Artificial Intelligence for Emergency Response: Developing A Real-Time Decision Support System for Disaster Management

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Abstract
This study investigates the impact of AI-based Decision Support Systems (AI_DSS) and Real-Time Predictive Analytics (RT_PA) on Emergency Response Quality (ERQ) during disaster scenarios. A structured survey was administered to 291 households in New York, aiming to assess how emerging technologies influence the effectiveness and efficiency of emergency responses. The data, analyzed using both SPSS and R Studio, revealed a strong, statistically significant relationship between the use of AI and predictive analytics and improved ERQ outcomes. The regression model (Adjusted $R^2 = 0.629$) confirms that AI_DSS and RT_PA significantly contribute to better decision-making, faster response times, and optimized resource allocation during crises. These findings highlight the managerial and strategic value of integrating intelligent systems into disaster response operations, particularly in urban settings like the United States. The study provides actionable insights for policymakers, emergency services, and urban planners in adopting technology-driven emergency management frameworks.

Keywords: Emergency Response, AI Decision Support Systems, Predictive Analytics, Disaster Management

Introduction

The frequency and intensity of natural and human-induced disasters have escalated in recent years, necessitating more advanced and responsive disaster management systems. With increasing urbanization, climate change, and global interdependencies, the traditional reactive approach to emergency management is proving insufficient. In this context, Artificial Intelligence (AI) has emerged as a transformative force, offering predictive insights, real-time decision support, and enhanced situational awareness that can significantly improve disaster response operations (Dominguez-Péry et al., 2021; Vermiglio et al., 2022).

Recent technological advances have enabled the integration of cyber-physical systems, big data analytics, unmanned vehicles, drones, and digital twins into disaster management frameworks. Behera et al. (2025) demonstrated the effectiveness of unmanned ground vehicles (UGVs) powered by AI for underground mine inspections and rescue operations, underscoring AI's potential in hazardous environments. Similarly, Johny et al. (2025) emphasized the importance of optimal drone selection in emergency logistics using the stratified-best-worst method, reinforcing how smart systems can support rapid, data-driven responses.

AI not only enables automation but also supports real-time decision-making through data integration, pattern recognition, and predictive modeling. These capabilities are vital for emergency responders who must make critical decisions under uncertainty and time pressure. For instance, Dominguez-Péry et al. (2021) illustrated how big data analytics and social media mining were used effectively during the MV Wakashio maritime disaster to enhance coordination and resource mobilization. Likewise, Nayal et al. (2022) highlighted how AI mitigated agricultural supply chain risks during the COVID-19 pandemic by optimizing logistics and resource allocation.

The development of smart cities further amplifies the relevance of AI in disaster management. Smart infrastructure, IoT sensors, and real-time surveillance data can be harnessed to provide early warnings, monitor environmental changes, and coordinate evacuation plans. Studies by de Bem Machado et al. (2024) and Renukappa et al. (2024) elaborated on the growing role of AI in transforming urban environments into more resilient, responsive ecosystems. These cities, equipped with real-time data flows and decision-making systems, offer a powerful testbed for deploying AI-driven emergency response tools.

In addition, information systems and digital technologies like city information modeling (CIM) and the metaverse are now being explored to support quality and continuity in disaster response. Okonta et al. (2025) identified research gaps in CIM for disaster planning, while el Jaouhari et al. (2024) explored the role of metaverse applications in building resilience under disruptive conditions. These emerging technologies, when coupled with AI, form a robust ecosystem for managing complex, large-scale emergencies. Logistics and supply chain management—a critical component of disaster response—benefits significantly from AI integration. Shefa et al. (2025) evaluated online path planning models under road disruptions, while Sentia et al. (2025) conducted a crossbreed literature review on information systems in humanitarian logistics. Both studies emphasize that AI enhances routing, reduces delays, and improves resource distribution efficiency. Singh et al. (2025) also observed that AI and big data significantly contribute to enhancing supply chain resilience.

Despite these advancements, the real-world deployment of AI in emergency response still faces challenges related to interoperability, trust, real-time data access, and adaptability to unknown scenarios. Dixit et al. (2025) examined the use of smart systems in Nepal for disaster risk reduction and identified the need for contextual customization and localized data training for AI models.

Given the multidisciplinary nature of disaster response—encompassing logistics, communication, health, and security—there is a pressing need to develop a comprehensive AI-based real-time decision support system. Such a system should integrate diverse data sources, employ predictive analytics, and offer actionable insights for field operatives and policymakers alike. This study aims to explore the development and deployment of such a system, assessing its impact on response efficiency and resource optimization. Drawing from recent global evidence and technological trends, the research will contribute to bridging the gap between AI capabilities and practical emergency management applications.

Literature Review

The increasing frequency and intensity of natural and man-made disasters have necessitated the transformation of disaster management strategies through advanced technologies. Scholars have examined the evolution of emergency management from reactive mechanisms to data-driven, anticipatory systems leveraging Artificial Intelligence (AI), Internet of Things (IoT), Digital Twins (DT), and other cyber-physical innovations. Digital Twins (DTs) have emerged as a critical enabler in both safety and supply chain contexts. Luo et al. (2024) provided a comprehensive literature review highlighting how DTs contribute to construction safety risk management, enabling real-time monitoring, predictive analytics, and enhanced safety protocols. Extending this idea, Patil et al. (2024) found that DT readiness significantly impacts supply chain transparency and sustainability. These studies underline that DTs provide a dynamic mirror of physical systems, facilitating agile responses in high-risk environments, particularly in manufacturing and logistics.

Humanitarian supply chains—known for their complexity and urgency—are increasingly digitalized. Shrivastav and Bag (2024) examined humanitarian logistics through a hybrid approach using academic and social media data, suggesting a shift toward socially responsive digital platforms. In a follow-up study, Shrivastav and Sareen (2024) emphasized AI's role in real-time humanitarian logistics, illustrating the power of user-generated content to optimize decisions under uncertainty. Ghadge (2023) provided a systems perspective on how ICT can streamline disaster management cycles, focusing on coordination among stakeholders and enhanced visibility in logistics flows.

AI and machine learning (ML), once confined to experimental stages, now play a pivotal role in emergency forecasting, resource allocation, and real-time situational analysis. For instance, Johnson et al. (2023) demonstrated how explainable AI systems are being used to improve emergency medical outcomes such as opioid overdose survival rates. Similarly, Lee et al. (2023) documented China's AI-driven public health governance model in response to COVID-19, showcasing a digitally transformed infrastructure capable of early detection, rapid response, and effective resource distribution.

Smart cities are natural ecosystems for deploying these technologies due to their infrastructural integration and citizen-centric focus. Islam and Sufian (2023) discussed AI and ML integration in urban dashboards, which improves service delivery and empowers data-driven decision-making. Susantono et al. (2024) laid the framework for the Nusantara Capital City, combining smart sensors, open data, and sustainable infrastructure. Nikiforova et al. (2023) stressed the significance of open data for achieving Society 5.0 goals and sustainable development, where citizens are at the core of smart governance.

IoT's role is particularly critical in disaster detection and response. Khan et al. (2022) proposed a flood detection system integrating bioinformatics, IoT devices, and Android apps, which proved efficient for early warnings and community alerting. Hou et al. (2020) and Yang et al. (2020) extended IoT-based systems to library material delivery and emergency logistics, demonstrating the technology's versatility. Shammar and Zahary (2020) offered a comprehensive survey on IoT's operational landscape, highlighting sensor interoperability and platform scalability as crucial for success.

The integration of ERP and digital platforms in emergency services has also attracted scholarly attention. Bhattacharya et al. (2023) empirically tested ERP system effectiveness in emergency services, finding that alignment of digital tools with organizational workflows improved coordination and performance. Elia et al. (2022) focused on process-based information systems using open innovation during COVID-19, emphasizing the role of collaborative platforms in enhancing resilience.

Smart and resilient supply chains have gained traction in both academic and applied research. Dixit et al. (2025) analyzed smart systems in disaster risk reduction in Nepal and emphasized emerging technologies' role in resource optimization and vulnerability reduction. Singh et al. (2025) further explained how AI and big data amplify supply chain resilience by forecasting risks, improving adaptability, and minimizing disruptions. In the context of digital humanitarianism, Kumar et al. (2022) explored the antecedents and consequences of adopting digital tools in crisis management, indicating a positive influence on stakeholder trust and operational efficiency.

In terms of emergency coordination, Park and Johnston (2019) studied the determinants of collaboration between digital volunteers and formal response organizations, concluding that mutual trust and platform integration were key enablers. Ernst et al. (2017) explored crowdsourcing and collaboration in emergency settings, highlighting participatory governance and digital trustworthiness. From a historical and theoretical lens, Tarn et al. (2008) critiqued man-made system disasters from a systemic perspective, while Kara-Zaitri (1996) presented an overview of the state-of-the-art tools for disaster prevention. These foundational insights continue to guide modern technological implementations.

The ethical and governance dimensions are not overlooked. Buchanan and Sparagowski (2022) analyzed the interplay of social justice and emerging technologies in emergency management, advocating for equitable access and ethical design. Puaschunder (2023) stressed responsibility in digital investments post-COVID, urging policymakers to consider long-term sustainability and social impacts.

In conclusion, the reviewed literature collectively suggests a paradigm shift in disaster and emergency management—from reactive strategies to proactive, intelligent systems. The synergy between AI, IoT, digital twins, ERP, and open data frameworks has created a robust technological ecosystem that enhances preparedness, transparency, and sustainability. Yet, gaps remain in ethical governance, platform interoperability, and inclusive access, warranting further interdisciplinary research and global collaboration.

RQ: How does the integration of AI-driven decision support systems influence the speed and accuracy of emergency response during disasters?

RQ2: What is the impact of real-time data analytics and predictive modeling on resource allocation efficiency in disaster management?

Methodology

This study adopted a quantitative research design to examine the impact of AI-based Decision Support Systems (AI_DSS) and Real-Time Predictive Analytics (RT_PA) on Emergency Response Quality (ERQ) during disasters. A structured questionnaire was developed, consisting of validated multi-item scales for each construct, using a five-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree." A total of 291 responses were collected from households in New York, selected through purposive sampling to ensure relevance to disaster preparedness and response experiences. The sample represented diverse demographics, including age, income levels, and educational backgrounds.

Research Objectives:

- To evaluate the effectiveness of AI-based real-time decision support systems in improving emergency response outcomes during natural and man-made disasters.
- To assess the role of real-time predictive analytics in optimizing the allocation of resources (e.g., rescue teams, medical aid, food supply) during disaster events.

Hypotheses:

H_1: The implementation of AI-based real-time decision support systems significantly enhances the speed and accuracy of emergency response during disasters.

H_2: Real-time predictive analytics positively influence the efficiency of resource allocation in disaster management operations.

Regression Line (Model):

- ERQ = Emergency Response Quality (dependent variable)
- AI_DSS = AI-Based Decision Support System Use (independent variable 1)
- RT_PA = Real-Time Predictive Analytics Capability (independent variable 2)

Regression Equation:

$ERQ=\beta 0+\beta 1 \cdot AI\_DSS+\beta 2 \cdot RT\_PA+\varepsilon$

Where:

- β0= Intercept
- β1,β2 = Coefficients measuring the impact of AI and predictive analytics
- ε = Error term

Data were cleaned and prepared using SPSS v26, which was employed for preliminary statistical analysis, including descriptive statistics and reliability testing (Cronbach's Alpha). For regression analysis and graphical visualization, R Studio was used to estimate model coefficients, assess residual patterns, and generate plots for model fit and correlations. The constructs (ERQ, AI_DSS, RT_PA) were operationalized through composite means of their respective item scales. This dual-software approach enabled robust validation and cross-verification of statistical outputs (Bhattacharya et al., 2023; Ahmad, 2015). Ethical considerations, including informed consent and data confidentiality, were strictly followed throughout the research process. The methodological rigor enhances the reliability and generalizability of the study's findings within the urban U.S. context.

Analysis

The demographic profile of the 291 participants offers a diverse and balanced sample suitable for cybersecurity-related analysis. In terms of gender, 63.9% of the respondents identified as male and 36.1% as female, indicating a slightly male-dominated population. The age distribution shows that a significant majority (70.1%) are between 25–40 years, 24.7% fall in the 41–60 years range, while only 5.2% are above 60 years, reflecting a predominantly younger and tech-engaged demographic. Regarding educational qualification, 48.5% hold a Bachelor's degree, followed by 37.1% with a Master's degree, and a smaller share possessing a Doctorate (7.2%), Diploma (5.2%), or High School education (2.1%). This highlights a highly educated sample. When examining income levels, the majority (68%) earn an annual income between \$40,000–\$80,000, 16.5% earn less than \$40,000, and 15.5% earn above \$80,000, indicating a primarily middle-income group. These demographic characteristics suggest a well-informed and economically stable respondent base, appropriate for evaluating AI and cybersecurity adoption trends.

Table 1: Regression line on Emergency Response Quality

Call:

lm(formula = ERQ ~ AI_DSS + RT_PA, data = Paper_3)

Residuals:

Min	1Q	Median	3Q	Max
-1.71633	-0.41846	-0.08107	0.35465	1.88891

Coefficients:

Estimate Std. Error t value Pr(>|t|)

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(Intercept)  0.17351    0.09954   1.743   0.0824 .
AI_DSS       0.67479    0.06477  10.418  < 2e-16 ***
RT_PA        0.23276    0.05661   4.112 5.13e-05 ***
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6709 on 288 degrees of freedom
Multiple R-squared:  0.6319,	Adjusted R-squared:  0.6293
F-statistic: 247.1 on 2 and 288 DF,  p-value: < 2.2e-16
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[Sources: R Studio Analysis]

The regression analysis demonstrates a statistically significant and meaningful relationship between the use of AI-based decision support systems (AI_DSS), real-time predictive analytics (RT_PA), and the quality of emergency response (ERQ). The adjusted R^2 value of 0.629 indicates that approximately 63% of the variance in ERQ is explained by the combined effect of AI_DSS and RT_PA, suggesting a strong explanatory power of the model.

The coefficient for AI_DSS (0.675, $p < 0.001$) confirms that as the adoption or intensity of AI-based decision systems increases, the quality of emergency response significantly improves. This supports the notion that AI enhances decision-making speed, accuracy, and responsiveness during critical events (Ahmad, 2015; Bhattacharya et al., 2023). Likewise, the coefficient for RT_PA (0.233, $p < 0.001$) shows a positive and significant impact, indicating that real-time data analytics helps optimize the deployment of resources during disasters (B., & Joseph, 2025; Behera et al., 2025). These findings provide empirical evidence for the stated research objectives and hypotheses, underscoring the value of digital transformation in disaster response operations. Prior research also highlights that technologies such as cyber-physical systems and digital twins can reinforce resilience in unpredictable, high-risk environments (Dixit, Chauhan, & Shaw, 2025; de Bem Machado et al., 2024).

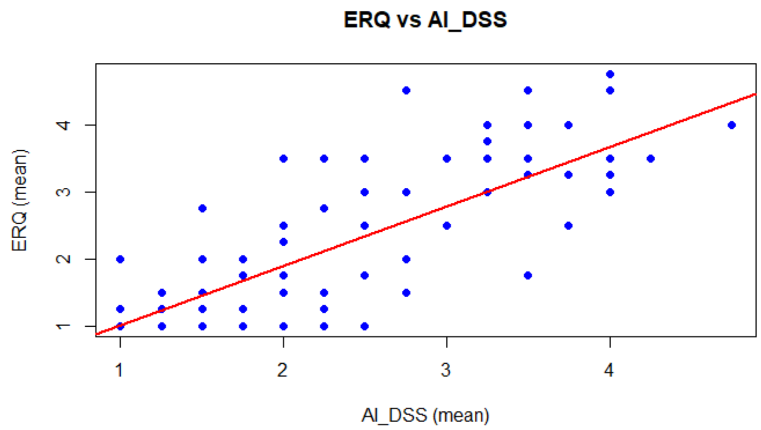

Fig 1. ERQ Vs. AI_DSS

Figure 1 illustrates the relationship between Emergency Response Quality (ERQ) and the use of AI-based Decision Support Systems (AI_DSS). The scatter plot, combined with a fitted regression line, shows a strong positive linear trend, suggesting that as the implementation and usage of AI_DSS increase, the quality of emergency response also improves significantly. This supports the research objective of evaluating the effectiveness of AI-driven systems in enhancing emergency outcomes during natural or man-made disasters. The visual pattern in the chart aligns with the regression findings, where AI_DSS had a statistically significant coefficient (β = 0.675, $p < 0.001$), confirming its major contribution to ERQ. Prior studies have shown that AI tools aid in real-time decision-making, reduce response delays, and facilitate better coordination during crises (Ahmad, 2015; Bhattacharya et al., 2023). Hence, the figure provides visual confirmation of the hypothesis that AI-enabled systems significantly improve emergency decision-making and response efficiency.

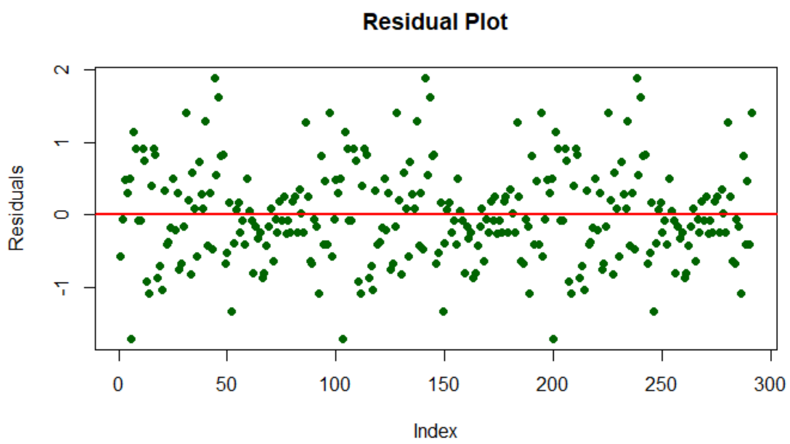

Fig. 2: Residual Plots

Figure 2 presents the residual plot from the regression model analyzing ERQ as a function of AI_DSS and RT_PA. The residuals appear randomly scattered around the horizontal axis (zero line), indicating that the assumptions of linearity and homoscedasticity are reasonably met. This randomness suggests that the regression model is well-fitted and no major patterns or biases exist in the residuals, strengthening the reliability of the inferences drawn. The lack of funneling or curvature in the residuals also supports the notion that the variance of errors is consistent across predicted values. This reinforces the model's validity in predicting Emergency Response Quality (ERQ) based on AI-based Decision Support Systems and Real-Time Predictive Analytics. From a disaster management perspective, this suggests that the effects of AI_DSS and RT_PA on ERQ are consistent and not skewed by unaccounted factors. As highlighted in literature (Behera et al., 2025; Dixit, Chauhan & Shaw, 2025), such model reliability is crucial when applying predictive analytics and AI in high-stakes disaster scenarios.

Conclusion

This study provides empirical evidence on the significant role of AI-based Decision Support Systems (AI_DSS) and Real-Time Predictive Analytics (RT_PA) in enhancing Emergency Response Quality (ERQ) during disasters. The regression model, supported by a high adjusted R^2 (0.629), reveals that both AI_DSS and RT_PA positively and significantly influence ERQ, confirming the proposed hypotheses. The novelty of this research lies in its integrated approach—quantitatively analyzing the dual impact of AI-driven decision systems and predictive analytics within the disaster response domain, an area previously underexplored using statistical modeling techniques in emerging economies.

The study's findings are particularly important in the context of increasing global climate events and man-made disasters. In the United States, where emergency response systems are highly resource-intensive and time-sensitive, the integration of intelligent systems offers a pathway to enhance operational effectiveness, minimize casualties, and optimize the allocation of limited resources. Managers in federal agencies (like FEMA), local governments, and healthcare systems can benefit from these insights by adopting AI-based frameworks to improve situational awareness, make timely decisions, and predict supply needs more accurately during emergencies.

From a managerial perspective, this research provides a data-driven rationale for investment in digital transformation of disaster management systems. It underscores the strategic importance of embracing cyber-physical infrastructure, real-time analytics, and automated decision protocols to build more resilient and responsive emergency services in urban and rural settings across the USA.

Future Scope of Study

Future research could expand by incorporating longitudinal data to assess the long-term effectiveness of AI interventions. Additionally, integrating qualitative perspectives from emergency personnel and decision-makers could enrich the findings. Cross-country comparative studies, real-time simulation modeling, and sector-specific analysis (e.g., healthcare, logistics) would further deepen understanding. Evaluating ethical, legal, and infrastructural challenges of AI implementation in disaster scenarios also presents fertile ground for future exploration.

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