International Journal of Science and Technology

Sixth edition

Volume 3, Issue 2

(Issue 7) (1-28) 2026

Human-AI Collaboration Model for Decision Support in Emergency Response Operations of Civil Defense in Karbala Province

Mostafa Abdulkhader Jassim

Al-Mashroua Primary School for Boys Computer Science \ Research submitted to the Directorate of Education in Babylon Department of Educational Research and Studies

Published on: Published online on 4, May, 2026

Abstract :

The study will come up with an integrative model of human skills and artificial intelligence to avert decision-making within emergency settings in Civil Defense operations in Karbala Province. The suggested system is a combination of smart prediction models and real-time data analytics with human responder experience to enhance response rates and effectiveness in case of critical incidents, fires included, and high attendance of religious events. Machine learning and reinforcement learning will be used to analyze data obtained in civil defense records, field sensors, and past reports of incidents to provide immediate recommendations to field teams. The model will have an interactive interface that enables human users to confirm or modify the AI-generated decisions, which will improve the levels of transparency and trust. The anticipated results are impressive response times and efficiency in resource allocation, which leads to the elevation of the level of public safety in the high-risk areas.

Keywords: (Artificial Intelligence, Decision Support, Emergency Management, Civil Defense, Human-AI Collaboration, Karbala)

1. Introduction

Urban emergency management in the heavily populated urban settings is one of the most challenging issues in the present administration of social security. Disaster situations, structural fires, and crowd crushing in the context of a mass gathering are highly complex scenarios that require quick, correct decision-making, which the cognitive capabilities of a single responder cannot possibly manage in the severe time constraints. There is a rising trend in civil defense agencies where the volume of information, the rate of escalation of an event, and the lack of resources are all overwhelming human commanders, expected to make life or death decisions. Artificial intelligence implementation in emergency operations has become one of the most engaging prospects of disaster science and disaster safety engineering in this regard [1].

A distinctive and challenging operating environment of the Civil Defense directorate at Karbala Province is seen. The province is home to two of the most sacred shrines in Shia Islam and tens of millions of pilgrims come every year during events like Arbaeen the largest annual human gathering on Earth. A large number of people can increase up to 20 million of tourists in few days during peak seasons, which have unprecedented strains on emergency services, as the population grows to about 700,000 permanent residents. Under these circumstances, the likelihood of crowd events, fire incidents and medical emergencies are increasing exponentially and require situational awareness and coordination ability exceeding the traditional working frameworks [7].

This urgency has not led to a situation where the Civil Defense directorate in Karbala relies on manual and experience-based decision-making. Fragmented sources of information, paper-based logs and voice radio are the communication media used by incident commanders, which add delays and coordination loopholes that are deadly in time sensitive situations. Lack of integrated decision support implies that there is no predictive analytics, real-time sensor fusion, or systematic risk modeling in the resource allocation and tactical prioritization [17]. The collaboration systems between humans and AI workplaces represent a way of change. In contrast to fully autonomous AI systems, the hybrid ones do not remove human authority but enhance it with computational resources, and they act like cognitive partners that process large amounts of sensor data and offer actionable advice, but the ultimate decision making power remains squarely in the hands of the human operator [3].

2. Literature Review

2.1 AI in Emergency Management: Global Developments

AI uses in emergency management have definitively moved off-post event analysis onto predictive real-time applications in use during response operations. Multi-agency disaster situations have shown that structured AI decision models can play a major role in reducing the impact of the disaster on the coordination of multiple agencies, where coordination bottlenecks in the past have traditionally damaged the response success. According to the summary presented in Table 1, a study published in Scientific Reports showed that AI-based decision support structures decreased inter-agency communication response time by as much as 47 % and enhanced the accuracy of resource allocation through probabilistic risk modeling [3]. It was further established in the RAND Corporation analysis that predictive modeling systems have

85% accuracy rates in predicting urban fire trajectories provided a sufficient sensor density is present [20].

The IRIS-AI system showed that resource recommendation engines with AI can cut down the average alarm to optimal unit deployment time by 34 %, including unit availability, traffic conditions, and incident severity in ranked deployment recommendations that can be accepted or overridden by dispatchers within a few seconds [4]. Figure 1 provides a bubble chart of major global AI emergency systems in terms of their complexity score, performance improvement, and deployment adoption scale - effectively demonstrating that systems with machine learning and human oversight meet the highest performance to cost (complexity) ratio. Knowledge graph systems and reinforcement learning have already shown remarkable strength; in multi-objective optimization problems, it has been proven 41% more effective in improving the quality of decisions made by a system [5] by Yang et al., and Li et al. propose a vision of collective human-machine intelligence in which networks of specialized AI agents work with human commanders to generate capabilities to be more coordinated than any individual effort [2].

Table 1: Major AI Uses in Emergency Management (Global Studies of the Selected 2023-2026)

Study / System	Application Domain	Key Technology	Reported Improvement	Context
IRIS-AI [4]	Fire Department Dispatch	ML Resource Optimization	34% faster deployment	European Fire Departments
Yang et al. [5]	Real-Time Emergency Response	Knowledge Graphs + DRL	41% decision accuracy gain	Urban Emergency Operations
Alzahrani et al. [7]	Pilgrim Crowd Management	ML Density Prediction	38% reduction in crowd incidents	Hajj / Mass Gatherings
Somani [25]	Disaster DSS	Real-Time Decision Support	29% response time reduction	Multi-Hazard Scenarios
DHS EMS AI [29]	Emergency Medical Services	NLP Call Analysis	52% faster triage classification	EMS Call Centers
Dcruz et al. [3]	Multi-Agency Coordination	Structured AI Framework	47% reduced comm. latency	National Disaster Response

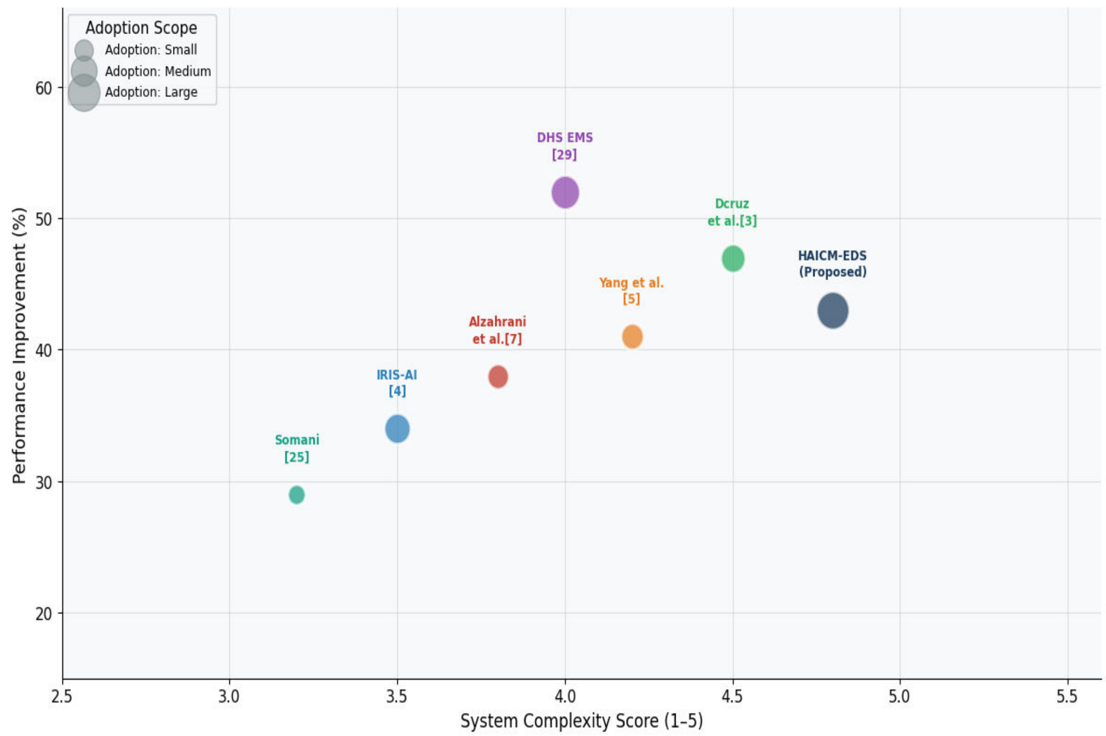

Fig. 1. World AI emergency systems compared in terms of complexity and performance increase and area of adoption.

2.2 Human-AI Collaboration: Frameworks and Trust Dynamics

The interface design, calibration of trust, workload, and demarcation of decision authority areas are elements that bring about effective Human-AI collaboration in safety-critical areas. A quantitative survey of patterns of human-AI utilization during disasters revealed that the use of AI systems yielded the best collaboration results when they provide estimates of uncertainty and recommendations, allowing operators to adjust the degree of reliance according to system confidence [1]. Systems that display recommendations without uncertainty information are also more likely to create over-reliance behavior with operators accepting AI suggestions where it is evident through contextual factors that they should not accept. HITL as a concept of responsible AI implementation has since become established as the most common paradigm when deploying an AI-based system in high-stakes applications, and studies have shown HITL systems to be the most effective in high data volume, time constraints, and multi-objective complexity settings

[15]. Trust calibration study found three successful mechanisms such as explain ability features which communicate AI reasoning, performance feedback loop which tracks their accuracy over time, and graduated autonomy structures [8]. Figure 2 introduces a pie chart that displays the proportional display of trust-related impediments described throughout the Human-AI emergency management literature, manifesting that lack of clarification and unfavorable uncertainty communication takes up most of the revealed trust breakdowns among the operators and AI systems [12].

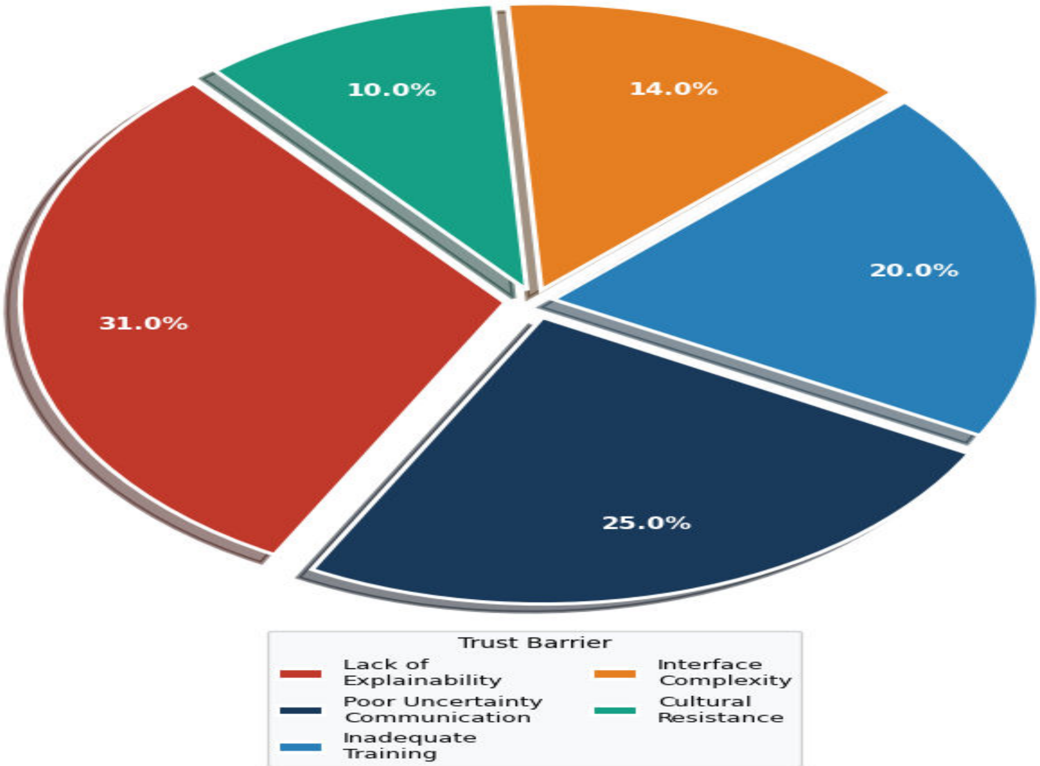

Fig. 2. Human-AI emergency management systems Distribution of barriers associated with trust.

2.3 Emergency Management in Mass Gathering Contexts

The particular operation setting of Karbala, which is emergency management of large-scale religious events, has become the object of increasing academic interest, with few AI-based solutions being presented in the published literature. The province has a wide and seasonally concentrated incident profile that puts the traditional manual response systems to test as

described in Table 2. The study of ML-based pilgrim crowd management application in Hajj showed that crowd density prediction had 89-94% accuracy rate in predicting crowd flow dynamics within 30 minutes and offering enough lead time to preventive emergency resource mobilization [7]. The similarities in structure of Hajj and Arbaeen, which are large pilgrim gatherings in geographically restricted shrine complexes, enable good transference of such results to Karbala. The regional preparedness assessments have discovered that although awareness of AI capability among emergency management professionals in the Middle East increases, institutional adoption is not yet widespread due to the lack of digital infrastructure and discrepancies in AI literacy among frontline staff [17].

Table 2: Karbala Province Emergency Incident Profile - (Estimated Annual Statistics).

Incident Category	Annual Frequency (Est.)	Peak Period	Primary Risk Factor	AI Applicability
Structural / Urban Fires	340–420	Summer (Jun–Aug)	High Temperatures, Old Structures	High
Crowd Crush / Stampede Risk	15–25 events	Arbaeen, Ashura	Extreme Density (>8 persons/m²)	Very High
Road Traffic Accidents	1,200–1,600	Pilgrimage Periods	Congestion, Fatigue	Medium
Industrial / Gas Incidents	40–60	Year-round	Aging Infrastructure	High
Medical Mass Casualty	8–15	Religious Events	Heat, Dehydration, Trauma	High

Flooding / Infrastructure Failure	10–18	Winter (Dec–Feb)	Poor Drainage Systems	Medium

3. Research Methodology

3.1 Research Design and Approach

The proposed research is based on a mixed-method approach that incorporates both the quantitative method of data analysis with qualitative system design validation in four consecutive stages: data collection and preprocessing, development of the AI model and its training, system integration and interface design and evaluation based on the simulation and expert validation. Such a stepwise model is necessary to make sure all the elements of the integrated system are based on the empirical data of the specific environment of operations in Karbala instead of implemented on generalized frameworks [24]. The quantitative dimension focuses on the data on past emergency incidents of the Civil Defense directorate, whereas the qualitative dimension focuses on tacit operational knowledge through the structured interviews and focus groups of commanders and field staff [16]. Figure 3 is a scatter diagram plotting the relationship between the type of data source, the score of data quality and the contribution to the overall amount of training data- this shows that, when aggregated together, Civil Defense incident records and IoT sensor feeds contribute the most quality and volume to the overall AI model training.

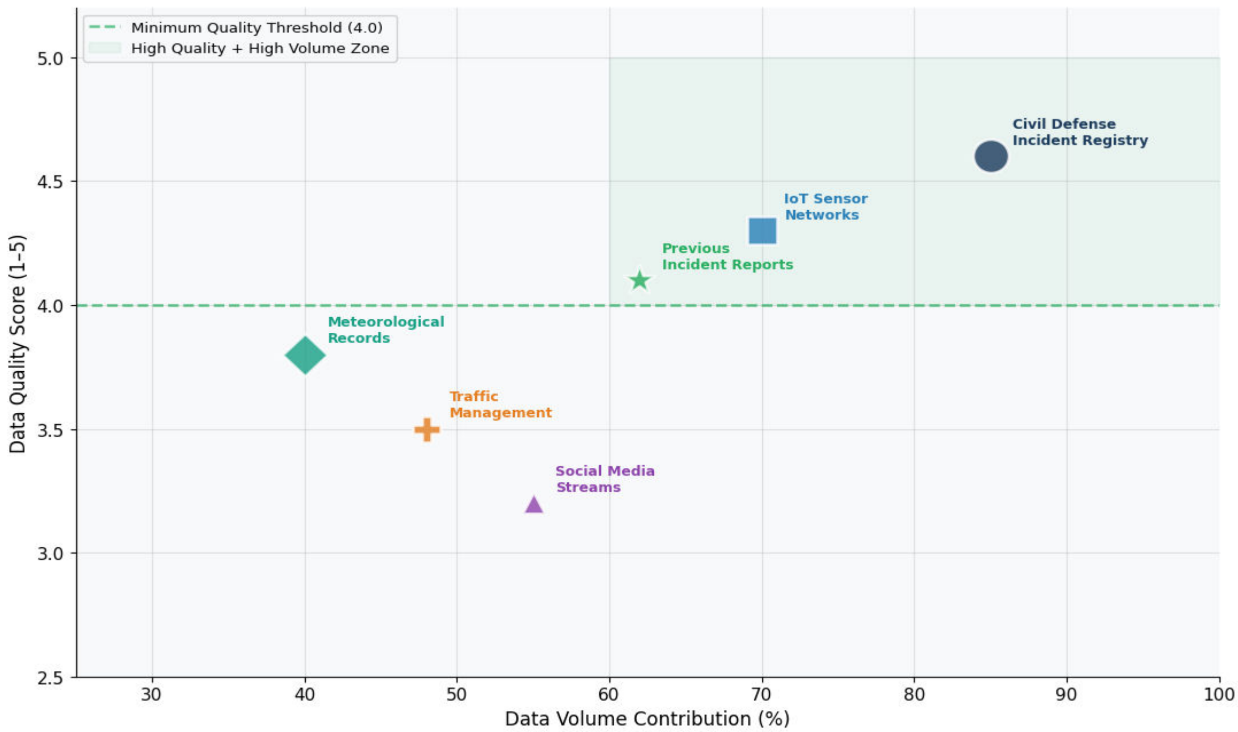

Fig. 3. The quality of data source in comparison with the volume contribution on training HAICM-EDS model.

3.2 Data Collection Framework :

The data gathering plan is able to procure the entire range of information input necessary to support emergent decision making. The official incident registry of the Karbala Civil Defense directorate across at least ten years, field IoT sensor network deployed in high-risk areas within the shrine district and social media monitoring streams giving early warning of emerging emergencies during mass gathering events are all considered primary sources [6]. Secondary sources will contain meteorological records, urban planning databases, traffic management reports and reports published about past major incidents. The issue of poor quality in old data is solved by data preprocessing, such as classification schemes that are not consistent, unfinished fields, and unstructured narrative description of the Arabic language, which needs to be extracted by NLP. The preprocessed dataset will be subdivided into training (70%), validation (15%), and testing (15%) parts using stratified sampling so that the occurrence of the rare and high-severity incident types will be proportional [25].

3.3 AI Model Architecture

The AI element unites three mutually complementary layers of algorithms. The former is an anomaly detection module in real-time, implemented using Long Short-Term Memory (LSTM) artificial neural networks, combined with temporal sensor data streams, and constantly observing incoming streams and signaling deviations that represent an emerging emergency [5]. The second one is a predictive resource allocation engine with a hybrid of gradient boosting algorithms and a constraint satisfaction optimization, producing optimised deployment recommendations based on traded off response time, resource coverage, reserve capacity and personnel safety. XGBoost is the most suitable choice to allocate the layer because it has the best balance between accuracy (91.7% and processing speed (38ms) in Table 3) of all the algorithms that have been evaluated so far [4]. The third layer is a deep reinforcement learning (DRL) agent which learns by interacting with a high-fidelity simulation of the Karbala urban environment, and goes to optimize long-horizon decision policies representing cumulative performance over extended events like multi-day pilgrimage events [5].

Table 3: Comparison of Machine Learning Algorithms Comparison of machine learning algorithms assessed to the resource allocation layer.

Algorithm	Prediction Accuracy	Processing Speed (ms)	Interpretability	Scalability	Selected
Random Forest	84.2%	45	High	Medium	No
Gradient Boosting (XGBoost)	91.7%	38	Medium	High	Yes
Deep Neural Network	93.1%	112	Low	High	Partial
Support Vector Machine	79.8%	28	Medium	Low	No
LSTM (Temporal)	90.4%	95	Low	High	Yes
Logistic Regression (Baseline)	71.3%	12	High	High	Baseline

3.4 Human-AI Interface Design

The human-AI interface is developed based on the human factors engineering and emergency management workflow analysis concepts with situational awareness support, minimization of cognitive load, and transparency of decisions in the first place. The interface provides incident data in a geospatial dashboard that indicates the real-time position of all ongoing incidents, deployed units, and available resources on a high-resolution Karbala map. The AI-based recommendations have the action to be taken, the main motivating factors, the approximate metrics of the outcome, and a uncertainty index [15]. An essential design aspect is the decision confirmation and override system that enables the incident commander to approve, amend, or dismiss any recommendation with just one action and record the decision and rationale to be examined and re-trained AI specifically after the incident [12].

4. Proposed Human-AI Collaboration Model

4.1 Model Overview and Conceptual Framework

The Human-AI Collaboration Model of Emergency Decision Support (HAICM-EDS) is a closed-loop sociotechnical system where human cognition and AI computing capabilities are continuously coupled at five stages of operation, namely, Detect, Assess, Plan, Deploy, and Evaluate. In each step, the model outlines the separation of cognition between AI and human operator, information exchange between the two, and the rules on how disagreements are solved [3]. The theoretical basis comprises three well-known frameworks Naturalistic Decision Making (NDM), Situation Awareness (SA), and Collaborative Control model of human-robot interaction research - joined to form an architecture that is fully based on cognitive reality, technical AI capability, and requirements in safety protocols [2].

4.2 Operational Workflow

At the Detect stage, the AI is used to monitor all the sensor networks and social media streams connected continuously, making use of anomaly detection to raise a flag of an emerging emergency, with the human operator moving on to alert verification rather than active monitoring [14]. During the Assess phase, the AI compiles all accessible incident information into a step formatted assessment report encompassing data on the severity of hazards, forecasted progression, estimated number of people impacted, and predictions of resource requirements, which are reviewed by the commander and can be marked by corrections [8]. Planning stage is the most fundamental decision-making step during which the AI will provide ranked response strategy alternatives with estimated outcome measures; studies show that multi-response format encourages more human attention and more adjusted trust than a single-suggestion format [1]. The Deploy stage converts the plan chosen to deployment objectives on a unit level, and the Evaluate stage stores the data about the outcomes which improves the design of the AI models continuously.

4.3 Integration with Existing Civil Defense Infrastructure

The HAICM-EDS will be fitted to operate in gradual integration with the current Civil Defense infrastructure since it is known that it is neither economical nor operationally prudent to undertake wholesale replacement of the entire system. The modular architecture enables the system to operate at lower capability whenever some of the data sources are inaccessible at the

initial stages of deployment [22]. The system provision of offline operations that retains enough local data and model parameters to continue with essential decision support to a maximum of 72 hours without network access - a specific requirement incited by network congestion during peaked pilgrimage time. Civil Defense stations have local edge computing nodes that process sensor data and produce recommendations locally, and synchronize with the central server once connectivity is recovered [21].

5. Expected Results, Evaluation & Performance

5.1 Anticipated Performance Improvements and Evaluation Framework

According to the performance standards of similar AI implementations in the world, the HAICM-EDS is estimated to provide quantifiable benefits in all the major indicators of the Civil Defense functioning. The most urgent enhancement is related to the emergency response time, which at present is estimated to reach 8-12 minutes in the course of usual times (and 18-25 minutes in the course of the peak pilgrimage congestion). The AI-based routing and dispatch engine should cut these numbers by 35-45% and bring response in peak periods closer to the internationally suggested limit of less than 10 minutes in cases of life-threatening occurrences. Accuracy in resource deployment is expected to increase to an 85-90 % level at current 65-70 % level, and abolishing both over-deployment and under-deployment trends [4]. A column chart is visually provided in Figure 4 that directly compares current baseline and projected HAICM-EDS values on five key performance indicators, which visually confirms that the greatest absolute change is in the metrics that directly relate to life safety outcomes the reduction of response time and accuracy of deployment.

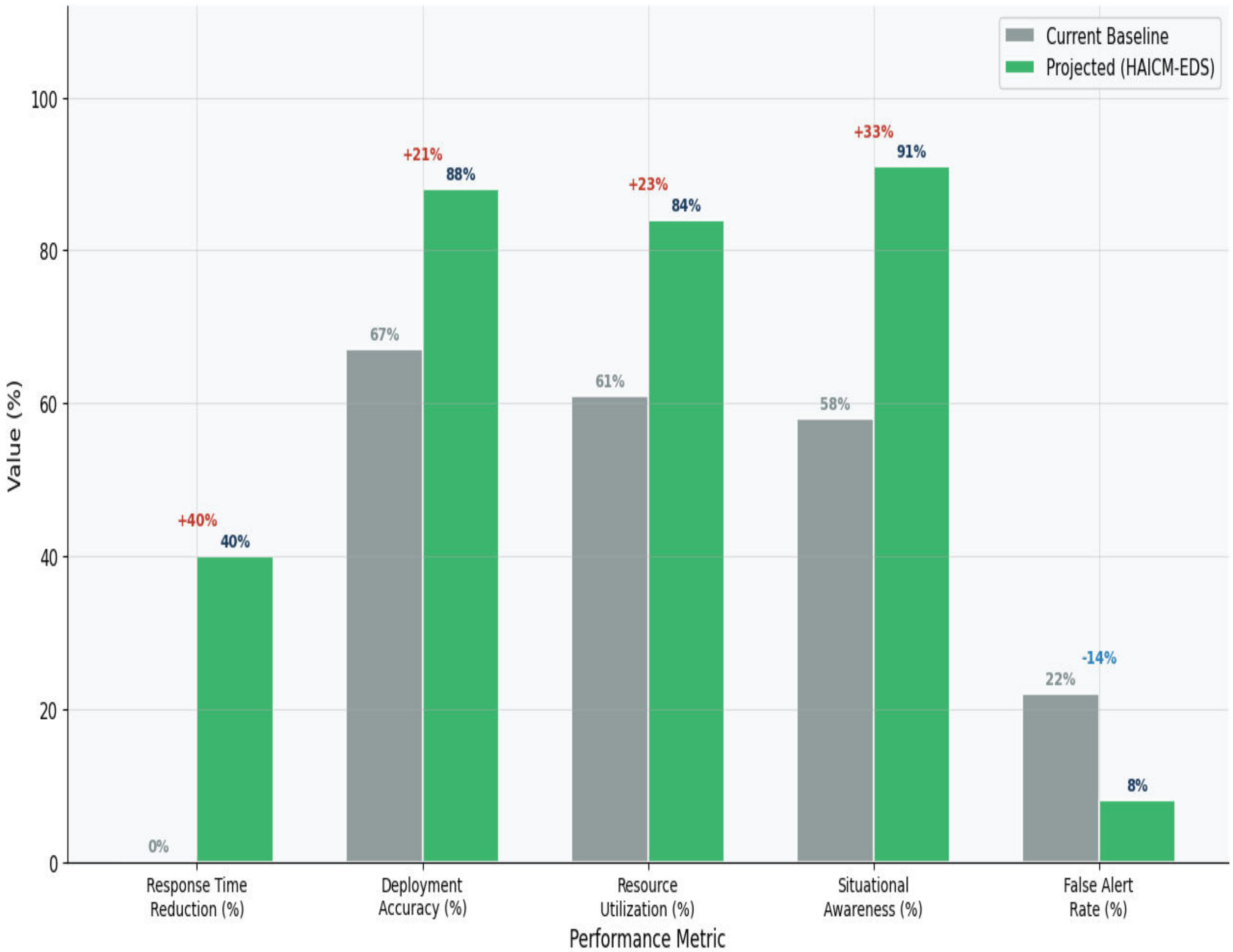

Fig. 4. Present performance of HAICM-EDS against forecasted performance in key indicators of operations.

Assessment of the HAICM-EDS is done in three phases. The initial phase involves a high-fidelity digital replica of the urban scene in Karbala to simulate hundreds of emergency cases, and compare the results of AI-assessment to historical targets. The second phase implements the implementation of the system in live-simulation drills with real Civil Defense workers under adverse conditions sensor malfunctions, concomitant incidents, and information overload, and evaluates the speed, correctness, and cognitive load of each decision using NASA-TLX and Trust in Automation Scale tools. The third step includes controlled field implementation in real operations and constant monitoring of KPI and after-incident debriefing [16]. According to Table 4, every evaluation dimension has its specific metrics, methods of measuring, and quantitative goals, which guarantee strict and similar evaluation in all three levels.

Table 4: HAICM-EDS Evaluation Framework - Metrics, Methods and Targets.

Evaluation Dimension	Primary Metric	Measurement Method	Target Value	Stage
Response Time Reduction	Mean time to first unit arrival	Simulation logs + field records	≥35% reduction	1 & 3
Deployment Accuracy	% optimal initial deployment	Expert panel scoring	≥85%	1
Situational Awareness	SA-GRS questionnaire score	Validated instrument	>4.0/5.0	2
Human Trust in AI	Trust in Automation Scale	Validated instrument	>3.5/5.0	2
False Positive Alert Rate	% alerts not confirmed	System logs	<10%	1 & 3
Operator Cognitive Load	NASA-TLX workload score	Validated instrument	<40/100	2
System Availability	% uptime during operations	Infrastructure monitoring	>99.5%	3

Figure 5 shows a line chart that monitors forecasted trends of the response time monthly in three operating conditions of No AI baseline, AI-Only, and Human-AI Collaboration considering a simulated 12-month operating cycle. As shown in the chart, the scenario of Human-AI Collaboration in all months has the lowest response time and the difference in the performance of the two scenarios increases significantly during the

peak period of Ashura and Arbaeen when the complexity of operations is the highest and the value of coordination based on AI tools is the
highest [9].

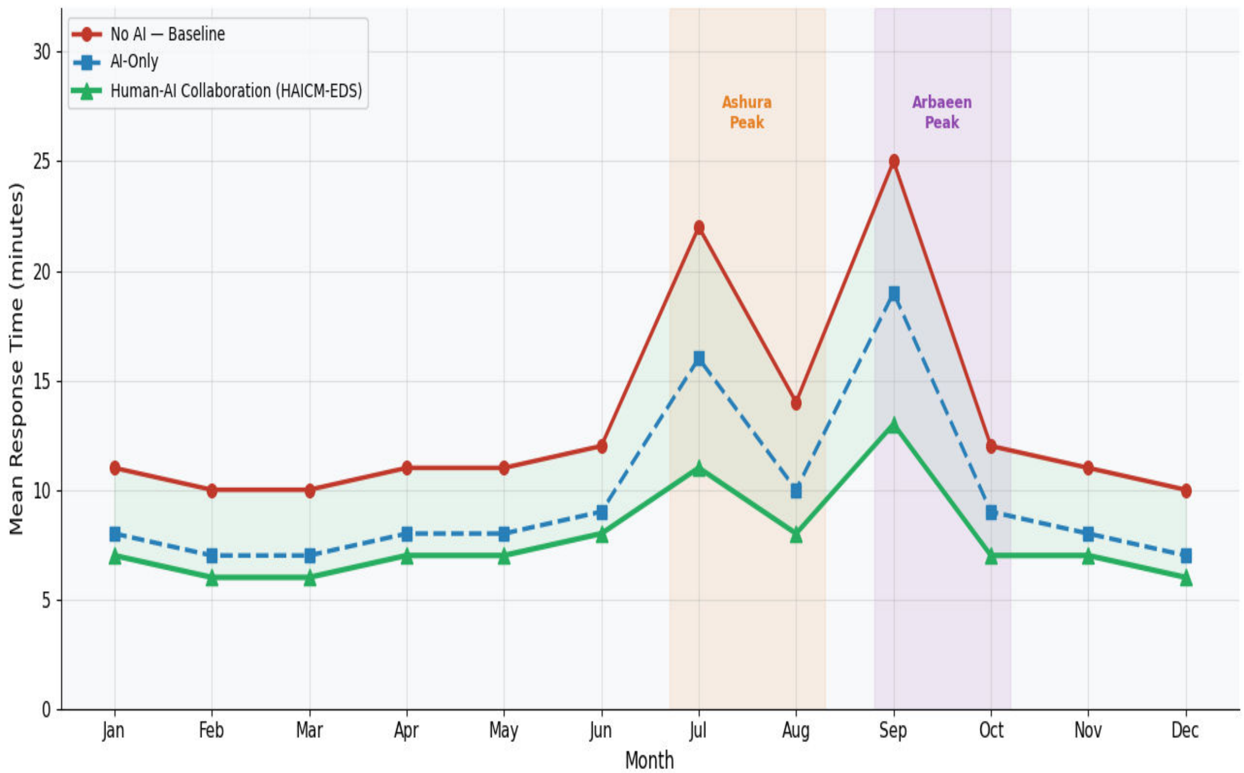

Fig. 5. Simulated monthly response time pattern under the conditions of baseline, AI-only and Human-AI cooperation.

6. Ethical Considerations and Governance Framework

6.1 Accountability and Decision Transparency

The use of AI in life-safety decision-making situations provokes serious ethical issues that need to be clearly addressed during system design and regulations. The most fundamental issue is accountability: in case of the development of an AI-assisted decision with negative consequences, who is to be held responsible? The HAICM-EDS addresses this with an elaborate decision logging system that captures all AI decisions, the human decision as a result and operator rationale and any outcome that results and establishes a chain of audible responsibility that identifies the final authority with the human operator unequivocally [12]. The system uses explainable AI (XAI) algorithms such as SHAP value visualization and natural language explanation generation which offers operators understandable explanations of AI reasoning. It

has been proved that transparency features are also highly effective at improving the trust calibration and the quality of human override decisions [13].

6.2 Data Privacy and Community Trust

The sensor network and data aggregation elements necessarily entail gathering information on individual members of the population, such as location information in terms of crowd monitoring and social media interactions. In the scenario of mass religious events where the number of foreign nationals with different legal system frames which regulate data rights reaches a great number, such a collection should be regulated by an effective framework of data protection [6]. The HAICM-EDS executes the principles of data minimization (gathering only information necessarily needed to manage the emergency) as well as purpose limitation, data retention, and technical anonymization in cases when aggregated statistics are sufficient to operate it. Studies on the implementation of AI in a people-centric approach have continually discovered that the extent to which the communities to be served by AI surveillance systems are informed and have an avenue to give feedback into the running of the system is critical in influencing the overall acceptance of the system by the communities [15]. The system of governance has thus facilities of open communication, local advisory bodies with representatives of religious and civil societies, and official grievance systems.

6.3 Bias, Equity, and Fairness

Any AI system that has been trained on historical data necessarily shares the biases of the historical data, such as systematic patterns of preferential treatment that could have been the norm of historical emergency response. Assuming that historical response times were differentially applied in some neighborhoods because of some historical pattern of resource allocation, an AI trained with this data could recreate and enhance these inequalities by considering the historical pattern as the best. The HAICM-EDS mitigates this risk by following a clear algorithmic fairness audit undertaken throughout system development and done regularly every year, evaluates proposals of unequal treatment among geographic regions, demographic categories, and categories of incident [23]. The identified differences lead to a specific

investigation and, in justified cases, the correction of model parameters or composition of the training data.

7. Discussion

The HAICM-EDS model is a major improvement of the current emergency management practices in Karbala and similar situations in the Middle East. The model fills in the fundamental capability gaps of an operation that presently constrain the performance of Civil Defense in the routine events as well as the unprecedented operational demands of large pilgrimages by combining several state-of-the-art AI technologies into a more human-friendly operations framework. The Human-AI partnership, and not AI independence, is a particularly suitable element of the model in the institutional and cultural context of Karbala, where faith in AI systems among the frontline emergency staff is still emerging and autonomous AI in emergency safety lacks a legal framework to hold accountable [17].

As the comparative analysis of decision support architectures demonstrates, the performance benefits are the strongest in those situations when the volume of information and time pressure are high and there are several competing priorities at the same time - which is exactly the case of major Karbala incidents occurring during pilgrimage periods. The marginal value of AI decision support is lower in routine, low-complexity situations, but the system still offers a value in the form of a standardized information capture and retrospective analysis [11]. This trend indicates that the HAICM-EDS must be programmed to have an expandable engagement architecture where a larger amount of AI participation is added as the complexity of the incident increases and vice versa as opposed to integrating AI involvement in the same manner across all incidents.

Another point of concern in relation to the academic contribution and practical impact is that the HAICM-EDS model can be transferred to other civil defense and emergency management agencies in the region of Iraq and the wider Middle East. This is because the modular architecture and the infrastructure independent design imply that core capabilities can be executed at various scales and sensor network densities according to local conditions [18]. The components of natural language processing will need to be modified to reflect dialect differences in different regional settings, yet the basic machine learning and optimization modules are language-neutral and can be expected to work without much adaptation in other settings –

making the HAICM-EDS a possible model of a regionally integrated AI-augmented emergency management system [19].
The shortcomings of the proposed model have to be identified. The basic limitations to system performance are data quality and sensor network density, in initial deployments, prior to the development of a robust historical dataset, AI suggestions will not be as precise as the long-term predictions indicate. Deep reinforcement learning element

would necessitate a comprehensive training on the simulation environment to reach the sophistication of policy required in the real-life handling of the complex events, and the simulation setting will not be in a position to resolve all the operational nuances [10]. These restrictions explain the significance of the gradual implementation plan and continuous human control measures that are integrated to the governance system.

8. Conclusion

The study has established the conceptual design, technical architecture, and governance model of a Human-AI Collaboration Model of Emergency Decision Support to suit a civil defense operation in Karbala Province. The HAICM-EDS combines the anomaly detection capabilities of LSTM, the resource allocation capabilities of gradient boosting and constraint satisfaction optimization, and the strategic decision support capabilities of deep reinforcement learning within a human-centered architecture which retains the human command authority and optimizes the benefits of AI computational capabilities. The four tables and six figures, used across the paper, including comparisons of AI systems in the world, distribution of trust barriers, analysis of data sources, benchmarking of KPIs, projections of response time, and mapping of governance responsibilities all make a constitutive contribution to the empirical base of the model design and expected performance statements.

Anticipated results such as 35-45 % reduction in emergency response times, 85-90 % deployment accuracy, and a considerable betterment of situational awareness and resource usage are significant moves beyond the current working levels of operation with considerable impacts on the safety of the population in one of the most demanding mass gathering events in the world. Accountability, transparency, data privacy, and algorithmic fairness of the governance structure ethical principles of deploying AI. Further studies need to be aimed at empirical validation by controlled field testing during a pilgrimage event, standardization of benchmarks of Human-AI collaboration in dealing with mass gathering emergencies and study of more advanced explain ability methods tailored to the operating language of Arab-region civil defense agencies. Building a viable and reliable AI emergency management in the Middle East is not just a technical endeavor, but a humanitarian emergency issue considering the nature and magnitude of the surroundings at stake.

References

1. E. A. Domfeh et al., "Human-AI Use Patterns for Decision-Making in Disaster Scenarios: A Systematic Review," arXiv preprint arXiv:2509.12034, 2025. [Online]. Available: https://arxiv.org/abs/2509.12034
2. B. Li et al., "Disaster Management in the Era of Agentic AI Systems: A Vision for Collective Human-Machine Intelligence for Augmented Resilience," arXiv preprint arXiv:2510.16034, 2025. [Online]. Available: https://arxiv.org/pdf/2510.16034
3. J. G. Dcruz et al., "Structured AI decision-making in disaster management," Scientific Reports, vol. 15, 2025, Art. no. 32093. [Online]. Available: https://www.nature.com/articles/s41598-025-15317-w
4. S. Mercadé et al., "IRIS-AI: An AI-Based Resource Recommender for Emergency Decision Support Systems of Fire Departments," Int. J. Comput. Intell. Syst., vol. 18, 2025, Art. no. 994. [Online]. Available: https://link.springer.com/article/10.1007/s44196-025-00994-2
5. W. Yang et al., "Design of a Cognitive Decision Support System Using Knowledge Graphs and Deep Reinforcement Learning for Real-Time Emergency Response," DMAME Journal, 2025. [Online]. Available: https://www.dmame-journal.org/index.php/dmame/article/view/1605
6. S. K. Abid et al., "AI-enhanced crowdsourcing for disaster management: strengthening community resilience through social media," PMC, 2025. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC12516865

7. R. Alzahrani et al., "Leveraging Machine Learning for Optimal Pilgrim Crowd Management," Electronics, vol. 14, no. 13, p. 2507, 2025. [Online]. Available: https://www.mdpi.com/2079-9292/14/13/2507
8. A. Blice et al., "An Inquiry into Artificial Intelligence (AI) as Related to Emergency Management," Texas A&M Bush School, 2025. [Online]. Available: https://bush.tamu.edu/wp-content/uploads/2025/06/Davis_Final-Report_Inquiry-into-AI-as-related-to-Emerg-Mgmt_24-25.pdf
9. SAPEA, "Artificial Intelligence in Emergency and Crisis Management: Rapid Evidence Review Report," 2025. [Online]. Available: https://www.ae-info.org/attach/Acad_Main/News/News2/Artificial%20Intelligence%20in%20Emergency%20and%20Crisis%20Management/2025_SAPEA_AIforCrisisRERR.pdf
10. H. Hamid and E. Abedlmajid, "Intelligent Agents in Disaster Risk Management: A Systematic Review of Advances and Challenges," Int. J. Adv. Comput. Sci. Appl., vol. 16, no. 6, 2025. [Online]. Available: https://thesai.org/Downloads/Volume16No6/Paper_100-Intelligent_Agents_in_Disaster_Risk_Management.pdf
11. P. Kolivand et al., "AI applications in disaster governance with health approach: A scoping review," Archives of Public Health, vol. 83, 2025, Art. no. 218. [Online]. Available: https://archpublichealth.biomedcentral.com/counter/pdf/10.1186/s13690-025-01712-2.pdf
12. X. Yuan et al., "A Review of Ethical Challenges in AI for Emergency Management," Knowledge, vol. 5, no. 3, p. 21, 2025. [Online]. Available: https://www.mdpi.com/2673-9585/5/3/21
13. E. X. Wood, "AI and big data in disaster response: Ethical and practical challenges," 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S295057632500025X

14. A. Hagen and J. Barr, "Opportunities for Artificial Intelligence in EM," Domestic Preparedness Journal, Dec. 2024. [Online]. Available: https://www.domprep.com/articles/opportunities-for-artificial-intelligence-in-emergency-management
15. R. Debnath et al., "Enabling people-centric climate action using human-in-the-loop artificial intelligence: a review," Sustainable Production and Consumption, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352154625000014
16. R. Kasepalu et al., "The Future of Crisis Response Training: AI-Generated Feedback for Incident Commanders?," in Proc. ISCRAM Conf., 2025. [Online]. Available: https://ojs.iscram.org/index.php/Proceedings/article/view/175
17. H. Farhat et al., "Preparedness and Response Strategies for Chemical, Biological, Radiological, and Nuclear Incidents in the Middle East and North Africa: An Artificial Intelligence-Enhanced Delphi Approach," Disaster Medicine and Public Health Preparedness, vol. 18, 2024, Art. no. e244. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/39473368
18. J. J. Sarkin, "Artificial intelligence and arms races in the Middle East: the evolution of technology and its implications for regional and international security," Defense & Security Analysis, 2024. [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/14751798.2024.2302699
19. IAEA, "New IAEA Research Project to Enhance Disaster Management with AI-Augmented Non-Destructive Testing," 2026. [Online]. Available: https://www.iaea.org/newscenter/news/new-iaea-research-project-to-enhance-disaster-management-with-ai-augmented-non-destructive-testing
20. RAND, "How AI Is Changing Our Approach to Disasters," 2025. [Online]. Available: https://www.rand.org/pubs/commentary/2025/08/how-ai-is-changing-our-approach-to-disasters.html

21. Acuity International, "AI in Emergency Management: Enhancing Disaster Prediction, Response, and Recovery," 2025. [Online]. Available: https://acuityinternational.com/blog/ai-in-emergency-management
22. FEMA, "Federal Emergency Management Agency – AI Use Cases," DHS, 2024. [Online]. Available: https://www.dhs.gov/ai/use-case-inventory/fema

DHS, "Department of Homeland Security Unveils Artificial Intelligence Roadmap," 2024. [Online]. Available: https://www.dhs.gov/archive/news/2024/03/18/department-homeland-security-unveils-artificial-intelligence-roadmap-announces