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Review article: Emergency Response Automation (ERA) as a Safety-Critical System: A Systematic Review of Reliability, Architecture, and Evolution (2010 – 2025)

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Abstract

Emergency Response Automation (ERA) is becoming a critical component of managing low-probability, high-consequence natural hazards and cascading technological emergencies under severe time pressure. This systematic review consolidates ERA research from a safety-science and reliability-engineering perspective, with particular emphasis on applications to earthquakes, floods, wildfires and other environmental hazards. Following PRISMA 2020 guidelines, we analysed 198 peer-reviewed studies (2010–2025) on automated, intelligent and data-driven emergency response technologies. A four-layer ERA framework—perception and monitoring, data and decision-making, automated response and control, and feedback and learning—was developed to integrate heterogeneous findings and trace the evolution of ERA. Empirical evidence from operational systems is contrasted with simulation-based demonstrations to assess reliability, availability, fault tolerance and human performance. Persistent challenges include data and model uncertainty under distributional shift, limited verification and validation of decision algorithms, opaque human–automation coordination, and gaps in interoperability, governance and trust. We outline a research agenda that links ERA development with resilience engineering, Safety-II and socio-technical systems design, and propose standardised metrics and evidence-grading principles to support reliable and trustworthy ERA deployment in complex infrastructures exposed to natural and technological hazards.

Keywords: emergency response automation, system reliability, system safety, intelligent decision-making, artificial intelligence, digital twin

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1 Introduction

In recent decades, disasters—particularly natural hazards and their cascading technological impacts—have become increasingly frequent and complex, spanning climate hazards, industrial accidents and public health crises(Yu et al., 2018). For example, the 1982 Edmonton well blowout in Canada was quickly controlled through prompt ignition, averting a major explosion(Gephart, 1988). In contrast, the 2003 Kaixian gas-well blowout in Chongqing released hydrogen sulfide, causing over 190 deaths and the evacuation of tens of thousands(Jianfeng et al., 2009). Such comparative cases highlight the core value of timely response and scientifically grounded decision-making in emergency management. Yet, despite unprecedented advances in sensing, communication and information technologies, emergency operations in many countries remain characterised by fragmented data streams, incompatible platforms and organisational "information silos". This raises a central question for this review: why do information silos persist in an era of highly advanced technology, and how can ERA be designed to overcome them in safety-critical emergency operations?

Driven by the rapid advancement of automation, artificial intelligence (AI), and digital twin technologies, the field of emergency management is undergoing a profound transformation (Kyrkou et al., 2022). The concept of Emergency Response Automation (ERA) has emerged as a comprehensive framework that integrates these technologies to enhance system responsiveness and reliability. ERA has demonstrated the potential to improve situational awareness, accelerate information processing, and enable coordinated resource allocation across multiple actors and domains(Yang et al., 2013). Its deployment in critical operations has been increasingly evident—for instance, supporting proactive containment strategies during the COVID-19 pandemic(Andrejevic and O'Neill, 2024), enabling automated resource scheduling after the Fukushima nuclear disaster(Nagatani et al., 2013), and improving response efficiency at China's Qinshan and Hongyanhe nuclear power plants(Chen et al., 2018). Greater reliance on automation also

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creates challenges: reliability, interoperability, accountability, and human–machine teaming in high-risk contexts. We examine each through a system-safety lens and propose measurable safeguards.

From the perspective of reliability engineering, ERA offers a unique opportunity to bridge intelligent automation with the quantitative assurance of system dependability, providing structured frameworks for assessing robustness, fault tolerance, and safety performance across heterogeneous emergency operations. Human responders still provide irreplaceable intuition, ethical reasoning, and adaptability—elements that current automated systems cannot fully replicate. Thus, the key challenge is to design intelligent systems that augment human judgment and build operational trust under time pressure.

Table 1. Overview of recent literature reviews in emergency response and disaster management.

Serial No.	Authors	Focus Area
1	H Saputra(Saputra et al., 2025)	An overview of IoT in the Urban/ Infrastructure direction
2	A Jazairy(Jazairy et al., 2025)	The Role of Drones in emergency logistics and material delivery.
3	R Damaševičius(Damaševičius et al., 2023)	Provide a comprehensive understanding of the Internet of Emergency Services and its implications for emergency response and disaster management.
4	L Dwarakanath(Dwarakanath et al., 2021)	A comprehensive review of the role of social media in emergency response after disasters based on machine learning.
5	U Lagap(Lagap and Ghaffarian, 2024)	The Application and Challenges of Digital Twin in Post-Disaster Risk Management.
6	Y Li(Li et al., 2024)	A Special Review of Digital Twins in Wildfire Management.
7	SM Khan(Khan et al., 2023)	Overall assessment of disaster management systems, with a focus on methods/tools and challenges.
8	SK Abid(Abid et al., 2025)	The Application of AI Methods Based on Social media and Crowdsourced Data in Disaster Management.
9	Y Feng(Feng and Cui, 2021)	A comprehensive review of the disaster emergency response system is conducted, including the current situation and future prospects.

Recent reviews on emergency response, summarized in Table 1, indicate that although prior studies

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have examined diverse technologies and their domain-specific applications, several research gaps remain. Existing literature is still fragmented, offering limited insights into cross-domain regularities and theoretical integration with reliability and safety science. Moreover, few studies provide a systematic synthesis linking technological evolution with operational, human, and organizational dimensions.

To address these gaps, this review adopts a safety-science and reliability-engineering perspective on ERA, with a primary focus on natural hazards and environmental emergencies. Drawing on a PRISMA-guided review of 198 peer-reviewed studies (2010–2025) on automated, intelligent and data-driven emergency response, we propose a four-layer ERA framework—perception and monitoring, data and decision-making, automated response and control, and feedback and learning—to integrate heterogeneous findings, identify cross-domain patterns and expose interoperability challenges that sustain information silos.

The review is guided by the following research questions:

RQ1: How do ERA capabilities at each layer align with reliability and system-safety metrics, including availability and uptime, fault tolerance and graceful degradation, timeliness and accuracy trade-offs, resilience under degraded communications, and human performance in natural and technological hazard contexts?

RQ2: Across hazards and settings—with particular emphasis on natural hazards—which ERA approaches show moderate or strong empirical support for improving safety-relevant outcomes, and which remain limited to simulations, prototypes or small-scale demonstrations?

RQ3: What failure modes, bias sources, interoperability barriers and human–automation coordination issues most threaten ERA dependability, and what assurance mechanisms have been proposed or implemented to mitigate these risks?

From a safety-science perspective, this review makes three main contributions. First, it proposes an

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integrative four-layer ERA architecture that links automation functions to risk-reduction mechanisms in safety-critical socio-technical systems, and identifies interoperability as a core design principle for overcoming information silos. Second, it maps ERA applications across hazard types, technologies and capabilities, revealing cross-domain patterns and systematic gaps in reliability assurance, including limited stress-testing under uncertainty, inadequate fail-safe and fail-operational design, and weak support for human–automation teaming. Third, it advances a research agenda that connects ERA with resilience engineering, Safety-II and the governance of emerging technologies, highlighting priorities for validating intelligent decision-making, allocating control between humans and automated agents, and establishing institutional arrangements for trustworthy ERA deployment.

The remainder of this paper is organised as follows. Section 2 describes the review methodology; Section 3 introduces the ERA framework and classifies the evidence base; Sections 4 and 5 analyse ERA capabilities, applications and reliability issues, with emphasis on natural-hazard scenarios; Section 6 synthesises cross-cutting trends, limitations and future directions; and Section 7 concludes with key implications for strengthening global disaster response.

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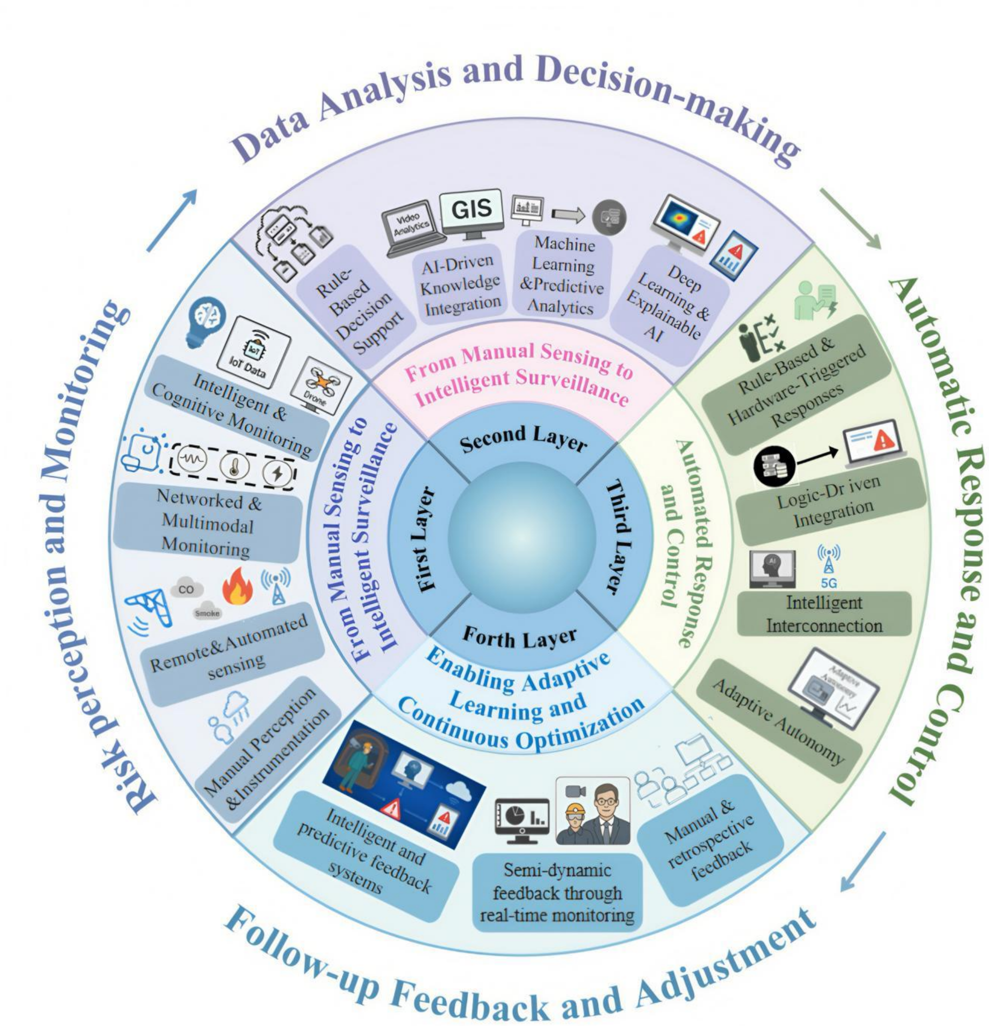

Fig.1 System framework diagram.

2 Methodology

This review focuses on Emergency Response Automation (ERA), defined as the integration of intelligent, automated, and data-driven technologies to support or partially substitute human

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decision-making and operational activities across all phases of emergency management.

Following the PRISMA guidelines(Page et al., 2021), we conducted a comprehensive search for 2010–2025 (last search across all sources: 27 September 2025). As illustrated in Fig. 2, the evidence base is heavily skewed towards recent work: 90.4% of the cited studies were published in 2010 or later, and almost 60% appeared between 2020 and 2025. Only a small number of classic references prior to 2000 were retained to provide historical and theoretical context. Fig. 3 presents the PRISMA 2020 flow of records through identification, screening, and inclusion. Searches spanned Web of Science, Scopus, IEEE Xplore, and PubMed, supplemented by Google Scholar (top 10% per year by relevance and citations; n = 54)(Zhang et al., 2019). The Boolean strategy combined three concept groups with "AND" :

(1) emergency ("emergency," "disaster," "pandemic," "incident," "accident");

(2) automation ("automate," "autonomous," "artificial intelligence");

(3) activities ("response," "planning," "monitoring," "prediction").

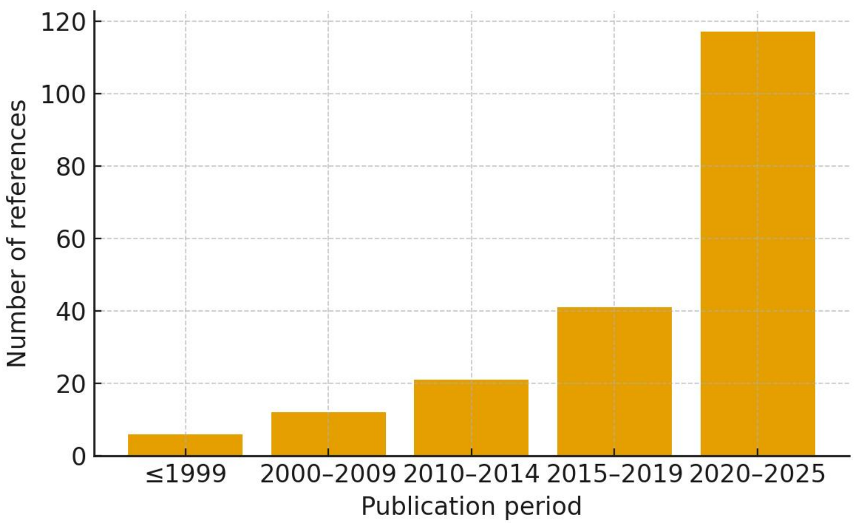

Fig. 2 Temporal distribution of ERA-related references.

After deduplication in EndNote, two reviewers independently screened titles/abstracts/full texts. Inclusion required peer-reviewed English studies (2010–2025) explicitly addressing automated, intelligent,

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or data-driven emergency response and providing empirical, modeling, or conceptual contributions. Discrepancies were resolved by consensus; Cohen's $\kappa = 0.86$ on a 20% random subset indicated high agreement. Ultimately, 198 studies were included.

We applied a concise five-domain Reliability & Reproducibility (R&R) rubric (0–2 each; total 0–10): (D1) external validity; (D2) completeness of quantitative safety metrics (e.g., latency, FAR/MDR, availability/uptime, recovery time/MTTR); (D3) baseline/comparator; (D4) sample/condition diversity; (D5) reporting transparency. Two reviewers scored independently and reconciled by consensus; agreement on a 20% calibration set was $\kappa = 0.86$. Totals map to High (8–10), Moderate (5–7), Low (0–4). Safeguards: if D2 = 0 the tier cannot exceed Moderate; if $\geqslant 2$ domains = 0 the tier is Low. NR (not reported) scored 0. To conserve space, tables report only the tier (H/M/L).

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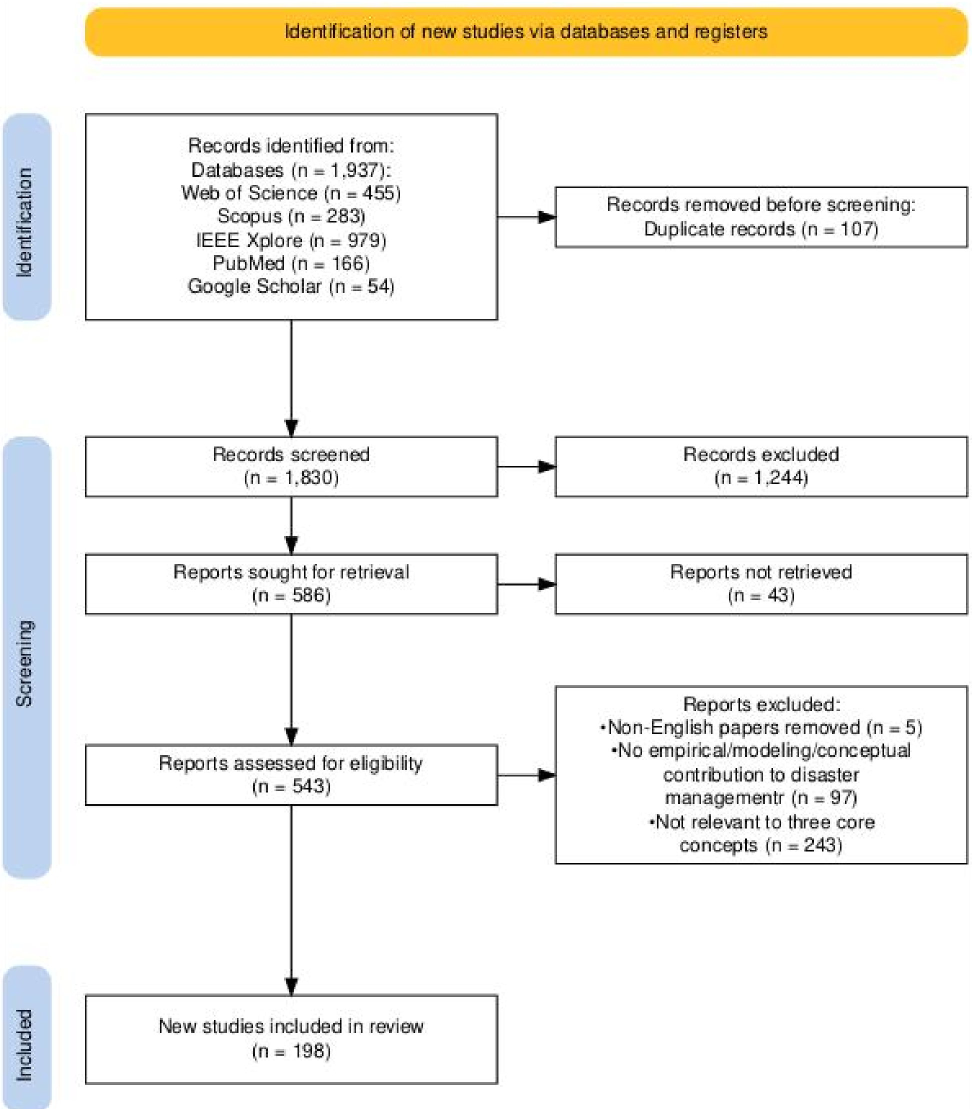

Fig.3 PRISMA 2020 flow diagram for the systematic review.

3 Composition and Definition

ERA refers to the automatic initiation and execution of emergency measures through sensors, data processing, and intelligent decision-making technologies, enabling rapid response to incidents such as

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security threats, natural disasters, and public health emergencies with minimal human intervention(Matracia et al., 2022).

3.1 System framework

The four-layer architecture of ERA proposed in this study was developed through a dual-path approach of empirical induction and theoretical validation.

First, using thematic synthesis, two researchers independently reviewed and cross-compared 198 selected studies through multiple iterative rounds. This process identified four recurring functional categories consistently appearing in ERA-related research—Perception, Decision-Making, Response & Control, and Feedback & Learning.

Second, this four-layer structure aligns with well-established automation paradigms in other domains. Comparable hierarchical closed-loop architectures can be observed in robotics(Brooks, 1991), industrial control systems(Nagorny et al., 2012), and reliability management frameworks(Hollnagel, 2018), all of which encompass a complete "Perceive–Reason–Act–Learn" process. Such consistency demonstrates that the ERA framework reflects a widely recognized structural logic across automation-intensive systems.

Finally, from the perspectives of systems engineering and cybernetics(González et al., 2021), the four-layer architecture ensures both functional completeness and logical closed-loop reliability.Therefore, the proposed architecture is grounded in both empirical evidence and cross-domain theoretical foundations, providing a robust scientific basis for the development of adaptive and reliable ERA systems (Fig. 1).

3.2 From Manual Sensing to Intelligent Surveillance

Over the past six decades, risk perception and monitoring technologies have evolved from manual field observations to intelligent, data-driven monitoring systems. Fig.4 illustrates this evolution, which can

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be summarized into four interrelated phases.

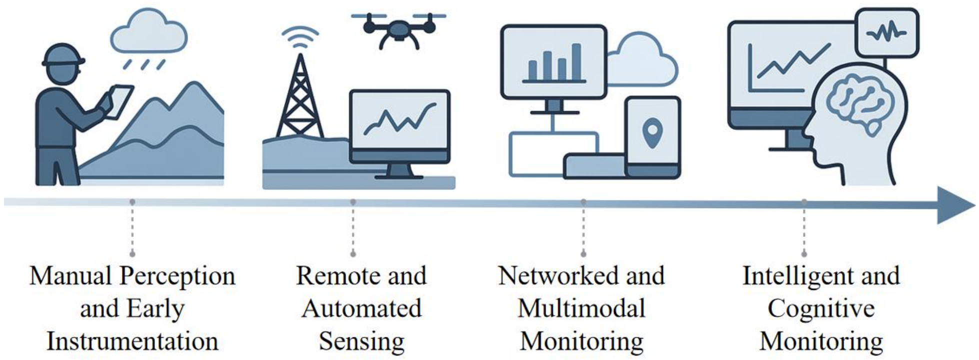

Fig.4 Diagram of the evolution of the risk perception and monitoring layer.

(1) Manual Perception and Early Instrumentation

In the earliest stage, disaster perception relied on human operators, analog instruments, and visual inspection. Meteorological observers manually recorded rainfall and seismic activity(Schweitzer and Lee, 2003); industrial workers conducted periodic checks using portable gas detectors(Hemingway et al., 2012); and public health surveillance depended on field sampling. Although these methods provided basic situational awareness, they were constrained by time delays(Fonollosa et al., 2018), limited coverage, and subjective bias(Dang et al., 2018). Automation was virtually absent—the perception layer of ERA remained entirely human-centered.

(2) Remote and Automated Sensing

With the rise of remote sensing satellites, radar networks, and early wireless sensor systems, monitoring gradually shifted toward automation(Ko et al., 2009; Kodali and Yerroju, 2017). Satellite-based systems enabled continuous observation of floods, landslides, and wildfires(Al-Hady et al., 2023; Mois et al., 2017); fixed gas and infrared sensors provided near-real-time industrial monitoring(Chraim et al., 2015; Jain and Kushwaha, 2012; Ni et al., 2018); and digital epidemiology systems aggregated hospital data for disease detection(Adiga et al., 2020). This phase marked the first integration of automated data acquisition into ERA, significantly improving detection timeliness and reliability.

(3) Networked and Multimodal Monitoring

The emergence of IoT and multi-sensor fusion technologies enabled risk perception to become multimodal—integrating visual, acoustic, thermal, and social data for comprehensive situational awareness(Alamdar et al., 2015). Seismic sensors linked with drones enhanced earthquake assessment(Contreras et al., 2021); fiber-optic sensors detected industrial leakage and overheating(Ashry et al., 2022); and mobile apps supplied real-time epidemic data(Moses et al., 2021). These networked sensing nodes laid the foundation for adaptive ERA architectures, where data streams directly informed early warning and resource allocation.

(4) Intelligent and Cognitive Monitoring

The current phase is characterized by the convergence of AI, edge computing, and digital twin technologies. Intelligent monitoring now extends beyond anomaly detection toward pattern recognition and predictive diagnostics. Deep learning models extract complex spatiotemporal features from multi-source data to identify emerging risk hotspots in real time. In public health, AI-driven systems integrate genomic sequencing data with population mobility and social indicators to forecast epidemic trajectories(Hadfield et al., 2018; Ongesa et al., 2025), COVID-19 early-warning system (EWS) uses hospital diagnostic data and thermal sensors for contactless screening(Ding et al., 2025; Haque et al., 2024). In industrial safety, computer vision and reinforcement learning models autonomously diagnose abnormal equipment behavior, while explainable AI enhances operator trust in automated alerts(Rivas and Abrao, 2020; Sayed and Gabbar, 2017). In natural disaster management ,forest fire monitoring relies on IoT, thermal imaging, drones, and AI algorithms to achieve early fire detection and spread prediction(Kavitha et al., 2023; Mehta et al., 2021), DMSEEW system combines GPS and seismic sensors with ML to enhance earthquake early warning accuracy(Becker et al., 2020). Additionally, the integration of big data technology enables automatic

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analysis of multi-source information such as social media, news reports, and police records to help predict and identify potential social security threats (e.g., the Violent Behavior Detection System (VBDS) applies deep learning to CCTV footage to detect violent behaviors(Shubber and Al-Ta'i, 2022)) .Based on natural language processing and machine learning technologies, automated systems can monitor large volumes of open data sources in real time, detect early warning information related to violence, riots, terrorist activities, and provide decision support(Florea et al., 2022; Montasari, 2024; Robertson et al., 2019). These advances are propelling ERA from reactive monitoring to proactive risk anticipation.

Across these phases, the transition from human-centered to human–machine hybrid perception has continuously enhanced the reliability, scalability, and cross-domain applicability of automated emergency response systems.

3.3 Evolution of Data-Driven Decision-Making

Serving as the cognitive core of ERA, the decision layer has progressed from deterministic, rule-based systems to adaptive, data-driven intelligent engines. Fig. 5 illustrates this evolution across four interrelated stages, each enhancing analytical capability and autonomy built upon its predecessors.

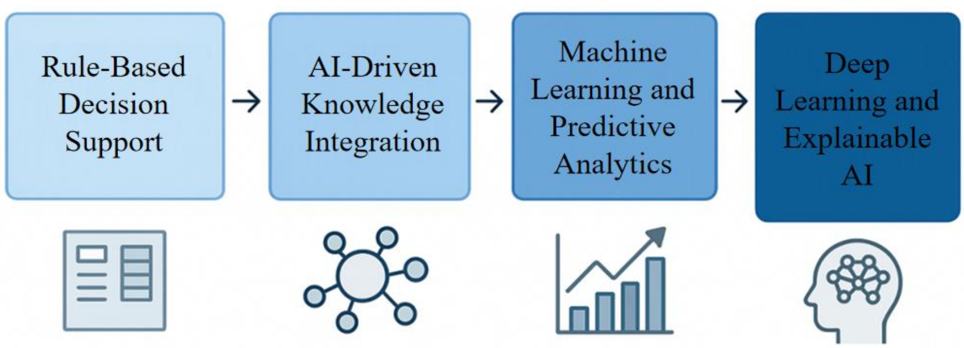

Fig.5 Diagram of the evolution of data analytics and the decision-making hierarchy.

(1) Rule-Based Decision Support

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Early systems relied on fixed logical rules and expert-defined procedures. Classical models such as Montgomery's sequential decision model(Montgomery and Svenson, 1976) and Simon's DSS framework (intelligence–design–choice) (Simon, 1960) structured decision processes through rule- and case-based reasoning. Applications in nuclear and chemical plants used predefined rules to ensure consistency and auditability. Although limited in real-time adaptability and cross-domain generalization, these systems established the transparent decision logic that underpinned later intelligent frameworks.

(2) AI-Driven Knowledge Integration

With the expansion of sensor networks and computing power, rule-based DSS evolved into hybrid AI systems combining symbolic reasoning and probabilistic inference. Bayesian networks and GIS-based tools enabled dynamic, multi-source situational assessment and predictive mapping(Bhatt and Zaveri, 2002). Group decision support(Cua and Heaton, 2007) and game theory–based optimization models enhanced interagency coordination under uncertainty(Brown and Vassiliou, 1993), reducing the isolation of single-agent frameworks. This phase bridged deterministic rules with adaptive analytical reasoning through AI-enabled knowledge integration.

(3) Machine Learning and Predictive Analytics

The proliferation of digital and sensor data shifted decision-making toward autonomous learning. Algorithms such as neural networks(Liao et al., 2011), SVMs(Taamneh and Taamneh, 2021), and random forests learned nonlinear risk–outcome relationships, enabling rapid forecasting of evolving emergencies(L. Wang et al., 2024). Applications included wildfire propagation prediction(Bot and Borges, 2022; Pereira et al., 2022; Sayad et al., 2019), explosion early warning, and evacuation optimization(Al-Hady et al., 2023) (Huang et al., 2024; Rüppel and Schatz, 2011; Zverovich et al., 2016). Unlike prior hybrid systems, these models derived decision rules directly from data, providing real-time adaptability to changing environments.

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(4) Deep Learning and Explainable AI

Recent advances have integrated deep learning–based perception technologies—such as natural language processing for text and social media analytics(Imran et al., 2014), computer vision for image and drone interpretation(Robertson et al., 2019), and multi-task learning for multi-hazard prediction—with explainable decision modules emphasizing transparency and human trust (For complex events, multi-task learning (MTL) has become pivotal, with Alam's MEDIC dataset demonstrating a 30% reduction in computational overhead without accuracy loss(Alam et al., 2023)) .Representative systems include AI-driven disaster response platforms (e.g., Fertier's AIC system dynamically generate response strategies(Fertier et al., 2020)), vision-based recognition frameworks (e.g., VGG/YOLO(Robertson et al., 2019)), medical emergency decision centers(Althouse et al., 2015), and generative AI decision support systems. These examples demonstrate how advanced neural architectures enable real-time linkage between perception and strategic decision-making. While these models substantially enhance accuracy and adaptability, they introduce new challenges in interpretability, ethical reliability, and human–machine collaboration.

Overall, the transition from rule-based determinism to data-driven adaptivity reflects a continuous enhancement in probabilistic reasoning, autonomous learning, and human–machine synergy—forming the intelligent, context-aware decision engine that now underpins reliable and adaptive emergency management.

3.4 Automated Response and Control

The automated response and control layer constitutes the operational core of the ERA system, translating analytical outputs from the decision-making layer into executable actions. Through automation

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platforms and standardized communication protocols, it integrates firefighting, power, communication, and transportation subsystems. Fig.6 illustrates its evolution along four major technological pathways, reflecting the convergence of perception, computation, and coordination capabilities.

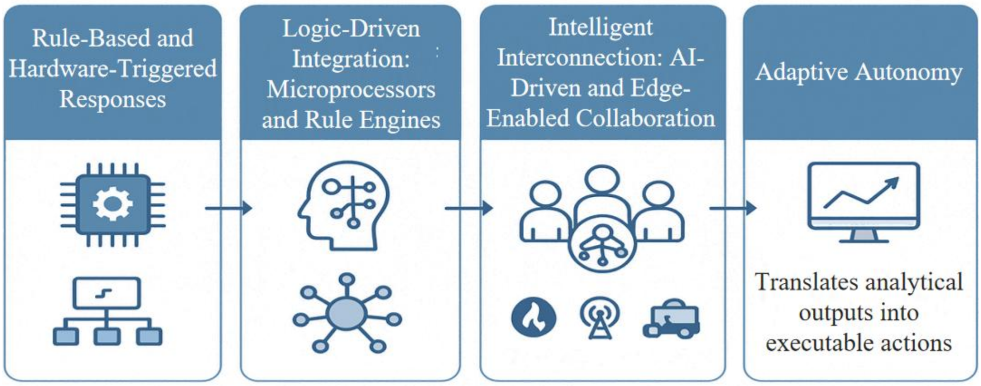

Fig.6 Diagram of the evolution of the automatic response and control layer.

(1) Rule-Based and Hardware-Triggered Responses

The initial stage of automation was dominated by single-sensor and threshold-triggered mechanisms, where systems were activated only upon anomaly detection. For instance, Graf's debris-flow monitoring system(Badoux et al., 2009) enabled early warning functions but remained entirely dependent on manual verification and intervention(Jafari et al., 2020). Automation during this stage was characterized by passivity and localization, featuring unidirectional signal transmission from sensors to operators, with limited inter-system communication or adaptive decision-making logic.

(2) Logic-Driven Integration

The second stage marked a transition from manual activation to programmable logic control, driven by the introduction of microprocessors and rule-based engines. Emergency response systems for hazardous materials(Zografos et al., 2000)and dynamic seismic mapping platforms (Bingli et al., 2014) enabled automation based on predefined rules and contextual thresholds. Concurrently, advances in mobile and wireless communication facilitated remote alerts and cross-platform coordination(Kuantama et al., 2013,

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2012). For example, Azid et al. developed an Android-based flood warning application utilizing web services for automatic notifications(Sung et al., 2022), while De Souza et al. integrated real-time hydrological monitoring with user geolocation to deliver context-aware SMS alerts(De Souza et al., 2015). Automation at this stage exhibited logic-driven and distributed characteristics, yet remained constrained by static rules and limited situational awareness.

(3) Intelligent Interconnection

With the integration of deep learning, the Internet of Things (IoT), and 5G/B5G communication networks(Dixit et al., 2022; Euchi, 2021), automated response systems entered the stage of intelligent interconnection. Technologies such as device-to-device communication(Ahmed et al., 2019; Ever et al., 2020)and the Internet of Emergency Services (IoES) enabled multi-channel, low-latency information exchange among heterogeneous agencies(Damaševičius et al., 2023). Multi-access edge computing and service-oriented architectures facilitated real-time deployment of adaptive services, while intelligent transportation systems provided the foundation for networked emergency mobility(Chen and Englund, 2018). AI models—including CNN-based incident detection(Kim et al., 2019)and deep recurrent neural network–based event classification(dos Santos et al., 2019)—further enhanced the precision of automated control. This phase can be summarized as the “AI + Edge + Connectivity” paradigm, representing a shift from deterministic rule execution to context-aware, data-driven orchestration.

(4) Adaptive Autonomy

Since the 2020s, ERA systems have evolved toward adaptive and decentralized coordination, enabling dynamic sharing of authority(Chen et al., 2008) and resources across multiple agencies (Janssen et al., 2010)(IoT + BIM systems for fire detection and suppression, integrating sprinkler control and escape route optimization(Annadurai et al., 2024; Jiang et al., 2023; Mondal et al., 2023)). Architectures based on ontology and multi-agent systems support semantic interoperability and autonomous negotiation among

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heterogeneous organizations(Maalel and Ghézala, 2019). Rule-/ontology-based emergency decision-support systems integrate event-driven reasoning and semantic inference to keep a continuously updated operational picture and support rapid task (re)allocation and resource redistribution(Cui et al., 2024). Meanwhile, the Matter-IoT framework improves device interoperability and response reliability through standardized protocols(Bhardwaj and Joshi, 2024). The emergence of the digital twin paradigm(Fan et al., 2021)further propels the transition from operational automation to cyber-physical co-evolution, where continuously updated situational data refine simulation models to optimize control strategies. Overall, this stage represents a transformation from passive automation to adaptive autonomy, emphasizing continuous learning, coordination, and optimization.

This evolution reflects not only technological iteration but also multidimensional integration pathways: (1) Vertical integration — standardizing data interfaces to link the perception, decision, and execution layers; (2) Horizontal integration — achieving semantic and protocol-level interoperability among heterogeneous response agencies;

(3) Cognitive integration — embedding learning algorithms for continual adaptation under uncertainty. Thus, automation in ERA is shifting from task automation toward autonomous collaboration, laying the foundation for a resilient, data-driven emergency management network.

3.5 Enabling Adaptive Learning and Continuous Optimization

The feedback layer represents the adaptive capability of ERA systems, operating as a continuous optimization loop across the disaster management cycle. Fig.7 illustrates how an effective feedback mechanism transforms ERA from rule-based static models into dynamic, data-driven systems capable of real-time self-optimization.

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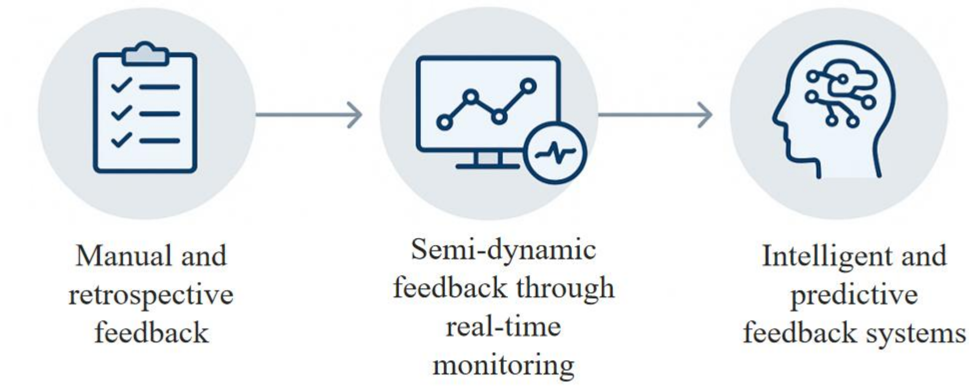

Fig.7 Diagram of the evolution of the subsequent feedback and adjustment layer.

(1) Manual and retrospective feedback

Early ERA studies primarily focused on retrospective analyses of emergency events or simulation exercises, heavily relying on manually written performance evaluations and post-incident reports(Ramabrahmam et al., 1996). During this period, feedback mechanisms lacked autonomous design; lessons learned were integrated manually, and complex resource coordination still depended on human intervention. Consequently, feedback played only a limited corrective role and was insufficient to support continuous system improvement.

(2) Semi-dynamic feedback through real-time monitoring

With advances in sensing, communication, and computational technologies, feedback layers gradually incorporated real-time monitoring and automated evaluation capabilities(Badoux et al., 2009; Ding et al., 2022; Gasparini et al., 2007). Researchers began improving alarm performance, enhancing the utilization of monitoring data, and integrating location-based path planning models to coordinate disaster logistics and resource deployment(Yi and Özdamar, 2007). The convergence of BIM–GIS–IoT technologies further enhanced system interoperability, enabling more efficient spatial and situational data exchange(Boguslawski et al., 2015; Sani and Abdul Rahman, 2018). These developments marked a shift from static, post-event analysis toward semi-dynamic feedback, where systems could trigger limited

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adaptive actions based on predefined thresholds or simple rule sets.

(3) Intelligent and predictive feedback systems

The rise of artificial intelligence, machine learning, and big data analytics has transformed the feedback layer into an intelligent decision support system. By integrating real-time medical, transportation, and social data streams via the Internet of Things, ERA systems can dynamically reallocate resources and adjust operational priorities in evolving scenarios(Zhang et al., 2014; G. Zhang et al., 2024). Deep learning algorithms detect emerging risk patterns and predict disaster evolution trends, allowing the system to proactively reconfigure response strategies before performance degradation occurs. For instance, real-time social media data mining assists public health agencies in adjusting medical resource allocation(Rathore et al., 2016), while reinforcement learning models continuously refine decision policies based on performance feedback(Arulkumaran et al., 2017; Li, 2024).

Overall, the evolution of the feedback layer reflects a paradigm shift from retrospective correction to continuous and predictive adaptation. This transformation establishes a solid theoretical foundation for the cross-domain application analysis discussed in the following section.

The above constitutes the four core layers of the ERA system, providing a foundational framework for the subsequent application scenario analysis.

4 Advantages of ERA

The advantages of ERA can be summarized in four points: data analysis, rapid response, precise location and intelligent dispatch.

4.1 Data-Driven Decision Advantages

The integration of AI and big data into ERA systems has enabled the consolidation of multi-source

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information, thereby enhancing prediction accuracy and situational awareness throughout the entire emergency management cycle. For instance, the Johns Hopkins University Global COVID-19 Surveillance Platform established a real-time data acquisition (Sheng et al., 2021)and reporting mechanism that significantly supported timely responses during large-scale public health crises(Kamel Boulos and Geraghty, 2020). Similar mechanisms have been implemented in Japan's Earthquake Early Warning System, where automated seismic data processing allows alerts to be issued within seconds(Kumar et al., 2022; H. Zhang et al., 2024).These systems demonstrate that automation can effectively augment human judgment in real-world emergency contexts. The National Oceanic and Atmospheric Administration (NOAA) in the United States provides another example: its AI-driven hurricane forecasting models generate automated predictions that support expert deliberations, while human coordinators ultimately decide when and how to issue community alerts(Jafarzadegan et al., 2023; Lam et al., 2023).

4.2 Temporal Efficiency in Rapid Response

Real-time monitoring and analytics enable Emergency Response Automation (ERA) systems to rapidly detect incidents and trigger timely responses, thereby minimizing latency. For example, Zheng et al. proposed the ChangeOS framework for multi-hazard decision support (Zheng et al., 2021); other implementations include a rapid emergency system for hydrogen leakage(C. Wang et al., 2024) and a real-time threshold-based flood emergency activation mechanism(Zhou et al., 2024). Technological responsiveness must align with human readiness and coordination. Automated alerts are effective only when responders can interpret and trust system outputs. Thus, ERA efficiency relies not just on computational speed but on training, trust, and teamwork enabling human–machine collaboration.

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4.3 Geospatial Precision in Resource Allocation

Accurate localization at the incident scene is a critical function of ERA systems(Ang et al., 2022; Khan et al., 2022). For instance, following the 2010 Haiti earthquake, Geographic Information System (GIS) technologies were employed to precisely identify the most severely affected regions(Corbane et al., 2011). Similarly, after the 2015 Nepal earthquake, the integration of satellite imagery and real-time unmanned aerial vehicle (UAV) data not only supported emergency response operations(Ge et al., 2015) but also provided rescue teams with precise navigation information. Liu and You and colleagues utilized UAVs to develop optimized resource allocation schemes, determine efficient distribution routes and equipment utilization plans, and design medical supply transportation strategies, thereby providing robust operational support for emergency missions(Liu and You, 2020). In addition, real-time tracking of rescue personnel and materials has ensured highly coordinated and efficient response operations(Balta et al., 2017; Damaševičius et al., 2023). Collectively, these applications demonstrate how fine-grained geospatial information and real-time tracking enable ERA systems to match resources to needs with high spatial precision.

4.4 Computational Optimization for Intelligent Dispatch

Intelligent dispatching systems leverage predictive modeling to optimize resource allocation and logistics scheduling. During the COVID-19 pandemic, numerous regions employed artificial intelligence and digital platforms to manage medical supplies and personnel, effectively alleviating shortages and enhancing coordination efficiency(Lv et al., 2021; Van Der Schaar et al., 2021). Compared with ground transportation, unmanned aerial vehicles (UAVs) reduced emergency medical delivery times by several minutes(Claesson et al., 2017)(UAVs shortened AED delivery by 2–8 minutes, and up to **7** minutes with optimized routing) (Roberts et al., 2023). However, achieving such benefits requires more than algorithmic sophistication. Institutional readiness—including regulatory flexibility and financial support—and robust

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data-sharing agreements play equally critical roles in determining whether automated dispatching can operate at scale. The strength of intelligent dispatching therefore lies in the synergistic interplay between technological capability and institutional collaboration, ensuring that automation functions within trustworthy, coordinated and well-regulated emergency management systems.

5 Typical Application Scenarios

Emergency response automation technology has been systematically applied in various fields, including natural disasters(Sun et al., 2020), industrial disasters(Aziz et al., 2014), public health(Murthy et al., 2017), social security and public safety emergency response automation(Chowdhury et al., 2023), and military combat and security emergency response automation(Sciences et al., 2017). Despite the diversity of application scenarios, the core logic of these systems all adhere to a closed-loop framework of "monitoring-assessment-decision-response"(Casartelli et al., 2025; Cook and Dorussen, 2021; Stoto et al., 2018).

This section summarizes the representative emergency response systems and platforms that frequently appear in the literature, clarifying their core functions, key technologies, application contexts, and strength of supporting evidence. The selection criteria for these systems include:

(1) recurrent appearance across multiple peer-reviewed studies;

(2) coverage of diverse technological pathways;

(3) demonstration of typical trade-offs among perception, decision-making, execution, and learning capabilities.

5.1 Cross-System Comparative Analysis

To ensure transparent cross-system comparison, each representative system was mapped to six

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commonly cited ERA capability dimensions:

(1) multi-source sensing and monitoring,

(2) decision support and automation,

(3) execution and deployment,

(4) interoperability and data sharing,

(5) robustness and fault tolerance,

(6) adaptive learning.

Each system's performance was semi-quantitatively rated as strong (S), medium (M), or weak (W) under an evidence-grading scheme emphasizing reproducibility and rigor. Ratings considered field or multi-site validation, comparative or pre–post analyses, sample size and reporting completeness, and the availability of quantitative indicators e.g., detection latency, false-alarm rate, task-success ratio. Studies with incomplete metrics or potential bias—such as missing control comparisons or unclear validation—were recorded and downgraded accordingly. Systems supported only by conceptual models or small pilots were rated lower. Table 2 presents the resulting capability matrix, interpreted with supporting evidence in Table 3.

From these evaluations, several convergent and divergent patterns emerge:

Common Features:

(1) Layered architecture: Most systems follow a perception → analysis → decision → execution sequence, validating the four-layer ERA framework.

(2) Sensing priority: Investment concentrates on early detection (sensor networks, remote sensing, video analytics) to ensure rapid situational awareness.

(3) Human-in-the-loop: While automated rules exist, critical decisions generally retain human oversight.

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(4) Limited adaptability: Few operational systems enable real-time learning; most remain in prototype stages.

(5) Interoperability gaps: Persistent data silos continue to hinder coordination and efficiency.

Based on these evaluations, several convergent patterns and distinct divergences can be identified:

Distinctive Features:

(1) Execution intensity: Logistics systems emphasize automated execution, whereas monitoring systems primarily support human decisions.

(2) Robustness requirements: Natural hazard systems must handle sensor noise and false alarms, while industrial systems rely on deterministic logic to reduce false positives.

(3) Evidence maturity: Some systems, such as medical UAV platforms, have field validation, whereas others remain in prototype or simulation stages.

(4) Privacy and ethics: Urban surveillance systems face privacy and public acceptance challenges absent in closed industrial settings.

Overall, the ERA framework demonstrates broad applicability, but system designs must balance trade-offs among sensing accuracy, automation, interoperability, and socio-legal constraints. Future research should advance ERA systems from conceptual models to reliable, interoperable, and operational solutions.

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Table 2. Representative systems.

Notes: [a]Evidence strength (H/M/L) follows the R&R rubric (see Methods): High = 8–10; Moderate = 5–7; Low = 0–4; NR = 0. If D2 = 0 ⇒ band ⩽ Moderate; if ⩾ 2 domains = 0 ⇒ band = Low.

System	Core function	Key technologies	Typical deployment / scenario	Reported effect / evidence	Evidence strength	Limitations / failure modes
ShakeAlert(Given et al., 2018)	Rapid earthquake detection and early warning	Dense seismic networks, automated classifiers (ML), alert distribution	Regional seismic early-warning (USA)	Seconds-to-minutes warnings; documented false-alarm incidents emphasize fault tolerance needs	Operational + case reports (medium)	False/late alerts in complex events; gaps where station density is low.
FPERS (flood platform) (Hamidi et al., 2023; Trepekli et al., 2022)	Real-time flood visualization & warning for resource allocation	Remote sensing, CCTV, GIS, threshold-trigger alarms	Riverine/urban flood forecasting and response	Visualized flood propagation to aid resource dispatch; operational case examples	Case studies (medium)	Misses flash/compound floods; sensitive to sensor gaps; weak multi-agency integration.
ERP-AS / EAL-based systems(Chen et al., 2018; Voytyuk et al., 2021)	Automated emergency classification and graded response for industrial/nuclear sites	Rule-based logic, dynamic thresholds, decision rules	Chemical plants, nuclear power plants	Faster and more consistent emergency classification; reported response-time improvements	Case/operational reports (medium-high)	Rules miss novel scenarios; strong dependence on accurate sensors and operator compliance.
Urban Domain Awareness Systems (e.g., NYPD DAS)(Levine et al., 2017)	City-scale situational awareness for public safety	Large-scale video analytics, data fusion, dashboards	Urban policing, large public events	Improved detection/monitoring capacity reported by implementing agencies	Agency reports / case descriptions (medium)	Relies on dense data/connectivity; privacy and governance constraints; risk of biased alerts.

UIoT fire monitoring(Bisquert et al., 2012; Chen et al., 2024; Ramadan et al., 2024; Zhou et al., 2023)	Fire source localization and spread tracking	UAVs, thermal imaging, IoT sensors, CV algorithms	Wildfire/structural fire monitoring	Real-time localization; performance degrades in smoky/occluded conditions	Prototype / pilot deployments (low-medium)	Detection degrades in smoke/occlusion; vulnerable to power/network loss; limited large-scale trials.
Healthcare Automation & Telemedicine System (COVID-19)(Li et al., 2021; Rathore et al., 2016; Shen et al., 2021)	Dynamic allocation of medical resources and AI-assisted remote diagnosis during pandemics	AI decision support, IoT networks, telemedicine platforms, data integration	Public health emergency / epidemic response	Automated staff scheduling, bed allocation, tele-consultation; improved triage efficiency reported during COVID-19	supported by multiple case studies and operational data from pandemic deployments(medium–high)	Heavy reliance on hospital IT; data quality and bias issues; uneven staff adoption.
Smart City Emergency Response Platforms (e.g., Singapore ITS)(Martinez et al., 2010; Telang et al., 2021)	Integrated urban traffic management and incident response	IoT sensors, AI analytics, traffic control systems, real-time data fusion	Urban safety / transportation / large-event management	Automated signal control and emergency-lane optimization; enhanced urban response coordination	validated through municipal implementation reports and performance summaries (medium)	Complex integration; core failures can cascade; legacy-system interoperability remains patchy.
Drone medical logistics (Homier et al.)(Homier et al., 2021)	Urgent medical delivery in mass-casualty / disrupted-access scenarios	UAV logistics, routing/dispatch algorithms, regulatory integration	Urban & disaster logistics	Empirical trial: median delivery 17 min vs 29 min by ground (41% faster)	Field trial / empirical (high)	Weather/airspace limits; small payload and endurance; needs tight EMS workflow integration.

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Table 3. System × Capability Matrix.

Notes: [a] Capability ratings are interpreted alongside the evidence band (R&R) to avoid overstating capabilities supported by weak evidence.

System / Capability	ShakeAlert	FPERS	ERP-AS / EAL	Urban DAS	UIoT (fire)	Healthcare Automation & Telemedicine System	Smart City Platform	Drone medical
Perception	Strong (seismic network + ML)	Strong (satellite + CCTV + sensors)	Medium	Strong (video + sensors)	Medium (thermal + optical + IoT)	Strong (health data + IoT)	Strong (IoT + traffic sensors)	Weak (logistics-focused)
Decision support	Medium (alert triggers)	Medium (threshold-based advisories)	Strong (EAL logic)	Medium (analyst-in-the-loop)	Medium (local fire tracking)	Strong (AI-driven triage & scheduling)	Strong (adaptive routing & AI optimization)	Medium (dispatch algorithm)
Execution and deployment	Weak	Medium	Medium	Medium	Medium	Strong	Strong	Strong
Interoperability / data sharing	Weak (islanded networks)	Medium	Low–Medium	Medium	Low	Medium–High	High	Medium
Robustness / fault tolerance	Weak (documented false alarms)	Medium	Medium	Medium	Low (sensor vulnerability)	Medium–High	High	Medium
Continuous learning / adaptation	Low	Low	Low	Low	Low	Medium	Medium – High	Low–Medium

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Building upon the preceding system-level and capability-level analyses, we now focus on the shared technological foundations that enable efficient ERA. Table 4 provides a cross-domain synthesis of the key enabling technologies. These technologies are widely deployed across different operational contexts and collectively support perception, decision-making, coordination, and adaptive control under conditions of uncertainty.

This integrative perspective aligns with the principles of the U.S. National Incident Management System (NIMS) and the Incident Command System (ICS), both of which emphasize interoperability, unified command, and flexible coordination. Similarly, a cross-domain ERA architecture emphasizes technological convergence over fragmentation, advocating a transition from domain-specific automation toward a systemic, learning-oriented, and trust-enhancing framework for intelligent emergency management.

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Table 4. Cross-domain Technology Matrix for ERA.

Technology	Environmental & Natural Hazards	Industrial & Infrastructure Emergencies	Public Health & Social Safety	Cross-domain Insights
Remote Sensing (Satellite, UAV, LiDAR)	Provides large-scale monitoring, terrain mapping, and damage assessment for floods, earthquakes, and wildfires.	Detects gas leaks, fires, and structural anomalies in critical facilities.	Supports environmental surveillance, crowd monitoring, and mobility management during crises.	Advantage: Enhances situational awareness and early impact assessment. Limitation: Limited accuracy in indoor/underground settings and affected by data latency.
IoT and Sensor Networks	Collects distributed data (temperature, vibration, water levels) to support real-time disaster detection.	Enables continuous monitoring of chemical concentrations, pressure, and equipment health.	Tracks medical supplies, patient status, and logistics for dynamic resource allocation.	Advantage: Provides fine-grained, real-time data connectivity. Limitation: Vulnerable to communication failure and interoperability issues.
Big Data & Cloud/Fog Computing	Supports predictive modeling and dynamic warning through multi-source data fusion.	Facilitates anomaly detection, failure prediction, and decision optimization.	Enables epidemic trend analysis and healthcare resource coordination.	Advantage: Integrates heterogeneous data for rapid decision-making. Limitation: Privacy, latency, and standardization remain major challenges.
Explainable Artificial Intelligence (XAI)	Improves interpretability of hazard forecasting and decision support models.	Assists in fault diagnosis, process optimization, and incident prediction.	Enhances transparency of automated triage and public health diagnostics.	Advantage: Builds user trust and facilitates human–AI collaboration. Limitation: Trade-off between interpretability and model performance.

Digital Twin Technology	Simulates disaster evolution and resource deployment for preparedness and recovery.	Mirrors industrial systems to predict failures and optimize maintenance.	Models hospital or urban systems for real-time health and mobility management.	Advantage: Enables virtual testing and proactive control. Limitation: Requires high-quality, continuous data and significant computational resources.
Next-generation Communication (5G/6G, Edge Computing)	Ensures low-latency data transmission for drone coordination and early warning dissemination.	Supports ultra-reliable communication for critical infrastructure operations.	Enables telemedicine, emergency alerts, and high-volume health data transfer.	Advantage: Provides reliable, real-time connectivity under extreme conditions. Limitation: High deployment cost and uneven global coverage.

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5.2 Summary

This section maps representative ERA systems onto a clearly defined capability matrix and integrates cross-system evidence. This approach reveals both the generic capability dimensions of ERA and the system-specific trade-offs involving robustness, interoperability, and operational autonomy. In doing so, it establishes an empirical bridge between conceptual frameworks and operational realities.

The innovation of this approach lies in two aspects:

(1) establishing a transparent evidence mapping from concrete systems to framework components;

(2) deriving cross-domain, non-siloed research priorities based on this mapping to guide future ERA development.

6 Discussion

Despite significant advances in automation and intelligence, contemporary ERA systems face persistent implementation bottlenecks rooted in technological, organizational, and societal factors. Based on evidence extracted from the literature, this section synthesizes major challenges, articulates implications for Safety Science practice, and proposes actionable, verifiable research directions to bridge current gaps.

6.1 Analysis of system limitations and challenges

Current ERA systems exhibit four primary limitations: data quality, system compatibility, privacy/security, and cost-effectiveness. We elucidate these issues with supporting literature.

ERA face dual challenges of accuracy and completeness at the data level. Errors, missing data,

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or delays in real-time data can directly lead to decision-making biases, while communication disruptions caused by damaged infrastructure in disaster-affected areas further exacerbate this issue(Cao et al., 2023; Rak et al., 2021). For example, in the 2018 Indonesian earthquake, severe damage to power and communication facilities caused the ERA to collapse, and technologies such as drones were unable to fully replace traditional methods due to limitations such as weather and battery life(Yulianto et al., 2020).

System compatibility and cross-domain coordination are another major challenge. Differences in technical standards and data formats across departments, regions, and even countries create information silos, and cross-border rescue operations also face regulatory conflicts(Suggett, 2012). In the 2015 Nepal earthquake, inconsistent system standards among countries made resource integration difficult(Rai et al., 2021), and the 2021 Ar River Valley flood incident also faced issues of ineffective communication between emergency response systems(Müller et al., 2023). The European GDPR imposes compliance constraints on cross-border data transmission(Voss, 2019).

Privacy security and social trust crises are increasingly prominent. The system's reliance on personal data may lead to leakage risks (Velev and Zlateva, 2023). On December 23, 2015, a coordinated cyberattack on Ukraine’s distribution utilities caused power outages affecting hundreds of thousands of customers(Sullivan and Kamensky, 2017). Personal information leakage incidents in multiple countries during the pandemic have exacerbated public concerns(Chan and Saqib, 2021; Wang et al., 2024). When using drones for rescue missions, network security issues must be considered (Papyan et al., 2024; Sindiramutty et al., 2024). Data confidentiality(Sciancalepore, 2024). Additionally, AI algorithm bias and decision-making opacity further erode trust, while insufficient technical capabilities among frontline personnel also constrain system effectiveness(Gevaert et al., 2021). Accordingly, we need corresponding methods to protect personal

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information, sensitive information, and other data(Seba et al., 2019).

Costs and talent shortages pose practical constraints. The procurement of hardware, software development, and ongoing maintenance require substantial funds, which may pose financial pressures for small and medium-sized enterprises or regions and departments with poorer economic conditions. Peer-reviewed assessments indicate that operating a West Coast EEW system such as ShakeAlert requires sustained annual O&M funding, and cost–benefit analyses show that avoided losses from even a single moderate earthquake can offset about a year of operations(Strauss and Allen, 2016) (Given et al., 2018), and developing countries in particular face a shortage of high-end technical talent.

These controversies fundamentally reflect the deep-seated contradiction between “technological availability” and “system reliability,” necessitating the establishment of an interdisciplinary research framework.

6.2 Implications for Safety Science practice

6.2.1Reliability engineering implications

ERA should be designed and evaluated against reliability metrics—availability/MTBF, fault tolerance, and time-critical performance. Tools such as FMEA and fault/causal graphs can localize failure propagation and support uncertainty-aware thresholds. Where the literature reports operational or multi-site evaluations, we recommend reporting FAR, missed detections, latency, and recovery time relative to baseline systems to enable evidence grading(Xu et al., 2012).

6.2.2Human factors and adoption

Human-in-the-loop (HITL) controls and explainable AI (XAI) should target workload, situation

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awareness, and calibrated trust. Training and rehearsal can reduce misuse/disuse, especially under degraded communications. We recommend tracking workload/trust alongside technical metrics, in line with our findings that explainable AI and human–machine collaboration are pivotal for trustworthy ERA(Hancock et al., 2011; Hoff and Bashir, 2015).

6.2.3Standards and interoperability

Cross-agency operations benefit from standards-aligned data models and interfaces consistent with incident-management practice(Elmhadhbi et al., 2020; Salvador et al., 2019). As a minimum viable interoperability set, we recommend (1) schema mappings and API/message profiles aligned with the roles and message types used in incident command, and (2) event-logging conventions for traceability across agencies and operational periods—directly addressing the interoperability gaps highlighted in 6.1 and reflecting the NIMS/ICS emphasis on unified coordination.

6.3 Next-generation ERA model framework

Building on the proposed four-layer ERA architecture, this study presents a next-generation integrated model that enables end-to-end collaboration and adaptive evolution across heterogeneous systems. Fig.8 illustrates this model, which extends conventional multilayer structures and provides a forward-looking framework for ERA development in complex, data-intensive environments.

At its core, the model introduces three interrelated pillars, serving both as technological enablers and methodological foundations:

(1) Digital Twin Middleware Platform (DTMP): Synchronizes virtual and physical systems to enable real-time simulation, validation, and adaptive optimization.

(2) AI–Expert Hybrid Decision Engine (AI-E): Integrates machine intelligence with expert

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reasoning to generate interpretable and trustworthy decisions.

(3) Intelligent IoT Edge Network (I-IEN): Combines 6G communications, blockchain-based data integrity assurance, and edge computing to ensure resilient connectivity and secure, low-latency information flow.

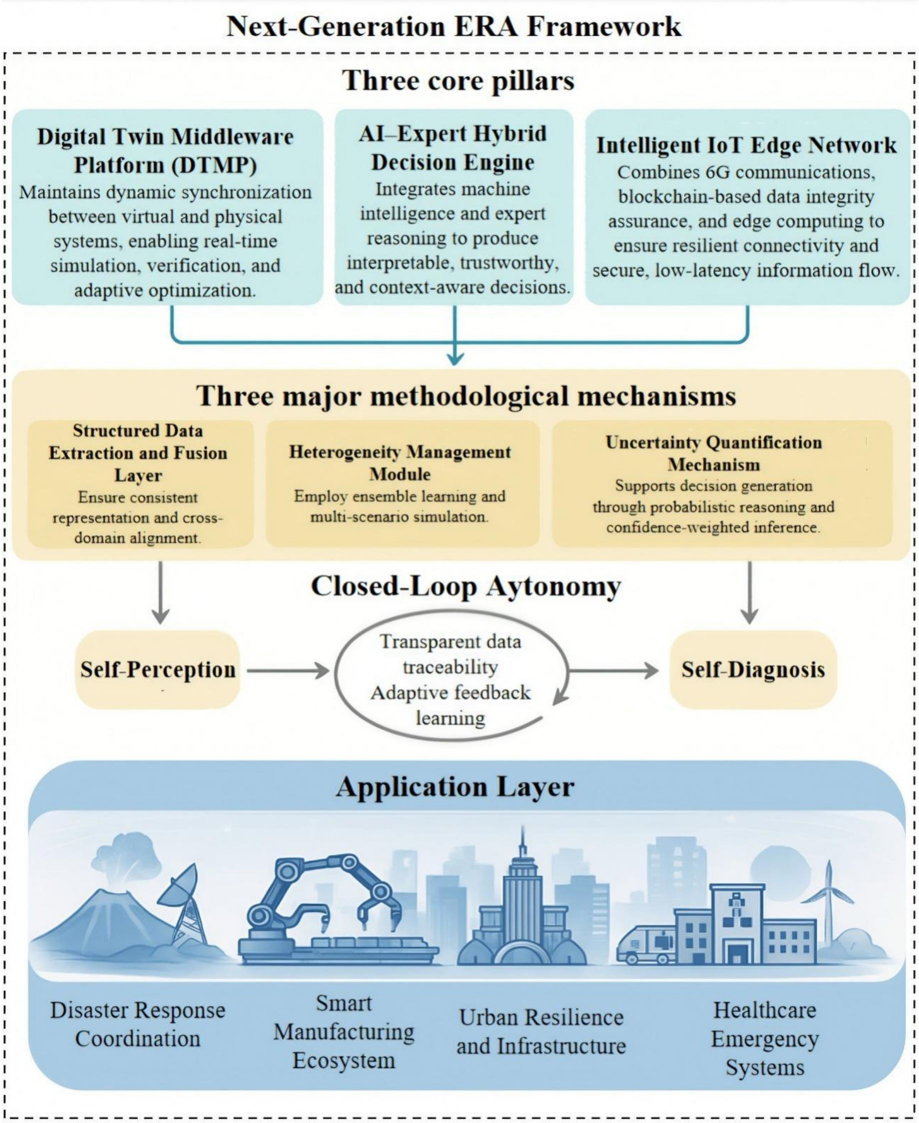

Fig.8 Key Interaction Flow of ERA System.

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Unlike conventional ERA systems that follow rigid workflows, this model emphasizes closed-loop autonomy—including self-perception, self-diagnosis, and self-deployment—supported by transparent data traceability and adaptive learning. This marks ERA's evolution from a toolset to an intelligent, self-organizing system.

Each pillar defines quantifiable research dimensions: DTMP enables assessment of predictive accuracy and latency reduction; AI-E allows evaluation of decision interpretability and human–machine trust; I-IEN facilitates measurement of communication resilience and coordination efficiency. These metrics provide a foundation for cross-domain empirical validation and address long-standing methodological gaps such as non-standardized evaluation and limited reproducibility.

To ensure comparability, the framework integrates three methodological mechanisms: structured data fusion, heterogeneity management through ensemble learning, and uncertainty quantification via probabilistic reasoning. Together, these mechanisms enhance robustness and transparency, advancing ERA toward an evidence-driven, adaptive system capable of learning, coordination, and evolution under uncertainty.

6.4 Theoretical positioning

To deepen the theoretical foundations of the next-generation ERA architecture, a comparative analysis was conducted with three representative theoretical models in the emergency response domain: the OODA loop(Brehmer, n.d.; Sullivan and Kamensky, 2017; Von Lubitz et al., 2008), the State Emergency Management System (SEMS) based on the Incident Command System (ICS) (Kano et al., 2007), and Resilience Engineering(Park et al., 2013). These models represent, respectively, iterative cognition, hierarchical coordination, and adaptive recovery perspectives that have shaped modern emergency management paradigms.

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Structurally, the ERA framework can be mapped onto these theories (Table 5). Its "perception–decision–communication–response" cycle parallels the OODA loop, while its communication and response layers support the collaborative and modular characteristics of SEMS. From a resilience perspective, ERA's functional chain of "identification–regulation–reconstruction–optimization" embodies the adaptive learning principles of Resilience Engineering. However, the significance of this alignment lies not in structural similarity, but in its transformation of the underlying cognitive and organizational logic—transitioning from human-coordinated systems to intelligent autonomous systems.

ERA extends these classical models in three key dimensions.

First, it generalizes the OODA loop through multimodal sensing and explainable AI, enabling autonomous perception and decision cycles that surpass human speed and situational coverage.

Second, it advances beyond SEMS's procedural rigidity by employing data-driven scheduling and blockchain-assisted coordination, thereby enhancing elasticity in heterogeneous, multi-agency operations.

Third, it evolves Resilience Engineering toward a proactive paradigm: by coupling digital twins and edge intelligence, the system can predict, simulate, and optimize response strategies in real time.

Yet, the theoretical strengths of ERA are context-dependent. In real-world environments, technical and environmental constraints may limit its advantages. The 2011 Fukushima nuclear accident illustrates this boundary: although multiple automated systems were deployed, high radiation and signal interference caused severe communication failures and delayed robotic operations. This underscores that automation alone cannot guarantee resilience unless systems incorporate environmentally adaptive redundancy, fault tolerance, and recovery coordination among agents. In other words, the theoretical superiority of ERA requires robust implementation

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mechanisms to withstand anomalous disturbances.

Therefore, the ERA framework should be viewed not as a replacement for human-centered models but as an evolutionary complement—enhancing decision efficiency and resilience through integration rather than substitution. Future theoretical exploration should focus on validating under which conditions ERA's advantages emerge, by linking architectural performance indicators with empirical data from real or simulated disaster scenarios. Such a comparative, evidence-based approach will substantiate the theoretical claims and delineate their operational boundaries.

Table 5. Advantages of ERA in case simulations.

Model	Key features	Performance in this case	ERA System Corresponding Capabilities
OODA Loop	Linear cycle: Observe → Orient → Decide → Act	The command center initiated a response based on sensor data, but communication disruptions and conflicting inputs caused several minutes of delay, hindering full situational coverage.	ERA integrates multi-source perception and AI-driven decision-making, automating the "Orient" and "Decide" functions and enabling rapid contingency simulations within seconds to enhance response speed and coverage.
SEMS	Emphasize organizational structure and division of responsibilities (ICS framework)	Inconsistent information channels and uncoordinated operations among firefighting, medical, and transportation agencies result in fragmented responses.	ERA employs a 6G–blockchain communication layer as a task-scheduling platform to enable cross-organizational coordination, consensus, and resource sharing, replacing static processes.
Resilience Engineering	Focus on system fault tolerance, recovery, and learning mechanisms.	During early disaster stages, localized system failures at transport and medical hubs create communication blind spots, delaying manual instructions and feedback.	The ERA system employs a self-feedback redeployment mechanism: when a robot fails and returns, the AI dynamically reschedules and reconstructs task paths based on real-time information, showcasing self-healing and adaptive learning.

6.5 Future trends

The future evolution of ERA is expected to advance along five interdependent technological trajectories: intelligent sensing, autonomous and explainable decision-making, resilient

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communication, digital-twin-based simulation, and intelligent multi-agent collaboration. Collectively, these pathways aim to overcome persistent limitations in data fragmentation, communication disruption, decision uncertainty, and coordination inefficiency. Nevertheless, progress in these domains must move beyond conceptual frameworks toward quantifiable, evidence-supported, and cross-domain validated technological advancements.

(1) Intelligent Sensing

Next-generation sensing systems will adopt multi-source, heterogeneous, and adaptive architectures, integrating MEMS, microwave, optical, and gas sensors for real-time detection of diverse hazards such as fires, toxic releases, and structural deformations (Donta et al., 2023; Nanda et al., 2023; Ortiz-Garcés et al., 2023). The convergence of user-edge computing (UEC) allows priority processing of critical data (e.g., UAV-acquired disaster imagery) in constrained environments(Sun et al., 2025), while blockchain integration enhances secure data storage and interagency information sharing (Habib et al., 2024; Treiblmaier and Rejeb, 2023). This fusion has the potential to mitigate data silos and transmission latency(Zhang et al., 2025). However, scalability remains a central technical bottleneck for large-scale blockchain implementation(Chamola et al., 2020; Satheesh et al., 2025). Future empirical work should report measurable indicators—detection latency, accuracy, and false alarm rate—to verify practical effectiveness under both simulated and field conditions.

(2) Autonomous and Explainable Decision-Making

AI-driven decision frameworks will increasingly emphasize adaptability, interpretability, and multimodal data fusion(Hsiao et al., 2025; Wibowo et al., 2025). The integration of Dempster–Shafer Theory (DST) with AI models enables conflict resolution under uncertainty(Fei et al., 2024), while generative AI tools (e.g., ChatGPT-type models) may support rapid scenario

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modeling and knowledge extraction under time or resource constraints(Maceika et al., 2024). Moreover, multimodal neural networks combining natural language processing and computer vision can leverage unstructured data from social media and sensor feeds to enhance situational awareness (Su et al., 2021). Yet, the real-world performance of these systems remains insufficiently validated. Future studies should systematically quantify gains in decision accuracy, processing efficiency, and operator trust relative to rule-based and expert systems, and explicitly incorporate explainability metrics and human–machine collaboration performance into evaluation protocols to strengthen operational reliability.

(3) Resilient Communication and Network Intelligence

Current 5G systems face inherent constraints in latency, energy consumption, and coverage. Emerging 6G architectures—integrating quantum communication, terahertz transmission, and low-Earth-orbit (LEO) satellite constellations—are poised to deliver seamless and resilient connectivity for emergency operations(Aldrees et al., 2025; Liu et al., 2025; Uusitalo et al., 2021). Meanwhile, the combination of software-defined networking (SDN) and UAV relay networks can dynamically reconstruct disrupted communication infrastructures, ensuring network continuity in disaster zones(Abir et al., 2023). These paradigms demand rigorous empirical verification, particularly under realistic operational loads, to quantify metrics such as end-to-end latency, packet loss, and network resilience. The convergence of AI and 6G technologies will ultimately enable a closed-loop emergency management ecosystem, integrating pre-disaster forecasting, real-time response, and post-disaster recovery (Ariyachandra and Wedawatta, 2023; Zio and Miqueles, 2024).

(4) Digital Twins and Simulation-Driven Decision-Making

Digital-twin-based platforms offer a dynamic, data-driven representation of disaster systems, facilitating predictive analytics and operational optimization(Ghaffarian, 2025). While their applications in industrial and construction safety are promising(Ariyachandra and Wedawatta, 2023), challenges persist regarding uncertainty quantification, cybersecurity, and standardization of modeling frameworks. Coupling digital twins with edge and distributed computing may further support low-latency, scalable strategy adaptation during real-time operations(Zio and Miqueles, 2024). Future research should focus on quantifying performance improvements, including reductions in decision latency, enhancements in resource allocation efficiency, and gains in predictive accuracy, while ensuring transparency in model validation and uncertainty assessment.

(5) Intelligent Multi-Agent Collaboration

Next-generation ERA operations will increasingly depend on collaborative intelligent entities—such as UAVs, ground robots, and AI-assisted agent swarms(Moosavi et al., 2024). Robotic systems already demonstrate strong performance in hazardous search-and-rescue and medical support missions(Pillai et al., 2024). Future architectures should integrate multi-agent coordination frameworks and human–machine collaboration models to optimize task allocation, minimize operational conflicts, and enhance system robustness(Daud et al., 2022; Mourtzis et al., 2024). Quantitative performance measures—such as task completion time, coverage efficiency, and safety indices—should become standardized evaluation criteria to enable cross-study comparability and cumulative evidence building.

7. Conclusion

These findings suggest that the central challenge for the coming decade is not only to make ERA more intelligent, but to make it systematically safer, more interoperable and more accountable. To this end, we argue that next-generation ERA should be explicitly guided by a set of design

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principles, among which privacy-by-design and fail-safe design must be treated as non-negotiable requirements rather than optional add-ons. Privacy-by-design calls for embedding data-protection and privacy safeguards into architectures, algorithms and workflows from the outset, using measures such as data minimisation, encryption, privacy-preserving analytics and transparent governance. Fail-safe (and, where necessary, fail-operational) design requires explicit hazard analysis, redundancy and graceful degradation, conservative automated actions under uncertainty and clear escalation paths to human control, verified through realistic stress-testing. Two additional, closely related principles emerge from the evidence base. Interoperability-by-design is essential to overcoming information silos: ERA should be built on common data models, open or well-documented interfaces and minimum interoperability profiles that allow heterogeneous systems and organisations to share information and coordinate actions during multi-hazard events. At the same time, human-centred and transparent automation is needed to ensure that ERA augments rather than replaces human expertise, by aligning automation levels and interfaces with human cognitive capacities and providing meaningful explanations of system recommendations. Taken together, these principles offer a concise roadmap for translating fragmented technological advances into reliable, trustworthy ERA systems for disaster risk reduction. Future research should therefore focus on co-designing architectures, metrics and governance mechanisms that embed privacy-by-design and fail-safe principles from the outset, while operationalising interoperability and human-centred automation in real multi-hazard environments.

Author contributions

Jian Liu conceived and designed the study, defined the research topic, developed the review framework, performed the literature search and screening, and conducted the data analysis. Qinlin

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Chu contributed to the literature search and screening, jointly wrote the manuscript, and prepared all figures. Rui Feng supervised the research, provided methodological guidance, contributed to the interpretation of the results, and critically revised the manuscript for important intellectual content. All authors read and approved the final version of the manuscript.

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Competing interests

The authors declare that they have no competing interests.

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