.2.1. ABM–LLM Integrated Simulation Platform Architecture

Building on the multi-agent and prospect theory simulation model proposed by [27], this study incorporates LLM capabilities and the Prompt + Tools interaction mechanism into the ABM framework to develop an intelligent emergency simulation platform. The platform integrates reasoning, generation, decision-making, and corrective capabilities, extending the traditional Multi-Agent System (MAS) and enabling a systematic representation of real-world emergency decision-making processes, as illustrated in Figure 2.

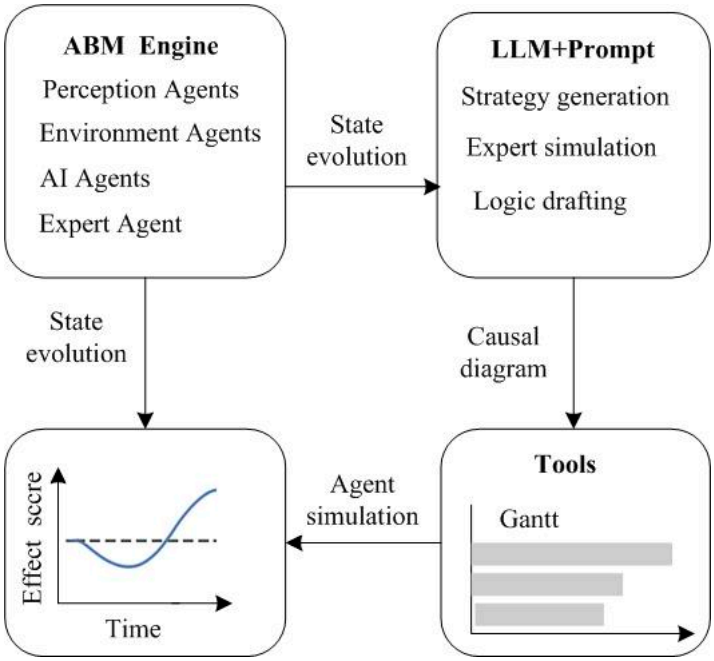


Figure 2. System Architecture of the ABM + LLM Integrated Simulation Platform.

Part 1: In the ABM–LLM intelligent emergency response simulation platform depicted in Figure 2, the Multi-Agent System operates through coordinated agents with clearly defined roles, simulating the full process from disaster perception to strategy generation and evaluation. The system defines four core types of agents, each responsible for specific functions that together reflect the complex dynamic behavior of the emergency management system. The ABM engine sets up the agents as follows. The environment agent simulates natural evolution processes such as fire spread, water level rise, and wind dispersion. The perception agent models real-time monitoring and reporting of environmental conditions by sensors, drones, or other devices. The AI agent, powered by large language models, performs image recognition, semantic generation, and strategy search, generating initial response plans. The expert agent embeds a prospect theory-driven behavioral function to simulate the risk preferences and cognitive biases of expert groups under different disaster scenarios. Based on the described setup, we developed a tailored simulation using a Python (v3.13) ABM platform. In this implementation, the Environment Agent leverages physics-based models like cellular automata for disaster progression. The Perception Agent updates a shared state dictionary with real-time structured data. Integrated with an LLM, the AI Agent uses engineered prompts—combining real-time data, emergency protocols, and task commands—to produce initial response plans. The Expert Agent applies a prospect theory-based value function, incorporating risk preference parameters to evaluate plans. The system outputs step-by-step logs, including disaster maps, AI-generated plans, and expert decision traces, for comprehensive response analysis.

Part 2: The agent module, integrating LLM with Prompt + Tools, receives disaster state evolution information from the ABM engine as semantic input. Leveraging the reasoning

capability of the LLM, the system can autonomously make decisions, while prompts guide the model to generate multiple response strategies, simulate expert cognitive judgment, and draft contextually coherent scenario-based plans. The Tools component provides the LLM with the ability to interact with the external environment, and these outputs are returned to the ABM system as AI candidate strategies for simulation testing.

Part 3: After strategy generation, the system invokes the XAI module, indicated in Figure 2 as the "Causal diagram" pathway, to provide local explanations of the strategy outcomes and analyze the causal paths underlying performance differences. For instance, if a particular strategy scores highly on response feasibility, the XAI module attributes this to factors such as reasonable path planning or accurate wind speed prediction, and the resulting causal diagram is presented to the expert agents to help them understand and trust the AI-generated strategy.

Part 4: Through the Tools module, the system visually presents simulation progress, task status, and resource allocation using graphs such as Gantt charts and curves, supporting human–AI collaboration, strategy comparison, and decision traceability. This module acts as the interactive interface for multi-round simulation games and final decision-making. After each simulation round, the system evaluates strategy performance based on key indicators such as the Life Safety Index (θ_1) and Risk Loss (θ_2), plotting performance–time curves. The evaluation results are fed back into the ABM engine and LLM module to adjust the logic of subsequent strategy generation, thus forming a closed-loop learning and optimization process.

2.2.2. Closed-Loop Simulation Process

The system employs a gridded spatial environment to enable dynamic interactions among critical emergency elements, including fire spread, personnel evacuation, and resource allocation. Each simulation round follows a closed-loop process: step 1, disaster state update, in which fire, flood, or other hazard conditions evolve in real time according to geographic diffusion rules; step 2, AI plan generation, where the AI agent leverages image inputs and semantic prompts to invoke the large language model and produce feasible response strategies; step 3, expert evaluation and revision, in which expert agents assess the AI-generated strategies based on their risk preferences and reference point valuations, modifying or rejecting plans as necessary; and step 4, strategy scoring and feedback, where the effectiveness of each strategy is comprehensively evaluated using a four-dimensional indicator system ($\theta_1 - \theta_4$), and the results are fed back into the learning module to guide subsequent simulation rounds.

2.2.3. Scalability Design and Simulation Validation Mechanism

To verify the robustness and generalizability of the system under multiple disaster types and disturbance scenarios, the platform predefines various initial perturbation conditions and resource constraint parameters, such as sudden wind changes, communication interruptions, and equipment failures, while also allowing users to customize simulation templates to flexibly accommodate different experimental needs. By adjusting external inputs and agent behavior rules, the system can be rapidly deployed and adapted to a variety of emergency events, including wildfires, floods, earthquakes, and landslides.

Furthermore, the platform demonstrates strong modular scalability. Its core architecture supports the integration of diverse decision-making algorithms, such as federated learning, graph neural networks, and reinforcement learning, and can seamlessly interface with multi-source heterogeneous data and external simulation systems, including digital twin platforms and emergency command systems. This provides a solid experimental foundation for conducting cross-disaster, cross-disciplinary, and cross-departmental emergency

strategy simulations. Overall, the intelligent emergency simulation platform not only offers a high-confidence sandbox environment for validating large language model mechanisms in emergency scenarios but also establishes a generalizable decision-making toolchain for future AI-assisted public governance.

3. Model Framework Design: The Scene–Learning–Decision Integrated Model

3.1. The Connotation of the "Scene–Learning–Decision" Model

This study systematically analyzes the dynamic evolutionary advantages of multi-agent modeling in emergency management and the suitability of prospect theory for characterizing expert decision behavior. Multi-Agent Systems (MASs) are capable of simulating decentralized coordination, behavioral interaction, and strategic adaptation among heterogeneous entities in complex and uncertain environments, and have been widely applied in disaster evacuation, emergency resource allocation, and command-chain simulation [26]. Meanwhile, prospect theory offers a rigorous behavioral modeling framework for "bounded rationality" decision-making under risk, enabling the quantification of expert preferences in terms of loss aversion, reference dependence, and decision weighting under uncertainty [28].

Building on these theoretical and methodological foundations, the proposed Scene–Learning–Decision (SLD) model constitutes a new paradigm for intelligent emergency decision-making in complex disaster scenarios. The core of the SLD model lies in integrating scenario-driven cognitive perception with learning-based strategy evolution to enable adaptive human–AI collaborative decision-making. Unlike traditional linear decision processes—characterized by "information collection–manual analysis–experience-based judgment"—the SLD framework establishes a dynamic decision mechanism capable of online adaptation. It leverages large-scale data to construct semantic representations of dynamic emergency environments, and incorporates both organizational learning and machine learning to drive iterative optimization of strategies. As a result, the model endows the emergency decision process with contextual understanding, continuous learning capability, and evolutionary adaptability, making it more suitable for high-uncertainty, multi-constraint emergency response conditions.

3.2. Components of the "Scene–Learning–Decision" Model

3.2.1. Scene Perception: Multi-Modal Dynamic Disaster Construction

Within intelligent emergency decision-making systems, the scene perception layer serves not only as the starting point for data input but also as the critical step for AI to generate its first intelligent responses. Firstly, the AI system collects raw disaster-related data in real time through distributed sensor networks, remote sensing satellites, drone surveillance, traffic cameras, and other multi-source sensing devices, capturing earthquake waveforms, meteorological changes, geological shifts, wildfire propagation images, water level changes, and more. Leveraging natural language processing (NLP) and computer vision, AI extracts key information from unstructured data to generate preliminary judgments on event types, affected areas, and hazard levels, thus completing the problem definition stage.

Secondly, based on data parsing, the AI system applies multi-modal fusion techniques to model disaster scenarios. By integrating geographic information systems (GIS) and graph neural networks (GNN), the system identifies the spatial distribution of affected regions, nearby risk points, infrastructure layouts, and population density, constructing a semantically enriched disaster knowledge graph [29]. This graph not only provides a

multidimensional, connected structure for disaster situational awareness but also serves as structured input for subsequent decision modules [30].

Thirdly, using the knowledge graph and historical case databases, the AI system employs integrated machine learning models, including reinforcement learning, graph neural networks, and transfer learning, for scenario comparison and optimized reasoning. Within seconds, the system can traverse all possible response scenarios, resource allocation paths, and strategy combinations, automatically selecting the optimal action path. This hybrid approach of experience-based analogy and real-time reasoning not only matches optimal response routes but also continuously optimizes strategy generation based on dynamic feedback [31]. Ultimately, the system outputs structured emergency instructions, scheduling maps, risk evolution diagrams, and resource allocation suggestions, significantly improving early response efficiency and strategy rationality.

3.2.2. Intelligent Learning: AI-Led Response Strategy Generation

In the learning stage, the system embeds the scene semantic graph into a large model with visual–language joint understanding capabilities. Through prompt engineering, the AI generates candidate response strategies. Each candidate strategy (e.g., A_1: conventional deployment, A_2: regional coordination, A_3: AI remote scheduling, A_4: AI-controlled operations) is associated with pre-defined objective function scores across indicators such as life and health, expected casualties, property loss, and response feasibility (θ_1, θ_2, θ_3, θ_4). These scores are generated from historical simulation data and dynamic predictions for the current scenario, and are further estimated using deep learning models to evaluate overall effectiveness. The primary goal of AI's first-round strategy generation is to cover diverse possible responses while providing interpretable metric information, offering standardized input for expert decision-making. This stage essentially completes the AI-led modeling process from disaster perception to preliminary response.

3.2.3. Collaborative Decision-Making: Expert Group Re-Optimization Based on Prospect Theory

Once candidate strategies are generated by machine learning, the decision module introduces expert group Agents for a second round of subjective evaluation and adjustment. To capture experts' behavioral choices under varying risk preferences and psychological expectations, prospect theory is embedded in the simulation system. Specifically, each expert Agent is assigned an individual reference point (R), a loss aversion coefficient (λ), and nonlinear weighting parameters (α^+, α^-), allowing asymmetric perception and psychological weighting of each AI-proposed strategy across the four metrics ($\theta_1 - \theta_4$).

In practice, each expert evaluates the AI-generated strategies A_1–A_4 by assigning prospect values, calculated as Equation (4):

The final score reflects each expert's subjective perception of gains and losses for the given strategy. After multiple experts complete their evaluations to form a scoring matrix, the system applies a consistency-weighted aggregation algorithm to produce a new optimized strategy, A_4', thereby achieving human–AI collaborative intelligent decision-making.

3.3. Decision-Making Process Based on the "Scene–Learning–Decision" Model

Within the context of LLM empowerment, the Scene–Learning–Decision (SLD) model integrates perception, intelligent generation, expert revision, and feedback optimization through a structured workflow, forming an intelligent emergency decision-making system with real-time responsiveness, adaptive optimization, and interpretability, as illustrated in Figure 3.

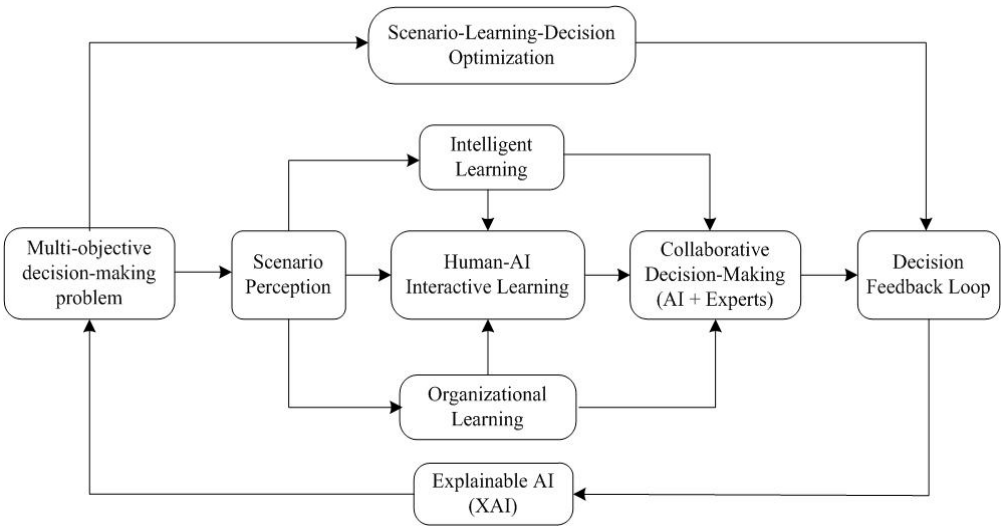


Figure 3. The Scene–Learning–Decision (SLD) Model.

Figure 3 illustrates the overall operational mechanism of the Scene–Learning–Decision (SLD) framework. The decision-making process based on the SLD model proceeds as follows.

First, in terms of decision problem modeling, emergency scenarios typically exhibit multi-objective conflicts, resource constraints, and high uncertainty; thus, it is crucial to establish a dynamic scenario representation mechanism. By integrating heterogeneous data sources such as remote sensing images, IoT sensor streams, social media reports, and emergency command logs [32], the perception layer constructs a semantic disaster knowledge graph via multimodal fusion methods, enabling a transition from physical state description to semantic-level situation understanding [33]. On this basis, the system identifies conflicting decision objectives—for example, maximizing life safety, minimizing response time, controlling disaster propagation, and adhering to resource constraints—which provides a formalized mathematical structure for subsequent learning and strategy optimization.

Second, the AI conducts the first-round decision. When a disaster occurs, the emergency command team queries the AI system for data, knowledge, images, videos, and response options. As an intelligent decision engine, the AI follows a pipeline of "problem understanding → scenario localization → machine learning → response generation." It first performs multimodal perception to localize the disaster using sensor inputs and satellite data. Then, by employing graph neural networks (GNNs) and deep reinforcement learning, the AI generates multiple response strategies optimized across key indicators such as life safety, economic loss, and operational feasibility [34,35]. Finally, the AI outputs executable decision products, including risk maps, resource allocation plans, evacuation routes, and intervention strategies within seconds—significantly accelerating the decision cycle.

Third, a second-round expert decision is conducted through human–AI collaborative refinement. Domain experts evaluate AI-generated strategies based on professional knowledge, operational feasibility, and socio-organizational constraints. Using structured feedback via semantic prompts and explainable AI (XAI) interfaces, experts examine causal reasoning, parameter sensitivities, and contextual validity in AI-generated outputs [36]. Through iterative human–AI interaction, the strategy evolves via collaborative intelligence—combining AI's computational exploration with expert judgment to avoid algorithmic bias and enhance decision trustworthiness. This process results in a consensus strategy that balances effectiveness, feasibility, and social acceptability.

In summary, the SLD decision-making process represents a collective intelligence paradigm where data-driven AI insights are fused with expert reasoning to achieve resilient emergency governance. Enabled by digital twin simulation and multi-agent adaptive

learning, the SLD framework provides a scalable pathway for real-time situational awareness, proactive risk mitigation, and accelerated emergency response.

4. Simulation Case Study

4.1. Experimental Background

In August 2022, City C experienced the combined climatic pressures of prolonged extreme heat ($\geq$40 °C) and severe drought, which triggered multiple large-scale forest fires across regions such as Jinyun Mountain, Fuling, and Banan. These incidents created a typical Wildland–Urban Interface (WUI) disaster scenario. Driven by complex terrain and dry vegetation, the fires spread rapidly, posing severe threats to local residents' safety, infrastructure operations, and ecosystem stability. The challenges were further exacerbated at night, when shifts in temperature, humidity, and unstable mountain wind fields significantly increased the difficulty of firefighting operations, while also heightening the need for real-time precision in decision-making and deployment.

This study selects the wildfire event that occurred in City C on 18 August 2022 as a prototype case. Based on publicly available reports and emergency response data, a high-risk scenario was reconstructed to simulate the event's conditions. On this foundation, a dual-round "AI–Expert" decision-making mechanism was introduced. By combining AI-driven situational awareness and strategy generation with Prospect Theory-based expert behavior modeling, we built an intelligent emergency response system that integrates perception, strategy learning, and iterative refinement. The system simulates the full cycle of multi-agent collaboration in a dynamic disaster context and quantitatively evaluates different response pathways. It thereby provides empirical support and technical infrastructure for improving human–AI collaborative decision-making during emergencies.

4.2. Data Sources

The experiment is based on an ABM + LLM multi-agent emergency response simulation system, integrated with an explainable AI (XAI) module that enables a closed-loop process of strategy generation, interpretation, evaluation, and feedback optimization. The data and model parameters are primarily derived from three sources:

(1) Public data on the 2022 forest fires in City C, collected from the internet. These include official reports such as the Annual Forest Fire Bulletin (2022) [37] issued by the Chongqing Emergency Management Bureau, and field reports by Xinhua News Agency on the Jinyun Mountain wildfire. Key information such as fire progression timelines, affected areas, and emergency response procedures was extracted to support the construction of a highly realistic simulation scenario.

(2) Expert Agent behavior modeling, which is based on emergency response protocols from the National Forest Firefighting Handbook, complemented by results from survey questionnaires conducted during live-fire drills organized by local fire departments. These data provide insights into experts' subjective behavioral patterns, including risk preferences, information weighting, and response sequences, which are then formalized into Prospect Theory-driven expert response functions.

(3) Artificial intelligence models, including GPT, DeepSeek, and Kimi, which serve as semantic understanding and strategy generation engines. These were integrated with pretrained image recognition models for wildfire remote sensing, enabling multimodal situational awareness. The AI engine supports text–image matching, strategy completion, and semantic explanation, providing the core foundation for the intelligent learning module.

4.3. Simulation Workflow and Modeling Mechanism

The simulation decision-making process builds on the Scene–Learning–Decision (SLD) integrated model proposed in Section 3, incorporating the value functions and decision-weighting mechanisms of Prospect Theory. This results in an emergency response simulation system characterized by dynamism, interactivity, and interpretability. The overall workflow consists of four main stages:

4.3.1. Scenario Simulation Layer: Complex Situational Construction and Semantic Extraction

A social systems simulation module is embedded in parallel to construct evolving emergency contexts, including auxiliary data such as public opinion heat maps and traffic accessibility maps. The system automatically outputs a semantic situational graph for each iteration, containing elements such as ignition points, evacuation routes, and command network structures. These serve as the contextual foundation for both AI and expert decision-making.

4.3.2. Learning Layer (AI First Response): Strategy Generation and Explainable Modeling

The AI large model, specifically the DeepSeek-R1, generates multiple candidate response strategies (A_1–A_4). This is achieved through a structured prompt engineering approach. For instance, the model is provided with a prompt structured as follows: "Act as an emergency command expert. The current scenario reports [fire front at location X, wind speed Y m/s, Z residents in threatened area]. Based on the standard emergency protocol, generate and prioritize 3 critical response actions. Justify each action." Each generated strategy is then scored against a four-dimensional evaluation system (θ_1–θ_4, representing life safety, health risk, property loss, and operational feasibility). In addition, the system generates an explainability map for each strategy, visually displaying factor attributions (e.g., wind speed sensitivity, route resistance coefficients), thereby enhancing decision transparency.

4.3.3. Expert Evaluation Layer: Subjective Refinement via Prospect Theory

A group of three types of experts—field commanders, firefighting specialists, and technical modelers—reassess the AI-generated strategies. Each expert is assigned a psychological parameter set (λ, α^+, α^-, R) to represent their degree of loss aversion and sensitivity to gains. Using Prospect Theory value functions, they re-score the strategies and produce an optimized plan A_4', achieving fine-grained improvement through human–AI interaction.

4.3.4. Multi-Round Feedback and Consensus-Building: Iterative Strategy Enhancement

If significant divergence remains among expert evaluations, the system initiates a game-theoretic consensus-building mechanism between AI and experts. Through multiple rounds of dialogue and strategy reconstruction, a final optimized strategy A_5' is produced. Each iteration includes an XAI-based interpretability map and visualization of projected outcomes, ensuring traceability and scientific accountability. This process fully supports intelligent emergency decision-making under human–AI collaboration.

4.4. Agent Decision-Making Process Based on the SLD Model

4.4.1. Multi-Objective Evaluation System

To comprehensively reflect the quality of emergency response, this study establishes the following decision evaluation indicators (Table 1):

Table 1. Multi-objective decision evaluation system.

Indicator Symbol	Indicator Name	Meaning
θ_1	Life Safety	Evacuation success rate, casualty control rate
θ_2	Health Risk	Comprehensive assessment of heatstroke, poisoning, and psychological stress
θ_3	Property Loss	Damaged area of houses/forests
θ_4	Response Feasibility	Dispatch efficiency, environmental adaptability, cost intensity

4.4.2. AI Initial Scoring Table

The AI initial scoring results in Table 2 provide the composite scores and parameter ratings for the four candidate schemes.

Table 2. AI initial scoring table.

Scheme ID	Scheme Description	θ_1	θ_2	θ_3	θ_4	Composite Score (AI)
A_1	Conventional deployment + manual command	0.78	0.82	0.85	0.70	0.60
A_2	Regional collaboration + multi-point joint scheduling	0.62	0.65	0.72	0.80	0.68
A_3	AI remote scheduling + UAVs + visual recognition support	0.48	0.52	0.60	0.85	0.75
A_4	AI control + multi-source remote sensing fusion + terrain-adaptive fire brigade	0.44	0.48	0.58	0.90	0.78

4.4.3. Expert Psychological Parameter Modeling Table

Three categories of experts (command, firefighting, and technical) set individual psychological parameters (reference point R, λ, α^+, α^-) based on AI-recommended schemes and XAI explanations. These parameters are then used in the prospect theory decision function for subjective evaluation. The expert parameters are as follows (Table 3):

Table 3. Expert psychological parameter modeling table.

Expert	Type	Reference Point R (θ_1, θ_2, θ_3, θ_4)	λ	α^+	α^-
E_1	Command	(0.50, 0.50, 0.70, 0.70)	2.0	0.88	0.72
E_2	Firefighting	(0.45, 0.48, 0.68, 0.72)	2.3	0.85	0.68
E_3	Technical	(0.48, 0.50, 0.65, 0.75)	2.1	0.87	0.70

The scores θ_1–θ_4 are substituted into the prospect theory function, and combined with expert reference points and psychological parameters to calculate the utility of each strategy.

4.4.4. Prospect Theory Scoring Table (Expert Weighted Scores)

Table 4 lists the comprehensive prospect values derived from expert-weighted prospect theory scoring.

Table 4. Prospect theory scoring table.

Scheme	θ_1	θ_2	θ_3	θ_4	E_1	E_2	E_3	Average
A_4'	0.42	0.46	0.58	0.92	0.92	0.90	0.93	0.92
A_4	0.44	0.48	0.58	0.90	0.88	0.87	0.89	0.88
A_3	0.48	0.52	0.60	0.85	0.82	0.74	0.78	0.78
A_2	0.62	0.65	0.72	0.80	0.68	0.57	0.60	0.62
A_1	0.78	0.82	0.85	0.70	0.55	0.50	0.52	0.52

4.5. Simulation Results Analysis

This experiment demonstrates that the integration of large-scale models with prospect theory in emergency response mechanisms provides significant advantages in addressing nonlinear, highly uncertain, and high-risk events. In the initial response stage, the AI system, by rapidly aggregating and analyzing multi-source heterogeneous data, can construct a complete semantic disaster map—including fire source identification, wind direction and speed, route accessibility, and public opinion heatmaps—within five seconds, thereby generating candidate strategies (A_1–A_4) across the four-dimensional indicator system (θ_1–θ_4). Compared with traditional expert-dominated processes, this approach reduces strategy generation time by approximately 70%, thus securing critical temporal advantages for field operations. Beyond speed, the integration of explainability modules (XAI) enables transparent and traceable strategy evaluation. For instance, in Scheme A_4, the high response feasibility score ($\theta_4 = 0.90$) was primarily attributed to enhanced terrain-adaptive scheduling algorithms and improved remote sensing image recognition, a result that could be directly visualized through Attribution Maps. Such explainability was acknowledged by more than 85% of experts as enabling at least partial comprehension of the AI's reasoning logic, thereby fostering trust and laying the foundation for consensus building.

Moreover, the incorporation of prospect theory substantially enhanced the acceptance and implementability of final strategies in the expert re-scoring phase. Under simulated psychological parameters (average $\lambda = 2.1$, $\alpha^{+} = 0.87$, $\alpha^{-} = 0.70$), experts displayed significant heterogeneity in loss sensitivity, and the reweighted results yielded an optimized strategy A_4' with an average score of 0.92—approximately 4.5% higher than the original A_4 (0.88). This improvement highlights not only the ability of prospect theory to capture risk aversion behaviors, but also the robustness of the dual-loop mechanism of "AI preassessment + expert re-weighting" under high-pressure conditions. Collectively, the system demonstrates high responsiveness in AI-driven prioritization, the corrective influence of psychological modeling in expert evaluations, and the balancing effect of collaborative optimization across technical, psychological, and social dimensions. Importantly, the system's traceability and interpretability offer verifiable evidence for post-event review, model calibration, and training in emergency management. Beyond forest fire response, the proposed human–AI collaborative framework shows strong generalizability and scalability to compound disasters such as earthquakes, landslides, and urban flooding, thereby laying the groundwork for a new paradigm in intelligent emergency decision-making.

5. Discussion

This study proposes and validates an intelligent emergency management framework, the "Scenario–Learning–Decision" (SLD) model, which integrates Large Language Models (LLMs), Multi-Agent Systems (MASs), and Prospect Theory. By reconstructing and optimizing strategies based on the 2022 forest fire case in City C, the model's effectiveness was verified in terms of multi-objective optimization, dynamic environment responsiveness, and cross-departmental coordination. The experimental results demonstrate that in emergency scenarios characterized by high uncertainty and strong interdependencies, the SLD framework significantly outperforms traditional GIS-, MIS-, or expert-system-based emergency response models, exhibiting stronger decision robustness, interpretability, and system adaptability. These findings align with the global paradigm shift in emergency management from "data-driven" approaches to "cognitive-enhanced intelligent decision-making" [38].

Compared with earlier emergency response models that relied heavily on GIS, MIS, and expert systems, this study leverages LLMs to markedly improve the efficiency of extracting and analyzing unstructured information such as social media sentiment and

emergency reports [39]. Unlike MAS simulation systems that depend on static optimization models, our research incorporates a "learning-centered" decision-making mechanism [40], enabling the model to dynamically update strategies as scenarios evolve [41]. Furthermore, the integration of Prospect Theory allows the system to simulate expert judgments under conditions of risk aversion and loss aversion, thereby reflecting decision-making behaviors that are closer to real-world practices (Table 5).

Table 5. Comparative advantages and improvements of this study over existing research.

Comparison Dimension	Characteristics of Existing Research	Advantages and Improvements of This Study
Decision Framework	"Scenario-response" emergency decision-making [42]; scenario evolution primarily through "simulation–optimization" [43]	This study introduces the "learning-oriented" decision-making concept and proposes the "Scenario–Learning–Decision (SLD)" closed-loop framework, which enables full-chain integration from scenario construction to model learning and dynamic intelligent decision-making.
Technical Approach	Mainly relying on MAS framework [44,45]	The framework integrates Large Language Models (LLM + prompt + tools) with Multi-Agent Systems (MASs), supporting real-time simulation, cross-departmental collaboration, and multi-objective optimization.
Human–AI Collaboration	Expert systems + manual intervention, lacking a dual-driven mechanism [46]	An AI-first generation and expert-second revision mechanism is implemented, balancing algorithmic efficiency with the deep integration of expert experience.

The Scenario–Learning–Decision (SLD) framework marks a paradigm shift in intelligent emergency management, moving beyond mere "technological integration" toward a systematic transformation. On the one hand, the framework establishes a closed-loop mechanism of scenario construction–strategy learning–intelligent decision-making, providing a unified pathway for the efficient integration of multi-source heterogeneous data, knowledge reasoning, and expert cognition. On the other hand, the proposed AI–Expert dual-cycle collaboration mechanism combines AI-generated first-round response strategies with expert-driven cognitive refinement, thereby ensuring both computational efficiency and improved acceptability and interpretability of decisions. This highlights the practical value of explainable AI (XAI) and human–AI collaborative modeling in emergency contexts. Moreover, the deep integration of Large Language Models (LLMs) and Multi-Agent Systems (MASs) bridges the technical gap between semantic reasoning and behavioral modeling, resulting in a holistic platform capable of semantic understanding, situational recognition, and multi-agent coordination. This integrated approach not only extends the functional boundaries of existing emergency decision-making systems but also provides a general methodological foundation for modeling multimodal, cross-domain complex systems.

Nevertheless, several limitations remain. First, the factual consistency of LLM-generated content may be constrained under extreme scenarios by the boundaries of training corpora. Second, expert behavior modeling in this study relies on historical drills and survey data, which may not capture the full range of human variability in more complex or unforeseen situations. Third, the implementation of real-time cross-departmental data sharing is still limited by issues of data security, legal compliance, and system interoperability.

Future research may advance the system along three directions. First, explainability mechanisms should be embedded into LLM-driven decision processes, employing tools such as attention heatmaps, causal graphs, and rule-tracing methods to make AI reasoning more transparent and auditable, thereby enhancing both trust and compliance. Second, disaster chain simulation should be strengthened by combining LLM-based semantic reasoning with causal modeling techniques such as Graph Neural Networks and Bayesian Networks, enabling the system to capture cascading multi-hazard dynamics for comprehensive risk management. Third, cross-scale collaborative simulation mechanisms should be developed by integrating hierarchical agent systems with nested knowledge graphs, supporting dynamic response and information linkage from the community level to urban and national scales, and thus promoting more agile and effective emergency management.

6. Conclusions and Significance

6.1. Conclusions

This study focuses on addressing the prevalent decision-making challenges in contemporary emergency management, characterized by the "response delay–strategy silo–cognitive disconnection" dilemma, by proposing a novel intelligent emergency decision-making paradigm that integrates Large Language Model (LLM) empowerment, Multi-Agent System (MAS) modeling, and human–AI collaborative mechanisms.

First, at the conceptual level, this study embeds "learnability" into the core of the emergency decision-making process and redefines the knowledge evolution pathway in the era of digital intelligence. Unlike traditional decision models dominated by static plans and expert intuition, learning-driven decision-making emphasizes the ability of decision agents—including humans and AI systems—to continuously acquire, revise, and optimize their cognition throughout the evolution of disaster scenarios. This learning process is not limited to model-level technical iteration but constitutes a bidirectional human–machine interaction, a "human teaches machine, machine teaches human" feedback loop. Machine learning injects evolutionary capacity into the system, providing the foundation for intelligent generation, while human–AI collaborative learning drives the system from mere task execution toward emergent intelligence, forming a progressive "data–learning–decision" pathway. This conceptual innovation addresses the urgent need for cognitive augmentation and adaptive systems in emergency management and opens, to some extent, the "black box" between information, cognition, and wisdom in traditional decision models, offering a new theoretical paradigm for intelligent governance in the digital era.

Second, at the modeling level, the study develops an innovative Scenario–Learning–Decision (SLD) closed-loop framework, integrating three core modules: scenario construction, intelligent learning, and strategy output. This framework bridges the gaps among information perception, knowledge generation, and multi-objective optimization in emergency response. The SLD model combines the semantic understanding capability of large language models, the behavioral cognition modeling of prospect theory, and the multi-agent dynamic interaction mechanisms of MAS, enabling rapid, interpretable, and adaptive response simulation in complex scenarios with multiple constraints and incomplete information.

Third, at the methodological level, this research pioneers the integration of LLM intelligence (LLM + prompting + tools) into traditional MAS simulation systems, creating enhanced agents with language perception, knowledge reasoning, and strategy generation capabilities. These agents can automatically process natural language inputs, orchestrate specific task tools, and perform real-time translation and optimization from human intent to response strategies. This approach provides a technical pathway for building cognitive emergency systems with general semantic understanding and domain-specific decision-

making capacity, laying both theoretical and practical foundations for future human–AI integrated emergency governance ecosystems.

6.2. Significance

The present study not only provides a theoretical foundation and technical architecture for building a learning-enabled emergency management system, but also demonstrates significant value in the broader context of social governance modernization. On the one hand, in terms of intelligent upgrading, the study integrates large language models (LLMs) with multi-agent collaboration mechanisms, enabling emergency systems to acquire autonomous learning, intelligent inference, and strategy evolution capabilities. This advances emergency decision-making from experience-driven judgments toward knowledge-enhanced and intelligence-emergent paradigms, thereby achieving a shift from passive response to proactive prediction. On the other hand, at the level of modern governance transformation, the proposed AI–Expert dual-loop decision mechanism enhances both the scientific rigor and transparency of emergency decision-making. This mechanism provides a reusable technical pathway for addressing compound disaster chains and large-scale emergency scenarios, contributing to the development of a modern national emergency management system characterized by rapid response, precise assessment, and coordinated governance. Overall, this study delivers a systematic technical contribution to enhancing national public safety governance capacity and societal resilience, and holds strategic significance for advancing the modernization of the national governance system and governance capabilities.

Overall, this study delivers a systematic technical contribution to enhancing national public safety governance capacity and societal resilience, and holds strategic significance for advancing the modernization of the national governance system and governance capabilities.

This study has preliminarily validated the Scenario–Learning–Decision (SLD) model through simulation and a reconstructed real-case scenario. The results confirm its potential to enhance coordination, interpretability, and decision robustness in complex emergencies. Nonetheless, further work is needed to strengthen model verification by testing its adaptability in diverse real-world situations such as floods, earthquakes, and public-health crises. Extending validation to practical operations will help assess the SLD framework's robustness, scalability, and policy relevance, ensuring that it evolves from a validated research prototype into a dependable decision-support tool for future emergency management systems.

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