Response to Referee #2

Dear Editor and Referee,

We would like to express our sincere gratitude to the referee for the time and effort dedicated to evaluating our manuscript during the open discussion phase. The constructive feedback and insightful comments provided have been incredibly valuable in identifying areas for improvement and enhancing the overall quality of our work.

We have carefully considered each point raised by the referee and addressed them in detail. For ease of review, the referee's comments are shown in *red italics*, our point-by-point responses are shown in black font, and the revised manuscript excerpts are highlighted in blue font. Below, we provide our detailed responses and explicitly outline the specific revisions made to the manuscript.

1. Table 1: In my opinion this table can be turned into a paragraph with proper referencing, and short explanations of the articles mentioned here, their contributions, and what they lack. It is a review article after all, and instead of giving a list of articles in a table format, I would much prefer to read how the authors think they contribute to the overall framework (or do they?).

Response:

We thank the Referee for this suggestion. In response, Table 1 has been removed and replaced with a narrative discussion of previous review studies. The revised text highlights the scope and contribution of prior reviews and clarifies the research gaps addressed in the present study. All subsequent tables have been renumbered accordingly.

Specific revisions are listed below:

1 Introduction

...

A growing body of literature reviews specific facets of disaster management. Early work addressed communication and information-sharing mechanisms, including machine learning for social media-assisted disaster response (Dwarakanath et al., 2021) and general emergency management systems (Feng and Cui, 2021). Subsequent studies expanded toward broader technological infrastructures, examining the Internet of Emergency Services (Damaševičius et al., 2023), disaster-management analytical tools (Khan et al., 2023), and IoT integration in urban emergency systems (Saputra et al., 2025). More recent reviews have focused on intelligent and data-driven technologies, including digital twins for wildfire and post-disaster risk management (Li et al., 2024; Lagap and Ghaffarian, 2024), AI-based social media analytics (Abid et al., 2025), and UAV-enabled emergency logistics (Jazairy et al., 2025). Taken together, these reviews confirm the breadth of ERA-related research, yet several important gaps remain. Most focus on isolated technologies or single disaster domains without integrating perception, decision-making, execution, and adaptive feedback within a unified architectural framework (Bhanye, 2025; Frykmer et al., 2021). Few examine ERA through a safety-science lens, leaving systemic attributes such as graceful degradation, interoperability, and human-automation coordination largely unaddressed. Existing reviews also rarely connect technological evolution with broader sociotechnical concerns including governance, trust, and adaptive learning, which are precisely the mechanisms that sustain the information silos undermining multi-agency emergency coordination.

2. Instead of presenting the review questions in a semi-bullet format, which in fact reads much like a draft, again I would much prefer to read them within a proper paragraph. In their current form, they break the flow. Again, a review article should be a synthesis, and also one where the reader can concentrate on the information without structural breaks. While the current format the authors choose may work in a presentation, not so much as a section in a review article. It would be best if the authors re-structured and somewhat merged the section from lines 95-120. The scientific questions and the article's contributions and how this review will approach these issues can better be edited together into one or maximum two paragraphs. Especially the last part (the whole paragraph describing the article's sections) reads like a list and does not add any novel contribution to the subject being reviewed, but can be turned to a roadmap for the reader who may want to focus on a specific part of the review if better structured as a sentence or two.

Response:

We appreciate the Referee's comment. We agree that the original presentation could be improved in terms of narrative flow and organization in this section. The semi-bulleted format interrupted the continuity of the discussion and was less effective than a fully integrated narrative presentation for a review article.

In response, we have substantially revised and reorganized this part of the Introduction (Section 1). The specific improvements are outlined below:

1. Integration of Research Questions: We have removed the presentation-style, semi-bulleted research questions and incorporated them into the end of Paragraph 1 as part of a coherent narrative introducing the central scientific questions of the review.

2. Consolidation and Streamlining of Structure (Lines 95–120): We have merged and streamlined the previously fragmented narratives regarding our research contributions, the PRISMA methodology, and the article structure. The lengthy, list-style description of subsequent sections has been reshaped into a more compact and logically coherent overview that provides a clearer roadmap for readers.

These revisions have improved the coherence, readability, and overall narrative flow of the introduction. We also recognized that this concern extended beyond the specific section identified by the Referee. Accordingly, we revisited the manuscript more broadly and revised other sections where similar issues of narrative flow, structural fragmentation, or presentation style were present.

Specific revisions are listed below:

1 Introduction

In recent decades, disasters have become increasingly frequent and complex, spanning climate hazards, industrial accidents, and public health crises (Yu et al., 2018). While the 1982 Edmonton well blowout in

Canada was swiftly controlled through prompt ignition (Gephart, 1988), the 2003 Kaixian gas-well blowout in Chongqing resulted in over 190 fatalities due to delayed containment (Jianfeng et al., 2009). These contrasting cases underscore that the core value of emergency management lies in timely response and scientifically grounded decision-making. Yet despite unprecedented advances in sensing and communication technologies, real-world emergency operations remain constrained by fragmented data streams, incompatible platforms, and organizational information silos. This tension raises a question that runs through the present review: why do information silos persist in an era of advanced technology, and how can emergency systems be designed to overcome them?

Driven by the maturation of automation, Artificial Intelligence (AI), cloud-edge computing, and digital twins, Emergency Response Automation (ERA) has emerged as a framework for bridging intelligent technologies with operational reliability (Kyrkou et al., 2022). 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 practical value has been increasingly demonstrated across diverse emergency contexts, including automated resource scheduling following the Fukushima nuclear disaster (Nagatani et al., 2013), proactive containment tracking during the COVID-19 pandemic (Andrejevic and O'Neill, 2024), and enhanced response coordination in nuclear power facilities (Chen et al., 2018). The shift toward data-driven autonomous systems, however, introduces persistent sociotechnical challenges. Reliability vulnerabilities, limited algorithmic interpretability, and fragile human-machine coordination under time pressure are among the most consequential. From a reliability engineering perspective, intelligent systems must not merely automate isolated tasks but augment human judgment, ensure fault tolerance, and maintain operational dependability when communication infrastructure degrades.

A growing body of literature reviews specific facets of disaster management. Early work addressed communication and information-sharing mechanisms, including machine learning for social media-assisted disaster response (Dwarakanath et al., 2021) and general emergency management systems (Feng and Cui, 2021). Subsequent studies expanded toward broader technological infrastructures, examining the Internet of Emergency Services (Damaševičius et al., 2023), disaster-management analytical tools (Khan et al., 2023), and IoT integration in urban emergency systems (Saputra et al., 2025). More recent reviews have focused on intelligent and data-driven technologies, including digital twins for wildfire and post-disaster risk management (Li et al., 2024; Lagap and Ghaffarian, 2024), AI-based social media analytics (Abid et al., 2025), and UAV-enabled emergency logistics (Jazairy et al., 2025). Taken together, these reviews confirm the breadth of ERA-related research, yet several important gaps remain. Most focus on isolated technologies or single disaster domains without integrating perception, decision-making, execution, and adaptive feedback within a unified architectural framework (Bhanye, 2025; Frykmer et al., 2021). Few examine ERA through a safety-science lens, leaving systemic attributes such as graceful degradation, interoperability, and human-automation coordination largely unaddressed. Existing reviews also rarely connect technological evolution with broader sociotechnical concerns including governance, trust, and adaptive learning, which are precisely the mechanisms that sustain the information silos undermining multi-agency emergency coordination.

To address these gaps, this review synthesizes 193 peer-reviewed studies on ERA, conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Enu et al., 2023; Page et al., 2021a), from the perspective of safety science and reliability engineering. We propose a four-layer architectural framework covering perception and monitoring, data and decision-making, automated response and control, and feedback and learning. This framework serves to integrate heterogeneous findings, trace the evolution of ERA across technological generations, and expose the interoperability bottlenecks that sustain information silos. Figure 1 presents the functional structure and evolutionary logic of the framework, providing a conceptual anchor for the synthesis that follows. Accordingly, Sections 2 and 3 establish the methodological foundations and structural definitions of ERA, before Sections 4 and 5 systematically evaluate the capabilities and real-world scenarios across the four architectural layers. Finally, Sections 6 and 7 contextualize these findings through a cross-cutting analysis of systemic limitations, institutional governance, and proactive future research directions.

3. Per my comment above, you may alternately consider making better use of the figure captions. "System framework diagram" on its own makes no sense, and for the readers who consider the figures first and the writing next, it needs better explanation of more how this figure contributes to the review rather than what they are looking at. The authors may consider working on the caption of this figure along with the previous paragraphs to provide unity and continuity, but most importantly, context.

Response:

We thank the Referee for this valuable suggestion. We agree that figure captions in a comprehensive review should be sufficiently informative and self-contained, helping readers understand not only the visual elements of a figure but also its relevance to the overall narrative and structure of the paper.

To address this concern, we have substantially revised the caption of Figure 1. Rather than merely describing the graphical components, the revised caption now explains how the four quadrants correspond to the major technological domains discussed in Sections 3–5 and how the concentric rings represent the evolutionary progression of emergency response automation systems across different development stages. In addition, the caption explicitly links the figure to the organizational structure of the review, enabling it to serve as a conceptual roadmap that guides readers through the subsequent sections. We believe that this revision improves the figure's interpretability and strengthens its integration with the overall synthesis presented in the manuscript.

Specific revisions are listed below:

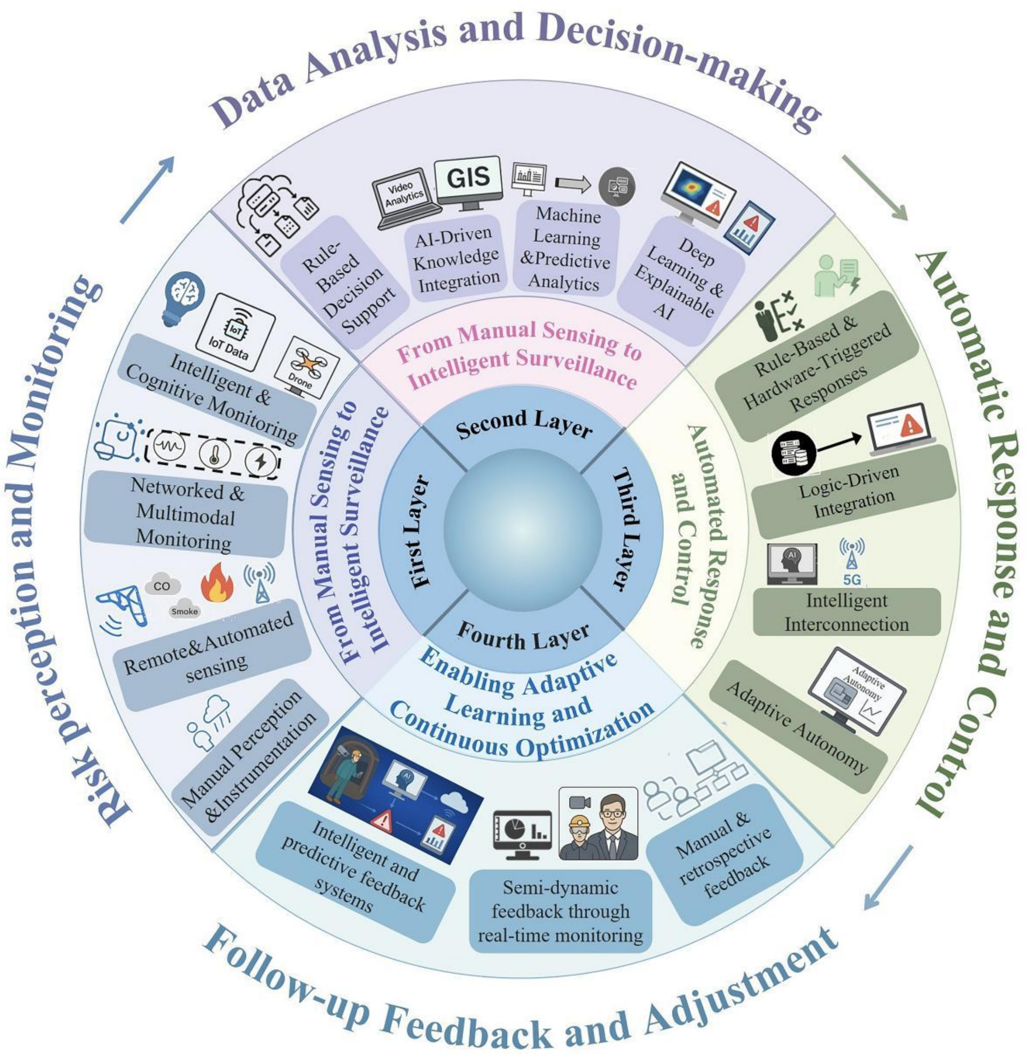

Figure 1 The four-layer architectural framework of Emergency Response Automation (ERA), serving as the organizational backbone of this review. The four quadrants represent the core functional layers examined across Sections 3–5: Risk Perception and Monitoring, Data Analysis and Decision-making, Automated Response and Control, and Follow-up Feedback and Adjustment. The concentric rings trace the technological evolution within each layer, from early manual and rule-based methods toward AI-driven and

autonomous paradigms, reflecting the developmental trajectory synthesized from 193 peer-reviewed studies. Interpreting this figure alongside the Introduction provides the conceptual map through which the cross-domain evidence in this review is structured and interpreted.

4. Because of the points raised in the previous paragraphs, the introductory sentence to Methodology section is repetitive.

Response:

We sincerely appreciate the Referee's keen eye for structural precision and textual detail throughout our manuscript.

The Referee is entirely correct. Upon re-examining the original text, we agreed that the introductory sentence of Section 2 redundantly restated the definition and scope of ERA that had already been established in the Introduction. This repetition caused unnecessary redundancy and slowed down the transition into the methodology. To address this issue, we have removed this repetitive introductory sentence in the revised manuscript, allowing Section 2 to open directly and concisely with the core methodological details.

5. My suggestion is to move Figures 2 and 3 to Appendix or Supplementary. Again, a review article's most important aspect is the "review" or the synthesis or the subject. The statistics are often secondary unless they contribute majorly to the subject being reviewed (for example, if the aim is to show the lack of literature on a certain subject to encourage researchers to consider this gap, literature statistics are important. And if this is the case with ERA, then the authors should mention it. If not, these figures don't do much for the main article).

Response:

We thank the Referee for this helpful suggestion. We agree that figures included in the main text should make a clear contribution to the objectives and synthesis of the review.

In response, the temporal-distribution figure (formerly Figure 2) has been moved from the main text to Appendix B, where it is now presented as Figure B1. The main text has been revised accordingly to briefly note that the rapid growth of ERA-related studies underscores the need for a comprehensive synthesis of the field.

For the PRISMA literature-screening flow diagram (formerly Figure 3 and now Figure 2), we respectfully chose to retain the figure in the methodology section. Because this review follows the PRISMA 2020 framework, we believe that retaining the screening flow diagram improves transparency and enables readers to readily understand the literature identification, screening, and selection process. We therefore consider its inclusion in the main text beneficial to the methodological clarity, transparency, and reproducibility of the review.

The numbering of the remaining figures and corresponding cross-references has been updated throughout the revised manuscript.

Specific revisions are listed below:

2 Methodology

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Following the PRISMA guidelines (Page et al., 2021a), we conducted a comprehensive search for 2010–2025 (last search across all sources: 7 Mar 2026). Among the studies included in this review, 43 were published between 2010 and 2015, 64 between 2016 and 2020, and 86 between 2021 and 2025, indicating a clear and accelerating growth in ERA-related research over the past decade. A small number of earlier references were retained to provide historical context. This rapid growth in ERA-related publications underscores the urgency of a systematic synthesis: the field is expanding faster than integrative frameworks can consolidate its findings. The full temporal distribution is presented in Appendix B.

Appendix B: Temporal Distribution of ERA-Related Publications

Figure B1 presents the temporal distribution of the 193 peer-reviewed studies systematically included in this review, grouped into three periods: 2010–2015 (n = 43), 2016–2020 (n = 64), and 2021–2025 (n = 86). Several pre-2010 references were retained only to provide historical and conceptual background and were not counted as part of the PRISMA-based systematic corpus. The distribution indicates a clear and accelerating growth in ERA-related research, particularly after 2020.

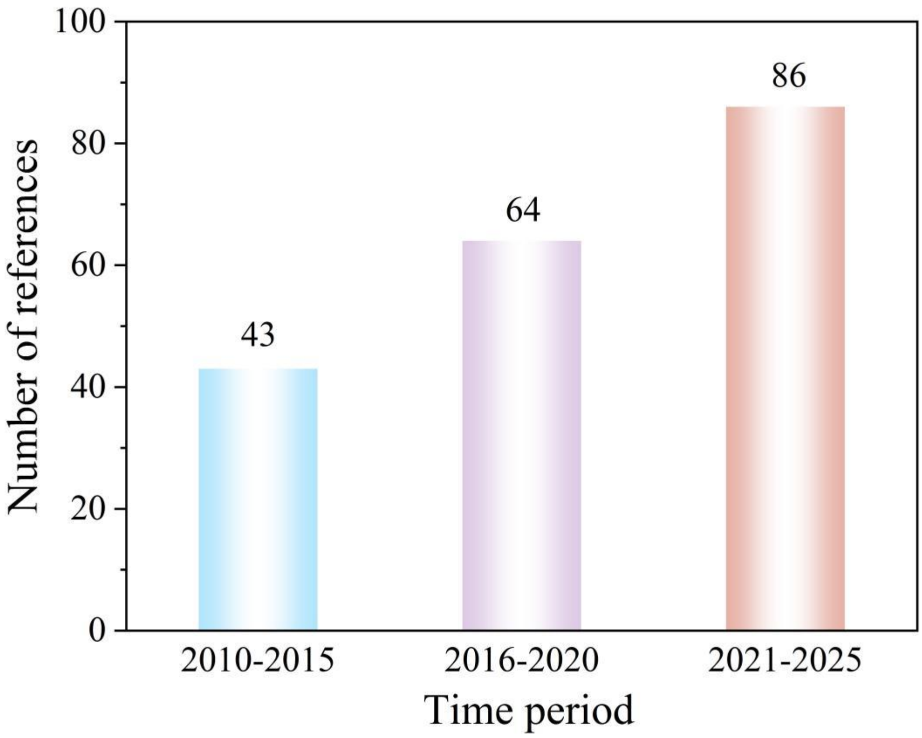

Figure B1. Temporal distribution of the 193 ERA-related studies included in the PRISMA-based systematic review (2010–2025). References published before 2010 are provided as background literature and are not included in the systematic review corpus.

6. Section 3. Composition and Definition: If this will be a separate section, even though only an introduction, I would expect it to be a bit longer, providing more information as to possibly the evolution of the concept, how this definition came to be. Also "composition" in the title doesn't make much sense to me, so unless it is better explained immediately after the section title, I suggest remove it altogether.

Response:

We thank the referee for this valuable suggestion. We agree that the original Section 3 was overly concise and did not provide sufficient context regarding the conceptual development of ERA.

Following your recommendation, we have removed the term “Composition” from the section title and renamed the section “3 Definition and Conceptual Evolution of ERA” to better reflect its purpose and functionality within the review.

We have also substantially revised and expanded this section to provide a clearer account of how the ERA concept has evolved alongside broader developments in emergency management, automation, and intelligent systems. The revised discussion now systematically traces the conceptual transition from early procedural and human-centred emergency protocols toward increasingly data-driven and intelligent systems, driven by the maturity of automation, computing, and communication technologies.

In addition, the revised section now more clearly explains how this cumulative evolution reflects the contemporary understanding of ERA as an integrated socio-technical system, establishing the theoretical foundation for the four-layer analytical framework utilized throughout the review. Simultaneously, we aimed to maintain the concise and transitional role of this section within the overall structure of the manuscript to ensure a balanced narrative.

Specific revisions are listed below:

3 Definition and Conceptual Evolution of ERA

Emergency Response Automation (ERA) refers to the automatic initiation and execution of emergency measures through sensors, data-processing systems, and intelligent decision-making technologies, enabling rapid responses to incidents such as natural disasters, industrial accidents, and public health emergencies with reduced reliance on manual intervention (Matracia et al., 2022). Although the term itself is relatively recent, the underlying concept has evolved over several decades, progressing from early procedural and human-centred emergency protocols toward increasingly data-driven and intelligent systems as automation, computing, and communication technologies matured.

The contemporary concept of ERA did not emerge from a single technological breakthrough, but rather from the convergence of several research traditions. Early foundations were established in industrial automation and control engineering, where closed-loop sensing, feedback, and control mechanisms provided the fundamental sense–decide–act logic for automated responses (Hollnagel, 2018). In parallel, emergency management research contributed organizational structures, incident command systems, and standardized response procedures that defined how emergency actions should be coordinated under crisis conditions (Jensen and Thompson, 2016). Advances in information systems, communication networks, and decision-support technologies further enabled real-time situational awareness, distributed coordination, and data-driven decision-making (Newman et al., 2017). The gradual integration of these developments transformed emergency response from a predominantly human-centred activity into a hybrid human–machine system capable of supporting increasingly complex and dynamic operational environments.

ERA is therefore best understood not as a single technology or predefined procedure, but as an integrated socio-technical system in which sensing, decision-making, execution, and organizational learning operate as interdependent functional processes.

7. Subsection 3.1 continues to mention methodology, and I suggest authors incorporate it above to Section 2.

Response:

We completely agree with the Referee's structural critique. Methodological descriptions and analytical procedures should be consolidated within a dedicated section to maintain structural purity and prevent content overlap across chapters. We have fully implemented your suggestion through the following structural reorganizations:

1. All methodological narratives, thematic analysis procedures, and data classification workflows originally present in Subsection 3.1 have been extracted and fully integrated into Section 2 (Methodology).

2. Concurrently, Subsection 3.1, from which the redundant methodological content was removed, has been thoroughly streamlined and optimized to ensure a more coherent and focused introductory narrative.

Specific revisions are listed below:

2 Methodology

...

To structure the synthesis, two reviewers independently conducted thematic analysis across the included studies through multiple iterative rounds of cross-comparison. This process identified four recurring functional categories consistently appearing across ERA-related research: perception and monitoring, data and decision-making, automated response and control, and feedback and adaptive learning. These categories form the basis of the four-layer architectural framework developed in this review, as illustrated in Figure 1. The included studies were further categorised according to these four layers, with the quantitative distribution summarised in Table 1. A temporal evolution analysis across three developmental phases (2010–2015, 2016–2020, and 2021–2025) was also conducted, as shown in Figure 3 (underlying data in Appendix C), revealing a progressive transition in research focus from rule-based and human-intensive approaches toward more intelligent, data-driven, and AI-enhanced systems. This temporal analysis provides a quantitative basis for the conceptual evolution examined in the sections that follow.

Table 1. Quantitative distribution of included studies across the four-layer ERA architecture (2010–2025)

Architecture layer	Core thematic focus	Number of studies	Proportion (%)
Perception layer	From manual sensing to intelligent surveillance	47	24.35
Decision-making layer	Evolution of data-driven decision-making	56	29.02
Response and control layer	Automated response and control mechanisms	47	24.35
Feedback layer	Enabling adaptive learning and continuous optimization	43	22.28
Total		193	100.00

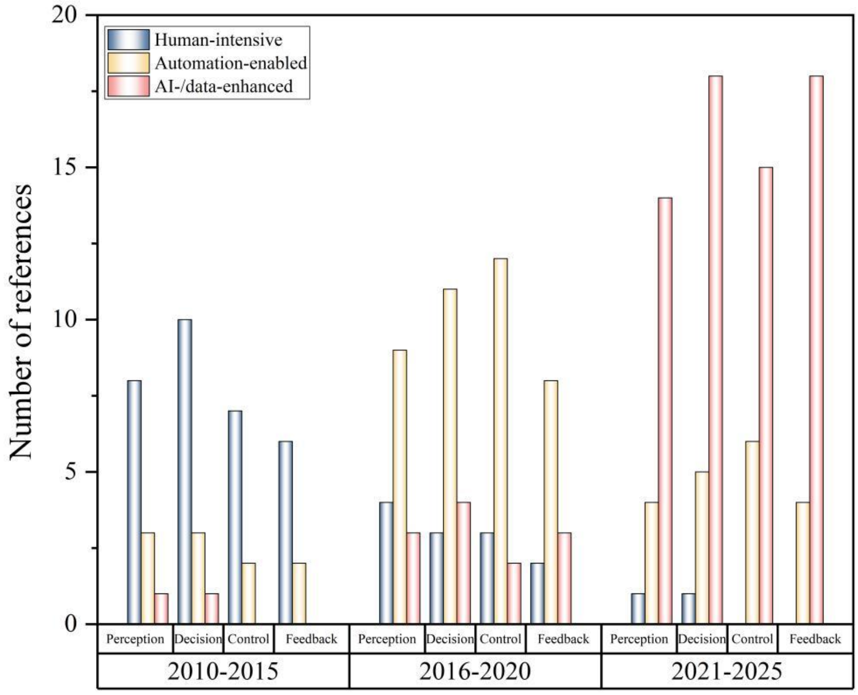

Figure 3. Evolution of the four ERA architectural layers across three developmental phases (2010–2025), based on quantitative categorisation of the reviewed studies. The distribution reflects a consistent shift from rule-based toward AI-driven approaches across all four layers.

3.1 System framework

The four-layer structure of ERA aligns with well-established automation paradigms in other domains. Comparable hierarchical closed-loop architectures can be observed in robotics (Prezas et al., 2024), 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. 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.

8. In 3.2 and 3.3 I find the subsection titles unnecessary. They break the flow.

Response:

We sincerely appreciate the Referee's insightful comment regarding the narrative flow and structural cohesion of Section 3. We agree that the previous use of multiple fragmented subsections interrupted the continuity of the evolutionary discussion and weakened the overall readability of the section.

In response to this suggestion, we reorganized Section 3 to improve thematic integration and narrative continuity. The previously separated subsections have been consolidated into a single subsection entitled "3.2 Technological Evolution Across the Four ERA Layers." This title was chosen because the revised subsection covers not only the evolution of sensing and monitoring, but also data-driven decision-making, automated response and control, and feedback/adaptive learning. We also converted the former subsection-style fragments into paragraph-level thematic transitions, so that the discussion now reads as a continuous evolutionary synthesis rather than a series of disconnected components.

Specific revisions are listed below:

3.2 Technological Evolution Across the Four ERA Layers

To systematically examine the evolution of ERA, this section analyses the development of four interrelated architectural layers: risk perception and monitoring, data-driven decision-making, automated response and control, and follow-up feedback and adjustment.

The risk perception and monitoring layer has evolved from manual observation toward intelligent and predictive surveillance systems, as illustrated in Figure 4. Early emergency monitoring relied heavily on human operators, analogue instruments, and field inspection. Meteorological observers manually recorded rainfall and seismic activity (Pagano et al., 2016), industrial personnel conducted periodic inspections using portable gas detectors (Hemingway et al., 2012) and public-health surveillance depended largely on manual sampling and reporting. Although these approaches provided basic situational awareness, they suffered from delayed response, limited spatial coverage, and subjective interpretation (Dang et al., 2018; Fonollosa et al., 2018).

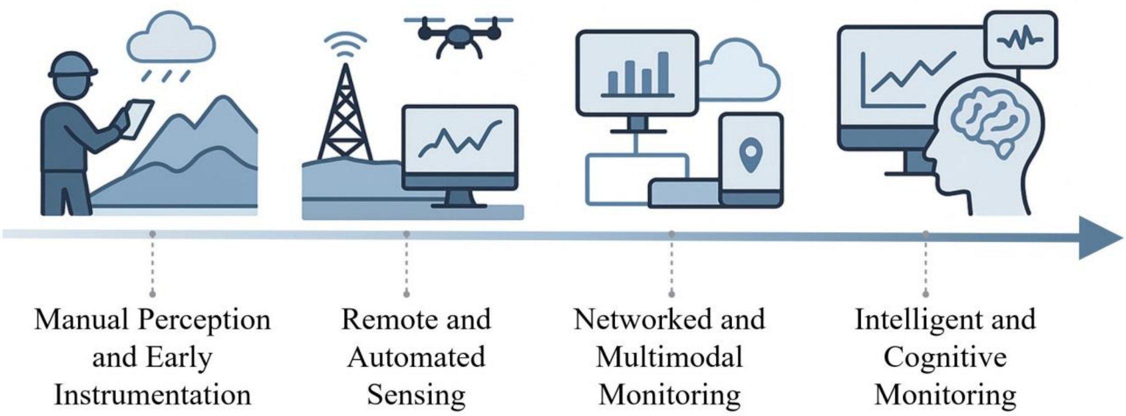

Figure 4. Evolution of the risk perception and monitoring layer in ERA systems, tracing the transition from manual observation toward intelligent and predictive surveillance. The figure illustrates how advances in sensing and monitoring capabilities have progressively improved the reliability, timeliness, and scalability of ERA across different hazard domains.

The development of remote sensing satellites, radar systems, and wireless sensor technologies gradually shifted emergency monitoring toward automated data acquisition (Kodali and Yerroju, 2017; Stähli et al., 2015). Satellite-based observation improved continuous monitoring of floods, landslides, and wildfires (Al-Hady et al., 2023; Mois et al., 2017), while fixed gas and infrared sensors enhanced industrial risk monitoring in near real time (Ni et al., 2018; Chraim et al., 2015; Jain and Kushwaha, 2012). In parallel, digital epidemiology systems began integrating hospital and regional health data for disease surveillance (Adiga et al., 2020). This stage marked the first integration of automated data acquisition into ERA, significantly improving detection timeliness and reliability.

With the emergence of IoT and multi-sensor fusion technologies, monitoring systems became increasingly multimodal and interconnected. Visual, thermal, acoustic, and social data streams were integrated to improve situational awareness across complex emergency scenarios (Alamdar et al., 2015). Applications included drone-assisted earthquake assessment (Contreras et al., 2021), fibre-optic sensing for industrial leakage detection (Ashry et al., 2022), and mobile-health applications for epidemic reporting and tracking (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.

Recent advances in artificial intelligence, edge computing, and digital-twin technologies have further transformed risk monitoring from reactive anomaly detection into predictive risk anticipation (Bongomin et al., 2025). Deep-learning models now extract spatiotemporal patterns from multi-source data to identify emerging hazards in real time (Zhao et al., 2024; Algiriyage et al., 2022). In public health, AI-driven systems integrate genomic sequencing data with population mobility and social indicators to forecast epidemic trajectories (Ongesa et al., 2025; Hadfield et al., 2018). For example, COVID-19 early-warning systems have combined hospital diagnostic data with thermal-sensor information to improve outbreak detection and monitoring capabilities (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 increasingly 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). Similar approaches have also been applied to earthquake early-warning systems, where GPS and seismic-sensor data are combined with machine-learning algorithms to improve warning accuracy (Becker et al., 2020). Additionally, the integration of big data technology enables automatic 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 (Montasari, 2024; Florea et al., 2022; Robertson et al., 2019). These advances are propelling ERA from reactive monitoring toward proactive risk anticipation, with the transition from human-centred to human–machine hybrid perception continuously enhancing reliability, scalability, and cross-domain applicability.

Serving as the cognitive core of ERA, the data-driven decision-making layer has evolved from deterministic rule-based systems toward adaptive and intelligent analytics, as illustrated in Figure 5. Early emergency decision-support systems relied primarily on fixed logical rules and expert-defined procedures. Classical models such as Simon's intelligence–design–choice framework (Simon, 1960) and Montgomery's sequential decision model provided structured approaches for emergency reasoning and operational coordination (Montgomery and Svenson, 1976). These systems were widely applied in industrial and nuclear safety contexts because they offered transparency and procedural consistency, although their adaptability under rapidly changing conditions remained limited.

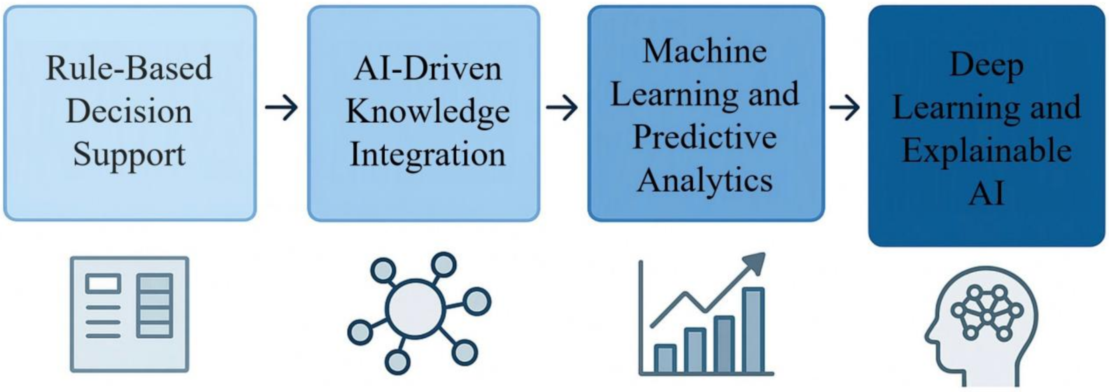

Figure 5. Evolution of the data-driven decision-making layer in ERA systems, showing the progression from rule-based reasoning toward adaptive and AI-enabled decision support. The figure highlights how analytical capabilities evolved alongside increasing challenges related to interpretability, uncertainty management, and human–automation coordination.

With the expansion of sensor networks and computing power, rule-based DSS evolved into hybrid AI systems combining symbolic reasoning and probabilistic inference (Uzma et al., 2025). Bayesian networks and GIS-based tools enabled dynamic, multi-source situational assessment and predictive mapping (Schneider et al., 2025; David et al., 2010). Group decision support (Coles et al., 2018) and game theory–based optimization models enhanced interagency coordination under uncertainty (Lei et al., 2023), reducing the isolation of single-agent frameworks. This phase bridged deterministic rules with adaptive analytical reasoning through AI-enabled knowledge integration.

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 (Huang et al., 2024; Zverovich et al., 2016; Rüppel and Schatz, 2011). Unlike prior hybrid systems, these models derived decision rules directly from data, providing real-time adaptability to changing environments (Al-Hady et al., 2023).

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 (Ayan et al., 2022). Although these approaches significantly enhance adaptability and analytical capability, they also introduce concerns related to interpretability, reliability, bias, and human–automation coordination. As a result, emergency decision-making has become increasingly adaptive, data-driven, and capable of operating under uncertain and rapidly evolving conditions.

The automated response and control layer has evolved from threshold-triggered mechanisms and localized automated actions toward increasingly autonomous, interconnected, and adaptive response systems, as illustrated in Figure 6. Early automation systems relied mainly on threshold-triggered mechanisms activated after anomaly detection (Esposito et al., 2022). Systems such as debris-flow warning platforms enabled basic early-warning functionality but remained heavily dependent on manual verification and intervention (Jafari et al., 2020; Badoux et al., 2009). At this stage, emergency automation remained localized, reactive, and weakly interconnected.

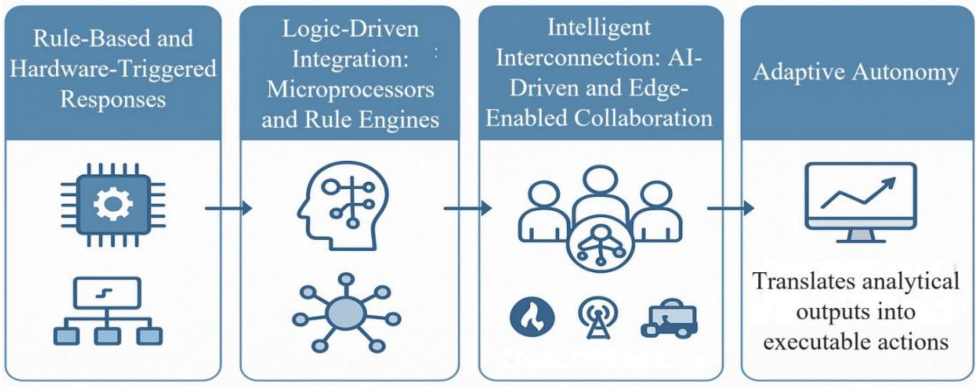

Figure 6. Evolution of the automated response and control layer in ERA systems, illustrating the shift from localized alarm-triggered automation toward interconnected and adaptive operational control. The figure synthesizes the convergence of communication, coordination, and orchestration capabilities while highlighting remaining interoperability challenges in multi-agency emergency response.

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, 2012). For example, Azid et al. (2022) developed an Android-based flood warning application utilizing web services for automatic notifications (Sung et al., 2022), while De Souza et al. (2015) 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.

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 (Ever et al., 2020; Ahmed et al., 2019) 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.

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). Recent examples include IoT- and BIM-enabled fire detection and suppression systems 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 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. These developments shifted ERA from isolated automated actions toward interconnected and coordinated operational control.

The follow-up feedback and adjustment layer has evolved from retrospective post-event assessment toward continuous learning and adaptive system optimization, as illustrated in Figure 7. Early emergency-management systems relied primarily on post-event reports and manually generated performance assessments to identify lessons learned after incidents or simulation exercises (Ramabrahmam et al., 1996). Feedback at this stage was largely retrospective and corrective, with limited capacity for continuous optimization.

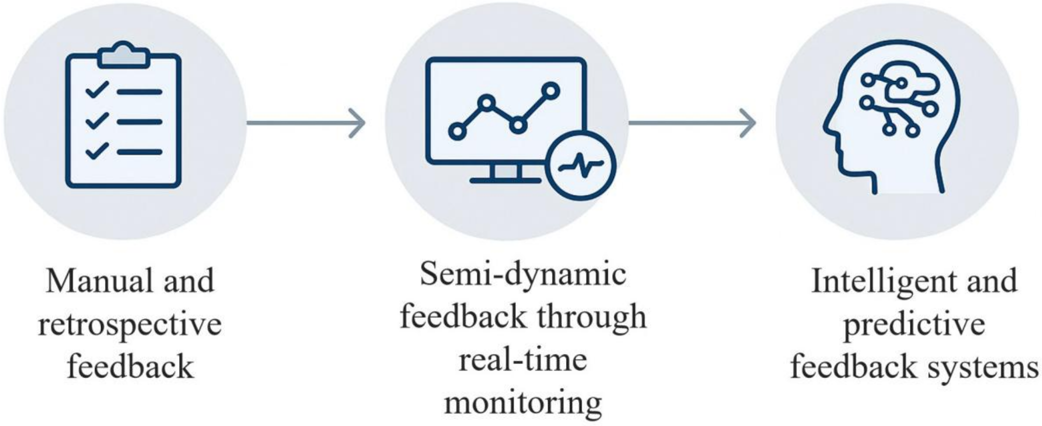

Figure 7. Evolution of the feedback and adjustment layer in ERA systems, tracing the transition from retrospective post-event evaluation toward continuous and predictive adaptation. The figure demonstrates how adaptive feedback mechanisms increasingly support operational resilience, dynamic learning, and real-time optimization in contemporary ERA systems.

Advances in sensing, communication, and computational technologies gradually enabled real-time monitoring and semi-automated evaluation processes (Ding et al., 2022; Newman et al., 2017; Sättele et al., 2015). Researchers improved alarm reliability, optimized monitoring-data utilization, and introduced location-based planning models to support disaster logistics and resource coordination (Girotto et al., 2024; Wang and Nie, 2023). The integration of BIM, GIS, and IoT technologies further enhanced interoperability and spatial information sharing across emergency-management systems (Sani and Abdul Rahman, 2018; Boguslawski et al., 2015), marking a shift from static post-event analysis toward semi-dynamic feedback.

The rise of AI and big-data analytics has since transformed feedback mechanisms into intelligent adaptive systems capable of continuous learning and proactive optimization. ERA systems can now continuously adjust operational priorities and resource allocation during evolving emergencies by integrating real-time medical, transportation, and social data streams (G. Zhang et al., 2024; Zhang et al., 2014). Deep-learning and reinforcement-learning methods further support proactive adaptation by identifying emerging risk patterns and refining decision policies through continuous performance feedback (Li, 2024; Arulkumaran et al., 2017; Rathore et al., 2016). Overall, the feedback layer has evolved from retrospective evaluation toward continuous and predictive adaptation, enabling ERA systems to progressively improve operational resilience, responsiveness, and coordination performance under dynamic conditions.

Across these four layers, the evolution of ERA reflects a broader transition from reactive and fragmented automation toward integrated, intelligent, and adaptive emergency-management systems.

9. The caption for Figure 4 can use a more detail. Same for Figure 5. Just describing the figures is barely enough for an article. How this figure contributes to the subject at hand should be detailed.

Response:

We appreciate the Referee's valuable suggestion. We agree that the original figure captions were overly brief and primarily descriptive, and did not sufficiently explain how the figures contribute to the broader synthesis and analytical framework of the review.In response, we revised and expanded the captions of the relevant figures throughout the manuscript to improve their clarity, interpretive value, and self-explanatory nature. The revised captions now more explicitly describe the conceptual role of each figure, including the technological transitions, integration pathways, and key challenges illustrated in the evolutionary framework.

Specific revisions are listed below:

The revised captions are provided below:

1. Revised Caption for Figure 1: Figure 1. The four-layer architectural framework of Emergency Response Automation (ERA), serving as the organizational backbone of this review. The four quadrants represent the core functional layers examined across Sections 3–5: Risk Perception and Monitoring, Data Analysis and Decision-making, Automated Response and Control, and Follow-up Feedback and Adjustment. The concentric rings trace the technological evolution within each layer, from early manual and rule-based methods toward AI-driven and autonomous paradigms, reflecting the developmental trajectory synthesized from 193 peer-reviewed studies. Interpreting this figure alongside the Introduction provides the conceptual map through which the cross-domain evidence in this review is structured and interpreted.

2. Revised Caption for Figure 2: Figure 2. PRISMA 2020 flow diagram for the systematic review, documenting the identification, screening, and inclusion of 193 studies (2010–2025).

3. Revised Caption for Figure 3: Figure 3. Evolution of the four ERA architectural layers across three developmental phases (2010 – 2025), based on quantitative categorisation of the reviewed studies. The distribution reflects a consistent shift from rule-based toward AI-driven approaches across all four layers.

4. Revised Caption for Figure 4: Figure 4. Evolution of the risk perception and monitoring layer in ERA systems, tracing the transition from manual observation toward intelligent and predictive surveillance. The figure illustrates how advances in sensing and monitoring capabilities have progressively improved the reliability, timeliness, and scalability of ERA across different hazard domains.

5. Revised Caption for Figure 5: Figure 5. Evolution of the data-driven decision-making layer in ERA systems, showing the progression from rule-based reasoning toward adaptive and AI-enabled decision support. The figure highlights how analytical capabilities evolved alongside increasing challenges related to interpretability, uncertainty management, and human–automation coordination.

6. Revised Caption for Figure 6: Figure 6. Evolution of the automated response and control layer in ERA systems, illustrating the shift from localized alarm-triggered automation toward interconnected and adaptive operational control. The figure synthesizes the convergence of communication, coordination, and orchestration capabilities while highlighting remaining interoperability challenges in multi-agency emergency response.

7. Revised Caption for Figure 7: Figure 7. Evolution of the feedback and adjustment layer in ERA systems, tracing the transition from retrospective post-event evaluation toward continuous and predictive adaptation. The figure demonstrates how adaptive feedback mechanisms increasingly support operational resilience, dynamic learning, and real-time optimization in contemporary ERA systems.

8. Revised Caption for Figure 8: Figure 8. Proposed next-generation architecture for ERA. The framework integrates three core technological pillars, methodological coordination mechanisms, and closed-loop adaptive control. It illustrates how the Digital Twin Middleware Platform (DTMP), the AI－Expert Hybrid Decision Engine (AI-E), and the Intelligent IoT Edge Network (I-IEN) interact to support resilient human－automation collaboration and adaptive emergency management across diverse hazard scenarios.

10. Similar issues on Section 4. The introduction (since this is a review) should be a bit more *explanatory. Not a single sentence. It would even be better if they included some references. For example, "the advantages of ERA have been detailed as.. by..." I, as a reader would like to see why only four points summarize the advantages of the framework. Is it because certain literature established this, or is it because the research thus far is limited.*

Response:

The Referee raises an important point regarding the introductory structure of Section 4. We agree that the introduction should do more than briefly describe the topic. It should also explain the rationale of the classification framework and provide sufficient literature context for the following discussion.

In response to this suggestion, we have substantially rewritten and expanded the introductory section of Section 4 to more explicitly justify the rationale of our taxonomy and clarify the boundaries of the current review. The main revisions are summarized as follows:

1. We introduced representative empirical studies to anchor the opening discussion and adopted a more interpretive synthesis style, as suggested by the Referee (e.g., "their operational advantages have been documented in…").

2. We clarified that, although the four dimensions discussed do not exhaust all theoretically possible benefits of ERA, they represent the themes most systematically examined and empirically validated across the 193 studies included in this review.

3. We explicitly linked these four dimensions to the four architectural layers established in Section 3 (perception, decision-making, control, and feedback). This revision better reflects the contemporary boundaries of the field by highlighting where automation has achieved measurable operational improvements and where empirical evidence remains limited.

Specific revisions are listed below:

4 Advantages of ERA

The operational advantages of ERA systems have been documented across a broad body of empirical and applied research. As the field has matured, four recurring dimensions have emerged consistently across the reviewed literature: data-driven decision support, temporal efficiency in rapid response, geospatial precision in resource allocation, and computational optimization for intelligent dispatch. These dimensions are not exhaustive of all possible ERA benefits, but reflect the aspects most systematically examined in the studies reviewed here (Kyrkou et al., 2022; Yang et al., 2013). Their identification through four architectural layers—perception, decision-making, control, and feedback—also reflects the boundaries of current research, highlighting where automated implementations have demonstrated quantifiable success and where broader empirical validation remains limited.

11. Lines 441-443 would better be incorporated into a paragraph with proper references (who applied these selection criteria to their research, or who established these as selection criteria) The way it reads now is much like an opinion piece than a review. My aim reading a review is mainly to find out about the studies in a certain field, and building a reading list for future research.

Response:

The Referee raises an important point regarding the objectivity of system selection in review articles. We agree that the classification and selection of systems should be grounded in recurring patterns in the literature rather than subjective author judgment.

In response to this comment, we revised the text around Lines 441–443 and incorporated it into the introduction of Section 5. The revised version no longer presents the selection criteria as a simple itemized list. Instead, the selection rationale is now explained through a literature-based narrative.

Specifically, we clarified that the systems discussed in this section were selected based on several commonly observed features in the literature, including recurrent discussion across peer-reviewed studies, coverage of different ERA technological pathways, and their ability to reflect typical trade-offs among perception, decision-making, execution, and feedback capabilities. We also clarified that this organization was intended to reflect recurring patterns in existing research rather than the authors' subjective assessment of technological importance.

Specific revisions are listed below:

5 Typical Application Scenarios

...

This section reviews emergency response systems and platforms that have been widely discussed in the existing literature (Kyrkou et al., 2022), with emphasis on their core functions, enabling technologies, application contexts, and supporting evidence. The systems included in this section were selected based on several considerations commonly adopted in systematic review studies (Page et al., 2021a): recurrent discussion across multiple peer-reviewed studies, coverage of different technological pathways within the ERA framework, and the ability to reflect typical trade-offs among perception, decision-making, execution, and learning capabilities (Hollnagel, 2018). This approach systematically aligns the selected cases with the established consensus and structural benchmarks of the broader literature.

12. Lines 448-453 can easily be turned into a paragraph, even a sentence.

Response:

We thank the Referee for this helpful suggestion regarding the presentation of the text. We agree that integrating these previously fragmented descriptions into a more structured and information-dense sentence improves the conciseness, readability, and overall academic tone of the manuscript.

Following this suggestion, we revised and consolidated the original text in Lines 448–453 into a single cohesive sentence to improve narrative flow and reduce unnecessary fragmentation.

Specific revisions are listed below:

5.1 Cross-System Comparative Analysis

To support consistent comparison across systems, each case was analysed according to six ERA capability dimensions: multi-source sensing and monitoring, decision support, operational execution, interoperability and data sharing, robustness and fault tolerance, and adaptive learning.

13. Same for lines 463-482. Also, previously it was mentioned that "This section summarizes the representative emergency response systems and platforms that frequently appear in the literature..." however I cannot see any reference to any literature. I gather that there are Tables, but again I would like to read a synthesis of the articles provided in these lists with proper in paragraph referencing. The authors may choose to include the Table in the

Appendix or a Supplementary file, alternatively.

Response:

We thank the Referee for this important comment regarding the methodological rigor and synthesis quality of the discussion section. We fully agree that comparative and generalised conclusions in a comprehensive review article should be explicitly supported by in-text references. In response to this suggestion, we revised the relevant section in two main ways.

First, we reorganized the originally fragmented discussion into two more cohesive thematic paragraphs focusing on (1) convergent patterns across ERA systems and (2) differences among application domains. This structural revision was intended to improve the logical flow of the discussion and strengthen the synthesis-oriented character of the review.

Second, we systematically incorporated explicit in-text references throughout the discussion (e.g., Esposito et al., 2022; Hoff and Bashir, 2015; Hancock et al., 2011; Homier et al., 2021; Jafari et al., 2020; Gevaert et al., 2021) to ensure that all comparative observations are directly grounded in representative empirical studies.

Specific revisions are listed below:

5.1 Cross-System Comparative Analysis

...

Across the reviewed systems, several convergent patterns emerge. Most follow a layered perception–analysis–decision–execution sequence, which broadly aligns with the four-layer ERA framework proposed in this review, with investment concentrated on early detection capabilities such as sensor networks, remote sensing, and video analytics (Esposito et al., 2022). Although automated rules support many routine functions, critical decisions generally retain human oversight in most operational systems (Hoff and Bashir, 2015; Hancock et al., 2011). In contrast, real-time adaptive learning remains limited, with many systems still operating at prototype stage. Persistent interoperability gaps and data silos continue to hinder multi-agency coordination.

Domain-specific divergences are also evident. Logistics systems place greater emphasis on automated execution, whereas monitoring systems are more commonly designed to support human decision-making (Jazairy et al., 2025). Natural hazard systems must handle sensor noise and false alarms, while industrial systems rely more on deterministic logic to reduce false positives (Jafari et al., 2020). Evidence maturity varies considerably across domains, and urban surveillance systems face additional privacy and governance challenges largely absent in closed industrial settings (Gevaert et al., 2021). Overall, ERA demonstrates broad applicability across hazard types and operational contexts, but trade-offs among sensing accuracy, automation depth, interoperability, and socio-legal constraints remain central challenges for its future development and large-scale deployment.

14. 5.2 and 6.3, again, please integrate the bullet points into proper paragraphs.

Response:

We once again thank the Referee for the careful reading and valuable suggestions. We fully agree that reducing fragmented list-style presentation can improve the narrative flow and overall readability of the manuscript. In response to this comment, we revised both Sections 5.2 and 6.3 by removing the itemized lists and integrating the content into continuous academic discussion.

For Section 5.2, the original bullet points were incorporated into the main narrative to establish a clearer empirical connection between the conceptual framework and operational realities without interrupting the continuity of the discussion.

For Section 6.3, the previous itemized structure was reorganized into a continuous explanatory paragraph in order to preserve technical clarity while improving structural coherence and readability.

Specific revisions are listed below:

5.2 Summary

This section maps representative ERA systems onto a clearly defined capability matrix and synthesizes cross-system evidence to reveal both the generic capability dimensions of ERA and the system-specific trade-offs involving robustness, interoperability, and operational autonomy. This approach establishes a transparent, evidence-based framework linking concrete systems to framework components and identifies cross-domain research priorities to guide future ERA development.

6.3 Next-generation ERA model framework

…

The model is built around three closely connected components. The Digital Twin Middleware Platform (DTMP) links virtual and physical environments to support real-time simulation, validation, and adaptive system adjustment. The AI–Expert Hybrid Decision Engine (AI-E) combines data-driven analytics with expert judgement to improve decision transparency and operational reliability. The Intelligent IoT Edge Network (I-IEN) integrates edge computing, next-generation communication technologies, and blockchain-supported data management to enhance connectivity and information security across distributed ERA environments.

15. Fig. 8 please expand the caption to include detailed information (see previous comments on Figures).

Response:

We fully agree with the Referee's valuable suggestion. Consistent with the revisions made to the preceding figures, we have substantially expanded the caption of Figure 8 to ensure that it functions as a standalone and self-explanatory conceptual framework.

Rather than merely describing the graphical components, the revised caption now clarifies the purpose of the framework, the roles of its three core technological pillars, and the mechanisms through which these components interact to support adaptive emergency response. Specifically, the caption explains how the Digital Twin Middleware Platform (DTMP), the AI–Expert Hybrid Decision Engine (AI-E), and the Intelligent IoT Edge Network (I-IEN) are integrated through methodological coordination and closed-loop feedback mechanisms. It also explicitly links the framework to the major application contexts discussed throughout the review, including natural hazards, industrial emergencies, and public-health crises.

Specific revisions are listed below:

Figure 8. The proposed next-generation ERA architectural model, integrating three core technological pillars, methodological coordination mechanisms, and closed-loop adaptive control. The framework synthesizes the major findings of this review into a forward-looking system architecture, illustrating how the Digital Twin Middleware Platform (DTMP), the AI–Expert Hybrid Decision Engine (AI-E), and the Intelligent IoT Edge Network (I-IEN) interact to support resilient human–automation collaboration and adaptive emergency

management across diverse hazard scenarios.

16. Table 5 can massively benefit from proper references. Right now I don't know if this is what the readers think or what their literature review rendered. Lines 661-668 which refer to the table also has no references.

Response:

We sincerely thank the Referee for this valuable observation. We agree that the conclusions summarized in Table 5 in the original manuscript (now Table 4 in the revised manuscript following the removal of the previous Table 1), as well as the associated discussion (formerly Lines 661–668), should be clearly supported by the reviewed literature rather than appearing as unsupported author interpretations.

To address this concern, we have added representative references both within the revised Table 4 and in the corresponding discussion section. In addition, a table note has been included to clarify that the reported advantages, limitations, and cross-domain observations are synthesized from recurring findings across the reviewed studies. These revisions improve the traceability and transparency of the evidence underlying the table and make it clearer that the summarized conclusions represent a literature-based synthesis rather than subjective author judgment.

The corresponding revisions can be found in Table 4 and the related discussion section of the revised manuscript.

Specific revisions are listed below:

5.1 Cross-System Comparative Analysis

...

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 (Kyrkou et al., 2022; Hollnagel, 2018).

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 (Elmhadhbi et al., 2020). 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 (González et al., 2021).

Table 4. Cross-domain Technology Matrix for ERA.

Note. Citations in each row indicate representative studies for the corresponding technology and application domain. The reported advantages and limitations synthesize common findings from the reviewed literature.

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 (Al-Hady et al., 2023).	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 (Algiriyage et al., 2022).
IoT and Sensor Networks	Collects distributed data (temperature, vibration, water levels) to support real-time disaster detection (Esposito et al., 2022).	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 (Damaševičius et al., 2023).
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 (Li, 2024; Arulkumaran et al., 2017; Rathore et al., 2016).	Advantage: Integrates heterogeneous data for rapid decision-making (Zhao et al., 2024; Algiriyage et al., 2022). Limitation: Privacy, latency, and standardization remain major challenges (Sheng et al., 2021).
Explainable Artificial Intelligence (XAI)	Improves interpretability of hazard forecasting and decision support models (Hsiao et al., 2025).	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 (Rivas and Abrao, 2020). Limitation: Trade-off between interpretability and model performance.

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Table 4 (continued).

Technology	Environmental & Natural Hazards	Industrial & Infrastructure Emergencies	Public Health & Social Safety	Cross-domain Insights
Digital Twin Technology	Simulates disaster evolution and resource deployment for preparedness and recovery (Li et al., 2024).	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 (Bongomin et al., 2025).
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 (Dixit et al., 2022).	Enables telemedicine, emergency alerts, and high-volume health data transfer (Su et al., 2021).	Advantage: Provides reliable, real-time connectivity under extreme conditions. Limitation: High deployment cost and uneven global coverage (Uusitalo et al., 2021).

17. Section 6.5 can also benefit from my previous comments of structure and flow.

Response:

We sincerely thank the Referee for this valuable suggestion regarding the structure and narrative flow of Section 6.5. We fully agree that presenting future trends in a fragmented or list-like format can weaken the continuity and synthesis expected in a review article.

In response to this comment, we substantially reorganized Section 6.5 by removing the previous bullet-style and numerically separated structure. Instead of discussing each technological direction as an isolated item, the revised section now presents future ERA development as an interconnected and evolving technological ecosystem.

Specifically, the revised text emphasizes the logical relationships among intelligent sensing, resilient communication, autonomous decision-making, digital twins, and multi-agent collaboration. These technological trajectories are now integrated into a continuous narrative organized around the broader operational flow of future ERA systems, progressing from perception and communication infrastructure to decision-making and coordinated execution.

In addition, we strengthened the synthesis-oriented nature of the discussion by explicitly highlighting common technical bottlenecks, cross-domain integration challenges, and the need for standardized empirical validation. This restructuring improves the overall readability, cohesion, and analytical depth of the section, while maintaining the technical details and literature support required for a comprehensive review article.

Specific revisions are listed below:

The future development of ERA is likely to converge around several interrelated technological directions, including intelligent sensing, explainable AI-driven decision-making, resilient communication infrastructures, digital-twin-enabled simulation, and collaborative multi-agent systems. These technologies are increasingly forming an integrated emergency-management ecosystem that combines real-time perception, adaptive analysis, autonomous coordination, and continuous feedback optimization. Current studies suggest that this convergence may help address persistent limitations in data fragmentation, communication disruption, decision uncertainty, and interagency coordination inefficiency. However, despite rapid technological progress, much of the existing evidence remains concentrated in simulation environments or prototype systems, highlighting the need for stronger operational validation across real-world emergency scenarios.

Recent advances in intelligent sensing and AI-driven analytics are reshaping how ERA systems perceive and interpret dynamic risk environments. Emerging sensing architectures increasingly integrate MEMS, microwave, optical, and gas sensors to support real-time monitoring of fires, toxic releases, and structural failures (Donta et al., 2023; Nanda et al., 2023; Ortiz-Garcés et al., 2023). At the same time, user-edge computing and distributed processing frameworks improve the prioritization of critical disaster data under resource-constrained conditions (Sun et al., 2025), while blockchain-supported information sharing may reduce transmission delays and enhance interagency data integrity (Habib et al., 2024; Treiblmaier and Rejeb, 2023). Parallel developments in explainable AI and multimodal learning are further expanding the analytical capability of ERA systems (Zhang et al., 2025). Techniques such as Dempster–Shafer Theory combined with AI reasoning can improve decision-making under uncertainty (Fei et al., 2024), whereas multimodal neural networks integrating natural language processing, computer vision, and social-media analytics enable richer situational awareness from heterogeneous data streams (Su et al., 2021). Generative AI tools may additionally support rapid scenario modeling and knowledge extraction during time-critical emergencies (Maceika et al., 2024). Nevertheless, current evidence indicates that the operational reliability, interpretability, and scalability of these systems remain insufficiently validated, particularly under complex field conditions (Hsiao et al., 2025; Wibowo et al., 2025). Future studies should therefore place greater emphasis on measurable operational indicators, including detection latency, false-alarm rates, decision accuracy, processing efficiency, and human–machine trust performance.

At the infrastructure and coordination level, resilient communication networks, digital twins, and intelligent multi-agent collaboration are expected to become increasingly central to next-generation ERA architectures. Emerging 6G ecosystems integrating terahertz transmission, quantum communication, and Low-Earth-Orbit satellite constellations may significantly improve connectivity resilience in disrupted disaster environments (Aldrees et al., 2025; Liu et al., 2025; Uusitalo et al., 2021). Similarly, Software-Defined Networking and UAV relay systems can dynamically reconstruct damaged communication infrastructures and maintain network continuity during emergencies (Abir et al., 2023). Meanwhile, digital-twin-based platforms are increasingly being explored as dynamic simulation environments capable of supporting predictive analytics, operational optimization, and adaptive strategy adjustment (Ghaffarian, 2025). Their integration with edge and distributed computing may further reduce response latency and improve large-scale coordination efficiency (Zio and Miqueles, 2024; Ariyachandra and Wedawatta, 2023). In parallel, collaborative intelligent entities—including UAV swarms, robotic systems, and AI-assisted agents

—are becoming more prominent in hazardous search-and-rescue, logistics, and medical-support operations (Moosavi et al., 2024; Pillai et al., 2024). Emerging multi-agent coordination and human–machine collaboration frameworks may improve task allocation, operational robustness, and adaptive response capability under uncertain conditions (Mourtzis et al., 2024; Daud et al., 2022). Across these domains, however, interoperability, cybersecurity, uncertainty quantification, and standardized evaluation protocols remain major unresolved challenges. Advancing ERA therefore requires a transition from conceptual and prototype-driven research toward operationally validated, interoperable, and cross-domain deployable systems supported by transparent performance metrics and cumulative empirical evidence.

Closing Statement

We thank the Referee once again for the valuable comments and constructive suggestions provided throughout the review process. We have carefully considered all comments and revised the manuscript accordingly. We hope that the revisions adequately address the Referee's concerns and have improved the clarity, coherence, and overall quality of the manuscript.