Intelligent Agents in Disaster Risk Management: A Systematic Review of Advances and Challenges

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***Abstract*—Artificial Intelligence (AI) has emerged as a transformative technology in the domain of Disaster Risk Management (DRM), offering new possibilities for forecasting, preparedness, and rapid response in the face of increasingly frequent and complex natural disasters. This systematic literature review synthesizes the state-of-the-art advances in AI-driven intelligent agents applied to DRM, covering domains such as early warning systems, geospatial analysis, damage assessment, evacuation planning, and decision support. It critically examines the technological innovations, implementation methods, and interdisciplinary approaches that have shaped the evolution of intelligent agent-based solutions in disaster scenarios. Through the analysis of over 7,800 scientific publications indexed in Scopus, Web of Science, and OpenAlex between 2010 and 2025, the review identifies key patterns, application domains, and persistent gaps such as data scarcity, lack of model interpretability, and limited operational deployment. The study also addresses ethical concerns related to AI deployment in high-stakes environments and proposes a roadmap for future integration of intelligent agents with IoT, UAVs, and real-time decision infrastructures. The findings contribute to a deeper understanding of how AI and multi-agent systems can reinforce disaster resilience and inform sustainable and adaptive disaster management strategies at both global and local levels.**

Keywords*—Intelligent agents; Artificial Intelligence; disaster risk management; predictive analytics; resilience; early warning systems; geospatial AI; disaster response; ethical challenges; machine learning; climate change adaptation

I. Introduction

The frequency and intensity of natural disasters have increased markedly over the past two decades, driven by accelerating climate change, rapid urbanization, and environmental degradation. From floods and wildfires to earthquakes and pandemics, recent events have exposed critical vulnerabilities in existing disaster risk management (DRM) systems. Traditional DRM approaches, while foundational, often fall short in handling the complexity, scale, and uncertainty of modern disaster scenarios.

Artificial Intelligence (AI) presents a significant opportunity to address these shortcomings. By leveraging techniques such as machine learning, natural language processing, computer vision, and multi-agent systems, AI can enhance situational awareness, enable predictive analytics, automate decision-making processes, and facilitate real-time response. However, despite the growing interest in AI for DRM, most existing studies focus on isolated use cases, neglecting to provide a comprehensive and structured analysis of the broader ecosystem of intelligent agents and their integration into disaster response frameworks.

This study responds to that gap by conducting a systematic literature review of intelligent agents applied to DRM, with the goal of mapping key advances, identifying implementation challenges, and highlighting future research opportunities. It contributes an interdisciplinary synthesis that goes beyond technical innovation to include organizational, ethical, and operational dimensions. Furthermore, the article distinguishes itself by focusing on intelligent agent architectures, their decision-making capabilities, and how these agents interact within multi-layered, real-world DRM systems.

The remainder of this paper is structured as follows: Section II presents the review methodology based on PRISMA guidelines; Section III details the main findings, categorized by application domains, technologies, and limitations; Section IV discusses current gaps and future research directions; and Section V concludes with practical implications and strategic recommendations for stakeholders.

II. Methodology

Recent advances in artificial intelligence (AI) have fueled the development of intelligent agents capable of enhancing decision-making, coordination, and automation in disaster risk management (DRM). Numerous studies have investigated the role of AI in supporting early warning systems, damage assessment, and emergency response. For example, Abid et al. [1] and Pang [3] emphasized how AI, especially machine learning and geospatial analysis, supports real-time monitoring and improves situational awareness during disasters. Similarly, Wheeler and Karimi [4] explored the application of deep learning models in satellite image interpretation to assess post-disaster damage at the building level.

Despite these contributions, existing literature often focuses on narrowly defined applications or specific types of disasters, without offering a global and systematic synthesis of intelligent agent architectures. Ramchurn et al. [5] introduced the concept of Human-Agent Collectives (HACs), highlighting the potential of mixed human-AI coordination, while Rashid et al. [15] developed a multi-agent flood forecasting system based on reinforcement learning, showing that intelligent agents can make autonomous, context-sensitive decisions in real time.

However, comprehensive overviews mapping the landscape of AI agent integration across the DRM cycle remain limited. Many reviews omit key issues such as trust, ethical risks, and system interoperability. Moreover, the challenges of implementing agent-based systems under data scarcity and infrastructural limitations—particularly in low-resource or high-risk regions—are not adequately addressed.

This review seeks to fill these gaps by synthesizing over 7,800 scientific publications from 2010 to 2025 and offering a structured analysis of intelligent agent applications in DRM. By covering both technological innovations and deployment barriers, it contributes to a deeper understanding of how agent-based AI can reinforce resilience, operational efficiency, and adaptive capacity across multiple disaster contexts.

This SLR followed strict methodological standards to ensure transparency, reproducibility, and comprehensiveness. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines was used to guide the review study selection process through three major stages: IDentification, Screening, and Inclusion.

A. Data Sources and Search Strategy

The bibliographic search was conducted in three academic databases: SCOPUS, Web of Science, and OpenAlex. These sources were chosen because they cover a wide range of peer reviewed material, conference papers and book chapters spanning artificial intelligence (AI), disaster risk management (DRM) and related studies. The search string was intentionally designed to retrieve a complete corpus of AI applications in disaster management literature. The query used was: Query: (”artificial intelligence” OR ”machine learning” OR ”deep learning”) AND (“disaster management” OR “disaster risk reduction” OR “natural disaster” OR “catastrophe naturelle” OR “emergency management” OR “hazard mitigation” OR “resilience” OR “early warning system”) This search resulted in a total of 13,880 articles.

B. Screening and Eligibility Criteria

A two-step screening process was applied:

1) Inclusion Criteria:

- Articles published between 2010 and 2025.
- Publications limited to peer-reviewed journal articles, conference papers, and chapter books.
- Only publications written in English were considered to maintain consistency in analysis.

2) Exclusion Criteria:

- Duplicate entries were removed.
- Articles outside the scope of the research theme (i.e., those not addressing AI or intelligent agents in the context of disaster risk management) were excluded after title, abstract, and, where necessary, full-text reviews.

After applying the inclusion and exclusion criteria, 7,991 articles were deemed eligible for detailed analysis.

C. Final Selection

A total of 7,823 articles were ultimately included for bibliometric, thematic and qualitative analysis after a comprehensive selection and validation process. This is the empirical basis for the findings and discussions in this study.

The complete selection process is presented (Figure 1, PRISMA flow diagram), which is sufficient to show transparency and clarity in the research methodology adopted.

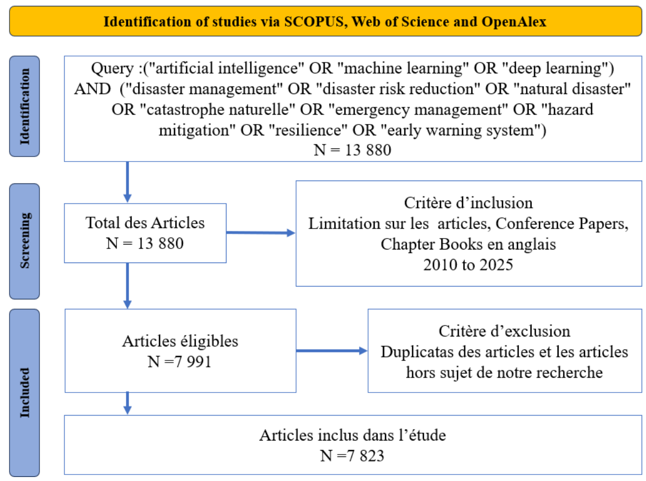

Fig. 1. Prisma approach.

III. Results and Discussion

The use of artificial intelligence (AI) has revolutionized the approaches to disaster management providing valuable resources to effectively foresee, respond, and recover for both natural as well as man-made disasters. AI is the intelligence exhibited by computer systems in order to act and think like humans in a multitude of interconnected machines and an intelligent [1]. Incorporation of AI in disaster management has significantly improved the capability to predict disasters in advance and support the affected during the disaster, giving birth to what is known as Intelligent Disaster Management (IDM) [2].

RAPID AI Summit 85 Intelligent Agents for disaster management use various AI methods, such as AI for robotics, AI for drones, machine learning, deep learning, sensing, and algorithms to predict disasters, and speed rescue operations [1]. These technologies have developed from primitive tools with poor decision-making abilities to fully automated and artificial intelligent systems capable of analyzing data and operating independently [1].

The underlying merit of AI in disaster management is the capability to track and analyze huge volumes of heterogeneous data types such as geospatial data, social media, and sensor data of wireless networks [3]. For example, the machine learning algorithms can learn models in change detection in satellite images to detect the areas mostly affected by disasters for coordinating disaster relief more efficiently [1]. Deep learning-based computer vision models [4] can evaluate building damage post-natural disaster with pre- and post-disaster satellite images, which automates a key step in decision support for disaster response.

Contemporary paradigms in disaster management admit that neither human beings nor machines working alone can meet the demanding requirements of disasters. Rather, meaningful disaster management calls for a combined effort between humans and intelligent sys- tems in an environment that is often referred to as a Human-Agent Collective (HAC) [5]. Such mechanisms interleave human and machine decision making and allow control to be flexibly transferred between human and agent members of agile teams, tracked through information infrastructures that author accountability [5].

Applications exist in all the stages of disaster management: the pre-disaster measures (like predictions and risk analysis), the in-disaster ones (like classifications and modeling) and the post-disaster ones (like assessing the damages) [2], Such as during the COVID-19 pandemic, drones or autonomous robots have been used in multiple disaster-response activities [6], and in the building fire, AI-based fire detection systems are implemented for real-time guidance of occupant evacuation [7].

While AI has tremendous potential to improve disaster management, there are some critical new challenges. Learning reliable predictors from noisy, heterogeneous and limited annotated data is a major challenge[8]. Moreover, there have been worrisome warnings on the potentially negative effects of unrestricted deployment of AI, which may even cause increased disaster impacts if improperly handled [2]. However, continued progress and sensitive use of intelligent agents in emergency response and management applications have great potential to enhance our ability to predict, respond and recover from disaster collectively.

A. Design Approaches for Intelligent Agents

The design of intelligent agents Figure2 for disaster management should carefully consider architectural approaches able to deal with the complexity and uncertainty of emergency scenarios. One widely used model of reasoning is the Belief-Desire-Intention (BDI) approach to reasoning about agents, which offers us a natural and expressive way of specifying agent behaviours in complex environments through describing the agent's mental states. The BDI model provides an effective means for agents to maintain a representation of their environment (beliefs), express desires and reasons for action (goals), and to express their decision of what to do in terms of a course of action (intents), strong to the case of disaster management [9]. This reasoning enables agents to have 'situational awareness' and adapt to changing situations without starting processing from scratch each time the situation changes [9] [10].

Agents are classified into careful agents, model based agents, goal based agents, utility based agents, and learning agents [11]. These agents fall into four further architectural categories; logic-based agents (relying on logical deduction to determine actions), reactive agents (mapping situations directly to actions), belief-desire-intention (BDI) agents (operating on structures representing mental states) and hybrids which utilize multiple architectures [11].

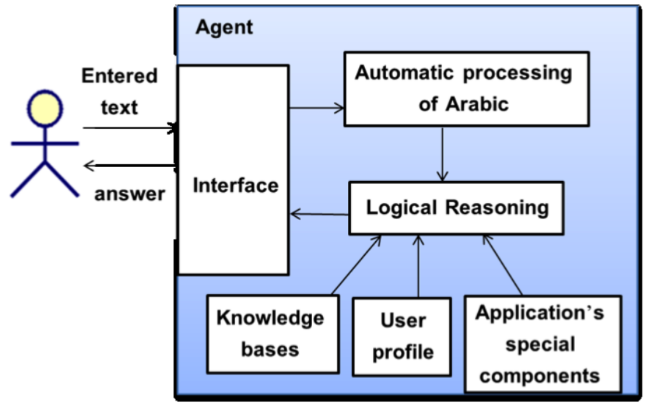

Fig. 2. General design approaches for intelligent agents.

Multi-agent systems (MAS) have become an effective paradigm for designing disaster management systems, where different specialists agents can cooperate to solve complex crisis situations[9]. These systems generally utilize a combination of heterogeneous dedicated agents such as situation assessment agents, resource agents, decision support agents, coordination agents, and prediction agents, which are specialized to address different aspects of disaster management [12]. The multi-agent nature allows for distributed knowledge and resource reasoning that are especially valuable in emergency situations of natural or human-caused disasters [9, 13].

Awareness-based modeling is also a critical design issue and is reflected in work like MAAP (Multiagent Awareness-based Process model), which keeps agents aware of relevant policies in support of better cooperation in disaster scenarios [14]. awareness enables agents to identify relevant information to consumer demands and coordinate in a crisis response.

Recent achievements in artificial intelligence have enabled the progress of more sophisticated design techniques. The multi-agent deep reinforcement learning (MADRL) integrates the multi-man formalized logic and deep reinforcement learning for managing the and uncertainty where high-dimensional data is involved in disaster situations [15]. This approach allows the agent to maximize its expected reward in an uncertain and noisy environment, where an approximate action value function is learned by agents using neural networks as function approximators [15].

Another important design pattern is represented by intelligent agent Decision Support Systems (DSS). These systems are commonly characterized by multi-level agent designs, with each level having a different role. For instance, a representation layer can describe the environment as a set of entities, the states of which evolve over time, and domain agents observe those states with respect to the domain informationodies [16]. These systems try to identify threats in uncertainty and under partial perception, so that crises can be avoided [16].

Contemporary agent architecture for disaster management also focuses on the important qualities of autonomy, complexity of decision making, adaptability, and impact power [17]. Autonomy enables agents to function without the need for human input, performing the ability to process real-time data and allocate resources. The intricacy of decision-making allows them to maneuver complex environments, weighing, for instance, regarding affected populations, available resources, and infrastructure limitations. Adaptability allows agents to adapt strategies in real time to changing conditions, while impact potential describes the ability to take actions that have consequences in terms of lives affected, economic damage, and long-term recovery [17].

The agentic AI systems are the state-of-the-art intelligent agent design for disaster management. Such systems would be able to process environmental data in real-time under crisis, allocate resources and change at the same time strategically as conditions and the input data change [18]. This self-scheduling ability is essential in efficient rapidity need based disruption response.

One of the major challenges in developing an intelligent agent for disaster control is to make the designing of the intelligent agents in way where it is can successfully work in uncertain and complex environments, compatible with different platforms and scenarios [19][20]. Meetin this challenge, modern design approaches focus in generic frameworks that can be extended to multiple domains with little adaptation, counting with domain knowledge provided by experts while retaining core capabilities that enable the autonomous changes in agent behavior code [19].

B. Implementation Methods and Technologies

Disaster intelligent agentsIn the research of disaster management, there are a series of artificial intelligence technologies that are applied to the depth of work on the problems of disaster predicting, rescue and recovery. The implementation of Decision Support Systems (DSS) is one of the fundamental frameworks for transferring human expertise to computers and for constructing models from this knowledge [21]. These systems attempt to reduce prospective risks through the early reconnaissance and the preparation of actions.

Numerous AI techniques are widely used to handle the inter-related problems in disaster management. These methods include Bayesian networks for more probabilistic reasoning, fuzzy logic for approximate reasoning with vague information and metadata techniques such as artificial neural networks, machine learning, genetic algorithms and swarm intelligence [21]. Hybrid methods in which fuzzy IF-THEN rules and optimization are coupled, are particularly useful for the acquisition and handling of fuzzy information in disasters.

Agents are a promising paradigm due to their distributed, parallel, collaborative, hybrid, flexible, recursive, adaptive, cooperative, and intelligent processing [22] Figure3 and a powerful implementation of disaster management systems. The fact that disaster management activities consist of physically and logically distributed tasks makes multi-agent systems (MAS) systems especially suited, enabling specialized agents to be allocated to specific tasks, and hence supporting scalable and collaborative decision making.

One usage of Multi-Agent Systems and Anytime Algorithms can be found with the advancement of reliable, fast, and robust distributed decision support system in disaster management [22]. This coupling renders such systems especially well-suited for flood early warning and forecasting systems, since that agents carry out intelligent, distributed, adaptive, scalable processing to take cooperative and collective decisions.

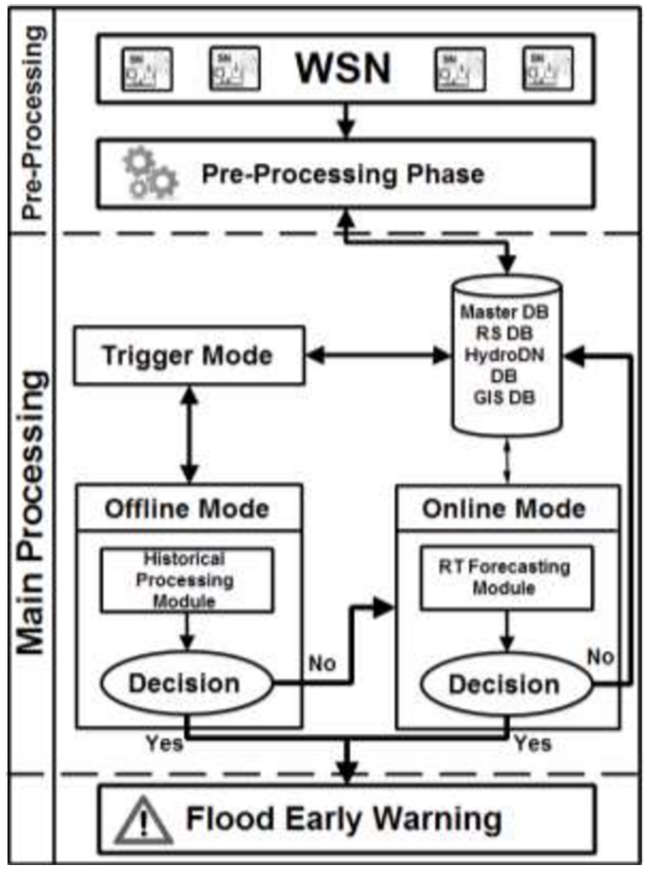

Fig. 3. General architecture of our decision support system.

Putting it to Practice The more recent approaches take advantage of the sophisticated artificial intelligence algorithms, for example deep reinforcement learning. Multi-agent deep reinforcement learning (MADRL) allows agents to maximize their expected rewards in presence of uncertain environments which learn action values by using neural networks as function approximators [15]. This strategy is especially useful in the case of flood prediction, for which the data is of high-dimension and uncertainty is high. One interesting solution applies multi-agent actor-critic and deep deterministic policy gradient algorithms on those problems.

From a technical point of view, AI-based disaster management solutions can be partitioned into a continuum between supervised learning [23] [24] In the most ideal conditions, the reference points for operations on a large-scale disaster dataset would be provided as the ”correct”, or ”desired”, or ”target” output of a system. For instance, higher than normal temperatures in the previous week, were associated with an increased risk of hospitalization ahead of a summer heatwave[23]Figure4.

The adoption of AI in disaster management is more and more realized by new algorithms and high performance computing (HPC) in order to predict the geospatial and temporal patterns of disasters with precision [25]. The machine learning and deep learning methods that are frequently used for tasks

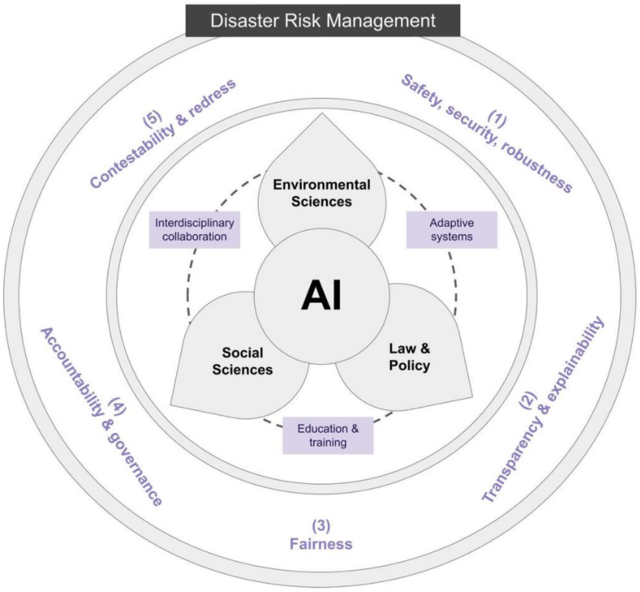

Fig. 4. Principles for regulating AI use in disaster risk management.

such as disaster prediction, risk evaluation, early warning systems, and disaster damage detection have increased the prediction accuracy, reduced computation time, and saved model generation costs [26].

These technologies are indeed promising but their application encounters many difficulties. These challenges include the requirement and quality of data, data diversity, integration with existing systems and technologies, ethical and social considerations, as well as the continued need for research and development [26] [27]. Privacy and security issues are especially important, because AI in disaster management may require the collection and analysis of privacy-sensitive data [26].

In spite of these difficulties, AI models have been successful in dealing with non-linear and large datasets hence are fitting for disaster management and monitoring (Kamolov, 2024). Technologies and methods such as big data analysis, machine learning and deep learning can be used to visualize, analyze and predict natural disasters through developed system [26]-[28].

Good design and deployment of agent systems for disaster needs to take account of how efficiently and synergy agents can be harnessed for action. This requirement calls for an unambiguous responsibility assignment among the agents and making the organizational structure of the MAS explicit [15]. Future work includes detailed development of the components, especially the forecasting decision-making and warning dissemination components; and integration of systems with external databases using APIs [15]. The following Table1 show the all general challenges

C. General Technological Challenges and Limitations

1) Data-related challenges:

a) Quality and availability of data: AI models need high-quality and diverse data for effective prediction and management of disasters, but acquiring comprehensive disaster data is still difficult [26, 27].

b) Dynamic datasets: There are significant difficulties in dealing with data rapidly changing due to disasters especially with noisy, heterogeneous and limited annotations [8].

c) High dimensionality of data: Information integration from multiple sources are considered as a challenging task in view of the large volume of data which is high dimensional and extracting useful features from this data becomes challenging to learn profitable patterns for prediction [8].

d) Bias in training data: Training data can be biased and hence lead to biased prediction or predictions that are unfair against under-represented regions or communities [8].

2) Model development and accuracy issues: Unclear statistical definition of ‘extreme’ event, which is challenging for the AI models to capture, and thus a standardization is harder to achieve [8].

a) Accuracy limitations: Despite the promising capabilities of AI in processing the nonlinear data for disaster monitoring, attaining credible prediction accuracy still is a challenging task [26], [28].

b) Incorporation of physics models: Incorporating AI with classical model based physics is challenging though may improve the accuracy [8].

c) Generalization in other contexts: The AI solutions which are trained on specific types of disasters or location can face difficulty in performing well in other form of disaster contexts [8].

3) Trust and interpretability concerns: Advanced AI models often operate as “black boxes” that are not, or may not even be, interpretable, thus may not be acceptable for critical decision-making contexts [8].

a) Uncertainty quantification: Most AI models are not good at quantifying uncertainty in their predictions, which is important for disaster relief [8].

b) (iii) Stakeholder trust: It is a challenge in developing AI models which are trusted by the stakeholders and compliant with regulations [8].

c) Reluctance in implementation: Reluctance to utilize AI in disaster management settings is due to the uncertainty of reliability and fairness [8].

4) Operational and implementation challenges: Connecting AI systems to the current disaster management technologies and infrastructure is subject to numerous technical challenges [26], [27]. Real-time Data Integration: Real-time integration of data in rapidly evolving disaster scenarios is a technically challenging task [8].

a) Deployment brokers: There are many practical challenges to transition from research models to operational deployment in the field of disasters [8].

b) Interpretation by non-experts: AI outputs could be hard for non-expert stakeholders and decision makers to interpret [8].

5) Ethical and social considerations: Data Privacy and Security: The gathering and analysis of private data during disasters pose notable privacy challenges [26], [27]. Fairness and Equity: Ensuring that disaster management systems based on AI are fair and equitable for all affected communities is challenging [26], [27]. Ethical Guidelines: Comprehensive guidelines are required to support transparent and ethical use of AI insights in disaster decision-making [28]. Challenges: The disaster risk analysis community needs to be aware of pitfalls in AI solutions [24], [26].

D. Multi-Agent Systems for Disaster Management

The multi-agent system is an effective framework for disaster management because they are capable of solving complex, distributed problems through collaborative intelligence. These systems are common and have a lot of advantages and can provide distributed, parallel, collaborative, hybrid, flexible, recursive, adaptive, cooperative, and intelligent processing in scalable environments and can be good candidates for multiple facets of disaster management [22].

The main benefit of MAS is their macroscopic nature, in which knowledge and resource reasoning can be distributed among specialized agents [9], [29]. A typical MAS for disaster management integrates different sorts of agents which are specific agents, including situation assessment agents, resource agents, decision support agents, coordination agents, and prediction agents. Each agent is trained in its own way and can model multimodal or unimodal data. Among the tasks they perform are receiving and processing situation updates, resource optimization, decision options generation, emergency control coordination and disaster trajectory prediction [12]. The BDI reasoning architecture is an important component in many multi-Agent systems for disaster management. This approach offers a natural means to define agent behavior in unstructured environments which are described in terms of mental states influenced by decision-making [9]. Your approach seems to be very useful in dynamic disaster scenarios as agents can continue to follow goal driven paths, without having to recalculate from the beginning when the world changes. This reinforces the situation-awareness characteristics of agents, such as in the ability to observe a dangerous alarm, take an intelligent action and prepare preventive acti ons in situations with limited time [9].

In the latest years, novel MADRL architectures that fuse deep reinforcement learning with multi-agent systems have emerged. Such advanced systems are very useful in dealing with problems of uncertainty in disaster prediction and management. In MADRL, multiple agents compete to maximize their expected total discounted rewards under uncertain or noisy transition and reward models. (d) Agents estimate action values using multilayered neural networks as function approximators [15]. This kind of method appears to be very promising in flood forecasting since it copes with complex high-dimensional data and uncertainty. To deal with these issues, the combination of MARL algorithms, like actor-critic algorithms and DDPG algorithm, is introduced to fulfill these requirements [15].

The architecture features multilayer-based agents with each serving a different functionalities for disaster management. For example, a representation layer could model the environment as a series of entities, that evolve over time, and factual agents are able to sense those changes as described in domain ontologies [16]. This layered strategy allows the system to identify threats in ambiguous or only partially perceived environments, before they develop into crises.

Organizations in MAS on the one hand need to specify how agent roles should interoperate and interact, but also need a mechanism to enforce interacting of roles. This involves specifying roles for each agent and developing procedures for information-sharing and joint decision-making [15]. As an illustration, when agents apply intelligent, distributed, adaptive, and scalable processing that help them in order to come up with cooperation or collective decision they help in flood forecasting and warning systems [22].

One such effective integration is that of multi-agent systems with Anytime Algorithms, thus producing dependable, efficient distributed DSS. This indissoluble link has been particularly exploited in the context of flood disaster management, where agents cooperate to execute different activities are make consensus in an efficient way [22].

Multi-agent systems are especially beneficial for disaster management, but face challenges such as addressing issues of interoperability, coordination mechanisms and inconsistent information. Future work will be focused on improving certain aspects, such as forecast decision making and warning dissemination, as well as on connecting systems to the outside world through the cloud to be able to use data from any organization also providing capabilities for full disaster management [15].

E. Intellent Agents Application and Use Cases

1) Early warning and predicting systems: Smart agents have been widely used especially in early earthquake warning by means of pattern recognition and data mining. Among other applications, AI-based systems can help predict the occurrence of natural disasters (e.g., hurricanes) and forecast their paths using weather data, satellite images, social network activities, and geolocated information [30]. Wildfire risk assessment AI algorithms process historical records of weather and vegetation cover and human activities to predict area with high risk of a break [30]. Machine learning algorithms that are applied on big data sets can predict with better accuracy for efficient disaster risk management [31]. For example, underwater seismic monitoring systems extract acoustic radiation of seismic events in order to provide the early tsunamigenic alerts based on fault feature identification [32], [33].

2) Damage monitoring and assessment: The AI systems which are based on computer visions are able to offer indispensable powers for post-disaster damage assessment. Deep learning models can semantically infer the extent of damage in individual buildings from before and after disaster satellite images, thus automating a significant bottleneck in decision support in disaster response [1] [4]. Convo- lutional neural networks (CNNs) based change detection models can identify the most impacted regions from disasters, aiding in disaster management [1]. Segmentation of buildings and damages using airborne light detection and ranging (lidar) data has also reached high accuracy rates in the case of heavily damaged areas [1] [34].

TABLE I. TECHNOLOGICAL CHALLENGES

Papers	**[27]**	**[8]**	**[8]**
Technological Challenges	Technological challenges in AI for disaster risk management include data quality, system interoperability, and model transparency.	Challenges include data scarcity, model interpretability, and integrating AI with existing systems.	Developing accurate predictors from noisy, heterogeneous, small sample sizes.
Operational Limitations	Operational limitations in implementing AI for disaster management include computational resource constraints, integration challenges, real-time processing demands, explainability and transparency requirements, bias and fairness concerns, and issues of responsibility and accountability.	Noisy, heterogeneous data, limited data, real-time integration challenges.	Limited data, real-time integration, model understandability, stakeholder trust.
Data Requirements	High-quality, diverse, and real-time data are essential for effective AI application in disaster risk management.	High-quality, diverse, and real-time data are essential for effective AI applications in extreme event analysis.	Noisy, heterogeneous, small samples, limited annotations, real-time integration.
Risk Reduction And Preparedness [45]	AI plays a significant role in predicting disasters, optimizing response efforts, and improving preparedness by analyzing data and providing early warnings.	AI plays a crucial role in enhancing flood management systems, improving predictions, and communication strategies for better risk reduction and preparedness for natural disasters.	AI improves disaster response, communication, and enhances disaster readiness and risk reduction.
Model Reliability And Trust	Concerns related to the accuracy, transparency, and trustworthiness of AI models used in disaster risk management.	Challenges include accuracy, transparency, and trustworthiness of AI models in disaster risk management.	Accurate, transparent, and reliable models crucial for stakeholder trust.

3) Evacuation planning and operations: EvacuationSim and evacSim Intelligent agents under evacuation simulation may employ advanced modelling and route optimisation used in evacuation planning. And with emergency tools that integrate inundation maps with semantic segmentation, it provides more information to first responders pre-, during and post-hurricanes, and help them to gain more insights in human-level decision-making [35]. These systems process heterogeneous data with hydrological inundation models and computer vision techniques in order to serve stakeholders with timely, rich and accurate knowledge [35]. AI Agent-based simulations explore different evacuation strategies, facilitating early detection of risks and decisions on the optimal planning of evacuation routes [36].

4) Reaction systems autopoietic ones: Robots and automation have obtained a larger attention in disaster response. Flying machines can penetrate deep into disaster areas to survey the damage and supply aid [1]. Several robot generations have led to the development of more sophisticated machines, moving from robots that could hardly make decisions to those that are fully automated, intelligent and artificial [1]. Autonomous robots have been particularly utilized amidst the COVID-19 pandemic to support a number of response efforts [1][6]. Ground, aerial, surface and underwater swarm robots collecting big data of the environmental data at disaster-stricken sites, and then processed by deep learning model for object classification and decision making [1][37] Figure5.

5) Safety building and fire detection: AI's role in building safety AI applications in building safety are all about early detection and response to disasters such as a fire. The Smart Building and Town Disaster Management Systems based on augmented reality (AR) allow for visibility and tracking of the occupants during a building fire [1][7]. Physical-virtual linked (PVL) disaster management services via AR technology in buildings These systems provide visualization information and optimal guidance for initial rapid response by interweaving the physical and virtual space in the buildings [1][7] Figure6 . Convolutional Neural Networks Automatic fire recognition systems based on convolutional neural networks for fire detection in surveillance video respond and alert suitably [1][21].

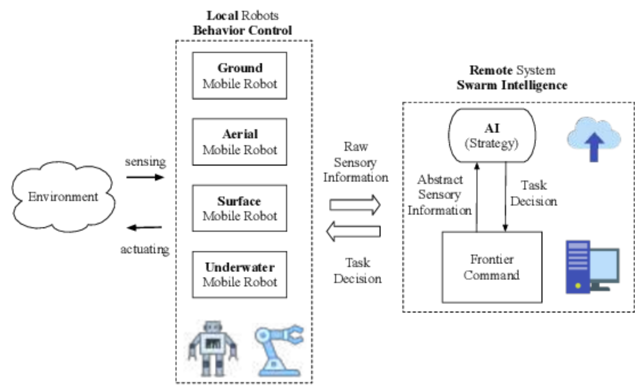

Fig. 5. Remote swarm AI and local robotic behaviour control.

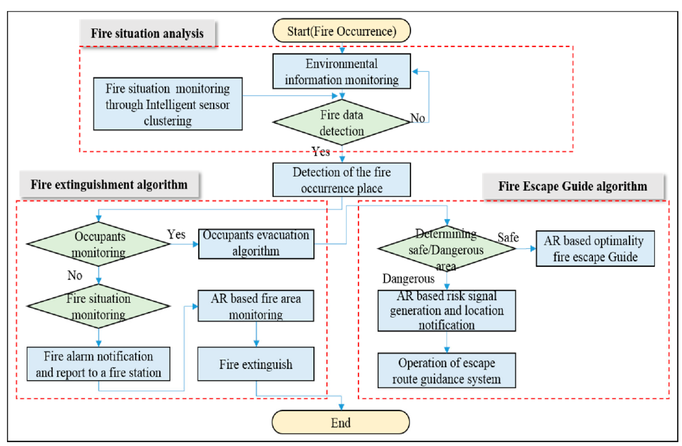

Fig. 6. The Fire extinguish and fire escape guidance algorithm.

6) Allocation of material and logistics: In climate related disasters, AI systems corner real time data regarding Effects of Disasters, Population dissemination, and Resources can utilized to optimize resource allocation [38]. These systems aid emergency responders in making rapid data-informed decisions about how best to allocate manpower, supplies, as wells as in prioritizing the rescue operations, indentifying the location of high-risk victims and the most vulnerable population in need of emergency help [38-40]. AI systems can give real-time situation updates, disaster location and intensity, and generate information about affected people and infrastructures and support logistics planning [30].

7) Simulated and training environments: Disaster-Rescue simulations are also a practical application area in which in silico tools are used to determine policies for emergency response and management in the physical world [39]. Such simulations have widely been adopted in academia, government, and industry for contingency peril anticipation, planning, and policy making [39]. Emergency simulation using AI Agent-based technology can provide a more realistic training of simulated victim care and in future will see a holistic approach to using the AI for training in more security personnel, gaining as close a simulated experience as possible to actual conditions [36].

8) Multi-hazard risk reduction: Then, more recently, AI applications have shown promise in better managing multiple-hazards, that are when two or more hazards occur at the same time and interact together to lead to larger scale impacts, or cascading hazard scenarios, that are when a first high-impact hazard sets off a successive chain of other hazards or events that spread through time, see [32][40]. Such applications can be considered in the context of building sustainable infrastructure, safer and resilient cities and human settlements complementing various Sustainable Development Goals [32].

F. Challenges in Deploing Intellent Agents

Despite their potential benefits, implementing intelligent agents for disaster management presents several significant challenges:

1) Data quality and availability: One challenge is simply getting enough great data to train the AI models. One of the challenges in disaster scenarios is there is usually either very little, unreliable or disparate data, which would make it difficult to train robust models to estimate the required predictions [27]. Learning to predict can be particularly difficult when dealing with noisy and heterogeneous data, in the presence of very limited annotations [8]. This is particularly a problem for rare events such as extreme weather events in which there may be an insufficient amount of historical data.

2) Privacy and security concerns: The application of AI in DRM generally means processing huge amounts of personal data, posing crucial issues for privacy and security [27]. Data privacy is a key concern as such systems collect and process sensitive data and privacy regulations and individual rights need to be taken into account[26]. Finding ways to collect data in a manner that is both robust and respects privacy continues to present difficulties.

3) Computational resource requirements: Numerous advanced AI methods, especially deep learning algorithms, require extensive computation resources [27]. This creates a problem in disaster areas especially in remote or inaccessible areas where computational infrastructure is either scarce or not available. Critical AI solutions that are needed most, when and where they are needed can be hampered by resource constraints.

4) Integration with existing systems: Smart agents should be able to seamlessly interoperate with existing service infrastructure for emergency management such as command and contro l centers, dispatch functions, and sensor networks [27]. Integration in turn is taken rather difficult by data structure and nature of systems that are heterogeneous making deployment cumbersome to implement [26].

5) Real-time performance requirements: Disaster situations require instant processing and analyzing massive datasets for quick response and situational awareness [27]. Finally, timely information integration is critical in immediate Response, which however is not an easy task [8]. Since time is of the essence in many disaster response scenarios, there is an inherent tradeoff between speed and accuracy.

6) Explainability and transparency: Intelligent predictive solutions for high-stake disaster scenarios should be transparent and explicable to gain trust from decision-makers [27]. Developing authentic, interpretable and trustworthy AI-models is not trivial [8]. First responders must be able to comprehend AI recommendations and their underlying rationales to meaningfully integrate such information into their decision processes.

7) Ethical implications: The broader ethical dimension of containing AI with respect to disaster management will also have to be addressed [26]. There are fears that unrestrained use of AI can have detrimental effects and may increase the potential impact of calamity if not properly regulated [2]. Ensuring that AI systems are designed and deployed in a manner that is fair and equitable and achieves impact on disaster reduction is a key challenge.

8) Local implementation challenges: There are particular challenges to using AI models to inform policy and decision-making at the local level, where effects of climate change are dynamic and location specific [41]. Local peculiarities might face specific priorities, facilities, and available resources and skills to deploy AI-based disaster management systems.

9) Risks of AI-Caused digital disasters: An unusual new worry is the possibility that AI systems might itself cause, or exacerbate, catastrophes. While [2] demonstrates the bright side of the AI in disaster management, the unlimited applications of the AI may face the transference of challenges and threats, which can turn the AI benefits into detriments and deteriorate disaster impacts. This risk calls for a prudent governance and overseeing of deploying AI in life threatening emergency systems.

G. Future Opportunities and Trends

Looking toward 2025, artificial intelligence applications, Intelligent Agents Figure7 in disaster risk management (Table II) are poised for significant advancement across multiple dimensions. The integration of AI with emerging technologies is expected to revolutionize how societies predict, respond to, and recover from disasters. One of the most promising developments is the continued refinement of prediction and early warning systems that analyze diverse data sources—including weather patterns, satellite imagery, and social media—to make increasingly accurate forecasts about natural disasters such as hurricanes, earthquakes, and tsunamis [27].

TABLE II. Summary of Methodologies, Technologies, Disaster Types, and Innovations in Disaster Risk Management Papers

Papers	Methodology	Technology Utilized	Disaster Types Addressed	Risk Management Strategies	Opportunities and Innovations	Case Studies or Examples
[1]	AI and GIS in disaster management.	AI, geospatial tech, GIS, remote sensing, ML.	Floods, earthquakes, virus outbreaks.	Risk assessment, mitigation, response by intelligent agents.	Innovations in intelligent agents for risk management.	Real-world AI applications in disaster management.
[35]	AI, geospatial data, semantic segmentation, ML for emergency response.	Open-source geospatial data, ML algorithms, computer vision, semantic segmentation.	Hurricanes, wildfires, earthquakes, other crisis events.	Geospatial encoding and route optimization.	Open-source geospatial data integration for emergency response.	Hurricane Florence in Lumberton, NC.
[6]	Visual analysis of 15 YouTube videos from 12 countries.	Autonomous robots, 4IR technologies.	COVID-19 pandemic.	4IR innovations to enhance disaster risk reduction.	Infrastructure improvements via 4IR innovation.	Analysis of 15 videos across 12 countries.
[37]	AIoT architecture with robots and deep learning.	AIoT, DL models, swarm robotics.	Fukushima nuclear disaster, Wenchuan earthquake, Taiwan disasters.	Data collection and decision-making with AIoT coordination.	Disaster response using AIoT and swarm robotics.	Fukushima and Wenchuan examples.
Park et al. (2018)	AR visualization, ICT integration, sensor-actuator linkages.	AR, ICT, sensors, actuators.	Fire disasters in buildings.	AR-based visualization and physical-virtual linkage.	Quick disaster response with AR guides.	Small AR-based testbed implementation.
Jung et al. (2020)	Big data and AI to support decision-making in disasters.	CNNs, GANs for detection; RL for wildfire prediction.	Wildfires, cold/heat waves, storms, floods, earthquakes.	Intelligent agent strategies for risk management.	New opportunities with CNNs and RL in risk management.	CNN used for automatic fire detection in surveillance videos.

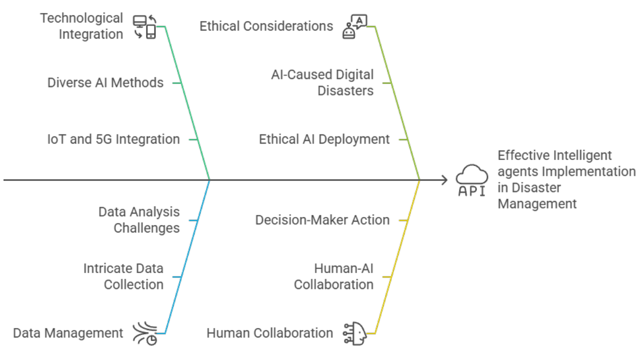

Fig. 7. Effective intelligent agents implementation in disaster management.

Automated damage assessment represents another area of significant future potential, with AI algorithms analyzing satellite imagery to rapidly evaluate disaster impacts and prioritize response efforts. This capability will be further enhanced through integration with unmanned aerial vehicles (UAVs), which can provide immediate visual data from affected areas, enabling faster and more targeted response [27]. The synergy between AI and UAVs extends beyond damage assessment to include the delivery of supplies and aid to affected communities, potentially transforming humanitarian logistics during disaster scenarios.

The convergence of AI with Internet of Things (IoT) devices and 5G networks is expected to create powerful new capabilities for real-time information gathering and rapid response coordination. These technologies working in concert will enable more comprehensive situational awareness and facilitate faster communication among response teams and affected populations [27]. This technological integration aligns with several United Nations Sustainable Development Goals, including SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 15 (Life on Land), by enhancing prediction capabilities and improving resource distribution to reduce disaster impacts [31].

Personalization of disaster response represents a significant emerging trend, with AI systems analyzing community-specific vulnerabilities to develop targeted interventions. This approach moves beyond one-size-fits-all disaster management toward strategies tailored to the unique needs and characteristics of affected populations [27]. Similarly, AI-driven resource allocation systems will optimize logistics and supply chain management during disasters, ensuring critical resources reach those most in need when traditional distribution channels are compromised [27]. Enhanced collaboration between humans and AI systems is expected to be a defining characteristic of future disaster management approaches. Technologies such as chatbots and voice assistants will facilitate communication between response organizations and affected communities, while AI systems will augment human responders' capabilities by providing real-time information, automating routine tasks, and reducing response times [27]. This represents a significant evolution from AI as merely an "enhancer factor" toward truly intelligent disaster management (IDM) systems that can address increasingly complex disaster scenarios [2].

The future of AI in disaster management must also address the growing complexity of modern disasters, including hybrid events and potentially AI-caused digital disasters. As conventional methods give way to AI-informed practices across all disaster phases—pre-disaster (predictions, risk assessments), in-disaster (classifications, modeling), and post-disaster (damage assessments, resource allocation)—the field will require new approaches that balance technological advancement with ethical considerations [2].

Despite these promising developments, challenges remain in implementing AI for disaster management, including diverse AI methods and hazards [44], intricate data collection processes, and ensuring decision-makers act on AI-generated information [31][42][43]. Addressing these challenges will require interdisciplinary collaboration among technologists, disaster management professionals, policymakers, and affected communities to develop systems that are both technologically sophisticated and contextually appropriate. As we move toward 2025, the trajectory of AI in disaster risk management points toward more integrated, responsive, and human-centered systems that leverage technological capabilities while remaining attentive to ethical considerations and sustainability goals. This evolution promises to transform disaster management from reactive response to proactive risk reduction, potentially saving countless lives and reducing the economic and social impacts of disasters worldwide.

IV. Conclusion

Artificial Intelligence (AI) and intelligent agents are catalysts for transforming the way we manage disaster risk and response, through their potential to enhance prediction, early warning, preparedness, real-time response and recovery. During the last decade AI technologies have advanced from self-contained, domain specific tools to integrated, adaptive systems that are up to the task to cope with growing complexity and urgency with which disaster scenarios are experienced around the globe. In particular, agents provide mechanisms for distributed decision-making, adaptability and autonomous coordination in disaster management systems, thus facilitating quick, scalable response to crises.

This systematic review has revealed significant progress made in utilising cutting-edge advances in machine learning and deep learning in order to forecast disasters, the use of robotics and UAV for damage assessment and search and rescue activities, natural language processing for real time social media analysis and geospatial data analytics for situational awareness. It has also drawn attention to the development of multi-agent learning techniques and deep reinforcement learning strategies as important solutions to handling dynamic and complex disaster environments.

But there are big holes and challenges. Quality and coverage of data still represent significant challenges, especially in low-resource settings and for rare types of disasters. Ethical considerations such as bias, privacy, and fairness remain important factors for the responsible use of AI in disasters. There is just as much pressing emphasis on technological challenges such as model interpretability, real-time performance, system interoperability and trust building among decision makers. Additionally, the changing nature of disasters — such as the development of hybrid crises and AI-facilitated digital disasters — calls for increasingly complex, humane, and ethically led AI solutions.

The future is promising as AI integrated with IoT, 5G technologies, autonomous systems and individualized analytics offer unprecedented opportunities to change the way disasters are managed. There is a trend towards more adaptable, anticipatory and resilient systems, being no longer a focus on only reacting to disasters, however looking at reducing risk and vulnerability. However, realizing this future vision will depend on multidisciplinary teamwork, ethical foresight, stakeholder engagement, and relentless innovation.

In summary, intelligent agents and artificial intelligence will change the way we will handle disaster risk management. By tackling the current technological and operational challenges and addressing the ethical dilemmas and risks, while building inclusive and sustainable innovation, AI has the potential to greatly improve global resilience and help protect human lives, the natural world and built infrastructural systems from an increasingly volatile and uncertain future.

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