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DEPARTMENT: INTERNET OF THINGS, PEOPLE, AND PROCESSES

A Survey of Large Language Models in Urban Natural Disaster Emergency Management: Progress, Application, and Challenges

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The continuous impact of global climate change and human activities on the natural environment has significantly increased the frequency and complexity of emergencies and natural disasters in urban areas, posing higher requirements for the existing emergency management system. The rise of large language models (LLMs) provides a novel solution for emergency management to become intelligent. This article systematically analyzes the latest application progress of LLMs in disaster emergency management and discusses in detail the key role of LLMs in various stages before, during, and after disasters. In addition, this article puts forward the possible application framework and technical route of LLMs in emergency management in the future. Finally, this article summarizes the current challenges of applying LLMs to intelligent emergency management and outlines valuable research directions for the future.

With the intensification of global climate change and the impact of human activities on the natural environment, the frequency and complexity of emergencies and natural disasters in urban areas are increasing, which brings unprecedented challenges to emergency management departments. As the center of the economy and population, cities are highly vulnerable carriers, bearing the impact of various natural disasters. Urban natural disasters are natural phenomena that occur in cities, are caused by natural factors, and seriously impact the urban infrastructure, residents' lives, and property safety. Urban natural disasters are mainly categorized into geological disasters (such as earthquakes and debris flow), meteorological disasters (such as storms and drought), marine disasters, and biological disasters.[1] Given the dense infrastructure and high population density in urban areas, natural disasters are characterized by multiple types, wide coverage, high frequency, and heavy losses. Once such a disaster occurs, it causes immeasurable losses to the safety of human lives and properties. Therefore, how to construct a systematic and complete emergency management system according to different natural disaster characteristics, improve the city's disaster resistance, disaster relief and recovery capabilities, and effectively safeguard people's life and property safety is a common concern of the state, all levels governments, the people, and many scholars.

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Urban natural disaster emergency management refers to the prevention, organization, coordination, decision making, and action measures formulated and implemented by the government and institutions at all levels to deal with the potential damage and losses caused by natural disasters. The emergency management of urban natural disasters is typically divided into four main stages: disaster prevention, preparedness, response, and recovery.[2] In the disaster prevention stage, efforts are made to mitigate or delay the impact of disasters through real-time monitoring, risk assessment, and preventive measures. In the disaster preparedness stage, targeted emergency response plans are formulated according to disasters, and personnel and resources are preallocated to ensure rapid response when disasters occur. In the disaster response stage, optimize resource deployment plans according to disaster occurrence effectively improve disaster response efficiency. In the disaster recovery stage, disaster losses and emergency response are assessed, and the corresponding recovery plans are formulated.

However, with the acceleration of urbanization and the escalation of disaster complexity, the deficiencies of traditional emergency management methods in disaster monitoring, emergency decision making, and resource allocation have become increasingly prominent. Although emerging technologies such as big data, the Internet of Things, and artificial intelligence provide richer tools and means for intelligent emergency response, there remains a lack of a complete and comprehensive emergency management framework that integrates and coordinates different technologies and methods to form a unified and efficient disaster emergency management system in practical applications.

In reality, the scenarios and types of disasters are complex and changeable, and there are significant differences in response needs and decision-making methods before, during, and after disasters. The current intelligent emergency response approaches still have the following limitations: 1) They focus mainly on a single disaster scenario or emergency response stage and lack systematic management of the whole lifecycle of disasters. 2) The adopted technologies are often independent of each other and lack the interconnection between data, which affects the information transmission between systems and makes it difficult to cope with complex and dynamic disaster scenarios. 3) The hierarchical nature of decision making is seldom considered, and it is challenging to coordinate the task priorities between different decision-making levels and functional departments, which affects the overall disaster response efficiency. Therefore, it is necessary to integrate different technologies and methods to build a comprehensive and multilevel disaster emergency management system.

The rise of large language models (LLMs) provides innovative solutions for intelligent emergency management. The massive emergency monitoring data pouring into the system and the large volume of multisource heterogeneous information pose a significant challenge to intelligent emergency response technology perception and analysis scenarios. It further restricts the flexibility of adjusting emergency response strategies based on real-time data and makes it difficult to cope with complex and dynamically changing natural disaster tasks. Figure 1 illustrates the application of LLMs in all stages of emergency management, including disaster prevention, preparedness, response, and recovery. LLMs disassemble complex emergency management tasks into multiple easy-to-solve subtasks and schedule different models or analytical methods to complete the subtasks to solve the overall emergency problem. In addition, by integrating multiple data sources and massive data for multitask training, LLMs form a comprehensive situational awareness of disasters and can manage the whole lifecycle of different disaster scenarios. Finally, LLMs can continuously acquire new knowledge, which enables them to continuously improve their emergency management capabilities to cope with new, complex, and changing urban disaster scenarios.

The contributions of this article are as follows. 1) This article systematically discusses the potential application of LLMs in disaster emergency management, especially their key role in urban natural disaster. 2) The study details how LLMs can provide intelligent emergency response in all stages of disasters and proposes a possible future technical framework. 3) This article further analyzes the challenges of intelligent emergency response with LLMs and proposes future research directions for reference. This article reveals the innovative application value of LLMs in improving disaster emergency management, offers a new perspective for the urban natural disaster emergency management field, and provides valuable guidance for future research and practice.

CURRENT APPLICATIONS OF LLMs IN EMERGENCY MANAGEMENT

From the occurrence to the end of disasters, emergency management is usually divided into four stages: pre-disaster risk assessment and early warning, emergency planning and preparation, disaster response and resource coordination, and post-disaster damage evaluation and recovery. As shown in Figure 2, these four stages collectively form the comprehensive process of disaster emergency response. Each stage possesses distinct objectives and requirements for emergency response while collaboratively interacting with one another to encompass the entire disaster lifecycle and ensure scientific, systematic, and efficient emergency response.

At present, LLMs have been preliminarily applied in disaster emergency management. Xia et al.[3] apply LLMs (T5) to typhoon question and answer and improve disaster information retrieval accuracy. This work establishes a foundation for the cross integration of LLMs into the disaster emergency management domain. Kumbam and Vejre[4] propose FloodLense, a real-time monitoring framework that integrates deep learning models with LLMs. This study demonstrates LLMs' ability to transform traditional environmental monitoring and disaster response. Goecks and Waytowich[5] propose DisasterResponseGPT for disaster response. DisasterResponseGPT can effectively generate disaster action guidelines to respond to disasters, and the results are comparable to human-developed plans. This demonstrates the potential of LLMs to revolutionize the development of disaster response strategies. Han et al.[6] fine-tuned the professional large model QuakeBERT. By classifying and filtering social media data that are related to disasters, QuakeBERT evaluated the physical and social impacts caused by disasters, thereby effectively improving the efficiency of post-disaster emergency response.

However, despite the progress made by LLMs in disaster emergency management, there remains a significant gap between their deep integration capabilities and the systematic requirements for intelligent emergency response. Specifically, the current application of LLMs in emergency management is largely confined to individual stages of the disaster lifecycle.

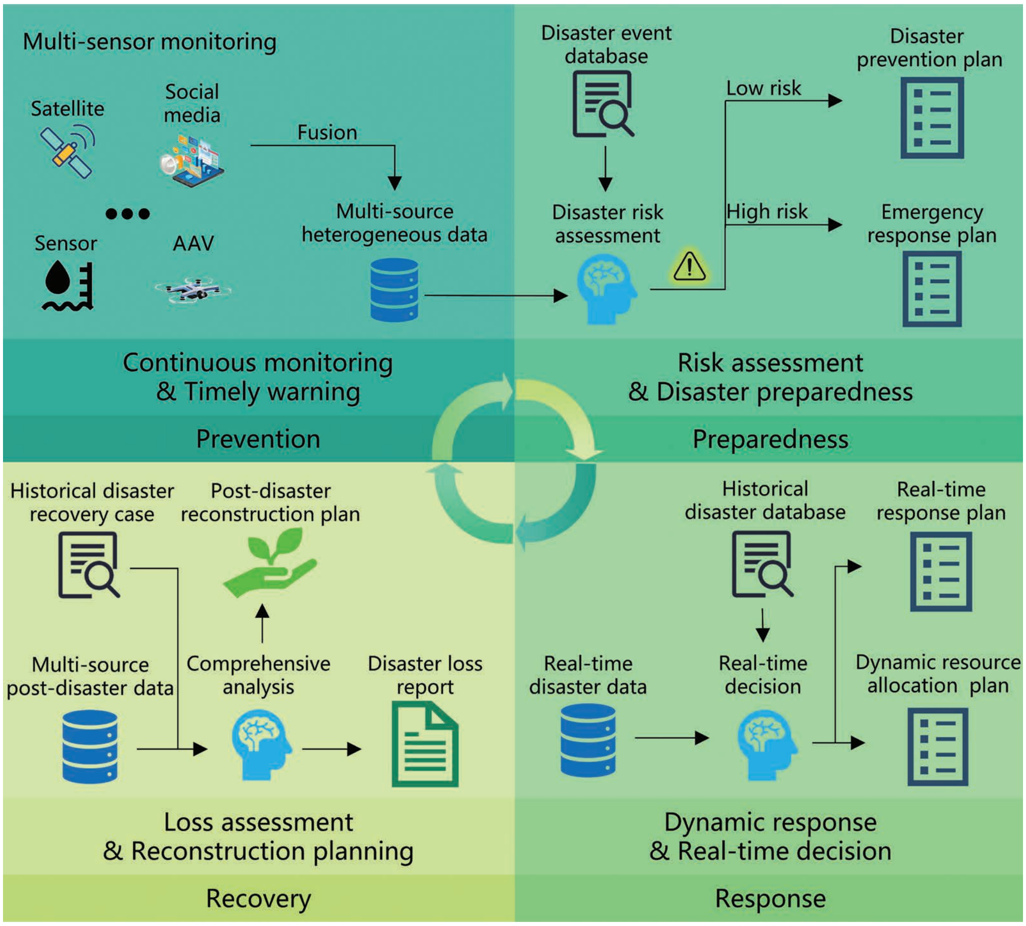

FIGURE 1. LLMs-driven intelligent emergency management for urban natural disasters. AAV: adeno-associated virus.

This results in a disconnect between disaster prediction, disaster response, and post-disaster recovery. Moreover, there is a lack of effective mechanisms to achieve deep functional integration across these scenarios, which limits the overall synergistic potential of LLMs in emergency management.

LLMs ENHANCE INTELLIGENT EMERGENCY MANAGEMENT OF DISASTERS

This section discusses the application of LLMs in critical disaster scenarios, including three stages:

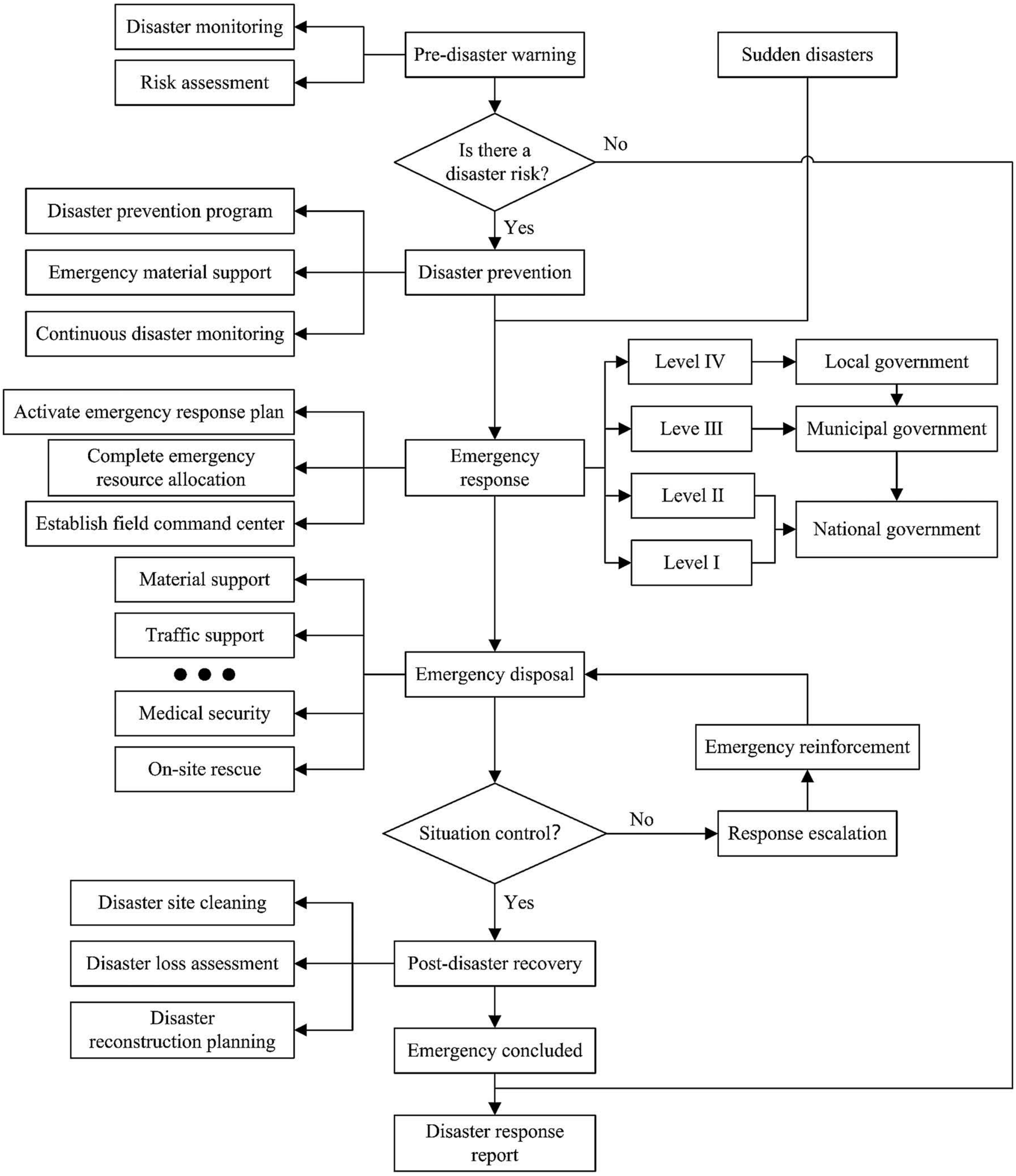

FIGURE 2. Emergency response process. The flowchart presents a comprehensive framework for disaster response management, covering the critical stages from pre-disaster monitoring to post-disaster recovery.

pre-disaster prevention and early warning, disaster emergency response, and post-disaster recovery.

Pre-Disaster Prevention and Early Warning

In this stage, the core tasks of LLMs are disaster monitoring, risk assessment, disaster early warning, and prevention. LLMs provide real-time monitoring of potential disaster risks and issue timely warnings to relevant departments.

First of all, LLMs leverage a variety of monitoring tools for monitoring, such as capturing users' comments on social media, analyzing satellite images of disaster risk areas, and obtaining local sensor data. Different data types have significant differences in spatial and temporal resolution, information dimension, and reliability. The integration of multisource disaster data can synthesize the strengths of each type, provide comprehensive and multidimensional information support for disaster emergency management, and effectively improve the efficiency and effectiveness of emergency response.

After obtaining real-time information on potential risk areas, LLMs perform disaster risk assessment tasks. By integrating real-time multisource heterogeneous data and historical disaster case databases, LLMs dig deeply into disaster-related knowledge, reasonably predict the future development trend of disasters, and evaluate disaster risks in the current environment. If there are no significant disaster risks, LLMs produce disaster prevention plans and recommend that the relevant departments strengthen the construction of infrastructure, such as emergency shelters, to improve the city's resilience. Conversely, LLMs should promptly issue warnings to the relevant departments and provide early-stage disaster emergency plans so that they can respond swiftly to the disaster.

Emergency Response in Disaster

In this section, we categorize disaster emergency response into three subsections: the emergency response system, the natural disaster chain effect, and the differentiated response to disasters. Through the organization of these three subsections, we highlight the multifaceted application potential of LLMs in disaster emergency management.

Emergency Response System

Emergency response is a core component of disaster management, which is a systematic process of minimizing human casualties, economic losses, and social disorder through rapid and concerted actions after a disaster.[7] Governments, nonprofit organizations, individuals, and community organizations from different sectors and levels collaborate to respond to disasters during emergency response. Multilevel, cross-departmental, and cross-jurisdictional relationships are necessary for the governance of modern urban emergency management, with collaborative and networked relationships constituting the core of urban emergency management.[8] In this stage, LLMs empower the emergency management system through a multilevel collaborative decision-making framework, providing support to emergency managers at different levels, helping them to make timely decisions according to the severity of the disaster, and ensuring the efficient implementation of emergency response. The overall structure of the disaster emergency organization system is shown in Figure 3.

Natural Disaster Chain Effect

Disaster evolution is characterized by significant temporal dynamics and chain-coupling effects, with its complexity stemming from the cross-temporal interaction between primary and secondary disasters.[9] In disaster emergency management, the disaster chain effect cannot be ignored. It makes the impact of disasters more complex and severe. Focusing only on the allocation of resources during the current disaster may make dealing with secondary disasters more difficult. In the emergency response to disasters, the core value of LLMs lies in transcending the static nature of traditional plans and constructing an adaptive emergency decision-making system through real-time, data-driven, and dynamic extrapolation. Rather than rigidly executing preset emergency response processes, LLMs conduct real-time analysis of disaster chain effects based on the spatiotemporal characteristics of disasters and multisource heterogeneous data, dynamically generating an all-encompassing response scheme that covers disaster containment, rescue coordination, and resource deployment.

Differentiated Response to Disasters

Significant differences exist in the spatiotemporal characteristics of emergency response across different disaster types. From the temporal dimension, disasters can be categorized into sudden onset and slow onset. Sudden-onset disasters typically erupt suddenly, making it difficult to provide early warning and leaving little preparation time for rescue. The primary tasks of LLMs are to assess the damage caused by disasters and generate rapid response strategies. Slow-onset disasters exhibit prolonged occurrence processes with clear pre-indicators. For these disasters, LLMs focus on long-term monitoring and risk warning through progressive risk early warning and disaster prevention resource allocation schemes to reduce the probability of disasters and mitigate their potential impacts. Regarding the spatial dimension, disasters exhibit significant variations between cities and villages and towns and cities with different physical geographic characteristics and infrastructure. LLMs optimize region-specific schemes by considering disaster risk profiles and the infrastructure conditions unique to each area. Additionally, LLMs integrate resource supply and demand information between different regions, such as materials distribution and rescue forces, to achieve cross-regional collaborative disaster relief. This spatial–temporal-coupled intelligent decision-making paradigm significantly improves the accuracy and robustness of emergency management in complex disaster scenarios.

Post-Disaster Recovery

Post-disaster recovery refers to the process of restoring and potentially enhancing the ecosystem to its original state after a natural disaster.[10] In this stage, the main tasks of LLMs are disaster damage assessment and post-disaster reconstruction planning, which facilitate the city's rational allocation of resources and ultimately realize its comprehensive recovery and sustainable development.

Following the conclusion of a disaster, the relevant departments need to promptly and effectively assess the damage caused by the disaster to determine subsequent assistance and reconstruction plans. After disaster emergency response efforts, LLMs store extensive disaster-related information to provide investigators with scientifically optimized routes. Furthermore, LLMs can integrate diverse post-disaster data, such as building damage, casualties, and property losses, to evaluate the disaster impacts from a global level and generate multidimensional post-disaster assessment reports to offer a scientific foundation for subsequent post-disaster recovery plans.

After the disaster loss assessment, relevant departments need to carry out the corresponding post-disaster reconstruction plans according to the loss caused by the disasters. Post-disaster reconstruction includes

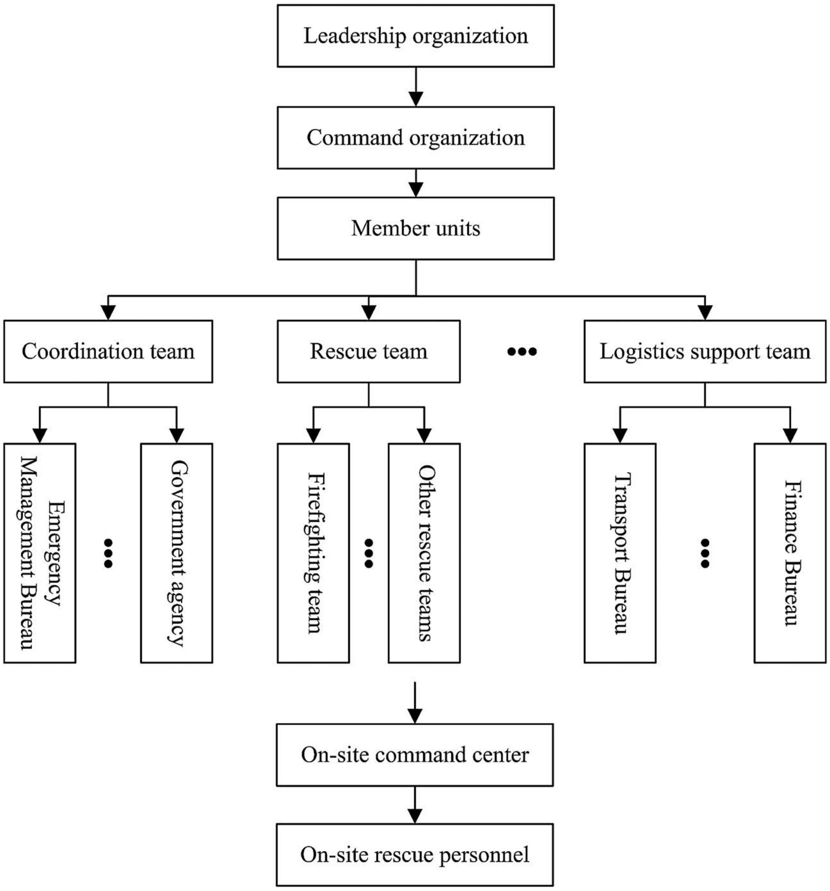

FIGURE 3. Hierarchical structure of disaster emergency response.

transportation infrastructure restoration, urban housing reconstruction, and resource procurement plans. The impact of disasters varies according to the extent of damage and the affected area, and expert experience may not always be applicable. LLMs can generate targeted recovery and reconstruction strategies for disaster-affected areas according to the specific characteristics of different disaster events, such as urban and rural differences and sudden-onset and slow-onset disasters, and consider the long-term risk prevention needs of disaster-affected areas in the plan to ensure post-disaster reconstruction possess better disaster resistance.

TECHNOLOGICAL ROUTE

This section introduces the primary techniques and methods of LLMs applied to urban natural disaster emergency management, including model capability enhancement, task-intelligent assignment, and external tool invocation. The overall technical framework is shown in Figure 4, which combines multi-agent systems (MASs)[11] and LLMs within the emergency management domain.

Model Capability Enhancement

First, the professional capacity of LLMs needs to be enhanced to address a broad spectrum of professional tasks in urban natural disaster and emergency management. The methods for enhancing LLMs' capabilities include pretraining and fine-tuning.

Pretraining

Pretraining refers to training neural network models on large-scale datasets to enhance their generalization capabilities, enabling them to be applied to various general tasks.[12] Currently, numerous pretrained LLMs have been developed, such as LLaVA[13] and DeepSeek.[14] Pretraining establishes a foundation framework for the capabilities of LLMs. By pretraining on large-scale corpora, LLMs acquire basic language understanding and generation skills, enabling them to be applied to various downstream tasks such as text generation, classification recognition, dialogue, and question answering. Depending on different types of pretraining models, users can employ fine-tuning or prompt engineering to adapt LLMs to emergency management scenarios quickly.

Fine-Tuning

Although pretraining has endowed LLMs with the ability to solve a variety of general tasks, their performance in the specialized domain of emergency management still exhibits notable limitations. An increasing amount of research has demonstrated that LLMs' capabilities can be further adapted to specific mission objectives, a process referred to as fine-tuning. In general, fine-tuning is categorized into two types: full fine-tuning and parameter-efficient fine-tuning (PEFT). Full fine-tuning refers to the training and adjustment of all model parameters on the basis of pretraining, enabling it to adapt to different downstream tasks. BERT[15] is the first to validate the full fine-tuning paradigm for natural language processing (NLP) tasks systematically. T5[16] introduces a unified text-to-text framework and adapts the model to various tasks such as summarization, question and answer, and text classification. ViT[17] extends the full fine-tuning paradigm from the NLP domain to the computer vision (CV) domain. In emergency management, full fine-tuning leverages domain-specific data to capture mission-specific characteristics (such as disaster type and response level) to improve model performance significantly.

PEFT is a fine-tuning method that leverages various deep learning techniques to reduce the number of trainable parameters while maintaining performance comparable to full fine-tuning. This approach can significantly reduce storage and computational costs. Based on the parameter update method, PEFT can be broadly categorized into four types: additive fine-tuning, partial fine-tuning, reparameterized fine-tuning, and hybrid fine-tuning.[18]

Additive fine-tuning introduces additional training modules to the pretrained model, freezes the original model parameters, and optimizes only the newly added training modules to achieve task-specific fine-tuning. Partial fine-tuning reduces the number of parameter updates by selectively optimizing the subset parameters of the pretrained model, such as specific layers, parameter types, or sparse subsets, while discarding unimportant parameters. Reparameterized fine-tuning uses a mathematical transformation to structurally compress the number of parameter updates and converts the fully fine-tuning parameters into low-rank, sparse, or other representations, thereby effectively reducing the number of trainable parameters and maintaining the model's performance. By considering the characteristics of the aforementioned three fine-tuning methods, hybrid fine-tuning aims to integrate the strengths of different fine-tuning techniques and enhance the adaptability and performance of the model in complex tasks by combining multiple PEFT methods.

In urban natural disaster emergency management, when the data and computing resources are sufficient, employing full-parameter fine-tuning technology is undoubtedly the most effective and appropriate choice. However, due to the limitations of various factors (such as limited resources and heterogeneous devices), the full fine-tuning method is challenging to adopt widely, making PEFT a more practical alternative. PEFT technology provides a new paradigm for lightweight model landing in emergency management, ensuring efficient performance while effectively addressing the challenges of resource-constrained environments.

Task-Intelligent Assignment

In urban natural disaster emergency management, LLMs combine with MASs to accomplish complex tasks in emergency management. An agent is an entity placed in the environment that can perceive different parameters and make decisions based on its objectives. The entity performs the necessary environmental actions by the decision.[19] As urban natural disaster emergency management involves multidimensional dynamic decision making and cross-domain coordination requirements, it is difficult for a single agent system to realize comprehensive perception and collaborative response across all factors. Therefore, constructing a multiagent cooperation architecture has become an essential approach to improve the effectiveness of complex disaster response.

An MAS consists of multiple interacting agents. Guided by common goals, these agents collaborate, divide tasks, and interact to complete tasks or solve problems. Specifically, in emergency management, the workflow of the MAS is described as follows:

- *Role-specific agent*: Each agent has specific responsibilities and handles specific aspects of disaster emergency management. Disaster

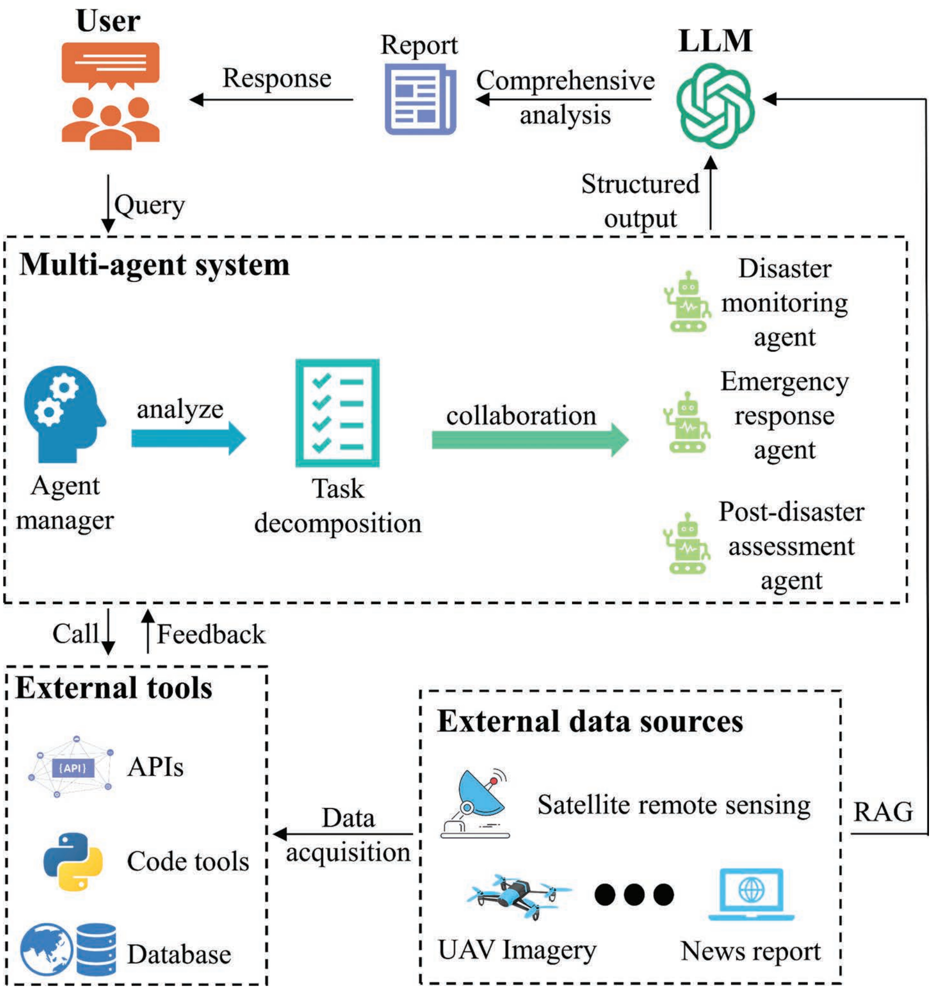

FIGURE 4. LLM-driven disaster management frame-work for full-cycle emergency response. APIs: application programming interfaces; RAG: retrieval-augmented generation.

monitoring agents collect real-time data from satellites, drones, and sensors to monitor abnormal disaster phenomena. Emergency response agents make real-time decisions regarding disaster events and dynamically manage the distribution of emergency supplies and rescue forces. Post-disaster assessment agents analyze disaster loss data and provide reasonable suggestions for the city's post-disaster reconstruction.

- *Task disassembly*: Task management agents break down complex tasks into smaller, more manageable subtasks that can be separately handled by different agents. For example, if a user submits a query about "making a typhoon emergency response plan," the task management agent breaks down the user query into different subtasks such as disaster monitoring, risk assessment, and resource scheduling, which are then processed by the corresponding specialized agents.
- *Task-collaborative processing*: Each agent in an MAS can communicate, negotiate, and collaborate with each other to solve complex problems that are challenging for a single agent to handle independently and jointly promote the progress of complex tasks. In addition, each agent possesses autonomy and initiative, meaning that it can independently execute the decision-making process and take appropriate actions to solve tasks. Agents can also leverage their historical data, perceived parameters, and information shared by other agents to predict potential future actions.[19]
- *Result integration and feedback*: Each agent submits the results of its subtasks to LLMs for structured integration. Subsequently, LLMs generate a report based on a comprehensive analysis of these results and provide feedback to users.

Based on the deep coupling architecture of the MAS and LLMs, urban natural disaster emergency management has realized the intelligent jump of the whole process from dynamic, collaborative response to closed-loop decision optimization. This significantly improves the timeliness and accuracy of disaster response and facilitates the paradigm transformation of emergency management from passive response to active prevention.

External Tool Invocation

Due to limitations in storage and training data, LLMs still encounter difficulties in certain professional tasks, such as the possibility that the learned information may be outdated, the inability to interact with the outside world, and the existence of hallucinations in answering questions. A practical solution is to use external tools to enhance the capabilities of LLMs. In this case, LLMs serve as the core of the system, analyze and understand the user's intentions, and select and invoke appropriate external tools to complete tasks.

The Model Context Protocol (MCP) is a technical protocol designed to improve the development efficiency of agents. Through standardized technical interfaces, MCP enables agents to flexibly invoke different external tools and services (such as application programming interface calls and database queries) according to specific task requirements, thus achieving seamless integration of external tools and services. Through the deep coordination of external tools, LLMs break through the limitations of static knowledge, realize dynamic knowledge integration and real-time decision-making closed loop, and promote the evolution of intelligent emergency response towards autonomy and specialization.

RESEARCH CHALLENGE

Based on the aforementioned research and discussion analysis, this section summarizes some critical challenges in applying LLMs to intelligent emergency response, namely, information uncertainty, numerical simulation, and hierarchical decision making.

Information Uncertainty

In the process of disaster development, the state of disaster is not static but will change dynamically with time and environment. Therefore, the information received by the command center is inherently uncertain, which prevents the command center from promptly grasping the complete overview of the disaster and its subsequent development trends. At the same time, the goals of emergency decision making are different in different stages of disaster. LLMs need to clarify the emergency objectives of each disaster stage and provide reasonable resource allocation and emergency rescue plans based on historical disaster data and current limited disaster information. However, how to ensure the rationality and effectiveness of the LLM-generated plans and avoid the waste or insufficiency of resources is still a difficulty to be overcome.

Numerical Simulation

Numerical simulation is a key tool in disaster emergency response for predicting the trend of disaster evolution, assessing potential risks, and estimating resource requirements. Traditional numerical simulations are constrained by single-model assumptions, making them challenging to adapt to dynamic and complex disaster scenarios. LLMs are expected to introduce more data-driven intelligence into numerical simulation. Numerical simulation depends on highly accurate scientific calculations, while LLMs focus on language understanding and cognitive ability. However, achieving efficient complementary integration between the two to enhance the diversity and flexibility of emergency decision-making programs remains a matter of further exploration.

Hierarchical Decision Making

In disaster emergency decision making, various roles are not at a single level but across multiple levels to cooperate with each other to cope with disasters.

These roles include victims, rescue teams, responsible units, leading agencies, relevant people, and so on. Roles at different decision-making levels have different needs for LLMs, and their decision-making characteristics and styles are also significantly different. The core challenge of LLMs is how to achieve cross-level demand adaptation from the affected individual to the command center and give corresponding decision support according to the needs, styles, and characteristics of these hierarchical roles.

FUTURE RESEARCH DIRECTIONS

Although current LLMs have achieved considerable progress, there remains a gap in intelligent emergency response. We outline several future development directions that are worthy of in-depth research to serve as a reference for researchers.

Multimodal Data Fusion

It is difficult to fully characterize the spatial and temporal evolution of disasters from a single data source due to modal limitations, and the fusion of multimodal data can achieve a comprehensive situational awareness of disaster intensity, diffusion path, and social impact. Future research can deepen the integration and application of LLMs with CV and remote sensing technology and improve the processing capability of LLMs on multimodal information.

Analysis of Disaster Chain Generation and Evolution

Currently, the chain reaction process and mechanism between these disasters are not straightforward enough, leading to difficulty in rationally deploying resources, which brings significant challenges to emergency management. Future research can utilize LLMs to mine the evolutionary relationships and potential impact pathways between different hazards to enhance the predictability and blocking efficiency of chained hazards.

Reliability and Interpretability

The current LLMs are often "black boxes," making emergency management programs difficult to interpret rationally. Future studies can consider combining knowledge graph technology or causal reasoning frameworks to enhance LLMs' evidence-based decision-making and explanation abilities. This will enable LLMs to explain "why" they make such emergency decisions when answering questions and provide a path to breaking the model-trust bottleneck in emergency scenarios.

CONCLUSION

This article summarized the current application of LLMs in disaster emergency management and explored their potential to advance this field toward intelligent emergency management. We expect that this article will offer a new perspective for future research in disaster emergency management and serve as a valuable reference for scholars in other related fields to promote the application of LLMs in intelligent emergency management.

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REFERENCES

1. J. C. Gill and B. D. Malamud, "Anthropogenic processes, natural hazards, and interactions in a multi-hazard framework," *Earth Sci. Rev.*, vol. 166, pp. 246–269, Mar. 2017, doi: 10.1016/j.earscirev.2017.01.002.
2. L. Zhou, X. Wu, Z. Xu, and H. Fujita, "Emergency decision making for natural disasters: An overview," *Int. J. Disaster Risk Reduct.*, vol. 27, pp. 567–576, Mar. 2018, doi: 10.1016/j.ijdrr.2017.09.037.
3. Y. Xia, Y. Huang, Q. Qiu, X. Zhang, L. Miao, and Y. Chen, "A question and answering service of typhoon disasters based on the T5 large language model," *ISPRS Int. J. Geo-Inf.*, vol. 13, no. 5, 2024, Art. no. 165, doi: 10.3390/ijgi13050165.
4. P. R. Kumbam and K. M. Vejre, "FloodLense: A framework for chatGPT-based real-time flood detection," 2024, *arXiv:2401.15501*.
5. V. G. Goecks and N. R. Waytowich, "DisasterResponseGPT: Large language models for accelerated plan of action development in disaster response scenarios," 2023, *arXiv:2306.17271*.
6. J. Han, Z. Zheng, X.-Z. Lu, K.-Y. Chen, and J.-R. Lin, "Enhanced earthquake impact analysis based on

social media texts via large language model," *Int. J. Disaster Risk Reduct.*, vol. 109, Jul. 2024, Art. no. 104574, doi: 10.1016/j.ijdrr.2024.104574.

7. Y. Feng and S. Cui, "A review of emergency response in disasters: Present and future perspectives," *Natural Hazards*, vol. 105, no. 1, pp. 1109–1138, 2021, doi: 10.1007/s11069-020-04297-x.
8. N. Kapucu, "Disaster and emergency management systems in urban areas," *Cities*, vol. 29, pp. S41–S49, Mar. 2012, doi: 10.1016/j.cities.2011.11.009.
9. G. E. Machlis, M. O. Román, and S. T. Pickett, "A framework for research on recurrent acute disasters," *Sci. Adv.*, vol. 8, no. 10, 2022, Art. no. eabk2458, doi: 10.1126/sciadv.abk2458.
10. I. Linkov and B. D. Trump, *The Science and Practice of Resilience*. Cham, Switzerland: Springer-Verlag, 2019.
11. L. Panait and S. Luke, "Cooperative multi-agent learning: The state of the art," *Auton. Agents Multi-Agent Syst.*, vol. 11, no. 3, pp. 387–434, 2005, doi: 10.1007/s10458-005-2631-2.
12. H. Bao, L. Dong, S. Piao, and F. Wei, "BEiT: BERT pre-training of image transformers," 2021, *arXiv:2106.08254*.
13. H. Liu, C. Li, Q. Wu, and Y. J. Lee, "Visual instruction tuning," *Adv. Neural Inf. Process. Syst.*, vol. 36, pp. 34,892–34,916, Jan. 2024.
14. D. Guo et al., "DeepSeek-R1: Incentivizing reasoning capability in LLMs via reinforcement learning," 2025, *arXiv:2501.12948*.
15. J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. 2019 Conf. North Amer. Chapter Assoc. Comput. Linguistics: Human Lang. Technol.*, 2019, vol. 1, pp. 4171–4186.
16. C. Raffel et al., "Exploring the limits of transfer learning with a unified text-to-text transformer," *J. Mach. Learn. Res.*, vol. 21, no. 140, pp. 1–67, 2020.
17. A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," 2020, *arXiv:2010.11929*.
18. L. Xu, H. Xie, S.-Z. J. Qin, X. Tao, and F. L. Wang, "Parameter-efficient fine-tuning methods for pretrained language models: A critical review and assessment," 2023, *arXiv:2312.12148*.
19. A. Dorri, S. S. Kanhere, and R. Jurdak, "Multiagent systems: A survey," *IEEE Access*, vol. 6, pp. 28,573–28,593, 2018.

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