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Research Article

AI in Social Good: LLM powered Interventions in Crisis Management and Disaster Response

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ABSTRACT

Large Language Models (LLMs) have emerged as transformative tools in crisis management and disaster response, offering real-time decision support, multilingual communication and rapid data synthesis for emergency responders and affected communities. This review examines the evolving landscape of LLM-based interventions in disaster scenarios, analysing their role in early warning systems, situational awareness, misinformation mitigation and humanitarian aid coordination. We provide a systematic evaluation of state-of-the-art models, including GPT-4, Claude and Mistral, highlighting their capabilities for processing unstructured crisis data from social media, satellite imagery and sensor networks. Additionally, we explore applications in emergency call triage, dynamic resource allocation and the automation of crisis communications to bridge information gaps in high-stakes environments. Although LLMs offer significant advantages, challenges persist in their reliability, bias and interpretability, necessitating robust fine-tuning, domain adaptation and human-in-the-loop strategies. We also discuss the ethical considerations surrounding the deployment of AI-driven crisis response tools, emphasising the importance of transparency, accountability and equitable access. This review presents recent advancements and case studies to highlight key research directions for enhancing the robustness, generalisation and real-world applicability of LLMs in humanitarian contexts. Interdisciplinary collaboration among AI researchers, policymakers and first responders plays a crucial role in ensuring that these technologies are effectively integrated into disaster management strategies. Leveraging LLMs as a force for social good requires ongoing refinement, ethical oversight and a commitment to developing AI systems that support equitable and efficient crisis response while mitigating the impact of global crises.

Keywords: Accountability, Artificial intelligence, Crisis management, Disaster response, Misinformation

1. Introduction

1.1. Background

The increasing frequency and severity of natural and human-induced disasters poses a significant challenge to global resilience. Climate change has intensified extreme weather events, including hurricanes, floods and wildfires, leading to unprecedented socioeconomic and infrastructural damage (IPCC, 2023). Rapid urbanisation and population growth in high-risk zones exacerbate vulnerabilities, while geopolitical conflicts contribute to large-scale humanitarian crises, often straining emergency response systems (UNDRR, 2022). These complex and evolving challenges require innovative solutions for disaster preparedness, response and recovery.

Artificial Intelligence (AI) has emerged as a transformative tool in crisis management, offering capabilities for early warning, situational awareness and resource optimisation[1]. In particular, Large Language Models (LLMs), such as OpenAI's GPT-4 and Meta's Llama, have demonstrated potential for processing vast volumes of unstructured data, extracting actionable insights and supporting decision making during emergencies[2]. LLMs have been increasingly used to assist in critical disaster response tasks, including real-time monitoring of social media for situational awareness[3], impact assessment of critical infrastructure[4] and flood disaster reporting through retrieval-augmented generation[5]. These models can be used to analyse real-time reports, detect misinformation and facilitate multilingual communication in disaster-affected regions[6]. However, despite their promise, concerns remain regarding their reliability, ethical implications and operational deployment in high-stakes environments.

Recent studies have highlighted the strengths and limitations of LLMs in disaster response. For example, CrisisSense-LLM, an instruction fine-tuned model, demonstrated improved classification of disaster-related tweets but still faced challenges with context understanding and bias[3]. Similarly, ChatGPT has shown utility in assisting with protective actions during climate hazards but has been criticised for providing incomplete or overly generalised advice[7]. Furthermore, AI-powered post-disaster reconstruction efforts using small language models (SLMs) have highlighted the potential of lightweight AI systems in rebuilding efforts but have also raised concerns about integrating community needs into automated planning processes[8].

1.2. Scope and objectives

This study explores the role of LLMs in disaster management, focusing on their applications across the disaster lifecycle-preparedness, response and recovery. It examines the current state of research, identifying key advancements in AI-driven emergency response and the potential for LLMs to support first responders, government agencies and humanitarian organisations.

A critical aspect of LLM deployment in crisis scenarios is its ability to synthesise real-time information and enhance decision support[9]. LLMs have been utilised in social media monitoring, emergency call triage and automated crisis communications, demonstrating their ability to process vast amounts of crisis-related data efficiently[10]. The use of LLMs in monitoring critical infrastructure failures during disasters has also been explored, highlighting their capacity to extract real-time insights from social media and open-source intelligence[4]. In addition, LLM-powered question-answering services have been developed to support disaster response, such as the T5-based typhoon information retrieval system, which integrates retrieval-augmented generation to improve disaster communication[6].

Despite these advancements, ethical considerations, such as model bias, data security and the risk of generating misleading content, must be addressed to ensure the responsible use of AI in disaster response[11]. Furthermore, concerns surrounding user intervention and trust in AI-powered disaster management systems have been raised, particularly in smart cities, where human-AI collaboration is essential for effective responses[12]. This study evaluates these challenges and proposes strategies for improving the robustness, transparency and interpretability of LLMs in high-risk settings.

1.3. Structure of the paper

The remainder of this paper is organised as follows. Section 2 provides an overview of the current research landscape, highlighting the key developments in LLM applications for crisis management. Section 3 discusses the challenges associated with LLM deployment including reliability, bias and ethical concerns. Section 4 presents real-world case studies demonstrating the effectiveness of AI-driven emergency response systems. Section 5 outlines future research directions focusing on improving model performance, integrating multimodal AI and developing governance frameworks for responsible AI deployment in disaster scenarios. Finally, Section 6 concludes with key takeaways and broader implications of LLMs in humanitarian technology. This review integrates recent advancements and identifies key gaps to offer a comprehensive perspective on the role of LLMs in crisis management with a focus on their ethical and effective implementation.

2. LLMs in Disaster Response: Current Research & Applications

2.1. Early warning systems & disaster forecasting

Early warning systems play a crucial role in mitigating the impacts of disasters by providing timely alerts to at-risk populations and response agencies. LLMs have demonstrated potential for enhancing these systems by integrating and analysing data from diverse sources, including meteorological reports, geospatial imagery and IoT-based sensor networks[9]. When combined with geospatial AI, LLMs can process complex climate patterns and generate early predictions for extreme weather events, such as hurricanes, wildfires and heatwaves[10]. Research has shown that LLMs, when trained with climate-specific datasets, can improve the accuracy of forecasting natural disasters by analysing historical weather trends and real-time sensor data[6].

One promising area of research involves LLM-enhanced earthquake prediction, where models process historical seismic data alongside real-time geophysical readings to assess risk probabilities[2]. Additionally, flood forecasting models have leveraged LLMs to synthesise river flow data, satellite imagery and climate variables, assisting disaster agencies in pre-emptively allocating resources. The use of retrieval-augmented generation (RAG) for flood disaster reporting has also been explored, with studies demonstrating that LLM-driven models can enhance early warning notifications through web-based retrieval and automated summarisation[5].

Despite these advancements, challenges regarding the interpretability of AI-generated forecasts remain, necessitating human oversight to ensure that model outputs align with domain expertise[13]. Furthermore, reliance on publicly available data sources presents risks related to misinformation and data bias, requiring future research into AI-driven validation mechanisms for disaster forecasting models[3].

2.2. Situational awareness and real-time data processing

Real-time situational awareness is essential for effective disaster response, enabling authorities to assess unfolding crises and efficiently coordinate interventions. LLMs play a pivotal role in this domain by processing unstructured data from multiple sources including social media posts, emergency call transcripts and satellite feeds[1]. The CrisisSense-LLM model has been fine-tuned to improve multi-label classification of disaster-related social media text, enabling more accurate crisis detection and event categorisation[3].

Social media mining has become an invaluable tool for tracking disaster-related events because platforms such as Twitter and Facebook provide real-time updates from affected communities. LLMs have been increasingly deployed to extract actionable insights from these data streams, identifying emerging hazards, damage reports and urgent assistance requests[11]. For example, AI-driven classifiers have been used to distinguish between critical and non-critical reports, assisting emergency responders in prioritising interventions. A recent study demonstrated that LLMs, when integrated with geospatial AI, can generate automated disaster impact assessments from social media images and text[4].

However, misinformation remains a significant challenge in crisis communication. Studies have shown that LLMs can be effective in identifying and counteracting false information during disasters, thus reducing the spread of misleading reports that could hinder emergency responses[14]. AI-driven fact-checking mechanisms have been integrated into disaster response systems to ensure that only verified information is disseminated, fostering trust and improving public compliance with official guidance[7].

2.3. Emergency communication & multilingual support

Disaster response efforts often occur in multilingual and culturally diverse regions, requiring efficient communication strategies to ensure that no affected community is left behind. LLMs have made considerable progress in automated translation and cross-lingual crisis communication, enabling emergency responders to interact with nonnative speakers and disseminate information effectively[9]. Recent advancements in multilingual AI models, such as the T5-based typhoon disaster information retrieval system, have demonstrated the potential of LLMs in providing rapid, language-adapted emergency responses[6].

AI-powered multilingual chatbots have been deployed in humanitarian settings to assist displaced individuals by providing real-time translation, emergency alerts and guidance on available aid services[10]. In addition, LLM-driven speech-to-text systems have enhanced emergency hotline efficiency, allowing call centres to transcribe, classify and route distress calls in multiple languages with improved accuracy. Studies have further explored how AI-powered voice assistants can provide immediate crisis responses in low-resource linguistic settings, addressing critical gaps in emergency communication for underserved populations[8].

While these advancements improve accessibility, linguistic bias remains a concern, particularly for underrepresented languages and dialects. Further fine-tuning of LLMs using region-specific datasets is necessary to enhance translation accuracy and contextual understanding[2]. The integration of AI-driven language models in disaster communication strategies should also prioritise ethical considerations, ensuring that marginalised communities are not disproportionately affected by model biases[12].

2.4. Humanitarian aid & resource optimisation

Efficient allocation of resources during disaster relief efforts is critical for minimising casualties and ensuring timely assistance. LLMs contribute to logistics automation, resource planning, medical triage and streamlining disaster management operations[13]. AI-driven prioritisation of medical services has been demonstrated through models that assist in triaging casualties based on severity levels derived from health records, real-time assessments and emergency call descriptions[1]. A study on disaster response optimisation highlighted the role of LLMs in analysing historical response patterns to improve the efficiency of rescue missions[7].

Furthermore, LLMs play a crucial role in automating humanitarian supply chain logistics by analysing demand forecasts and transport routes to ensure the efficient delivery of food, water and medical aid[15]. By integrating AI with satellite imagery and geospatial intelligence, response agencies can identify accessible evacuation routes, monitor infrastructure damage and improve overall disaster resilience[11]. The emergen CITY project explored how AI-enhanced digital twins can be leveraged for disaster relief operations, allowing authorities to simulate and optimise crisis responses in real time[12].

Despite these benefits, AI-based resource allocation faces challenges related to bias and fairness, because LLMs trained on historical data may inadvertently reinforce inequalities in aid distribution. Addressing these concerns requires a combination of human oversight and algorithmic transparency to ensure equitable disaster response strategies[14]. Researchers have suggested integrating human-AI collaboration frameworks to mitigate risks associated with biased predictions, ensuring that AI-enhanced humanitarian operations remain ethical and inclusive[4].

3. Challenges and Ethical Considerations

Despite the potential of LLMs to enhance disaster response, their deployment raises significant challenges related to reliability, fairness, privacy and human-AI collaboration. Given that these models operate in high-stakes environments, where erroneous decisions could have severe consequences, addressing these concerns is crucial for ensuring their ethical and effective use in crisis management[2]. Recent research has highlighted key areas of concern, including the risks of LLM-generated misinformation, biases in AI-driven disaster relief strategies, privacy vulnerabilities in crisis data processing and the need for transparent AI-human collaboration frameworks[12,3].

3.1. Reliability & model robustness

One of the key limitations of LLMs in disaster response is their susceptibility to factual inaccuracies and hallucinations, where models generate plausible but incorrect or misleading information[11]. This issue is particularly concerning in emergency situations, where incorrect advice, misclassified crisis reports or inaccurate forecasting can lead to inappropriate interventions or delays in critical aid distribution[10]. Research on instruction fine-tuning for disaster-specific AI models has demonstrated improvements in accuracy; however, models still struggle with real-time event detection owing to the unpredictable nature of crises[3].

To mitigate these risks, hybrid AI human verification systems have been proposed, ensuring that the LLM-generated outputs are validated by domain experts before deployment. Additionally, incorporating Retrieval-Augmented Generation (RAG) techniques allows models to cross-check information against verified disaster response databases, improving factual accuracy and reducing the risk of generating misleading content[13]. Studies have also suggested integrating LLMs with geospatial AI and multimodal sensor networks to enhance real-time accuracy in crisis forecasting[6].

Further research is required to enhance LLM robustness in dynamic crisis environments, particularly in processing incomplete, ambiguous or contradictory information streams from multiple sources[1]. Developing explainable AI (XAI) frameworks that provide insights into how models arrive at specific decisions is essential for ensuring their reliability in disaster scenarios[15].

3.2. Bias and Equity Concerns in AI-Driven Disaster Response

AI plays a pivotal role in disaster response, yet it raises significant concerns regarding bias and equity in decision making. AI models, particularly those deployed for emergency management, can unintentionally perpetuate disparities owing to algorithmic biases embedded in data sources and training processes[16].

One of the key ethical challenges in AI-driven disaster response is algorithmic bias. AI models rely on historical data to make predictions and automate decision-making; however, if the underlying data contain biases, such as skewed representation of affected populations, then the AI system may reinforce these inequities[17]. For example, predictive models may prioritise well-documented disaster-prone regions while underestimating the needs of marginalised or underrepresented communities[18].

Bias in AI-driven resource allocation exacerbates disparities in disaster management. AI-based decision support systems determine the distribution of emergency aid; however, flawed data inputs can lead to inequitable outcomes[19]. Studies have shown that AI models trained on disaster datasets with inadequate representation of low-income or rural areas tend to prioritise responses in urban settings, leaving remote communities underserved[20].

Language bias in crisis communication is a critical issue in AI-driven disaster management. Many AI models are predominantly trained on English-language datasets, limiting their ability to interpret and generate emergency messages in less commonly spoken languages[21]. This disparity can hinder timely response efforts in multilingual regions, particularly in developing countries where local dialects play a crucial role in emergency communication[18].

To address these biases, it is essential to expand the training data for geographical representation. AI models should be trained on diverse datasets that encompass disaster scenarios from different socioeconomic and cultural contexts[20]. Incorporating real-time bias-detection mechanisms with human oversight is also crucial for mitigating algorithmic discrimination. AI systems must be continuously monitored and audited by human experts to ensure fair and unbiased decision making in disaster response[16].

Reinforcement Learning with Human Feedback (RLHF) offers a promising approach for bias mitigation. By integrating the expertise of emergency responders and community representatives, AI models can refine their decision-making processes based on real-world insights, rather than purely data-driven trends[17]. In addition, bias mitigation strategies can be strengthened by enforcing ethical AI governance frameworks that mandate transparency, accountability and fairness in AI deployment[19].

Ensuring an equitable AI-driven disaster response requires a multifaceted approach that incorporates unbiased data representation, real-time human oversight and continuous model improvement through community engagement. By addressing bias at every stage of AI deployment, disaster management systems can become more inclusive, fair and effective in safeguarding vulnerable populations.

3.3. Privacy & data security

Handling sensitive information in disaster response presents significant ethical and legal challenges, particularly regarding data protection, consent and surveillance risks[13]. LLMs trained on publicly available crisis data may inadvertently process personal identifiers, geolocation data or medical records, raising concerns regarding privacy violations and unauthorised access[15]. AI-driven crisis monitoring systems have also raised ethical concerns, particularly when deployed in politically sensitive regions, where data collection could be misused[4].

Moreover, governments and emergency agencies increasingly rely on AI-powered surveillance systems, such as real-time social media monitoring and biometric recognition, to assess disaster situations and coordinate responses[9]. While these technologies improve situational awareness, they also risk overreach and potential misuse, particularly in politically sensitive or conflict-affected regions where AI-driven surveillance may be weaponized against certain groups[10].

To ensure ethical AI deployment, stringent data protection policies should be implemented, ensuring compliance with international privacy frameworks such as the EU General Data Protection Regulation (GDPR) and the UN Guiding Principles on Business and Human Rights[14]. In addition, the development of privacy-preserving AI techniques such as federated learning and differential privacy can enable disaster response models to operate without compromising individual confidentiality. Recent work has also explored secure AI-driven disaster communication protocols, ensuring encrypted information exchange between emergency responders and AI systems[12].

3.4. Human-AI collaboration & interpretability

Despite advancements in AI-driven disaster response, human expertise remains indispensable in crisis decision making. LLMs, while powerful in synthesising and analysing disaster-related data, lack the contextual awareness and ethical judgement required for high stakes interventions[1]. Consequently, human-AI collaboration frameworks are essential for balancing automation with accountability[11].

One of the key challenges in AI-assisted decision making is the "black-box" nature of LLMs, where model outputs lack transparency, making it difficult for emergency responders to understand the reasoning behind recommendations[2]. This opacity can lead to distrust among first responders, policymakers and affected communities, thus limiting the adoption of AI tools in disaster management[9]. Recent studies have explored the use of explainable AI (XAI) in crisis scenarios by developing interpretable models that justify LLM-generated outputs.

To enhance trust and transparency, researchers are working on explainable AI (XAI) approaches that provide interpretable justifications for LLM-generated outputs[6]. Additionally, fostering interdisciplinary collaboration between AI researchers, emergency professionals and policymakers is crucial in designing AI systems that align with real-world crisis management needs[13]. The integration of human-AI collaboration models, such as LLM-powered decision-support tools for emergency responders, has been proposed to ensure that AI recommendations are validated by experts before implementation[4].

4. Case Studies and Real-World Deployments

The deployment of LLMs in disaster response is no longer theoretical. Several real-world applications have demonstrated their efficacy in crisis detection, emergency communication and response planning. This section presents three case studies illustrating how LLMs have been used in social media monitoring, emergency call centres and disaster response planning and provides insights into their advantages and limitations.

4.1. Case study 1: LLMs in social media-driven crisis detection

On 6 February 2023 a 7.8-magnitude earthquake struck Turkey and Syria, leading to widespread devastation and loss of life. The sheer scale of disasters overwhelmed traditional emergency services, necessitating alternative methods for real-time information gathering and crisis detection. Social media platforms, particularly Twitter and WhatsApp, have become critical sources of real-time updates from affected communities, volunteers and relief organisations[13].

LLM-powered natural language processing (NLP) models were deployed to monitor and classify emergency messages from social media in real time. These AI-driven systems can identify distress signals from tweets and WhatsApp messages, classifying requests for help such as medical aid, shelter, food and missing persons and filtering misinformation to ensure accurate reporting of crisis events[3].

One of the key findings from the deployment of LLMs is their ability to prioritise urgent requests by distinguishing critical distress calls from general updates[9]. This automated classification helped aid agencies allocate resources more efficiently. Research has shown that AI models such as CrisisSense-LLM, fine-tuned for disaster informatics, can improve disaster classification in multilingual settings, but still require enhancements for low-resource languages[3]. The case study underscores the potential of LLMs in real-time disaster intelligence gathering but also highlights the need for multilingual fine-tuning to improve equity in crisis detection, integration with geospatial mapping tools to locate affected individuals and human-in-the-loop verification to reduce classification errors and ensure accuracy[2].

4.2. Case study 2: AI-assisted emergency call centres

Emergency call centres often face high call volumes during major disasters, leading to delays in dispatching first responders. To address this, several cities in the United States and Europe have experimented with LLM-powered AI triage assistants to support human operators in handling distress calls more efficiently[11]. These AI systems function by transcribing emergency calls in real time, classifying the severity of the reported incident, such as medical emergencies, fires, crimes and infrastructure collapses and generating automated response suggestions for 911 operators to expedite decision making[1].

A study conducted in New York City (2023) showed that LLM-assisted 911 dispatch systems reduced call processing times by 27% and improved triage accuracy by 19% compared with traditional manual methods[1]. This efficiency gain was attributed to automated categorisation of emergency calls, allowing urgent cases to be prioritised, multilingual capabilities enabling non-English speakers to receive immediate assistance through AI-powered translation and enhanced coordination with first responders, as AI-generated incident summaries were directly relayed to firefighters, paramedics and law enforcement[15].

However, concerns remain regarding AI hallucinations, in which LLMs misinterpret distress descriptions and ethical risks, particularly regarding privacy and data security in emergency recordings[2]. Studies have suggested that integrating AI-driven call triage systems with secure AI governance frameworks can mitigate these risks while improving the accuracy of automated emergency response[12]. Additionally, research on AI-powered multilingual emergency call classification has highlighted challenges in bias reduction and interpretability, necessitating human oversight in high-stakes decision-making[6].

The integration of LLMs in emergency call centres has significantly improved response efficiency; however, human oversight remains essential. Future research should focus on enhancing AI interpretability, minimising biases in call classification and ensuring robust data privacy protection[13].

4.3. Case study 3: Disaster response GPT for actionable decision making

One of the most promising applications of LLMs in disaster response is their ability to generate action plans for emergency teams. Disaster Response GPT, an AI-driven planning tool, has been developed to assist relief agencies and government bodies in designing rapid response strategies for unfolding crises[11]. This system allows users to input disaster scenarios, specifying the type of emergency such as earthquakes, floods or pandemics. LLMs then generate a structured response plan, including resource allocation, evacuation protocols and medical triage guidelines, which response teams can refine and customise before implementation[5].

A comparative study between AI-generated and human-planned response strategies revealed that Disaster Response GPT reduced response planning time by 35%, provided faster adaptation to real-time crisis developments and improved resource distribution accuracy by optimising supply chain logistics[1]. However, several challenges remain to be overcome. LLMs often struggle with real-world uncertainties such as spontaneous road closures that affect evacuation routes[7]. Ethical concerns also arise, as AI-driven recommendations must be validated to avoid discriminatory biases in resource allocation. Furthermore, while AI can accelerate decision making, human experts must validate and adapt AI-generated plans to ensure contextual relevance and ethical deployment[2].

Disaster Response GPT has demonstrated significant advantages in accelerating response planning but requires human validation to ensure contextual relevance and ethical deployment. Future developments should focus on incorporating real-time sensor data, enhancing model interpretability and refining AI-human coordination frameworks[15]. Research has also explored the use of AI-driven digital twins to simulate disaster scenarios and optimise resource allocation in real time, demonstrating the potential for AI-enhanced disaster response[12]. These case studies illustrate the growing role of LLMs in crisis detection, emergency communications and response planning. Although AI offers enhanced efficiency, multilingual support and predictive insights, its deployment in disaster scenarios must be guided by ethical oversight, human collaboration and continuous improvement to ensure fair and effective disaster response strategies[13]. AI-enhanced crisis planning tools, such as Disaster Response GPT and AI-powered social media monitoring platforms, have shown substantial promise, but further work is needed to improve model accuracy, enhance fairness in resource allocation and integrate multimodal AI for real-time disaster intelligence[6]. Incorporating AI capabilities with human judgment and governance principles improves disaster response efforts and promotes adaptability, transparency and fairness[12].

5. Domain-Specific Fine-Tuning Methods for Large Language Models in Disaster Response

5.1. Pretraining on disaster-specific corpora

Large Language Models (LLMs) can significantly enhance disaster response efficiency through pretraining on domain-specific corpora. Training LLMs on historical disaster reports, humanitarian response manuals, emergency protocols and past crisis communication records enables them to develop a nuanced understanding of disaster-related terminology and situational complexities[2]. Incorporating open-access datasets from relief organisations, governmental emergency response agencies and climate research institutes further improves the model's domain-specific knowledge, enhancing its ability to generate accurate and contextually appropriate responses[13].

5.2. Supervised fine-tuning with crisis-specific tasks

Supervised fine-tuning is crucial for improving LLM performance in emergency situations. This process involves annotating and refining models using labelled datasets focused on emergency classification tasks[6]. By training LLMs to differentiate between critical and non-critical distress calls, these models can facilitate faster emergency response[22]. Additionally, fine-tuning enables models to categorise different types of disaster aid requests, thereby allowing for more efficient resource allocation[2]. Furthermore, LLMs can be optimised to summarise damage assessments from raw reports, reducing information overload for first responders and improving decision-making in crisis situations[13].

5.3. Retrieval-Augmented Generation (RAG) for real-time updates

Retrieval-Augmented Generation (RAG) techniques enhance LLM outputs by dynamically fetching verified disaster-related knowledge from authoritative sources such as government databases, meteorological centres and humanitarian organisations[23]. Integrating RAG methods ensures that AI-generated recommendations remain updated in real time, thereby minimising the risk of outdated or inaccurate responses[2]. This approach also strengthens trust in AI-driven disaster response frameworks by providing fact-checked, evidence-based information, thereby improving the reliability and effectiveness of emergency support systems[6].

5.4 Reinforcement Learning with Human Feedback (RLHF) for crisis contexts

Incorporating feedback from emergency responders into LLM training enhances decision-making during crises. Reinforcement Learning with Human Feedback (RLHF) enables AI models to refine their recommendations over time based on expert assessments of disaster response actions[24]. This approach optimises resource allocation strategies, ensuring that aid distribution is conducted more efficiently in real-time disaster scenarios[2]. In addition, it improves evacuation planning by integrating dynamic updates based on evolving disaster conditions[13]. AI-driven insights and human expertise can be better coordinated through this approach, strengthening overall emergency response measures[22].

5.5 Low-resource NLP adaptation for underrepresented languages

Disaster communication often requires multilingual support to ensure inclusivity in crisis response. Fine-tuning LLMs on region-specific linguistic datasets enhances translation accuracy and improves the interpretation of emergency messages for diverse populations[6]. Addressing linguistic disparities in disaster response can be achieved through the development of multilingual emergency response benchmarks, allowing AI models to cater to a broader range of linguistic needs[23]. Improving LLM performance on underrepresented languages further facilitates the dissemination of crucial information during global disasters, ensuring that emergency alerts and instructions are accessible to all affected communities[2].

5.6 Real-time model updating through crowdsourced feedback

Emergency responders and affected communities play a vital role in refining AI-generated outputs by providing iterative feedback, enabling continuous improvements in LLM responses[24]. The use of federated learning techniques ensures that models can be updated securely while preserving data privacy and adhering to ethical AI governance principles[2]. By incorporating real-time feedback from those on the ground, LLMs can become more adaptive and responsive to the evolving nature of disaster scenarios.

The integration of these domain-specific fine-tuning methods enhances the reliability, contextual awareness and responsiveness of LLMs for disaster management. As a result, AI-driven disaster response systems can contribute more effectively to global disaster resilience, providing real-time support and improving coordination in emergency situations.

6. Future Research Directions

6.1. Regulatory considerations for AI in disaster management

The integration of artificial intelligence (AI) in disaster management necessitates a comprehensive regulatory framework that balances technological advancements with risk mitigation. Current discussions on AI regulation highlight the challenges posed by the transboundary nature of AI, which complicates enforcement and necessitates principle-based approaches that focus on both processes and outcomes[25]. The European Commission's AI regulatory framework categorises AI applications into four risk levels, establishing a structured legal approach for assessing AI's role in critical sectors such as disaster management[26]. Additionally, the United Kingdom's pro-innovation regulatory stance on AI emphasises principles such as safety, transparency, fairness, accountability and contestability to ensure responsible AI deployment[27]. The application of these regulatory frameworks to AI-driven disaster response systems ensures that AI technologies align with ethical and legal standards while optimising disaster risk reduction strategies[28].

6.2. AI ethics and governance in disaster response

Ethical considerations in AI-driven disaster response frameworks are critical for ensuring transparency, fairness and accountability. AI models used in disaster risk reduction must be designed to avoid biases, particularly in social media-based situational awareness systems, which risk marginalising communities with limited digital access[29]. Moreover, AI governance frameworks must incorporate oversight mechanisms to regulate AI usage in disaster management, particularly in cases where mispredictions can have severe humanitarian consequences. Additionally, privacy and data security concerns must be addressed as AI systems increasingly rely on large-scale data mining for disaster forecasting. This necessitates the development of adaptive legal frameworks that integrate AI governance with environmental and disaster law considerations[25].

6.3. AI auditing mechanisms and risk mitigation strategies

The auditing of AI systems in disaster management is essential to ensure compliance with ethical and legal standards. AI auditing involves the examination of algorithmic decision-making processes to identify biases, ensure fairness and mitigate unintended consequences[30]. In financial and governance contexts, AI auditing frameworks have already been implemented to assess compliance, fairness and accountability, offering valuable lessons for AI applications in disaster management[27]. Specifically, AI auditing mechanisms in disaster response should focus on the following:

- **Algorithmic transparency** to enhance trust and accountability[30].
- **Bias mitigation strategies** to ensure equitable disaster response across diverse communities[27].
- **Explainable AI (XAI) techniques** to provide insights into AI-generated predictions and their implications for disaster preparedness and response[30].

Future research can enhance the reliability, accountability and fairness of AI-driven disaster management systems through the development of robust regulatory frameworks, the establishment of ethical AI governance and the implementation of comprehensive auditing mechanisms[29].

7. Conclusion

The use of Large Language Models (LLMs) in crisis management represents a major step forward in enhancing disaster preparedness, response coordination and humanitarian aid distribution. The case studies examined in this study demonstrate the tangible benefits of AI-driven emergency response, from social media crisis detection to AI-assisted triage in emergency call centres[10]. However, significant challenges remain, particularly in ensuring model reliability and mitigating hallucinations in high-stakes environments[11]. Addressing biases in AI-driven decision making and ensuring equitable disaster responses remains a priority, as language models trained on historically skewed datasets may inadvertently reinforce disparities in emergency management[13]. Additionally, safeguarding privacy and security in AI-assisted emergency communications is essential because crisis response systems often process sensitive information that must be handled ethically and in compliance with regulatory frameworks[1]. Enhancing human-AI collaboration is another crucial factor, as AI-generated outputs require validation and oversight to maintain trust, transparency and accountability in disaster management decision-making[2].

To realise the full potential of LLMs in disaster response, interdisciplinary collaboration between AI researchers, emergency responders, policymakers and humanitarian organisations is essential. Future advancements in disaster-specific AI fine-tuning, multimodal intelligence integration and ethical AI governance frameworks will be key to ensuring responsible AI adoption in crisis management. AI-enhanced disaster planning tools such as Disaster Response GPT and digital twin-based crisis simulations provide promising pathways for AI-driven disaster preparedness and response[12].

The ethical and effective use of AI enables disaster response agencies to strengthen resilience, optimise decision making and safeguard lives during crises. Research into LLM-powered multilingual emergency response systems, bias-aware AI frameworks and real-time AI-driven disaster simulations will help bridge the existing gaps in AI-enabled disaster management[6]. Through continuous model refinement, policy innovation and cross-sector collaboration, AI-driven disaster response strategies can become more transparent, efficient and socially responsible.

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