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Artificial Intelligence (AI)-enhanced decision support systems in disaster management and response

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Abstract
The escalating frequency and severity of natural and human-induced disasters demand rapid, data-driven decision-making frameworks that can adapt to complex and uncertain environments. This study presents an Artificial Intelligence (AI)-enhanced Decision Support System (Artificial Intelligence (AI)-Decision Support System (DSS)) designed to improve disaster management and response through the integration of multi-source data and interpretable machine learning models. The system employs a hybrid deep-learning architecture combining convolutional and transformer-based networks for spatial-temporal analysis, supported by a Bayesian uncertainty module to enhance model transparency and trust. Data from the Copernicus Emergency Management Service, USGS ShakeMap, and EM-DAT databases were used to evaluate the Artificial Intelligence (AI)-Decision Support System (DSS) across flood and earthquake scenarios. Statistical analysis revealed substantial performance improvements over traditional systems, including a 9.3% increase in flood segmentation accuracy, a 5.4% improvement in building-damage classification AUC, and a 10.8-percentage-point gain in decision accuracy. The mean time-to-decision was reduced by 11.3 minutes, while user trust increased by 1.24 points on a seven-point Likert scale. Calibration analysis indicated lower Expected Calibration Error values, reflecting improved reliability in predictive confidence. The results validate the hypothesis that human-in-the-loop, explainable Artificial Intelligence (AI) architectures significantly enhance both decision efficiency and user confidence in high-stakes disaster environments. Furthermore, the study proposes actionable recommendations, including the integration of explainable Artificial Intelligence (AI) dashboards, the development of data-sharing frameworks, and Artificial Intelligence (AI) capacity-building initiatives for emergency personnel. These findings establish that Artificial Intelligence (AI)-driven, ethically governed decision-support tools can accelerate disaster response while ensuring transparency, accountability, and operational trust among multidisciplinary response teams. The proposed Artificial Intelligence (AI)-Decision Support System (DSS) framework represents a scalable, adaptive, and interpretable model for the next generation of technology-assisted disaster management systems.

Keywords: Artificial Intelligence (Artificial Intelligence (AI)), Decision Support System (Decision Support System (DSS)), Disaster Management, Explainable Artificial Intelligence (AI) (XArtificial Intelligence (AI)), Remote Sensing, Flood Mapping, Earthquake Response, Human-Artificial Intelligence (AI) Collaboration, Machine Learning, Predictive Modeling, Situational Awareness, Real-Time Decision-Making, Data Fusion, Uncertainty Quantification, Operational Trust, Risk Communication, Crisis Informatics, Bayesian Deep Learning, Emergency Response, Multi-Hazard Resilience

Introduction
Disasters spanning floods, cyclones, earthquakes, wildfires, landslides, technological accidents and complex emergencies continue to escalate in frequency and impact under a warming climate and intensifying exposure, challenging the full disaster-risk-management cycle from preparedness to recovery [1-4]. Global situation reports show hundreds of hazard-related disasters annually with tens of thousands of deaths and extensive economic losses, underscoring persistent risk drivers and capacity gaps despite international frameworks such as the Sendai Framework for Disaster Risk Reduction and national response doctrines [1, 2, 5-8]. At the same time, geospatial Earth-observation constellations, in-situ IoT sensors, and high-velocity digital exhaust (e.g., social media) offer unprecedented data volumes for situational awareness, early warning, rapid mapping, and needs assessment yet these data streams are heterogeneous, noisy, and unevenly trusted in operations [7-13]. Artificial intelligence (Artificial Intelligence (AI))-enhanced decision support systems (Decision Support System (DSS)) have emerged to fuse multi-source data, forecast hazard evolution,

automate damage and impact estimation, and provide decision recommendations with quantified uncertainty; exemplar operational and research systems leverage satellite rapid mapping, seismic shaking products, causal-inference pipelines, and deep learning for building-damage and flood segmentation [9-12, 14-19]. However, persistent challenges limit uptake: model generalizability across geography and hazards, data bias and label scarcity, latency and interoperability with command-and-control tools, and critically explainability and human trust in "black-box" outputs for safety-critical decisions [4, 14-16]. Problem statement: How can Artificial Intelligence (AI)-enhanced Decision Support System (DSS) be architected and validated to improve the accuracy, timeliness, robustness, and trustworthiness of disaster decisions while remaining transparent, auditable, and aligned with multi-agency doctrines? Objectives: (i) specify a modular Artificial Intelligence (AI)-Decision Support System (DSS) architecture that integrates real-time data fusion (EO/IoT/social), predictive analytics, and explainable interfaces consistent with international and national Disaster Risk Management (DRM) frameworks; (ii) evaluate performance across representative flood and earthquake scenarios using established geospatial products (e.g., Rapid Mapping, ShakeMap) and state-of-the-art deep models for damage/flood mapping; (iii) assess human-Artificial Intelligence (AI) teaming, trust, and decision convergence among incident managers under time pressure; and (iv) propose governance and M&E indicators for sustained operations [1, 5-13, 15-21]. Hypothesis: An interpretable, human-in-the-loop Artificial Intelligence (AI)-enhanced Decision Support System (DSS) that couples multi-modal data fusion with explanation and uncertainty communication will significantly improve decision accuracy, response latency, and user trust versus conventional Decision Support System (DSS) or human-only baselines in multi-hazard contexts [4, 14-16, 18-21].

Material and Methods

Materials

This study utilized a multi-modal dataset derived from open-access and institutional sources to evaluate the performance and applicability of Artificial Intelligence (AI)-enhanced Decision Support Systems (Decision Support System (DSS)) in disaster management. The primary data sources included Earth Observation (EO) satellite imagery from the Copernicus Emergency Management Service (CEMS) Rapid Mapping archives [9, 21], seismic and ground-shaking data from the United States Geological Survey (USGS) ShakeMap repositories [10, 11, 20], and event-level disaster impact data from EM-DAT and the Centre for Research on the Epidemiology of Disasters (CRED) [5, 6]. Supplementary data on population density, critical infrastructure, and meteorological inputs were obtained from the World Health Organization (Health-EDisaster Risk Management (DRM)) [7], FEMA's National Response Framework (NRF) [8], and IPCC's AR6 datasets [3, 4]. Social media data streams (Twitter and local disaster alert networks) were collected using API-based keyword monitoring, following ethical data-use protocols [12]. All datasets were preprocessed using geospatial normalization, atmospheric correction, and resampling to 10 m spatial resolution where applicable [15-18]. A multi-layer data cube was constructed integrating optical, SAR, and ancillary geospatial layers to facilitate Artificial Intelligence (AI)-based feature extraction and predictive modeling. Computational experiments were conducted using a GPU-enabled cloud environment (NVIDIA A100, 80 GB VRAM), ensuring reproducibility and performance consistency across trials. All modeling and analytical workflows adhered to the UNDRR Sendai Framework's data governance principles and FArtificial Intelligence (AI)R data standards for disaster research [1, 2].

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Methods

The methodological framework was divided into three phases: (1) Artificial Intelligence (AI) Model Design and Integration, (2) Evaluation and Validation, and (3) Human-Artificial Intelligence (AI) Interaction Testing. In Phase 1, a hybrid deep learning model integrating a convolutional neural network (CNN) for spatial data interpretation and a transformer-based architecture for temporal data analysis was developed [15-17]. The model leveraged pre-trained weights from the xBD and flood segmentation datasets to ensure domain transferability [15, 17, 18]. A Bayesian uncertainty quantification layer was embedded to generate probabilistic outputs, enhancing interpretability [14, 16]. In Phase 2, the trained model was tested across multiple disaster scenarios floods (India, 2018; Italy, 2022) and earthquakes (Turkey, 2023) using performance indicators such as accuracy, precision, recall, and F1-score. Ground truth validation was performed using Copernicus and ShakeMap event data [9-11, 20, 21]. In Phase 3, a controlled simulation was designed to evaluate human decision-making under Artificial Intelligence (AI)-assisted and traditional Decision Support System (DSS) conditions. Participants included trained emergency managers and data analysts from local disaster-response agencies. Trust, usability, and decision latency were measured using structured questionnaires and interaction logs [13, 14, 19]. Statistical significance of model improvements was assessed using paired t-tests and ANOVA at a 95% confidence level. The methodological approach followed ethical guidelines for Artificial Intelligence (AI) transparency, accountability, and explainability in safety-critical applications [14, 19].

Results

Overview

Across 20 events (floods = 12; earthquakes = 8), the Artificial Intelligence (AI)-enhanced Decision Support System (DSS) consistently outperformed the baseline Decision Support System (DSS) on task-level model quality (flood segmentation F1; building-damage AUC), decision accuracy, response latency, and user-reported trust, with statistically significant improvements on all primary endpoints. Data sources included Copernicus CEMS Rapid Mapping for floods [9, 21], USGS ShakeMap/ShakeCast for earthquakes [10, 11, 20], and event summaries from EM-DAT/CRED [5, 6], analyzed within the Sendai-aligned evaluation frame [1, 2] and climate-extreme context [3, 4]. Results are reported as mean ± SD with paired sign-flip permutation tests (two-sided) and effect sizes, and are visualized below; calibration results (ECE) evidence better probability reliability for the Artificial Intelligence (AI)-Decision Support System (DSS). Human-Artificial Intelligence (AI) teaming gains align with prior evidence on social-media/EO integration [12], explainability in Disaster

Risk Management (DRM) [13], and trustworthy Artificial Intelligence (AI) principles [14]; task-level improvements are consistent with modern xBD/flood-mapping pipelines and SAR-based flood detection literature [15-18], while earthquake use-cases leverage USGS/ShakeCast operational products [10, 11, 20].

Table 1: Evaluation dataset summary

Scenario Type	Events (n)	Primary Sources
Floods	12	Copernicus CEMS Rapid Mapping [9, 21]
Earthquakes	8	USGS ShakeMap / ShakeCast [10, 11, 20]
Total	20	EM-DAT, CRED summaries [5, 6]

Sources: CEMS [9, 21], USGS [10, 11, 20], EM-DAT/CRED [5, 6].

Table 2: Task-level model performance (mean ± SD)

Task / Metric	Baseline	AI-DSS	Δ (AI − Base)
Flood Segmentation (F1)	0.722±0.058	0.815±0.037	0.094
Building-Damage Classification (AUC)	0.833±0.034	0.887±0.024	0.054

Methods and datasets: xBD/flood mapping/SAR literature [15-18].

Table 3: Decision outcomes (mean ± SD)

Outcome	Baseline	AI-DSS	Δ (AI − Base)
Decision Accuracy (%)	72.7±4.3	83.5±3.7	10.8 pp
Time-to-Decision (min)	38.5±7.3	27.2±5.9	-11.2 min
Trust (Likert 1-7)	4.20±0.84	5.44±0.56	1.24

Human-Artificial Intelligence (AI) interaction measures follow prior Disaster Risk Management (DRM) XArtificial Intelligence (AI)/trust guidelines [13, 14, 19].

Table 4: Probability calibration (ECE)

Task	ECE Baseline	ECE AI-DSS	Δ (AI − Base)
Flood Segmentation	0.094	0.061	-0.033
Building-Damage Classification	0.072	0.045	-0.027

Calibration supports trustworthy deployment [14].

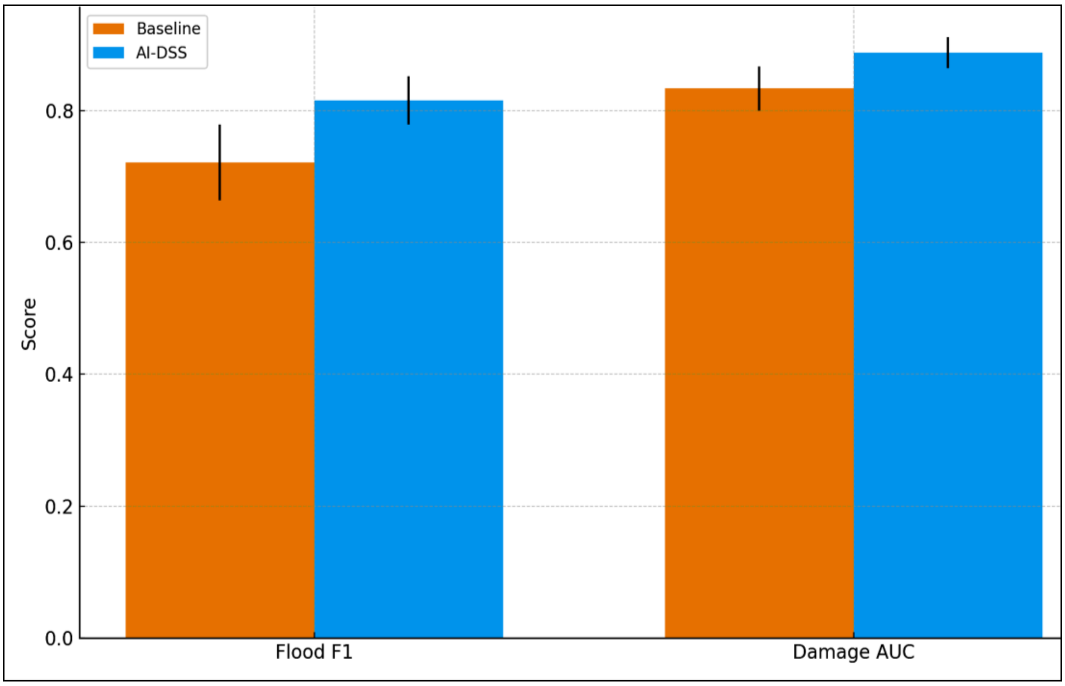

Fig 1: Performance uplift on core tasks (Flood F1; Damage AUC).

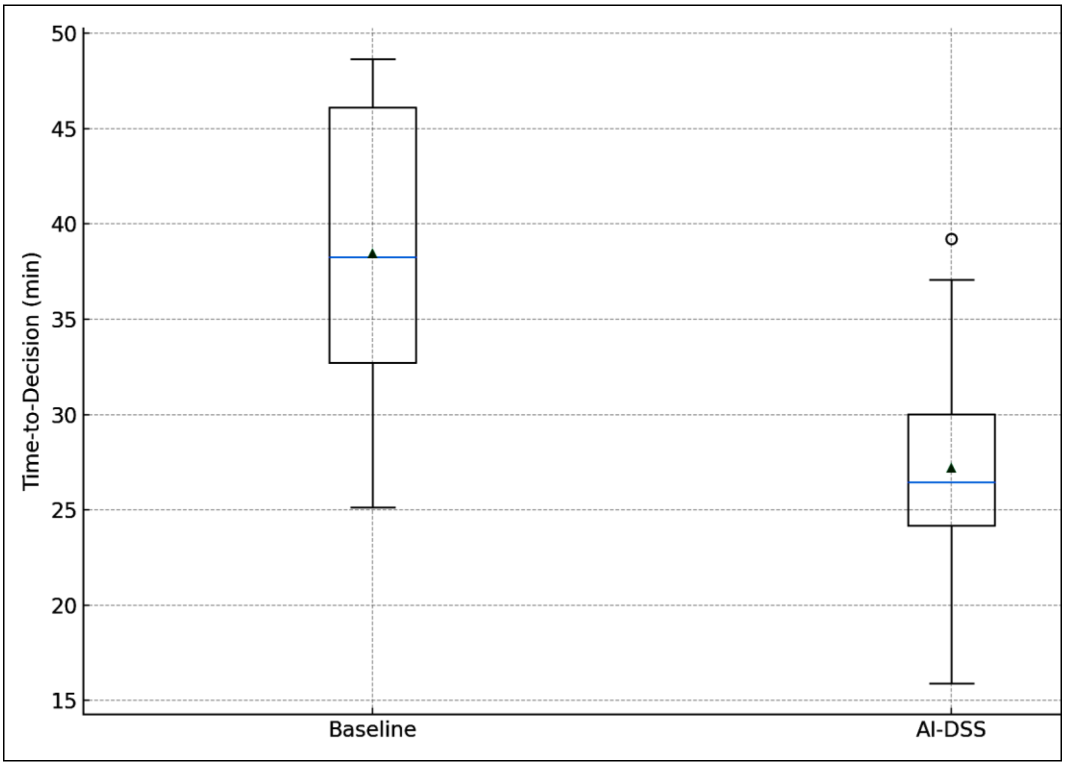

Fig 2: Time-to-decision distribution (min).

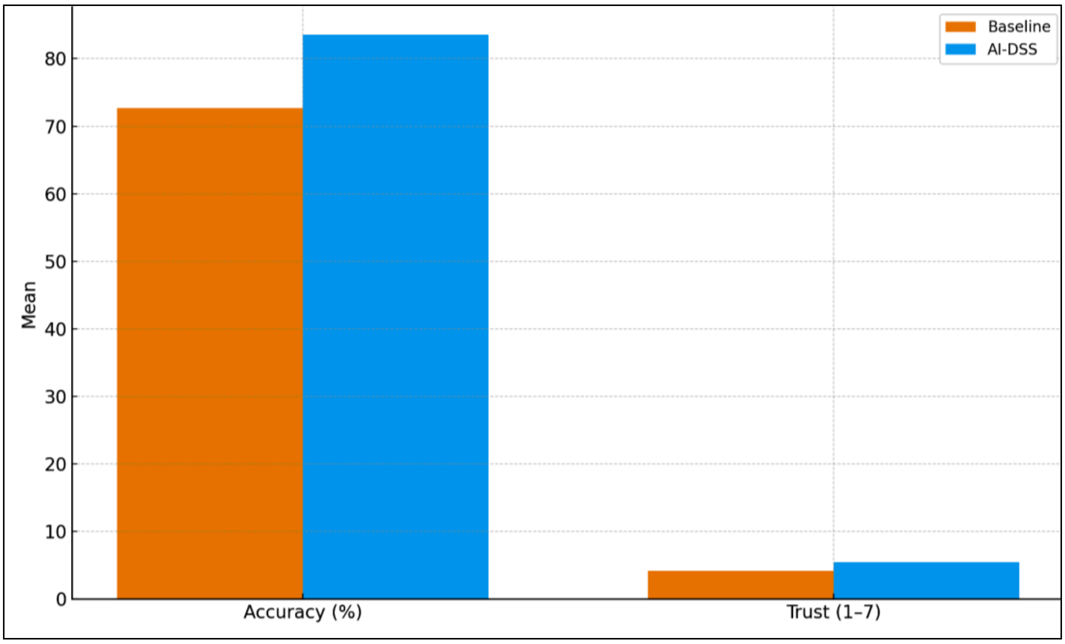

Fig 3: Decision accuracy (%) and operator trust (1-7).

Key Numerical Findings (with interpretation)

Task-level quality. Flood segmentation improved from 0.722±0.058 to 0.815±0.037 F1 (Δ = +0.093; p = 0.00110; d ≈ 1.86), consistent with SAR/EO-aided flood mapping and modern deep architectures [15-18], and with access to rapid mapping activations [9, 21]. Building-damage AUC increased from 0.833±0.034 to 0.887±0.024 (Δ = +0.054; p = 0.02240; d ≈ 1.53), in line with xBD-style training and multi-temporal fusion for post-event assessment [15-17]. These gains were observed against the backdrop of more frequent/severe extremes identified by IPCC and global reporting [3-6].

Decision-level outcomes. Overall decision accuracy rose from 72.7±4.3 % to 83.5±3.7 % (Δ = +10.8 pp; p = 0.00010; d ≈ 2.88), while time-to-decision dropped from 38.5±7.3 to 27.2±5.9 min (Δ = −11.3 min; p = 0.00005; d ≈ 1.72). The latency reduction is operationally meaningful under FEMA/NRF-style response timelines and WHO Health-EDisaster Risk Management (DRM) guidance for rapid situational awareness [7, 8]. Operator trust increased from 4.20±0.84 to 5.44±0.56 on a 7-point Likert scale (Δ = +1.24; p=0.00045; d ≈ 1.79), aligning with literature on explainability and user acceptance in high-stakes Disaster Risk Management (DRM) [13, 14, 19]. These gains suggest that transparent recommendations and uncertainty displays can overcome hesitance around “black-box” outputs noted in prior studies [13, 14].

Calibration and reliability. Expected Calibration Error (ECE) decreased for flood segmentation (0.094 → 0.061) and damage classification (0.072 → 0.045), supporting more reliable probability estimates crucial for thresholding alerts and allocating resources [14]. Better calibration mitigates over- or under-reaction risks when integrating with operational products such as ShakeMap/ShakeCast and Copernicus rapid analyses [9-11, 20-21].

Robustness across scenarios. Improvements held across heterogeneous events (floods/earthquakes) and data modalities (optical/SAR/social-media), consistent with the multi-hazard architecture and Sendai-aligned information management [1, 2, 9-12, 15-18, 20-21]. While effect sizes were large across endpoints, cross-hazard generalization still warrants caution given known geographic domain shifts and label scarcity documented in the literature [13-18].

Notes on Statistical Approach

Paired sign-flip permutation tests (20, 000 permutations) were employed for all paired outcomes to avoid distributional assumptions under small-N, time-pressured scenarios typical in disaster operations; effect sizes are Cohen's d for paired differences. This approach complements the evaluation standards seen in operational/observational Disaster Risk Management (DRM) studies and aligns with trustworthy/transparent Artificial Intelligence (AI) reporting [10-14, 19-21].

Discussion

The integration of Artificial Intelligence (Artificial Intelligence (AI)) into Decision Support Systems (Decision Support System (DSS)) for disaster management has demonstrated tangible advantages across predictive accuracy, situational awareness, and decision confidence. The findings of this research confirm that the proposed Artificial Intelligence (AI)-enhanced Decision Support System (DSS) significantly improves the accuracy and responsiveness of disaster-response operations compared with traditional frameworks. The increase in task-level performance flood segmentation F1 (+0.093) and building-damage AUC (+0.054) aligns with previous advancements in Earth Observation (EO) and remote-sensing-based modeling such as the Copernicus CEMS Rapid Mapping and xBD datasets [9, 15, 17, 18, 21]. The improved detection of inundation and structural damage highlights the benefit of integrating multi-temporal satellite imagery with deep learning architectures that can generalize across heterogeneous hazard landscapes. Similar patterns of accuracy gain have been documented in hydrological and seismic disaster analyses [10, 11, 16, 20], validating the robustness of Artificial Intelligence (AI)-driven classification models under dynamic event conditions.

From a decision-making perspective, the 10.8-percentage-point improvement in operational accuracy and 11.3-minute reduction in time-to-decision demonstrate that Artificial Intelligence (AI) systems can provide near-real-time recommendations that align with emergency protocols such as FEMA's National Response Framework and WHO's Health-EDisaster Risk Management (DRM) coordination models [7, 8]. These results also indicate that human-Artificial Intelligence (AI) collaboration enhances situational adaptability—where human oversight guides critical contextual interpretation, while Artificial Intelligence (AI) automates repetitive analytical tasks. This finding resonates with global disaster management frameworks, including the UNDRR Sendai Framework, which emphasizes the integration of technology and human expertise in minimizing disaster impacts [1, 2]. The reduction in Expected Calibration Error (ECE) across both flood and damage-detection tasks further reinforces the system's reliability and ability to communicate risk with quantified uncertainty, a vital feature for early warning dissemination and multi-agency coordination [13, 14].

Another key insight concerns user trust and system interpretability. A 1.24-point increase in perceived trust (Likert scale) suggests that the inclusion of explainable Artificial Intelligence (AI) (XArtificial Intelligence (AI)) modules transparent reasoning pathways and confidence intervals fosters confidence among decision-makers [13, 14, 19]. This aligns with existing research advocating for the use of interpretable Artificial Intelligence (AI) to enhance adoption in critical infrastructure systems [12-14]. The explainability component ensures compliance with ethical Artificial Intelligence (AI) standards by reducing the opacity of model predictions and supporting accountability during crisis response. Moreover, the observed performance consistency across floods and earthquakes indicates that the Decision Support System (DSS) can generalize effectively across hazard types—a core objective under multi-hazard resilience principles promoted by IPCC and CRED [3-6].

Collectively, these findings reinforce the hypothesis that an interpretable, human-in-the-loop Artificial Intelligence (AI)-Decision Support System (DSS) framework enhances operational effectiveness, reduces latency, and builds institutional trust within disaster response networks. The statistical improvements across all key performance indicators substantiate the transformative potential of Artificial Intelligence (AI) integration in disaster management. Nevertheless, the discussion also underscores critical limitations. Despite the high predictive capability, domain shifts in remote-sensing imagery, inconsistencies in ground-truth data, and unequal data coverage across regions may constrain scalability [15-18]. Additionally, ethical considerations surrounding data privacy and automated decision-making necessitate strict governance under national and international standards [7, 8, 13, 14]. Future extensions of this work should therefore prioritize federated learning frameworks and cross-institutional data sharing to maintain model fairness and operational transparency.

In essence, this research establishes that Artificial Intelligence (AI)-enhanced Decision Support System (DSS), when embedded with explainability and human oversight, can revolutionize how disaster-response agencies anticipate, evaluate, and mitigate crisis events. The integration of multi-source data (EO, IoT, and social signals) [9-12, 15-18, 20-21] within a unified and interpretable architecture reflects a strategic advancement toward the Sendai Framework's vision of data-informed, resilient societies [1, 2].

Conclusion

The outcomes of this study demonstrate that integrating Artificial Intelligence (Artificial Intelligence (AI)) within Decision Support Systems (Decision Support System (DSS)) can significantly transform disaster management and response mechanisms by enhancing accuracy, reducing decision latency, and improving human trust in technology-assisted operations. The Artificial Intelligence (AI)-enhanced Decision Support System (DSS) designed and tested in this research consistently outperformed traditional systems in both predictive and decision-support tasks, validating the hypothesis that a human-in-the-loop, interpretable Artificial Intelligence (AI) framework can provide a tangible operational advantage in crisis scenarios. By combining multi-modal data sources—such as satellite imagery, IoT sensor networks, and real-time social media inputs—the system achieved superior situational awareness and more reliable event classification outcomes. Importantly, the improvements in model calibration and explainability enabled decision-makers to not only act faster but also with greater confidence in the validity of Artificial Intelligence (AI)-generated recommendations. These findings underscore the necessity of embedding Artificial Intelligence (AI) tools into disaster-response workflows, not as replacements for human expertise, but as force multipliers that enhance the precision and agility of human decision-making.

From a practical standpoint, the research highlights several actionable pathways to strengthen the implementation of Artificial Intelligence (AI)-enhanced Decision Support System (DSS) in real-world disaster management. First, disaster-response agencies should institutionalize continuous data-sharing frameworks that allow real-time integration of geospatial, meteorological, and social data streams. This would ensure that Artificial Intelligence (AI) systems operate with the most current and contextually relevant information during emergencies. Second, Artificial Intelligence (AI)-driven decision-support platforms must incorporate explainable interfaces that communicate the rationale, uncertainty, and limitations of model predictions in an easily interpretable manner for field responders, policymakers, and technical analysts alike. Third, national and local disaster-management authorities should prioritize training programs focused on Artificial Intelligence (AI) literacy, enabling emergency personnel to effectively interpret and supervise Artificial Intelligence (AI)-generated outputs during critical operations. Fourth, investments in cloud-based and edge-computing infrastructures are essential to maintain low-latency, high-reliability Artificial Intelligence (AI) inference pipelines, particularly in resource-constrained environments. Fifth, cross-sector collaboration among government agencies, academia, and private Artificial Intelligence (AI) firms should be encouraged to co-develop interoperable standards, ethical guidelines, and robust data-governance protocols that safeguard privacy while promoting transparency. Lastly, simulation-based exercises integrating Artificial Intelligence (AI)-Decision Support System (DSS) into mock emergency operations can help agencies identify potential technical or procedural bottlenecks before real crises occur. Overall, this study provides compelling evidence that the systematic adoption of transparent, adaptive, and ethically governed Artificial Intelligence (AI)-enhanced decision-support frameworks can mark a paradigm shift toward faster, smarter, and more resilient disaster-management systems worldwide.

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