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Artificial intelligence in humanitarian aid: A review and future research agenda

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ABSTRACT

As crises, both natural and man-made, continue to escalate in frequency and complexity, the need for effective and timely humanitarian interventions has become increasingly critical. Artificial intelligence (AI) has emerged as a transformative tool in enhancing humanitarian aid, addressing all stages of the crisis management cycle. Despite growing interest in AI's application within the humanitarian field, the existing literature remains fragmented, with limited synthesis of its overall impact. This study adopts a systematic literature review approach to provide a comprehensive analysis of AI's utilization in humanitarian aid across the crisis cycle, as well as its role in broader humanitarian settings outside of immediate crisis contexts. Based on 60 selected studies, the findings reveal that AI applications in both the pre- and post-crisis phases can be grouped into four specific categories, and that AI's role in broader humanitarian contexts can similarly be divided into four focus areas. Specifically, the categories in the pre-crisis phase include site selection, medical services enhancement, early warning, and information flow, and the categories in the post-crisis phase include distribution and delivery, damage assessment, online and textual insights, and routing optimization. The review highlights AI's significant potential to enhance the effectiveness and efficiency of humanitarian efforts, offering valuable insights for organizations seeking to harness AI's transformative power.

1. Introduction

The goal of artificial intelligence (AI) is to enable machines to emulate human thought processes, yet surpass human efficiency (Misselhorn, 2018). This involves endowing machines with the ability to autonomously collect and analyze information from their surroundings to perform tasks, make decisions, and solve problems-actions that typically require human reasoning (Brynjolfsson and McAfee, 2017; Von Krogh, 2018). The integration of AI into humanitarian aid marks a transformative shift in global relief efforts, offering unprecedented opportunities. With an increasing number of crises, both natural and man-made, the need for effective humanitarian assistance-which encompasses the provision of essential services and resources, including but not limited to, food, water, medical care, and shelter (Sahebjamnia et al., 2017)- is more critical than ever (Chin et al., 2024). If we consider the occurrence of natural disasters only, the year 2024 saw a total of 393 recorded events worldwide (EM-DAT, 2025). International humanitarian organizations frequently struggle to meet the needs of affected populations, often reaching less than half of those in need (Dubey et al., 2021). The success of humanitarian aid relies profoundly on timely and well-coordinated actions across all phases of a crisis: pre-crisis forecasting, mitigation and preparation, in-crisis response, and post-crisis recovery (Sperling and Schryen, 2022). AI has emerged as a powerful tool in addressing the significant challenges faced by the humanitarian sector, offering exceptional possibilities by augmenting human capabilities to predict, respond to, and mitigate the impacts of crises more effectively (De Boeck et al., 2023).

An increasing body of literature has started to explore the diverse applications of AI in the humanitarian field as scholars have begun to map out the way AI can revolutionize disaster preparedness, response, and recovery, while also examining its role in humanitarian work outside the immediate crisis cycle, such as the willingness to adopt AI technologies in humanitarian aid (e.g., Behl et al., 2022a). Despite growing interest, the emerging literature is becoming fragmented, with studies often focusing only on a specific phase of the cycle or one specific aspect of relief support (e.g., Wang et al., 2024). Because studies have

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approached AI in humanitarian aid from various perspectives, utilizing different AI methodologies, this has resulted in a lack of cohesion in the findings of the topic. To provide a comprehensive and cohesive understanding of the AI-humanitarian aid nexus, which is very important considering how heavily the world relies on aid being effective every time a crisis occurs, it is vital to synthesize the existing literature, identify key themes, and highlight both gaps and successes. Therefore, this systematic literature review aims to answer the following two key research questions: RQ1 "How is AI utilized in humanitarian aid across the crisis cycle?", and RQ2: "How has AI been connected to humanitarian aid outside the crisis cycle?"

By addressing these questions, this study will provide an extensive overview of the current state of knowledge on the AI-humanitarian aid nexus and outline a roadmap for future research to further advance this critical field. It will also provide practical insights for humanitarian organizations, offering guidance on how AI can be harnessed to improve aid efforts. In addition, it will examine ethical, governance, and bias-related considerations to support the responsible and equitable use of AI in humanitarian contexts. Given the rapid evolution of AI technology and the increasing frequency of complex crises, the present is the ideal time to examine the literature on the AI-humanitarian aid nexus. To the best of our knowledge, this is the first attempt to provide a comprehensive review of AI and humanitarian aid that encompasses all types of crises. Determining how AI has been applied in different crisis phases-preparedness, response, and recovery-will help delineate where AI shows significant potential and where its application remains limited. Therefore, by studying the scope of AI within humanitarian contexts, this review serves as a valuable resource for both researchers and practitioners seeking to enhance the effectiveness of humanitarian aid.

2. AI and humanitarian aid

The field of AI is vast and continues to expand, encompassing a wide range of computer-based systems and applications designed to perceive, interpret, and learn from experiences, thereby enhancing human capabilities. This allows systems to achieve performance levels beyond people's abilities and enables robots to perform tasks that may be hazardous for humans (Ahmed et al., 2022). AI is often associated with popular terms such as machine learning, deep learning, neural networks, optimization techniques, predictive analytics, natural language processing, computer vision, expert systems, robotics, autonomous systems, and more (e.g., Karimiziarani and Moradkhani, 2023; Madianou, 2021; Pereira et al., 2023). It has many broad areas, and each area contains specific subfields and techniques. For example, machine learning encompasses reinforcement learning, supervised learning, and unsupervised learning. Deep learning, a subset of machine learning, typically operates within these three paradigms, most commonly supervised and unsupervised learning, by using multi-layered neural networks to automatically learn representations from large datasets (Trigka and Dritsas, 2025). Computer vision includes recognition, tracking, and detection, while natural language processing covers applications like sentiment analysis. A notable interdisciplinary application that combines computer vision and natural language processing, while relying heavily on deep learning, is text-to-image generation, where models synthesize images from textual descriptions (Ramzan et al., 2022). Additionally, soft computing is a broad field that incorporates techniques for handling uncertainty and approximation, including fuzzy logic systems and evolutionary algorithms (Ahmed et al., 2022; Chakraverty et al., 2019).

AI holds significant potential to revolutionize humanitarian aid, which is considered a malleable concept that spans a variety of activities (Paulmann, 2013). The effectiveness of humanitarian aid is closely linked to its ability to manage crises efficiently across different stages of the crisis management cycle. This cycle, also known as emergency management or disaster management lifecycle, includes stages such as preparedness, response, and recovery. Some frameworks further incorporate resilience-building, mitigation, risk reduction, and prevention. Over time, this framework, which is widely used in the literature, has evolved through the contributions of scholars, practitioners, and organizations (Bamforth, 2017; Dorasamy et al., 2013). The stages of this cycle represent a continuous process aimed at minimizing the impact of crises and ensuring effective response and recovery efforts. The preparedness stage, i.e. the pre-disaster phase, emphasizes systematic preparation for future contingencies, involving collaborative efforts that must adapt to changing circumstances (Alexander, 2015). The response stage focuses on immediate actions taken during and shortly after a crisis to manage its impact, while the recovery stage involves rebuilding and restoring communities to their pre-disaster conditions (Alexander, 2015; Canton, 2019). Since the response stage also addresses post-crisis needs, like recovery albeit at different times, these two stages are often grouped under the broader post-crisis phase (Wei et al., 2020).

As the humanitarian sector evolves, integrating modern technologies like AI will be crucial in tackling the complex challenges posed by contemporary crises. For example, in the pre-crisis phase, predictive analytics and machine learning can improve risk assessment and early warning systems by identifying patterns, predicting potential disasters, and anticipating resource needs (Linardos et al., 2022). Rodríguez et al. (2010) note that it is critical that humanitarian action be undertaken not only once a disaster occurs, but also before it happens. Once a crisis unfolds, AI-driven tools such as computer vision and natural language processing can help prioritize areas for intervention and streamline resource distribution (Alam et al., 2020). AI also plays a key role in recovery efforts by analyzing data and optimizing resource allocation, leading to quicker and more effective reconstruction (Shin et al., 2019). Therefore, although humanitarian aid is primarily associated with the post-crisis phase, as its definition often encompasses assisting people in distress (Rose et al., 2013), AI's applicability can be seen across all stages of crisis or disaster management (Behl et al., 2022a), making the distinction between phases relevant to attain an overview of AI in humanitarian aid. Recognizing the different perspectives on the AI-humanitarian aid nexus in the literature informed the planning of our first research question (Tranfield et al., 2003), which aims to review how existing literature on the application of AI in humanitarian aid is distributed between the pre-crisis (preparedness) and post-crisis phases (response and recovery).

While the topic of 'AI and humanitarian aid' is closely linked to the disaster management cycle, it also extends beyond this framework. Although the role of AI in disaster management is crucial, understanding its broader implications in humanitarian contexts is equally important. For example, the success of AI applications in humanitarian aid may be influenced by ethical considerations, public perception, and the willingness to adopt the technologies. Within the domain of ethics, for instance, it is essential to determine whether appropriate frameworks exist for auditing AI systems in humanitarian contexts to ensure interpretability, accountability, fairness, human oversight, and rigorous quality and bias checks. This will help prevent the deployment of opaque or biased systems that could undermine trust, reinforce existing inequalities, or fail to deliver meaningful benefits to vulnerable populations (Gevaert et al., 2024). This broader perspective led to the development of our second research question which explores how the literature addresses the connection between AI and humanitarian aid outside the crisis management cycle. Engaging with these issues will provide a comprehensive understanding of the relationship between AI and humanitarian aid, both within and beyond the disaster management framework.

3. Methodology

3.1. Procedure and selection of articles

To rigorously evaluate the existing literature and address our two research questions, we conducted a systematic literature review (SLR) following an evidence-informed approach recommended by Tranfield et al. (2003). A SLR is effective for identifying, assessing, and synthesizing all the available literature on a topic through a transparent and reproducible process (Fan et al., 2022), making it a suitable method for achieving the objectives of this study. The first stage of our methodology included planning the review. Upon recognizing the need for the review, the authors collaborated to establish the review protocol, which outlined the search strategy for determining which studies to include or exclude in the research. Through consensus, we identified the search terms and decided on the databases for the data collection.

The second stage of our methodology involved conducting a literature search using EBSCO host's Business Source Ultimate, Scopus, IEEE Xplore, and Web of Science Core Collection to ensure methodological rigor. Together, these databases, encompass a broad range of relevant and recognized journals. The approach of using more than one database aligns with practices observed in similar systematic reviews (e.g., Lythreatis et al., 2022; Shneor and Vik, 2020). The searches were performed using the keyword combinations "artificial intelligence and humanitarian aid" OR "AI and humanitarian aid" OR "artificial intelligence and humanitarian assistance" OR "AI and humanitarian assistance". We applied SmartText searching and expanders to get related words and equivalent subjects in our search. Examples include terms such as disaster relief, humanitarian intervention, machine learning, disaster prevention, and humanitarian action (see Table 2 in the supplementary document for notes on equivalent terms). The final search was conducted in May 2025 without time restrictions to ensure the inclusion of all potentially relevant studies. The initial search in the databases produced 4993 documents. The results were subsequently refined by limiting the search to articles that were written in the English language and published in academic journals (Lythreatis et al., 2022). This resulted in 1328 articles. Subsequently, following popular approaches (e.g., Acar et al., 2019; Votto et al., 2021), we analyzed the titles and abstracts, removing irrelevant articles and duplicates. This process reduced the number to 125 articles. The next step involved reading the full texts of the remaining articles for a detailed assessment and excluding those that did not align with our research questions (Tranfield et al., 2003), narrowing the sample down to 58 articles. Two additional studies were identified through cross-referencing, resulting in a final sample of 60 articles (see Fig. 1).

In line with Tranfield et al. (2003)'s recommendations, to minimize human bias and error, we formed a data-extraction sheet that recorded information about each article, including the title, authors' names, year of publication, publication journal, research aim, type of AI technology covered, context, study nature, and summary of main findings. It served as the repository for descriptive coding, forming the basis of our initial article classification. This structured data extraction table represents the first layer of our coding framework (see Table 3 in the supplementary document for the coding guidebook).

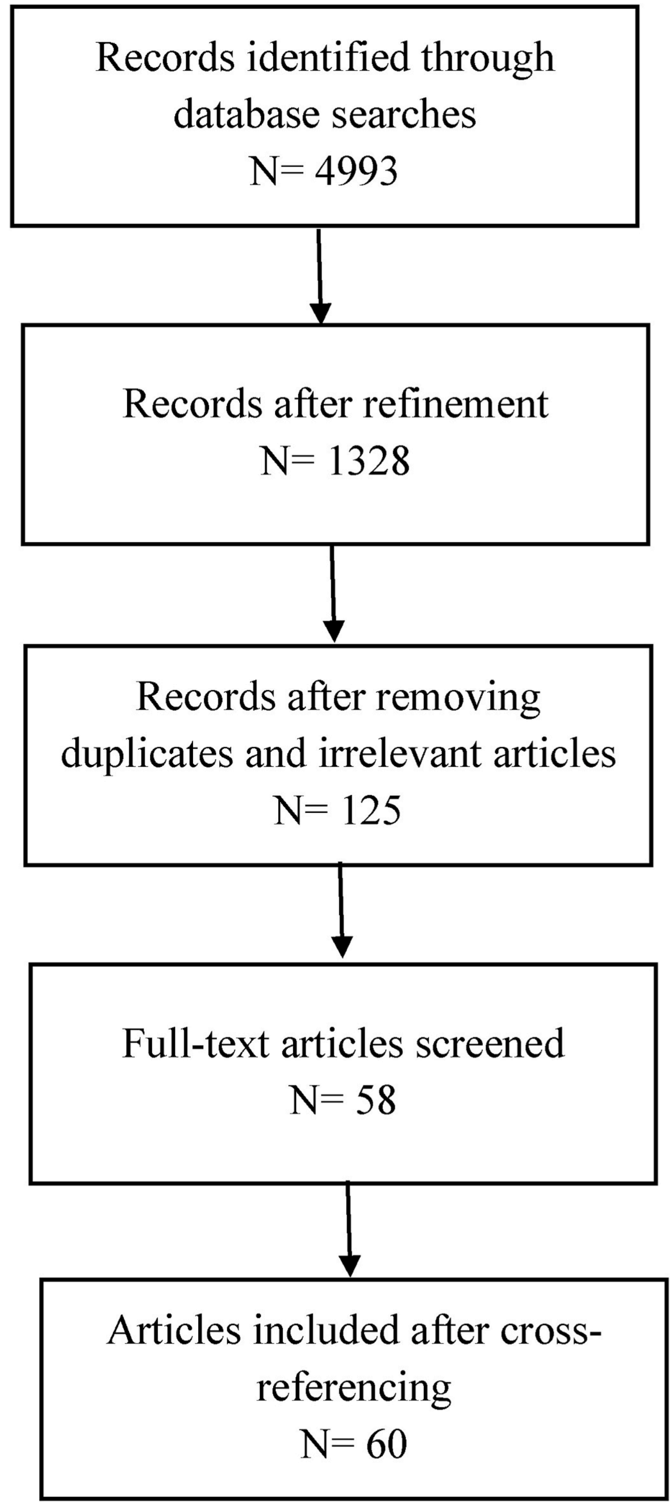

Fig. 1. Literature search process.

3.2. Data analysis and synthesis

The third stage of our review process involved the analysis and synthesis of data (Tranfield et al., 2003). We employed Mayring's (2014) structuring content analysis approach, chosen for its ability to systematically reduce large text data by organizing the material into cohesive categories of unified themes. This category-based coding approach is well-regarded and widely used in research (e.g., Hanelt et al., 2021; Lythreatis et al., 2022). It entails five key steps: (1) developing a category system derived from the research questions, (2) coding relevant text passages according to this category system, (3) refining the created classification framework, (4) re-coding the text using the updated categories, and (5) analyzing and discussing the results. Accordingly, we began by deductively deriving the main categories from the literature to answer our research questions. We then refined the category system by subdividing the developed categories (Mayring, 2014). This coding was performed by two researchers, with discrepancies resolved through discussion to ensure reliability and consistency in the analysis.

In alignment with our research questions, we formed 'AI applications in humanitarian aid pre-crisis', 'AI applications in humanitarian aid post-crisis', and 'AI in broader humanitarian contexts' as the original categories. We then used the key constructs and findings from each article and revised the category system by splitting the initial categories into sub-categories that more specifically represented the articles (Mayring, 2014). For example, the 'AI applications in humanitarian aid post-crisis' category was split into the sub-categories of **Distribution and Delivery**, **Damage Assessment**, **Online and Textual Insights**, and **Routing Optimization**. After applying these sub-categories, we again revised the system by breaking down the sub-categories into more specific features of the studies. For example, the **Routing Optimization** sub-category includes *Fairness Optimization* and *Delay Minimization*. The final coding schema, including all categories, sub-categories, and illustrative examples, is demonstrated in Fig. 3 in the next section, where we present the review findings.

4. Findings

4.1. Descriptive analysis

As shown in Fig. 2, the intersection of AI and humanitarian aid remains an emerging area of research. A clear observation in the publication timeline is a significant increase in studies from 2020. Specifically, only 14 studies were identified prior to 2020, while 46 have been published since, indicating that the volume of research has more than tripled in recent years. The most substantial growth has occurred in the last three years, with 8 studies published in 2022, 11 in 2023, and 14 in 2024. We have also already identified 5 articles for 2025. Notably, only two studies were published before 2015, underscoring that the application of AI in the humanitarian field is a relatively recent development. This surge in research activity may be attributed to the rapid advancements in AI technologies such as machine learning, deep learning, and natural language processing, which have progressed significantly since the year 2010 (Trappey et al., 2020).

In terms of publication outlets, a significant proportion of the articles were published in journals focused on operations research. Additionally, as expected, the majority of the studies (75 %) employed a quantitative research approach, while six studies utilized a mixed-methods approach. Regarding the AI technologies used in the studies, machine learning and its various subfields were predominant, with 18 studies employing these techniques. Just over half of the articles (31 studies) focused exclusively on natural disasters as the crisis type. A list of our sample, including the authors' names, publication year, publication outlet, research approach, and specific AI aspect considered, is provided in Table 1 in the supplementary document.

4.2. AI application in humanitarian aid across the crisis cycle

To examine how AI has been applied across and outside the crisis cycle, we developed three initial categories: 'AI applications in humanitarian aid pre-crisis', 'AI applications in humanitarian aid post-crisis', and 'AI in broader humanitarian contexts'. The category 'AI applications in humanitarian aid pre-crisis' focuses on preparedness activities designed to mitigate potential crises and respond effectively when a disaster occurs. Our review found sixteen studies that fall into this category, highlighting various ways AI has been applied to enhance crisis readiness. Based on their specific topics, these studies were grouped into four sub-categories: **Information Flow**, **Site Selection**, **Early Warning**, and **Medical Service Enhancement**.

The sub-category **Information Flow** was dominant, encompassing eight studies. These studies emphasize the role of AI in enhancing the coordination, communication, and decision-making processes among humanitarian actors. Within this sub-category, *Coordination* and *Management Frameworks* stood out as focus areas, both reflecting the centrality of AI in structuring how humanitarian actors exchange, interpret, and act on information before crises unfold. For example, within *Coordination*, Shayganmehr et al. (2024) developed a hierarchical fuzzy expert system to assess the readiness of aid organizations in terms of trust and coordination. In parallel, other studies proposed innovative *management frameworks*, such as Gupta et al. (2022), who introduced a cloud-based AI system to predict outcomes and design robust disaster management strategies through algorithm-based communication. Complementing these efforts, other studies addressed *Integration Systems*, exploring cross-sectoral information exchange. Trusilo and Danks (2023) investigated the integration of AI with military intelligence systems to improve humanitarian notification processes, while Chin et al. (2024) explored how AI and human intelligence can work together as a cross-cultural knowledge-creation system to improve decision-making processes in international humanitarian logistics. Further studies included in this sub-category are illustrated in Fig. 3.

Site Selection was the second most represented sub-category in the pre-crisis stage, comprising four studies focused on optimizing the placement of critical resources. Wang et al. (2024) developed an AI model using machine learning techniques, specifically Variational Graph Autoencoder and Random Forest, for the proactive planning and selection of emergency shelter locations based on urban demand factors, while Florez et al. (2015) created a decision-making support model using AI to effectively store and position relief items for disasters. Jafarian et al. (2025) employed a fuzzy inference system to support dynamic decisions around shelter activation and evacuation routing.

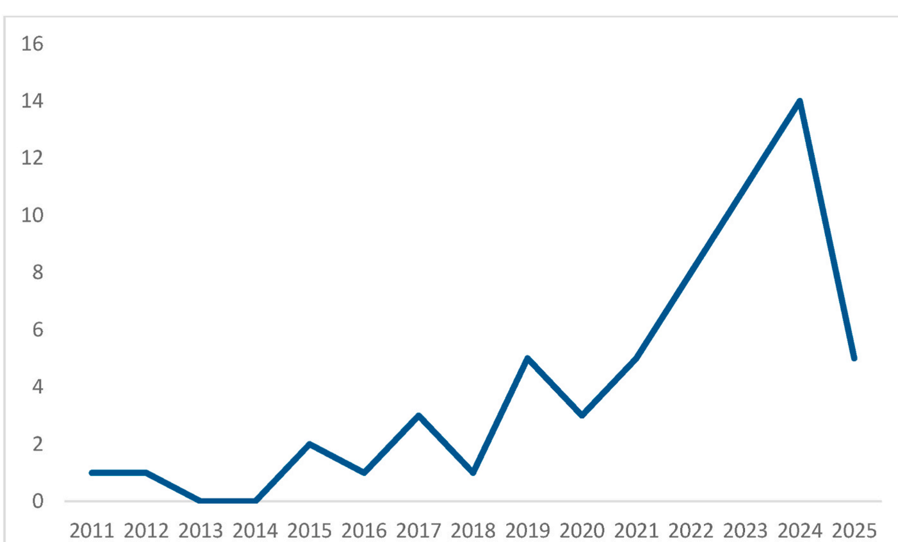

Fig. 2. Year of publication for the sample.

The sub-category **Early Warning** included two studies that detect and monitor the emergence of disasters. Isaev et al. (2024) used machine learning, specifically the XGBoost Regressor algorithm, for a forecast-based preparedness strategy that activates before an agricultural crisis emerges to protect food security and livelihoods in vulnerable regions. Sufi and Khalil (2022) employed Natural Language Processing to analyze multilingual tweets to extract location-specific sentiments to determine where possible disasters may occur.

In the **Medical Service Enhancement** sub-category, we identified a study related to *demand forecasting* and another to *event prediction*. Abreu et al. (2023) proposed a data-driven forecasting method using neural networks to predict emergency medical service demands, thus improving response planning, while Grekousis and Liu (2019) introduced a three-level, spatial-based forecasting approach, integrating artificial neural networks and evolutionary algorithms to predict future emergency medical events and enhance response efficiency.

The category 'AI applications in humanitarian aid post-crisis' encompasses various activities aimed at alleviating the aftermath of crises through efficiently allocating different resources to those in need, assessing damage, and supporting recovery efforts. Our review identified thirty studies that fall into this category, demonstrating the different ways AI has been applied to improve post-crisis response and recovery. These studies were organized into four sub-categories according to their specific focus areas: **Distribution and Delivery**, **Damage Assessment**, **Online and Textual Insights**, and **Routing Optimization**, each reflecting distinct yet interconnected aspects of AI's role in post-crisis humanitarian efforts.

Distribution and Delivery emerged as an important sub-category in this phase, with nine studies showcasing the critical role of AI in optimizing the logistics of relief efforts. These studies demonstrated AI's capacity to enhance the efficiency and timeliness of resource distribution, from Biswas et al. (2024)'s AI-based framework for targeting areas that are most at risk or in urgent need to Jana et al. (2022)'s probabilistic fuzzy goal programming model that refined the transportation of supplies. Other examples include Sahebjamnia et al. (2017) who designed a Hybrid Decision Support System that integrates a simulator, rule-based inference engine, and knowledge-based system to enhance the distribution of relief items during large-scale disasters, and Fikar et al. (2016) who combined agent-based simulation with heuristic and metaheuristic techniques to enhance the distribution of relief supplies by routing them through transfer points to reach the areas in need. Whilst most studies in this sub-category focused on *Distribution Strategies*, three addressed *Delivery Optimization*. For example, Shin et al. (2019) applied Ant Colony Optimization to improve the scheduling of relief deliveries across crisis-affected road networks. Collectively, these studies underscore AI's potential to streamline logistical operations and ensure that aid reaches those in need more effectively. Refer to Fig. 3 for additional studies included in this sub-category and its subdivisions.

The **Damage Assessment** sub-category had the highest number of studies in the post-crisis phase, with ten leveraging AI to evaluate the impacts of disasters, a crucial step in directing relief efforts and helping with recovery and rebuilding. Key thematic features within this sub-category include Damage Detection, Structural Integrity, and Visualization. Within *Damage Detection*, Rodríguez et al. (2011), the earliest study in our sample, developed a decision support system using fuzzy rule-based AI techniques for disaster severity assessment, aiding the implementation of humanitarian response efforts. In a subsequent study, Rodríguez et al. (2012) created a system employing inductive rule-building and a knowledge-based approach to assess damage across various disaster scenarios, providing technological support for humanitarian non-governmental organizations (NGOs). Quinn et al. (2018) utilized machine learning and deep learning methods to analyze remote sensing imagery for assessing structural damage in inaccessible areas. More recently, Zhao et al. (2024) applied AI foundation models to enhance the speed and effectiveness of post-disaster assessments in the Gaza Strip. In the *Structural Integrity* subdivision, Galera-Zarco and Floros (2023) developed a deep learning model to assess building structural integrity after disasters, integrating AI with Building Information Modelling for rapid and accurate evaluations, thus enhancing decision-making and efficiency in humanitarian aid. Additionally, within *Visualization*, Alkhateeb et al. (2024) used a text-to-image AI model to reconstruct post-conflict landscapes in a Syrian city, aiding community rehabilitation. Together, these AI-driven applications not only support immediate humanitarian response but also inform long-term recovery planning.

The **Online and Textual Insights** sub-category, comprising nine studies, examined how AI can be utilized to analyze various types of data to enhance crisis response. Robertson et al. (2019) concentrated on classifying social media images to prioritize urgent needs during disasters, and Alam et al. (2020) explored how AI techniques from Natural Language Processing and Computer Vision can be used to process and interpret both textual and visual data from Twitter to improve response during disasters. These studies underscore AI's capability to leverage data to provide real-time insights, thereby improving the effectiveness of humanitarian actions. In addition, Marutschke et al. (2024) created an AI-based language model to analyze qualitative texts on social capital formation in post-crisis recovery, providing insights into community development following disasters.

Finally, the **Routing Optimization** sub-category saw the least number of articles in the 'AI applications in humanitarian aid post-crisis' category, with two studies that concentrated on optimizing the logistics of emergency services, focusing on *fairness optimization* and *delay minimization*. Aringhieri et al. (2022) used machine learning within a hybrid algorithm to optimize ambulance routes for transporting patients during a disaster to ensure fairness and equity, while Tikani and Setak (2019) developed optimization algorithms to minimize delays in ambulance services and efficiently route ambulances.

4.3. AI in humanitarian aid outside the crisis cycle

The category 'AI in broader humanitarian contexts' encompasses fourteen studies, revealing diverse considerations of the AI-humanitarian aid nexus, without focusing on any particular phase of the crisis cycle. These studies are organized into four sub-categories: **Ethics and Risks**, **Food Banks**, **Acceptance and Adoption**, and **Impact.**

The sub-category **Ethics and Risks** underscores the importance of addressing ethical concerns associated with AI in humanitarian contexts. Our review identified seven studies focusing on this aspect, making it the most prominent sub-category within the broader context of AI in humanitarian aid. The studies highlight critical issues such as algorithmic bias, data privacy, surveillance, fairness, accountability, transparency, injustice, and ethical misalignment of AI implementation within humanitarian aid. For example, Kreutzer et al. (2019) proposed a Natural Language Processing-based framework for humanitarian needs assessments, integrating technical design with practical and ethical safeguards to improve qualitative data use while addressing infrastructural limits, data bias, and governance challenges in crisis settings. Madianou (2021) critiqued the ethical implications of AI chatbots in humanitarian contexts, exposing how they often reproduce power asymmetries, cultural insensitivity, and data risks while failing to deliver meaningful accountability or participation for affected communities. Additionally, Guillén and Teodoro (2023) outlined eight key ethical requirements for AI predictive tools in humanitarian settings. The focus areas and further studies in this sub-category can be seen in Fig. 3.

The **Acceptance and Adoption** sub-category explores perceptions of AI and the readiness to embrace this technology. Kankanamge et al. (2021) investigated public perceptions of AI applications in humanitarian aid to understand differences in appreciation across age, education, and professional roles. Behl et al. (2022a) explored factors that affect the willingness and readiness of government agencies to adopt AI technologies for disaster relief operations.

Fig. 3. Findings (Alqithami, 2025; Amani et al., 2025; Behl et al., 2022b; Chen et al., 2025; Frank et al., 2017; Nguyen et al., 2023; Othman et al., 2017; Pereira & Shafique, 2024; Rodríguez-Espíndola et al., 2020; van Steenbergen et al., 2023; Xiu et al., 2023).

The two studies in the **Food Banks** sub-category address the *logistics* and *predictions* of food distribution. Applying convolutional neural networks and reinforcement learning, Wu and Tai (2024) focused on enhancing the efficiency and effectiveness of inbound logistics in humanitarian organizations, specifically food banks, by improving food quality management and warehousing. Brock and Davis (2015) compared various methods for predicting food donations to food banks and found that using advanced neural network models offered the highest accuracy.

Lastly, the **Impact** sub-category assesses how AI influences the transparency, sustainability, and overall effectiveness of humanitarian aid. Khan et al. (2022) and Dubey et al. (2022) analyzed AI's role in enhancing aid transparency and sustainability, while Guerrero et al. (2023) evaluated AI's contribution to achieving the Sustainable Development Goals (SDGs) across various countries.

5. Discussion and contribution

The findings of this review answered our first research question "How is AI utilized in humanitarian aid across the crisis cycle?" The results reveal that AI applications can be divided into two key phases: the pre-crisis phase, which focuses on enhancing preparedness, and the post-crisis phase, which involves response and recovery efforts. Each of these can be further categorized into four groups based on focus.

In the pre-crisis phase, the findings indicate that most existing literature on the AI-humanitarian aid nexus has been related to how AI can help improve the information flow among humanitarian actors, contributing to more efficient aid delivery. This emphasis is crucial, as effective coordination is recognized as a cornerstone of successful humanitarian operations (Moshtari and Gonçalves, 2017). The focus on information flow highlights the sector's recognition that streamlined communication is essential when a crisis unfolds.

It was surprising to find only two studies that applied AI for emergency medical enhancement in the pre-crisis category, despite AI's extensive role in the broader medical field in the literature. Given AI's demonstrated capabilities in predictive analytics and demand forecasting in healthcare, this limited representation suggests a significant research gap in applying these strengths to humanitarian preparedness. Equally unexpected was finding only two studies that leveraged AI for early warning or crisis forecasting, considering that one of AI's core advantages lies in detecting early indicators and signals (Isaev et al., 2024). Nevertheless, the identification of sixteen studies exploring AI's role in preparedness underscores the increasing appreciation of its importance in humanitarian aid. This trend aligns with existing literature emphasizing that preparedness is critical to the success of humanitarian interventions (e.g., Frennesson et al., 2021). Notably, the emphasis on the pre-crisis phase has been more recent compared to AI applications in post-crisis scenarios.

In the post-crisis phase, the review reveals a greater number of studies exploring AI's application in response and recovery efforts, nearly double those found in the pre-crisis stage. While particular focus has been placed on AI's role in optimizing the logistics of relief resource distribution and deriving insights from online sources, damage assessment accounted for the majority of studies. In fact, it was the largest subcategory in our analysis. The studies assessing damage demonstrate AI's diverse capabilities, not only in responding to crises but also in guiding recovery processes. This broader integration of advanced AI techniques in humanitarian aid specifically highlights AI's potential to revolutionize recovery planning by providing more accurate and timely insights into structural integrity and the scale of damage (e.g., Galera-Zarco and Floros, 2023).

Additionally, the review illustrates that a wide range of AI techniques and tools, including innovative frameworks, have been applied across different areas of the humanitarian sector, rather than relying on just a few approaches. A significant proportion of the studies included in this SLR employed machine learning and deep learning methods, reflecting the dominance of these approaches over other forms of AI. Nevertheless, in some cases, multiple AI techniques were combined, sometimes two or three, to create novel frameworks that effectively measure preparedness, response, and recovery (e.g., Sahebjamnia et al., 2017; Wang et al., 2024). This demonstrates the versatility and adaptability of AI in addressing the complex and dynamic challenges of the humanitarian sector. The combination of AI techniques also shows the ability of this technology to tailor humanitarian efforts to specific needs and contexts, increasing the likelihood of more effective and contextually relevant humanitarian interventions.

Moreover, the review highlights the power of AI in leveraging social media data, which not only aids in predicting crises but also ensures faster and more effective responses (e.g., Alam et al., 2020; Sufi and Khalil, 2022). These social media-related studies emphasize AI's ability to deliver valuable real-time insights, thus enhancing decision-making processes and significantly improving the efficiency of humanitarian operations. Notably, X (Twitter) emerged as the most commonly used social media platform in these studies, underscoring its role as a rich source of timely, crowdsourced information for crisis monitoring and response.

The findings also answered our second research question: "How has AI been connected to humanitarian aid outside the crisis cycle?" Compared to studies focused on the different stages of the crisis management framework, those examining AI connections beyond the immediate crisis cycle were fewer in number. Within this domain, four primary focus areas emerged, with ethics and risks being prevalent themes. The focus on ethical considerations in the AI-humanitarian aid nexus reflects a growing awareness of the need to balance technological advancement with moral and societal concerns. However, unlike the other sub-categories, there is a noticeable lack of practical applications of AI in this group. In addition, a surprising observation is that despite the critical role of perceptions and attitudes of individuals in successfully adopting new technologies (Lai, 2017), only two studies in the sample examined this aspect. Moreover, while AI's contribution to achieving the SDGs is widely recognized in the broader literature, only one study in this review explored AI's impact on SDGs in the context of humanitarian aid.

Several studies that focused on ethics and risks raised concerns about data quality and geographic bias in humanitarian AI, particularly the overrepresentation of Global North contexts. Guillén and Teodoro (2023) emphasized the risks of poor-quality, non-representative data and argued for oversight to reduce bias and Beduschi (2022) warned of AI reinforcing global inequalities due to limited contextual testing in the Global South. Gevaert et al. (2021) similarly noted incomplete geospatial data in low- and middle-income countries and called for inclusive, localized evaluation, while Madianou (2021) illustrated these issues through failures of chatbot systems in refugee camps in Kenya and Lebanon. Similarly, Kreutzer et al. (2019) discussed low-resource language gaps and proposed technical solutions including community-sourced datasets, offline-compatible tools, and collaboration with local stakeholders. They also connected their NLP work to broader governance standards in AI ethics. Gevaert et al. (2024) audited building map datasets used in Tanzania and the Philippines, applying statistical fairness frameworks, including equality of opportunity and predictive parity, adapted from the broader Trustworthy AI literature, and found discrepancies by geography. This underscores the importance of dataset auditing before deployment in humanitarian contexts. Understanding these concerns is crucial to ensure that humanitarian AI systems are effective for diverse regions, especially in the Global South.

Outside the ethics-focused sub-category, Weber et al. (2023) reported that their AI system performed better on images from Europe than on those from Africa or Asia, though they did not explore mitigation strategies. A key observation is that most studies in our sample acknowledged dataset bias without proposing cleaning mechanisms (e.g., Alkhateeb et al., 2024; Quinn et al., 2018). Zhao et al. (2024), however, claimed to mitigate bias from global datasets by using region-specific pretrained models for crisis mapping in Gaza. In addition, while some studies evaluated AI across multiple disaster datasets (e.g., Gevaert et al., 2024; Kreutzer et al., 2019; Mao et al., 2024), very few tested performance across crisis types. Bansal et al. (2021) tested their classifier on various disasters, but their summarization model remains untested on new disaster types like pandemics.

Moreover, several studies advocated for frameworks that integrate human judgment to enhance AI effectiveness and accountability. For instance, Chin et al. (2024) proposed an integrated framework for combining human and machine intelligence in humanitarian logistics, while Polushko et al. (2024) introduced a semi-automatic, human-in-the-loop strategy for labeling flood imagery, highlighting the need for human validation to improve data quality and model reliability. A number of other studies also acknowledged the importance of maintaining human oversight to mitigate bias (e.g., Biswas et al., 2024; Guillén and Teodoro, 2023; Kreutzer et al., 2019; Veber, 2024). However, this consensus is not universal. Sandino et al. (2020), for example, proposed a fully autonomous model with minimal human input, raising questions about the trade-offs between efficiency and ethical safeguards in high-stakes humanitarian applications.

Additionally, despite the critical importance of model interpretability in AI applications, relatively few studies in our review address this issue. While methods such as Shapley Additive Explanations (SHAP), which have become widely adopted for explaining complex model behavior, are applied in some cases (e.g., Khanmohammadi et al., 2023), their overall use remains limited within this body of literature. This suggests that, although interpretability techniques are gaining traction broadly, there is still a need for greater emphasis on transparency and explainability in humanitarian AI research.

The theoretical contributions of this review lie in its comprehensive mapping of the interface between AI and humanitarian aid which is called for (e.g., Zarei et al., 2024). The study contributes by exploring AI's utilization across and outside the crisis cycle. In addressing the first research question, the review provides a structured and systematic understanding of how AI supports the preparedness, response, and recovery phases in different ways and approaches. In doing so, it also answers research calls to explore technology in the often-overlooked preparedness phase (e.g., Altay and Narayanan, 2022). The review contributes to the crisis management framework by embedding AI as a central element within its different stages, highlighting its potential to truly transform the overall efficiency and effectiveness, and thus impact, of humanitarian aid operations. Specifically, it offers insights into the ways AI enhances decision-making processes, coordination, resource allocation and delivery, and rebuilding efforts collectively. The review advances the theoretical understanding that AI's role in humanitarian aid is inherently multifaceted and phase-specific, supporting arguments that crisis management requires differentiated technological strategies (Moshtari and Gonçalves, 2017).

The dominance of studies in the pre-crisis stage focusing on information flow frameworks and cross-sector integration demonstrates that AI is increasingly theorized not solely as an operational tool, but as a relational technology that shapes inter-organizational networks. This supports and extends coordination theory in humanitarian studies (Van Wassenhove, 2006), calling for more nuanced explanations of how AI mediates information asymmetries and collective action among diverse actors.

This review also contributes to the literature through its identification of underexplored areas in AI-humanitarian research. By highlighting critical gaps in current knowledge and practice within this domain and showing where AI has not yet been fully utilized, the study guides future research and practical applications. It opens new opportunities for innovation, design, and targeted interventions. It also helps scholars and practitioners focus on critical but neglected realms, which could lead to a more balanced integration of AI in humanitarian efforts. This review shows that such a balance is currently lacking.

In answering the second research question, this study extends the existing body of knowledge by showing AI's connection with humanitarian aid beyond the dominant and immediate crisis management cycle, delving into broader humanitarian contexts such as ethics and public perceptions. By doing so, it broadens the traditional focus of AI applications and highlights AI's ability to support and contribute to long-term humanitarian goals (Vinuesa et al., 2020), while also exposing important gaps in ethical considerations that need to be answered. Ultimately, this review is critical for realizing the full impact and limitations of advanced AI technologies in revolutionizing humanitarian aid efforts.

6. Practical implications

The findings of this review provide crucial insights for international humanitarian organizations, NGOs, local community groups, policymakers, government agencies, and AI designers on how AI can be practically applied to enhance humanitarian aid efforts. As the number and complexity of crises continue to rise, this review offers a guide for assessing current AI adoption and identifying opportunities to improve efficiency and effectiveness in humanitarian aid. The findings of this review demonstrate that AI has the potential to significantly improve transparency, sustainability, and long-term development within humanitarian operations (Dubey et al., 2022). A specific finding is that AI optimizes information flow and coordination among humanitarian stakeholders, ensuring faster and more informed decision-making. This suggests that by investing in AI-based communication and coordination tools, organizations can significantly improve pre-crisis planning and readiness, facilitating quicker and more effective mobilization in times of need. Public-private partnerships should be encouraged to develop and deploy such AI solutions, ensuring interoperability between humanitarian, military, and civil systems. This study shows humanitarian organizations the importance of concentrating on AI's role in preparedness, rather than solely on crisis response, ensuring that they are better equipped before disasters occur. The findings also suggest that humanitarian groups should invest in leveraging AI to analyze real-time data, especially social media inputs, as this can result in actionable insights for improved preparedness and response.

In the post-crisis phase specifically, AI proves highly effective in resource logistics, damage assessment, and online insights extraction-three critical areas for response and recovery efforts. Our review demonstrates that AI-driven tools such as metaheuristic optimization, fuzzy logic, agent-based simulation, and knowledge-based systems can improve the precision and timeliness of aid delivery. For example, AI-based routing systems, as shown by Fikar et al. (2016) and Jana et al. (2022), ensure that relief resources are deployed faster and with greater accuracy, minimizing delays that could exacerbate the impact of disasters. Thus, this review provides practical solutions for addressing logistical challenges in disaster response, encouraging humanitarian organizations to adopt diverse AI-driven tools for routing and resource management. Furthermore, AI's ability to enhance damage detection and structural integrity assessments, as seen in the work of Rodríguez et al. (2011) and Galera-Zarco and Floros (2023) who relied on fuzzy systems and deep learning, improves the accuracy and speed of evaluations. This capability would allow organizations to prioritize recovery efforts more effectively and develop long-term rebuilding plans with greater precision. Additionally, AI-powered online insights extraction can be operationalized by humanitarian organizations through dedicated monitoring systems that track emerging needs and risks in real time, ensuring more agile and informed post-crisis response planning.

For AI designers, the review stresses the importance of addressing ethical risks when developing AI frameworks for humanitarian purposes. Ensuring that AI applications are ethically sound is vital for maintaining trust and legitimacy in humanitarian contexts. AI systems must be designed and audited to mitigate geographic and contextual biases, especially given the risk of exacerbating inequalities between the Global North and Global South (Beduschi, 2022). Additionally, the review points out that AI acceptance can vary depending on demographic factors, as illustrated by Kankanamge et al. (2021). Therefore, AI solutions should be designed with sensitivity to the characteristics of affected communities, ensuring that the technology is both useful and inclusive. Collaboration with local stakeholders and adoption of human-in-the-loop approaches are practical strategies to enhance ethical compliance and contextual relevance.

7. Future research directions

This review highlights a significant gap in the rigorous benchmarking of AI systems across diverse crisis types and geographic regions, underscoring the need for future research to prioritize the development of standardized evaluation frameworks to assess AI model performance across multiple crisis contexts (e.g., pandemics, conflicts, floods, earthquakes) and across both Global North and South settings. Such comparison, currently lacking, is essential to uncover geographic and data biases inherent in current approaches, which often favor well-resourced environments (Gevaert et al., 2021). Addressing this gap requires a dual approach: first, identifying models with strong generalizability and scalability through rigorous evaluation that incorporates technical innovations and algorithmic fairness metrics for detecting and mitigating biases arising from differences across crisis types (e.g., causal modelling approaches to disentangle confounding factors; differing data characteristics and dynamics across pandemics versus natural disasters) as well as geographic and social disparities, including socioeconomic factors, urban-rural divides, and underrepresented populations; and second, creating context-sensitive theoretical frameworks that account for infrastructural, cultural, and governance differences to guide the equitable and effective implementation of AI technologies in varied humanitarian settings. Additionally, given the infrastructural constraints common in many humanitarian environments (Madianou, 2021; Kreutzer et al., 2019), research should explore the design and validation of low-compute, offline-compatible AI systems through real-world field trials to ensure their practical applicability. To meet these constraints, researchers can look at efficient on-device approaches such as MobileNet or TinyML, designed to run tasks without heavy computing power or reliable internet (Howard et al., 2017). Research should also focus on adapting more complex AI models for offline use by applying model compression techniques, such as quantization, pruning, and knowledge distillation, that reduce model size and resource requirements, making them suitable for deployment in low-resource settings.

Moreover, there is a notable deficit of concrete governance and ethical frameworks tailored to humanitarian AI. Future research should focus on designing domain-specific auditing frameworks that adapt established ethical principles, such as the EU's Trustworthy AI guidelines, UNESO's AI ethics recommendations, the ICRC's data responsibility standards, and WHO's AI ethics guidelines, to humanitarian contexts. Although ethical concerns are frequently discussed in principle, operationalizing AI ethics in real-world deployments remains vague and underexplored. Future research should move beyond theoretical discussions to empirically test how ethical frameworks can be embedded into the design, deployment, and oversight of humanitarian AI systems. This includes evaluating governance models that are both technically feasible and adaptable across diverse humanitarian settings.

Furthermore, explainability and human–AI collaboration require deeper theoretical and empirical engagement. Most AI tools discussed in the literature remain opaque, which may hinder practitioner trust and limit effective use. Future research should prioritize explainable AI (XAI) methods that clearly communicate system reasoning to users with varying technical backgrounds (e.g., counterfactual explanations, visual saliency maps, interactive dashboards). There is a growing need to explore emerging and underexplored XAI approaches, such as neuro-symbolic methods (Zhang and Sheng, 2024) which represent promising directions for addressing current challenges. Equally important is investigating how humanitarian workers interpret and interact with these tools, and what training is necessary to ensure effective use. The review found no studies exploring such training or usability among humanitarian staff, representing a critical research opportunity.

It is essential to recognize the need for conceptual models of hybrid intelligence, where human expertise complements machine decision-making, enhancing legitimacy, accountability, and community trust. This includes research into how AI can augment rather than replace human judgment in humanitarian contexts. Identifying optimal modes of human–AI collaboration, particularly in high-stakes, time-sensitive environments, will be vital for enabling more ethical, context-aware humanitarian interventions. This should go beyond solely collaborative labelling of crisis data. Technical safeguards such as mandatory uncertainty quantification may help to prevent over-reliance on AI-generated recommendations.

In addition, AI applications in the preparedness phase of humanitarian aid, particularly for early detection and sensing, remain underexplored despite AI's recognized potential for predictive analytics. Researchers should give greater attention to detecting early warnings of unfolding crises, investigating not only technical solutions but also the ethical, logistical, and infrastructural barriers that constrain real-world use, moving beyond technological determinism to understand the socio-technical systems shaping humanitarian preparedness.

Another underdeveloped area is public perception and willingness to adopt AI in humanitarian contexts. Understanding public attitudes, trust dynamics, and readiness to embrace AI technologies is essential for the successful implementation and integration of these tools in humanitarian efforts (e.g., Uren and Edwards, 2023). Future research should build out this stream to ensure AI applications align not only with organizational goals but also with the expectations and needs of communities they intend to serve.

The review also revealed a disparity in research between AI's role in logistics versus other humanitarian functions. Much of the current literature focuses on logistics, while non-logistical aspects of humanitarian aid, such as education, well-being, and community development, remain neglected. Future research should balance this by investigating how AI can improve non-logistical aspects of humanitarian operations. This would contribute to a more holistic understanding of AI's role in humanitarian aid beyond logistics, reflecting the diverse needs of crisis-affected populations.

Further, an essential area for future exploration is the long-term impact of AI on humanitarian aid functions, such as its role in enhancing prolonged community resilience. Longitudinal studies are crucial to understanding how AI affects the sustainability of interventions and whether it contributes to building long-term impact in affected communities. This aspect has been largely overlooked in the current literature, and future research should address this gap by examining the lasting effects of AI on both humanitarian organizations and the communities they support.

Another critical area for future research is the economic impact of AI integration in humanitarian aid. Research should rigorously assess how AI can contribute to cost reductions, for example by improving supply chain efficiency and enhancing predictive capabilities for crisis management. Evaluating the return on investment and cost-effectiveness of AI-driven interventions will be vital to justify their adoption, especially in the context of shrinking budgets and heightened scrutiny over aid spending (Efe, 2022). Given donor fatigue and budget cuts that have led to declining resources despite rising needs, future research should also address the growing funding challenges facing humanitarian organizations. Investigating how AI can improve preparedness, help optimize resource allocation, and demonstrate value for money will be crucial to securing new funding streams.

Finally, there is a need for field-based validation and participatory design of AI systems. Too many projects remain at the prototype or simulation stage, lacking real-world testing. Future research should adopt interdisciplinary and collaborative design methodologies that involve local communities, NGOs, and government agencies throughout the development and evaluation process. This will help ensure AI solutions are not only technically robust but also socially acceptable, ethically grounded, and practically deployable in the complex realities of humanitarian response.

8. Conclusion and limitations

This systematic literature review aimed to highlight the significant potential of AI in transforming humanitarian aid across the crisis cycle, as well as its role in broader humanitarian settings outside of the immediate crisis cycle. By doing so, this study offered a cohesive understanding of AI's potential in humanitarian aid and identified both gaps and opportunities for enhancing the AI-humanitarian aid nexus. By synthesizing the findings of 60 studies, the review uncovered eight key focus areas of AI application in pre- and post-crisis settings, along with four key areas in broader contexts. The findings revealed that AI plays a crucial role in the pre-crisis preparedness stage, particularly in improving coordination and site selection, while post-crisis applications account for the majority of studies and focus on optimizing resource distribution, assessing damage, and extracting insights from online sources. Broader applications of AI in humanitarian contexts raise important ethical concerns, especially regarding algorithmic bias, data privacy, and interpretability, which need to be addressed as AI adoption expands. This review also highlighted the importance of frameworks that balance technological innovation with contextual sensitivity and human oversight. While AI has demonstrated considerable promise in augmenting the potency and performance of aid efforts, gaps remain in its application across certain areas of humanitarian work. Addressing these gaps presents opportunities for future research and practical advancements. The review also offers valuable insights for humanitarian organizations on how to strategically use AI to improve the impact of their interventions.

Nevertheless, the review is not without limitations. First, while it provides a comprehensive synthesis of AI applications in humanitarian aid, the scope is restricted to the 60 selected studies from four databases, which may not fully capture all developments in this rapidly evolving field. Second, the review focused on published articles in the English language, potentially excluding relevant but unpublished insights or contributions in non-English languages. Third, the articles were manually coded, which may introduce some level of subjectivity, despite efforts to minimize this by using more than one coder and conducting several rounds of review and verification (Hanelt et al., 2021). Fourth, the categorization of AI applications into sub-categories, while useful for analysis and synthesis, may oversimplify the complex and interdisciplinary nature of AI-humanitarian interactions. Lastly, the review was limited to answering two specific research questions, and exploring additional or more granular questions in future reviews could yield further valuable insights into this multifaceted topic.

CRediT authorship contribution statement

Sophie Lythreatis: Writing – original draft, Project administration, Methodology, Formal analysis, Conceptualization. **Fulya Acikgoz:** Writing – review & editing, Supervision, Conceptualization. **Noura Yassine:** Writing – review & editing.

Declaration of competing interest

We declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.technovation.2025.103415.

Data availability

No data was used for the research described in the article.

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