



# Bridging AI and Humanitarianism: An HCI-Informed Framework for Responsible AI Adoption

Tigmanshu Bhatnagar  
Global Disability Innovation Hub  
UCL  
London, United Kingdom  
UCL Interaction Centre  
UCL  
London, United Kingdom  
t.bhatnagar.18@ucl.ac.uk

Maarya Omar  
Computer Science  
UCL  
London, United Kingdom  
maarya.omar@ucl.ac.uk

Davor Orlic  
International Research Centre on  
Artificial Intelligence (IRCAI) under  
the auspices of UNESCO  
Jozef Stefan Institute  
Ljubljana, Slovenia  
davor.orlic@gmail.com

James Smith  
UCL Centre for Humanitarianism and  
Social Inclusion, Institute of  
Epidemiology and Health Care  
University College London  
London, United Kingdom  
james.smith.12@ucl.ac.uk

Catherine Holloway  
Global Disability Innovation Hub  
UCL  
London, United Kingdom  
UCL Interaction Centre  
UCL  
London, United Kingdom  
c.holloway@ucl.ac.uk

Maria Kett  
UCL Centre for Humanitarianism and  
Social Inclusion, Institute of  
Epidemiology and Health Care  
University College London  
London, United Kingdom  
m.kett@ucl.ac.uk

## Abstract

Advances in artificial intelligence (AI) hold transformative potential for humanitarian practice. Yet aligning this potential with the demands of humanitarian practice in dynamic and often resource-austere contexts remains a challenge. While research on Responsible AI provides high-level guidance, humanitarian practice demands nuanced approaches for which human-computer interaction (HCI) can provide a strong foundation. However, existing literature lacks a comprehensive examination of how HCI principles can inform responsible AI adoption in humanitarian practice. To address this gap, we conducted a reflexive thematic analysis of 34 interviews with AI technology experts, humanitarian practitioners, and humanitarian policy developers. Our contributions are twofold. First, we empirically identify three cross-cutting themes—AI risks in humanitarian practice, organisational readiness, and collaboration—that highlight common tensions in adopting AI for humanitarian practice. Second, by analysing their interconnectivities, we reveal intertwined obstacles and propose a conceptual HCI-informed framework.

## CCS Concepts

• **Human-Centred Computing**; • **Human-Computer Interaction**; • **Empirical studies in HCI**;

## Keywords

Crisis/Disaster, AI Ethics, Interview, Qualitative Methods

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## 1 Introduction

Humanitarian organisations increasingly use AI to anticipate crises, improve efficiency and logistics, and intervene with new applications to reduce staff workload and the impact of humanitarian crises across the preparedness, response, and recovery cycles [7, 8, 51, 55]. However, integrating AI introduces complex ethical, operational, and governance challenges, necessitating a thorough understanding of the broader logistical and operational frameworks that shape humanitarian practice [17, 27, 84]. Understanding this complexity is crucial if AI is to support responsible, timely and coordinated humanitarian action, ultimately improving operational effectiveness and efficiency.

Using AI in humanitarian practice can introduce risks due to historical data inconsistencies and a lack of governance measures, leading to inaccurate outcomes and perpetuating existing inequalities [77]. Notable cases, such as UNHCR's sharing of Rohingya refugee biometric data [78] and the ICRC's data breach [80], highlight the dangers associated with data used in AI applications. Additionally, mistrust in AI—often linked to deeply problematic military, security and surveillance applications [33]—and concerns over the dependency on private companies complicate its implementation and adoption in humanitarian contexts [75]. Existing research has not comprehensively examined how human-computer interaction (HCI) can be adapted to address the unique ethical and operational complexities of AI in humanitarian contexts, leaving a critical gap in guidelines to inform responsible design and deployment.



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The intersection of HCI and humanitarian practice underscores the potential role of technology that is designed with user-centred principles to address complex and urgent issues and is used ethically and safely [12, 24]. Central to this effort has been a commitment to the preservation of user dignity, particularly for vulnerable people and populations [3, 66]. For instance, displaced households often have access to mobile technologies, which can provide essential information and services that enhance user autonomy [15, 52]. Additionally, HCI for Peace [36] and Migration Research [60] aims to use HCI research to understand and reduce the impact of armed conflict and better understand the complex political and social aspects of displacement. Participatory design practices are particularly useful in such contexts to strengthen the effectiveness of humanitarian technologies by fostering collaboration among stakeholders, ensuring that solutions are practical, culturally relevant, and contextually appropriate [4, 53].

However, HCI research contributions require ongoing, critical reflection to ensure alignment with developments in humanitarian contexts, specifically with AI. This paper draws insights from a thematic analysis of 34 interviews with AI technology experts, humanitarian practitioners, and humanitarian policy developers. It addresses the question of what HCI can offer to guide the ethical and practical adoption of AI in humanitarian practice. To address this overarching question, we further examine two sub-questions: 1) How AI-related challenges manifest in humanitarian work, and specifically, how they intersect with ethical, organisational and operational paradigms; 2) How advances in relevant HCI principles can be adapted to mitigate these challenges and enhance responsible AI adoption.

The interviews focused on challenges to and strategies for the adoption of AI into humanitarian practice. We identified three cross-cutting themes: AI risks in humanitarian work, organisational readiness, and collaboration. By examining the intersections between these themes, we identified interconnected barriers and consolidated the insights to a tangible and implementable solution framework. In doing so, this paper presents two key contributions: empirical insights from interviews with AI, policy and humanitarian experts, as well as an HCI-informed conceptual framework (ECHO) to support responsible AI adoption. The framework provides a structure for building ethical capacity, enhancing organisational readiness, and fostering equitable collaborations for the responsible development and deployment of AI systems in humanitarian contexts.

## 2 Related Work

This section offers essential background information on humanitarian practice and the increasing integration of AI in the field. It examines the challenges associated with adopting AI for humanitarian efforts and reviews existing work in HCI literature relevant to humanitarian work.

### 2.1 Humanitarian Practice and AI

Scholarly literature consistently defines humanitarian action as a multifaceted approach to alleviating crisis-induced distress, encompassing emergency medical care, food distribution, shelter provision, water, sanitation and hygiene and critical infrastructure

support [9, 41, 81, 85]. At the core of humanitarian practice are four fundamental humanitarian principles: humanity, neutrality, impartiality, and independence, some of which are intended to ensure humanitarian assistance is delivered based on more objective needs assessments, transcending political, ethnic, commercial or strategic considerations [64]. While these core principles are increasingly contested, they are frequently invoked to define the boundaries of dominant forms of contemporary humanitarian action.

Contemporary humanitarian literature increasingly highlights the intricate relationship between political landscapes and aid effectiveness [34]. Geopolitical instabilities, armed conflicts, and strategic national interests significantly complicate humanitarian interventions, often creating systemic barriers that compromise accessibility and undermine commitments to neutrality [9]. The growing collective threat posed by the climate emergency and anthropogenic hazards also demands adaptive strategies integrating risk assessment, early warning systems, and community-based resilience programmes [50, 63].

The rapid development of AI has revealed potential new scenarios for early anticipatory interventions in humanitarian contexts, which has played a role in forecasting situations and taking proactive measures. For example, the International Federation of Red Cross and Red Crescent (IFRC) forecast-based financing programme analyses weather data and market trends to allocate resources for early interventions [83]. Project Jetson by the UN High Commissioner for Refugees (UNHCR) forecasts displaced people's movements, helping manage and mitigate the impact of large-scale displacements [86], while the World Food Programme's (WFP) HungerMap Live system forecasts food insecurity to enable timely anticipatory interventions in regions at risk of famine [87].

During a crisis, data can be swiftly analysed to extract critical insights to improve humanitarian response. For instance, Australia's Emergency Situation Awareness Platform [18] tracks real-time Twitter activity during disasters, providing critical insights to help emergency responders coordinate efforts during bushfires, floods, and earthquakes. Across contexts, social media data and surveys can also be analysed swiftly to improve the effectiveness, quality and efficiency of humanitarian response [88].

In the recovery phase of a humanitarian crisis, the International Committee of the Red Cross and Red Crescent (ICRC)'s Trace the Face initiative uses facial recognition to automate the identification of missing persons, helping refugees reconnect with separated family members [73]. Automated aerial imagery analysis can assess disaster damage [26], analyse and provide insights into crowd management and resource allocation through real-time image analysis and identify changes in geographical landscapes post-disaster [28].

These examples demonstrate some of the potential applications of AI in various phases of humanitarian response. The integration of AI in humanitarian action presents significant opportunities to strengthen the effectiveness of relief efforts. However, the adoption of AI also poses a multitude of challenges that include data limitations, ethical considerations, operational barriers, and key risks such as bias, privacy violations, and unequal access to AI-driven solutions. These are discussed in the next section.

## 2.2 Challenges to the Adoption of AI in Humanitarian Practice

Adopting AI in humanitarian contexts has a few challenges and risks that can undermine its effectiveness and potentially harm affected people. One of the most pressing issues is the lack of high-quality, relevant data in humanitarian contexts. The available data is often incomplete, outdated, or biased, leading to inaccurate predictions and decisions [54]. Infrastructure limitations further complicate the adoption of AI technologies in humanitarian contexts, as many humanitarian programmes are implemented in areas with inadequate technological infrastructure, unreliable internet connectivity, inconsistent power supply, and insufficient computational resources [76].

Ethical concerns surrounding AI also present substantial challenges [57, 89]. AI systems risk perpetuating biases embedded in their training data or algorithms, potentially exacerbating existing inequalities and disproportionately affecting vulnerable people [25]. Organisations must navigate the critical challenge of ensuring that AI adheres to core principles such as “*do no harm*” while safeguarding dignity and equity [84]. Moreover, there is a pressing need for adherence to human rights frameworks and humanitarian law that guarantee respect for privacy and non-discrimination even in the design and roll-out of AI technologies [89].

A significant gap in capacity and expertise within humanitarian organisations currently hinders the effective integration of AI solutions [14]. Many organisations struggle to attract personnel with specialised knowledge in AI or adequately train existing staff. This lack of technical expertise limits their ability to effectively develop, deploy, and oversee AI technologies. Additionally, resource constraints pose a substantial barrier; humanitarian organisations often operate on limited budgets, which make it difficult to secure funding for innovative AI initiatives [11]. Donors may hesitate to invest in what they perceive as high-risk technologies, particularly when compared to more immediate needs [7, 90]. Furthermore, political conditions often jeopardise the sustainability of donor funding, which is essential for long-term engagement in protracted crises. This affects humanitarian organisations’ ability to plan and implement sustained interventions [37, 91].

Finally, effective AI deployment requires context-sensitive approaches tailored to the specific demands presented by diverse humanitarian crises. System usability and participation in design are crucial [84]; involving affected people to shape technology design and deployment promotes inclusivity and cultural relevance [57]. By prioritising local needs and ensuring that AI tools are designed with input from those they aim to support, humanitarian organisations can enhance the effectiveness of their interventions.

Establishing accountability in decentralised humanitarian contexts is another vital yet challenging aspect of AI adoption [72]. Clear roles and responsibilities among stakeholders—including technology providers, NGOs, and governments—are necessary to maintain ethical standards and ensure transparency [69]. Relatedly, strong data protection measures are essential to safeguard sensitive information in humanitarian settings [45, 92].

Addressing these challenges requires technical and organisational solutions and a paradigm shift in the design and deployment of AI systems. HCI offers valuable insights and methodologies that

can guide the development of AI systems tailored to the complex demands of humanitarian contexts.

## 2.3 HCI’s Role in Humanitarian Practice

HCI has its roots in human factors engineering, particularly during the World Wars, where the focus was on optimising human-machine interactions in high-stakes environments that demanded operational efficiency [31]. Over time, the subject grew, evolved and expanded [59], emphasising intuitive user-centred design. This evolution has a critical role in humanitarian contexts [46, 49], where technology use must also account for heightened cognitive loads, environmental stressors, and extreme operating conditions [35, 68, 93]. For instance, humanitarian workers in Turkey during the COVID-19 pandemic relied on digital tools to remotely support refugees, navigating complex temporal, infrastructural, and informational challenges [22]. Similarly, the Venezuelan diaspora used social media platforms to provide “infrastructural care”, demonstrating how technology mediates relationships and resources during the rise in violent crime amidst food and medicinal shortages [21]. Projects like the UN’s QualMiner highlight the potential of combining qualitative data analytics with data-sharing platforms to enhance coordination and decision-making in crises [44]. In such interactions, the prevention of errors and the provision of clear recovery pathways—cornerstones of early HCI principles—remain essential when designing resilient systems for use in humanitarian crises [93].

By integrating contemporary HCI frameworks such as Responsible AI [71], Participatory Design [20] and Value-Sensitive Design (VSD) [65], HCI research offers tools to navigate the ethical, organisational, and contextual complexities of AI deployment in humanitarian contexts. Responsible AI frameworks build on explainability, embedding trust, accountability, and ethics into the AI lifecycle. In humanitarian action, these frameworks prioritise protecting dignity [2], human rights [7], the welfare of affected people [84] and maintaining ethical standards throughout AI deployment [32]. Coppi et al. [16] argue that explainable AI bridges the gap between complex algorithms and end-users, fostering trust. It is a cornerstone of AI usability and is particularly vital in humanitarian contexts, where aid workers and affected populations depend on AI for high-stakes decision-making [7, 62, 90, 94]. Users’ ability to understand and interpret AI outputs significantly influences their willingness to adopt these technologies [23]. Talhouk et al. [66] demonstrate how HCI research can preserve and uplift dignity through technology designed for refugee communities. Similarly, Sadek et al. [61] argue that integrating VSD into Responsible AI enhances fairness, transparency, and accountability. They propose guidelines that align AI systems with societal values using collaborative methods, empathy-driven design, iterative feedback, and knowledge sharing. Inclusivity is also a key HCI principle, ensuring that AI systems are adaptable to diverse user groups, including those with varying levels of technological literacy [56]. Achieving this requires participatory design approaches that actively engage users. These approaches ensure that AI systems are culturally and contextually appropriate, enhancing their adoption and effectiveness [19, 95].

In summary, while integrating AI into humanitarian action offers transformative potential, adoption challenges—ranging from

data limitations to ethical concerns—necessitate robust frameworks and approaches. HCI principles provide a strong foundation for addressing these challenges through user-centred, participatory, and context-sensitive designs. However, existing literature lacks a comprehensive examination of how HCI principles can be adapted to meet the specific demands of AI use in humanitarian contexts.

### 3 METHODS

This study investigates the evolving humanitarian sector landscape, focusing on AI and its intersection with HCI. Semi-structured interviews were conducted with 34 participants divided into three groups:

- Humanitarian Practitioners (n = 15): Practitioners offering diverse, practice-oriented insights directly relevant to operational challenges and opportunities.
- Humanitarian Policy Developers (n = 5): Participants providing strategic and theoretical perspectives covering broad humanitarian sectors and projects.
- AI technology experts working in humanitarian and development projects (n = 14): Specialists offering technical insights into the design and application of AI in humanitarian contexts.

The study emphasised the operational perspectives of practitioners and technology developers because their experiences with AI tools and challenges are practice-oriented, more varied and directly relevant to everyday humanitarian practice. These insights are complemented by policymakers' broader strategic insights as they work across multiple projects and sectors. All the interviews were conducted online via videoconferencing software, allowing participation by people working with various organisations and based in diverse geographical locations.

#### 3.1 Interview Protocol

Data collection involved qualitative semi-structured interviews for a guided discussion and exploratory dialogue [1]. The authors and the expert advisory committee designed the interview guide iteratively, drawing on prior literature to extract meaningful responses to the research questions. It was carefully designed to avoid leading questions or assumptions. To ensure consistency, all interviewers agreed to use a standardised semi-structured interviewing protocol.

The interview consisted of four parts. The first part focused on the participant's background, journey, and interest in humanitarian data, as well as, more recently, AI and the challenges of working in their context. The second part explored the changing landscape of the humanitarian sector and the growing discourse around, or use of, AI. This section explored changes, collaborations, decision-making processes, human relations and development, and implementation guidance. The third part investigated the significant challenges associated with the impactful and appropriate uptake of AI and focused on technical and practical implementation hurdles and critical gaps in the ecosystem. The final part sought recommendations for upcoming changes and opportunities expected of AI while teasing out some of the main lessons learnt by the participants in their respective professional journeys.

The semi-structured format ensured that while the conversation followed a planned trajectory, participants were also allowed to

introduce additional insights, enriching the data collected. All the interviews were conducted in English. Ethical approval for this study was granted by the Departmental Ethics Committee of UCL Interaction Centre (UCLIC\_1920\_011\_Staff\_Holloway\_Williams). While the interview protocols were standard, the distress protocol, which the committee cleared, focused on mitigating distress for the researchers and participants through debriefing and contacting the university's Mental Health team in case the interviews reveal upsetting anecdotes from humanitarian settings that affect the researchers or the participants.

#### 3.2 Participants

The three groups were recruited via the collective professional networks of the project's advisory committee members and by snowball sampling. Inclusion criteria required that participants be experts in their respective fields, meaning they had over five years of experience in the humanitarian sector or held a senior leadership position in their organisation before joining a humanitarian organisation.

All participants were informed about the study, what it entailed, and their data rights to seek informed consent for the interview. The experts participated voluntarily and were not provided with an honorarium. The interviews lasted between 50 and 70 minutes. Four researchers led the interviews, one of whom is a Professor of Humanitarianism, one an early-career Lecturer in Innovation, one Senior Research Assistant in AI, and the fourth a Junior Research Assistant in AI Ethics.

#### 3.3 Analysis

The recordings of all 34 interviews were transcribed and prepared for analysis. A reflexive thematic analysis was performed in four phases: code generation, construction of theme, revising, and refining. For the first round of the analysis, the first and second authors selected two interviews from each of the three groups (six interviews in total) to create an initial set of inductive codes. Based on the guidance produced by Braun et al. [10], the six interviews were coded by the two authors who discussed their respective strategies, insights and classification types and drafted a combined initial codebook of 87 codes using Nvivo 14. Axial coding reduced the initial set of codes to 44 by grouping related concepts and eliminating redundancies. This phase involved careful consideration of overlaps and distinctions between codes to enhance coherence. The two researchers then coded all the remaining interviews.

The coding was done independently, but the first four authors regularly met after coding each batch of seven interviews to discuss the procedure and revise the codes iteratively. A final meeting was organised at the end of the coding process with everyone. These discussions between the authors ensured that coding was aligned, allowing for the identification of similar codes, discussion regarding new codes, and the resolution of issues when applying codes to certain verbatims. Due to the collaborative staged nature of the process, inter-rater reliability is not reported [10]. A list of the final codes is provided in Table 2.

All authors then discussed, revised, and refined the clustering of the codes using affinity diagramming and the interrelatedness of the concepts. This was an interactive and iterative process. Following

**Table 1: The table summarises key information about the participants, including their years of experience in the humanitarian sector, the type of organisation they currently work with, and their country of residence. To protect their anonymity, names, roles, and organisational affiliations have been redacted.**

| ID     | Gender               | Years of Experience in Humanitarian Projects | Current Organisation Type | Country of Residence |
|--------|----------------------|--|---------------------------|----------------------|
| H1     | Female               | 14   | Nonprofit Organisation    | Kenya                |
| H2     | Male                 | 25   | Humanitarian Start-up     | Netherlands          |
| H3     | Male                 | 12   | UN                        | USA                  |
| H4     | Male                 | 18   | Nonprofit Organisation    | Denmark              |
| H5     | Male                 | 28   | UN                        | Spain                |
| H6     | Male                 | 23   | UN                        | USA                  |
| H7     | Male                 | 22   | Humanitarian Start-up     | Switzerland          |
| H8     | Male                 | 11   | UN                        | Switzerland          |
| H9     | Female               | 2  | Nonprofit Organisation    | Germany              |
| H10    | Male                 | 6  | Academic                  | USA                  |
| H11    | Female               | 18   | Nonprofit Organisation    | UK                   |
| H12    | Male                 | 6  | Self Employed             | USA                  |
| H13    | Female               | 10   | Nonprofit Organisation    | Kenya                |
| H14    | Male                 | 5  | Nonprofit Organisation    | Kenya                |
| H15    | Male                 | 25   | Academic                  | USA                  |
|        |                      | Mean = 15 years<br>SD = 8.09                 |                           |                      |
| P1     | Male                 | 10   | Academic                  | UK                   |
| P2     | Male                 | 22   | Nonprofit Organisation    | Switzerland          |
| P3     | Male                 | 20   | Nonprofit Organisation    | Switzerland          |
| P4     | Female               | 9  | Think Tank                | USA                  |
| P5     | Female               | 11   | Academic                  | Scotland             |
|        |                      | Mean = 14.44 years<br>SD = 5.46              |                           |                      |
| T1     | Female               | 6  | UN                        | Italy                |
| T2     | Male                 | 2  | UN                        | Italy                |
| T3     | Male                 | 5  | Nonprofit Organisation    | Netherlands          |
| T4     | Male                 | 10   | Tech Company              | USA                  |
| T5     | Male                 | 9  | Tech Company              | USA                  |
| T6     | Male                 | 7  | Tech Start-up             | Switzerland          |
| T7     | Male                 | 7  | Tech Start-up             | France               |
| T8     | Male                 | 17   | Tech Company              | Netherlands          |
| T9     | Male                 | 7  | Tech Company              | Spain                |
| T10    | Male                 | 5  | Tech Company              | France               |
| T11    | Male                 | 14   | Tech Company              | USA                  |
| T12    | Male                 | 14   | Nonprofit Organisation    | Switzerland          |
| T13    | Male                 | 5  | Academic                  | Nigeria              |
| T14    | Male                 | 14   | Tech Company              | Switzerland          |
| n = 34 | 27 Males<br>7 Female | Mean = 8.71 years<br>SD = 4.28               | 9 types of organisations  | 13 countries         |

Braun and Clarke’s thematic mapping exercise, the researchers agreed on themes from the codes during discussions [10]. The applied themes were revised against the whole dataset and all codes before they were accepted.

After identifying the themes, we analysed how they intersect and influence one another, finding them to be deeply intertwined and interdependent. To navigate the complexities and translate insights into actionable steps, a structured framework is necessary. This

framework ensures that AI development aligns with humanitarian principles while maintaining consistency and best practices. Rooted in HCI methods, the initial framework was synthesised through an iterative process, allowing for continuous refinement, evolution and adaptation.

**Table 2: Codebook for the final high-level codes categorised across the three themes, their subcategories and codes.**

| Theme   | Subcategory                            | Codes  |
|---|--|--|
| AI Risks in Humanitarian Work                   | Bias and Representation                | <ul style="list-style-type: none"> <li>• Privacy and anonymised data</li> <li>• Consent as the only protection for affected populations</li> <li>• Handling personal data in humanitarian contexts</li> <li>• Bias in data and training emerges from societal participation</li> <li>• Amplified societal biases through AI</li> <li>• Need for diverse models to address biases</li> </ul>  |
|   |  | <ul style="list-style-type: none"> <li>• Premature adoption of LLM tools</li> <li>• Stop and reflect when AI tools impact human lives</li> <li>• Negative impacts of commercial AI applications</li> <li>• AI solutions amplifying societal issues and reinforcing politics</li> <li>• Risk assessment tools for decision-making</li> </ul>  |
|   | Ethical Dilemmas                       | <ul style="list-style-type: none"> <li>• Opaque design of AI tools</li> <li>• Limited discussions about AI and data with local partners</li> <li>• Top-down regulatory frameworks lacking inclusivity</li> <li>• Challenges in risk classification and failure reporting</li> <li>• Training and education to enable informed adoption</li> <li>• Limited public understanding of AI basics and implications</li> <li>• Start with basic data and AI principles</li> <li>• Limited appreciation of preconditions and challenges in AI adoption</li> <li>• Overemphasis on hype rather than real-world utility</li> </ul>   |
|   | Data Transparency and Accessibility    | <ul style="list-style-type: none"> <li>• AI governance debates within organisations</li> <li>• Centralised vs. localized AI implementation</li> <li>• Organisational values shaping AI adoption</li> <li>• Leadership buy-in as critical for AI integration</li> <li>• Accountability mechanisms for AI developers</li> <li>• Participatory approaches in AI governance</li> <li>• Legal and regulatory frameworks</li> <li>• Translating policies into actionable frameworks</li> <li>• High costs of infrastructure and GPUs for AI systems</li> <li>• Limited funding for humanitarian AI initiatives</li> <li>• Donor push is critical for AI integration</li> <li>• Tech-driven funding cycles leading to techno-solutionism</li> <li>• Peacetime financing for capacity building</li> <li>• Iterative feedback loops for sustainable AI tools</li> <li>• Balancing funding between immediate disaster needs and preparedness programs</li> </ul> |
| Organisational Readiness                        | Gaps in Literacy                       |  |
|   | Leadership                             |  |
|   | Governance                             |  |
|   | Sustainability of AI Projects          |  |
| Collaboration for AI Development and Deployment | Cross-Sector Collaboration             | <ul style="list-style-type: none"> <li>• Collaboration with academia and the public sector</li> <li>• Partnerships with the tech sector</li> <li>• Humanitarian organisation collaboration</li> <li>• Balancing decision-making power between local and external stakeholders</li> </ul>   |
|   | Ethical Considerations in Partnerships | <ul style="list-style-type: none"> <li>• Trust-building as critical for collaboration</li> <li>• Risks in working with local stakeholders</li> <li>• Ensuring participatory approaches in AI model design</li> <li>• Cultural considerations</li> <li>• Developers disconnected from ground realities</li> </ul>   |

### 3.4 Positionality

The authors lived and worked in London. Their research backgrounds include a mix of design, innovation, humanitarianism, politics, and AI, with scholarly work on multiple topics. The transcripts were coded by two authors who have previously been engaged

in work spanning humanitarianism, ethics, politics and innovation processes with over four years of experience. However, they were both new to AI. Hence, regular discussions within the wider research team ensured consistency in coding and interpretation. Reflexive discussions were conducted to account for independent

perspectives and their potential influence on interpretation. Themes were revised and refined in consultation with all authors, leveraging the interdisciplinary expertise of the team to mitigate bias and ensure rigour. There were no personal or professional conflicts of interest between the study participants and the researchers.

## 4 Findings

### 4.1 AI Risks in Humanitarian Work

As AI is increasingly integrated into aspects of humanitarian response, risks and governance issues have become more apparent as central concerns. Across interviews with all three professional groups, concerns about data privacy, bias, and AI governance were consistently raised. It is important to note here that while concerns about data over-collection, bias, and privacy exist broadly about AI, their consequences are amplified in humanitarian contexts. In politically and socially sensitive environments, where misused data or a lack of governance in the development or use of AI can endanger lives, undermine trust, and exacerbate existing inequalities.

**4.1.1 Data Privacy and Ownership.** Humanitarian organisations often manage large volumes of sensitive data, collected in politically and socially volatile environments. Ensuring data privacy in such contexts is critical, particularly where governments or other actors might misuse the information to nefarious ends. H15 highlights this issue: *“The primary levers of protection that organisations have is to choose not to engage with data and when not to collect it. It’s usually over-collection that causes unique data assets that bad actors, sometimes including sovereign states is required to share with.”* The practice of over-collecting data, combined with its underuse, frequently leads to ethical dilemma challenges. A notable example occurred in 2018 when UNHCR collected biometric data from Rohingya refugees in Bangladesh to streamline aid distribution. The subsequent sharing of this data with Myanmar authorities raised serious safety concerns, exposing gaps in informed consent processes and data protection [92]. This case underscores the urgent need for robust ethical guidelines and safeguards to prevent actions that cause harm.

Policy experts argue that data governance must extend beyond protection to include comprehensive management frameworks. As P3 notes: *“Data protection is fine, but data governance is the bigger issue... Implementing all of this is very complex... We have a big focus on data responsibility.”* Effective data governance ensures data is managed, accessed, and used responsibly, minimising the risks associated with its misuse. The 2017 breach of the Red Rose platform, used for cash transfer programmes, exemplifies the consequences of inadequate security governance. This breach exposed recipients’ names, geolocations, and financial details, potentially endangering vulnerable people and undermining trust in humanitarian operations [74]. Such incidents highlight the need for robust governance frameworks as well as security measures that prioritise accountability, security, and the ethical handling of sensitive information, particularly in high-stakes settings.

**4.1.2 Bias and Representation.** AI systems rely heavily on the quality and representativeness of the data on which they are trained, posing significant ethical challenges in many humanitarian contexts

where data is often incomplete or biased. H9 underscores this concern: *“In many regions, data collection is biased due to socio-cultural factors. For instance, where only men have access to mobile phones, data inherently reflects male experiences, excluding women.”* Such biases lead to the development of AI models or outputs that fail to adequately represent the needs of all affected people, potentially reinforcing inequalities and further marginalising underrepresented people and groups. For example, a GSMA report highlighted that 200 million fewer women globally own mobile phones compared to men, with women 14% less likely to own one [96]. This gender gap in access to certain technologies can result in datasets that do not fully capture diverse needs, ultimately producing AI-driven decisions that may exacerbate disparities rather than address them.

Policy experts stress the importance of establishing ethical frameworks to tackle these biases effectively. As P4 explains: *“AI holds a lot of potential, but just reminding folks to start with the basics... People with outdated or incompatible data systems often expect AI to solve their problems, but AI won’t fix infrastructural issues.”* Before deploying AI tools, organisations must address foundational challenges in data collection to ensure processes are ethical, inclusive, and representative.

Technical experts also underscore the need for standardised data management practices to minimise risks and enhance interoperability across organisations. T1 stresses: *“We need to improve the quality of data and its integration... Data from the field versus data going to HQ is often different, so foundation models could help enhance data quality.”* Initiatives such as the Humanitarian Data Insights Project (HDIP) illustrate how standardised data models can tackle these challenges. Created by DataKind, Save the Children, and Microsoft, HDIP automates quality checks, reconciles data discrepancies, and turns complex datasets into actionable insights [97]. The standardisation of data models ensures that AI systems are reliable, equitable, and effective in humanitarian contexts.

**4.1.3 Ethical Challenges.** While the ability of AI to analyse large datasets and predict trends has the potential to enhance humanitarian operations, it also presents substantial ethical risks, particularly concerning dual-use scenarios. AI tools developed for humanitarian purposes can be repurposed for military or political gain, raising pressing concerns. H6 provides a stark example: *“We can predict how many people might be displaced... Yet, with very little modification, the same code could determine how many people you’d need to kill to displace a certain number.”* This dual-use potential underscores the need for profound ethical discourse to explore the possibilities while developing and deploying AI in humanitarian contexts. Without appropriate safeguards, these tools risk being weaponised and exploited at the expense of their intended humanitarian functions. A pertinent example is the U.S. Department of Defence’s Project Maven, which uses AI to analyse drone surveillance footage. Originally designed to improve insight gathering, the project raised ethical concerns about the militarisation of AI, particularly its potential to enable targeted strikes without adequate human oversight [47]. Such cases highlight the importance of establishing clear boundaries and governance frameworks to ensure AI tools are not misused.

Policy experts caution against the premature adoption of AI without adequately addressing these ethical risks. As P3 warns: *“Let’s*

not start with a product that we will deploy and see in 5-10 years that we made huge mistakes because we didn't have the checks and balances from the beginning." Incremental approaches to AI adoption are often recommended to mitigate potential risks. H8 advocates for the phased integration of AI technologies: "People are going to grab on abruptly... rather than incrementally incorporating AI into a workflow... incremental innovation is a suitable approach to avoid potential risks." Careful implementation ensures that tools are integrated responsibly, avoiding unintended consequences and allowing time to address ethical, technical, and social challenges.

Internally, many data scientists may prioritise algorithmic accuracy over ethical implications, focusing on whether a model meets its performance metrics without considering the downstream ethical implications of its application. H6 noted: "*Their [tech developers'] primary concern was whether the algorithm met its performance metrics—was it accurate and reliable?—rather than considering the ethical implications of the task itself.*" This perspective highlights a fundamental gap in education and governance. Computer science curricula often lack a robust focus on ethics and data responsibility, leaving practitioners ill-prepared to address the moral complexities of their work.

Finally, ethical challenges in AI adoption are not always confined to the humanitarian sector; they often reflect broader societal and educational gaps. H6 aptly captured this observation: "*What is a humanitarian problem or what is a reflection of society there?*" This question underscores the difficulty in distinguishing between systemic technological issues and problems unique to societal contexts.

**4.1.4 Data Transparency and Accessibility.** Data transparency is a critical yet complex issue in humanitarian operations, where the need for openness often conflicts with the imperative to protect sensitive information. H13 articulates this tension: "*There's a genuine discussion about openness versus accessibility, particularly in the humanitarian space, where locations of displaced communities in Myanmar or movements of people from Afghanistan to Europe are incredibly sensitive. Should this information be open, knowing it could fuel anti-migrant rhetoric in Europe?*" At the same time, some argue that data produced by publicly funded organisations should be made widely available for the common good. H1 advocates for open licenses in satellite imagery and mapping data to ensure that these resources are freely available for humanitarian response: "*Open licenses around satellite imagery—kind of the first layer of data—would mean more recent inventory is made available. This would make the next stages of building onto the data much easier.*" By using open-source data, humanitarian organisations can reduce their dependence on private companies and ensure that their AI tools are built on publicly accessible resources. On one hand, open data can facilitate collaboration, improve AI tools, and enhance operational effectiveness. On the other hand, publicly accessible data can be exploited for political or social harm, particularly in politically volatile contexts. This highlights the need for balancing transparency across with safeguarding vulnerable people.

Policy experts emphasise the importance of context-sensitive data governance frameworks to navigate these challenges. As P5 explains: "*The guardrails and safeguards for AI and tools like GPT*

*should also include guidelines on how to use the data.*" These frameworks must account for the specific risks associated with different data types and contexts to ensure responsible usage. For example, disclosing the locations of displaced people in conflict zones could lead to their targeting, undermining the humanitarian imperative and the commitment to avoid harm. Several organisations have taken steps to address these issues. The Centre for Humanitarian Data promotes responsible data sharing to enhance collaboration while protecting vulnerable populations [98]. Similarly, the Inter-Agency Standing Committee has issued operational guidelines that advocate for ethical data management practices to mitigate related risks [99]. However, gaps remain, as has been highlighted by Human Rights Watch, which notes that inadequate data protection often leaves vulnerable people at risk of exploitation or misuse [92].

## 4.2 Organisational Readiness

One key challenge in the adoption of AI in the humanitarian sector concerns the need to ensure that organisations have the necessary literacy, infrastructure, and capacity to implement AI ethically and effectively. This theme explores how humanitarian practitioners, policy experts, and technology experts perceive organisational readiness and the steps required to overcome barriers to AI adoption, with a focus on gaps in literacy, leadership buy-in, and the governance frameworks that must be established to ensure responsible and sustainable AI integration.

**4.2.1 Gaps in Literacy.** A critical barrier to AI adoption in the humanitarian sector is a widespread lack of understanding. Participants emphasised the urgent need for training and education on AI. H15 outlined four critical dimensions for AI's readiness: "*Competency, capacity, capability, and culture. Competency is, can you use it well, can you use it successfully? Capability is, do you have access to the specific AI technology? Capacity is, can you use it at the appropriate scale? And culture is, do you have the right environment, organisational identity, and values to use it responsibly and effectively?*" H15 further explained: "*They [humanitarian organisations] don't understand what that can do, right? They are not educated in that, and then the agencies themselves don't have a plan... It's like teaching trigonometry or discrete mathematics when we can't add, count, and do multiplication tables.*"

Training and education programmes must also account for culturally diverse, crisis-affected contexts where resources are scarce, and staff often work under substantial pressures and time constraints. Technology experts also underscored the infrastructural barriers that magnify literacy challenges in humanitarian contexts. As T2 noted: "*In many contexts, these organisations can't even afford a Microsoft license. OK, that sounds crazy, but they don't have an Outlook account.*" This lack of basic infrastructure makes it challenging to adopt AI technologies and highlights the digital divide within the humanitarian sector and, in comparison, to other sectors. Organisations that cannot invest in basic tools will struggle in even greater measure to implement AI systems, exacerbating existing inequalities between well-resourced and under-resourced humanitarian organisations and entities.

Finally, unlike private-sector entities, humanitarian organisations must also address fundamental gaps in data collection, analysis, and management before considering advanced AI solutions.



These insights demonstrate that the humanitarian sector requires foundational capacity-strengthening investments that align with its unique operational demands and deficits.

**4.2.2 Leadership.** Large humanitarian organisations often grapple with deeply entrenched practices, making change a slow and complex process. Leaders can play a pivotal role in overcoming this inertia by advocating for appropriate AI adoption, securing resources, and aligning the workforce with the organisation's strategic goals. Their commitment ensures that AI technologies are integrated responsibly and effectively. Policy experts stress the importance of leadership in establishing governance frameworks for AI adoption. H13 highlights this role: *"Our current leadership here is definitely switched on and is trying to drive this agenda... However, the actual situation on the ground is that you're trying to change how 800 people work... and that drives the entire organisation's response."*

The above quote highlights a unique challenge in the sector. AI governance debates often revolve around whether to centralise decision-making or localise implementation strategies to suit specific contexts. Decision-makers must navigate these complexities to balance standardisation with the need for contextual relevance. The opinion of the interviewees demonstrated that leaders must ensure that AI initiatives uphold relevant humanitarian principles. This requires a governing roadmap or internal policy for employees. By creating a roadmap for the integration of AI, institutional leaders can foster accountability and prevent the misapplication of adopted technologies. P4 underscores the need for clear governing guidelines that define the uses of AI and the role of human oversight: *"It's not just about saying 'Don't do it,' but understanding when to turn to an expert or when it's OK to continue alone."* Such frameworks provide a structured approach to decision-making, ensuring that AI deployments remain consistent with organisational goals and ethical commitments.

Resource constraints also pose significant challenges, as leaders must prioritise funding and resources for AI projects alongside other operational demands. However, strong and well-informed organisational and sectoral leadership can bridge the gap between the theoretical potential of AI and its practical applications. By championing innovation and maintaining alignment with organisational values, leaders can enable the responsible deployment of AI technologies in response to pressing humanitarian challenges.

**4.2.3 Governance.** Governance frameworks are critical to ensuring the ethical and effective use of AI in humanitarian contexts as there is a need to go beyond data protection and address broader responsibilities such as accountability, inclusivity, and actionable implementation. For instance, T3 emphasised the importance of integrating early standard action protocols as a key element of effective governance and one that requires buy-in from the organisation: *"These are programmes that help local organisations establish standard operating procedures (SOPs) to initiate humanitarian responses before disasters occur. The process involves embedding AI models into a larger system and agreeing with stakeholders on specific metrics that trigger action... It's not just about AI, but also about the organisational transformation needed to ensure readiness."*

On this, accountability emerged as a key concern, with participants emphasising that AI developers and implementers must be held responsible for the outcomes and consequences attributable

to their technologies. On this issue T7 emphasised: *"If you ask the organisation what their decision-making process is, no one knows. There's no governance in place."* Mechanisms such as audit trails and explainability features were seen as essential for aligning AI systems with organisational values and enabling transparent evaluation of decisions.

Legal and regulatory frameworks are meant to guide governance. However, as T1 observed, the proliferation of policies such as the EU AI Act [100] and the US Blueprint for an AI Bill of Rights [101] creates a fragmented landscape that is difficult to navigate. *"Now every government is coming up with their own policy... Everyone is trying to contextualise and bring this to perspective for their purposes."* Complimenting this challenge, a recurring concern was the gap between high-level AI policies and practical implementation. Many governance frameworks lack the actionable tools needed to guide the design, monitoring, and evaluation of AI systems. Participants stressed the importance of translating these policies into operational resources, such as checklists or protocols, to address challenges like data quality and bias effectively.

**4.2.4 Sustainability of AI Projects.** While certain forms of AI may present operational efficiency gains, their long-term impact depends on adaptability and sustained performance in ever-changing environments. Even when organisations are prepared to adopt AI, scalability and sustainability challenges remain significant. Humanitarian contexts are dynamic and unpredictable, making it difficult to develop AI models that can adapt to changing circumstances. H11 emphasised: *"Sometimes it can take 6 to 9 months to develop a model, and by that time if it was an actual crisis, the need for that process may have already been overtaken by events."* This highlights the difficulties inherent to the creation of AI systems that can respond in a timely and effective manner to real-time crises.

Financial constraints further complicate the scaling of AI solutions, as T3 noted: *"Cloud credits for GPU servers are becoming a larger fraction of our budget... It's harder to develop and operate AI technologies at scale."* Beyond technical costs, organisations face other funding challenges unique to the humanitarian sector. Skilled personnel and robust training are essential for maintaining and refining AI systems, but many organisations lack resources to address these longer-term needs. Donor priorities often focus on immediate crisis response rather than longer-term investments, such as AI capacity strengthening. This misalignment limits the ability of humanitarian organisations to sustain AI initiatives over time, creating a reliance on short-term project cycles that can hinder the space for longer-term innovation.

The risks associated with short-term cycles exacerbate sustainability concerns. H12 shared an experience of a humanitarian organisation procuring a startup to design a digital platform for data collection from people affected by crises. Despite funding the system's development and owning the data, the organisation faced unsustainable membership fees in subsequent years to access the platform's functionality: *"It's like having a Netflix subscription—you can see all the shows but can't watch anything without paying the fee."* This dependency on proprietary systems not only generated financial demands but also hindered the organisation's ability to operate and utilise the system.

The sustainability of AI projects also depends on ensuring that local organisations can take ownership of these systems. H1 highlighted the shift from grassroots efforts to structured local engagement: *“Historically, much of the mapping data was driven by self-organised communities. Now, we are increasingly seeing formal organisations, such as government GIS departments, stepping in with teams actively involved in on-the-ground mapping and data validation.”* This shift illustrates the potential for local organisations to manage AI systems, ensuring contextual relevance and resilience.

Hence, to make AI projects sustainable, participants advocated for more flexible funding models and peacetime financing mechanisms that enable capacity strengthening and infrastructure development. These approaches ensure that organisations are prepared for possible crisis events and capable of sustaining AI initiatives over the long term.

### 4.3 Collaborations for AI Development and Deployment

The successful integration of AI in humanitarian work relies heavily on cross-sectoral partnerships, local engagement, and collaboration. Each sector brings unique strengths, enabling holistic solutions to complex challenges. This theme explores the perspectives of humanitarian practitioners, policy experts, and technology experts on the role of partnerships in AI development and deployment.

**4.3.1 Cross-Sector Collaboration.** Academic institutions contribute critical research and technical expertise, while public sector agencies provide contextual understanding and access to essential data. These collaborations are necessary to build something robust and relevant. However, H4 highlighted concerns about the approach typically adopted by academic centres: *“I’ve observed a lot of collaborations between academia and humanitarian actors, which is encouraging. However, one concern I’ve noticed is that academia, particularly some computer scientists, sometimes approaches these problems in isolation. They may not fully understand the humanitarian sector, its principles, or human rights and ethics. They see a problem they think they can solve with a model, but the ethical concerns around developing those models often take a backseat.”* This underscores the need for deeper engagement between academia and humanitarian organisations to ensure that AI solutions are both technically robust and ethically grounded.

Collaboration among humanitarian organisations also has the potential to foster resource pooling, knowledge sharing, and the establishment of standardised protocols. T3 illustrated the value of cross-organisational efforts in disaster preparedness: *“We take data from meteorological agencies and researchers, translate it into humanitarian impact, and help local organisations establish early action protocols.”* These collaborations ensure that AI tools are contextually relevant, maximising their utility in crisis response and preparedness efforts.

Many humanitarian organisations lack the internal capacity for AI development, relying instead on external tech companies. Partnerships with the tech sector can be useful but must be approached carefully when it comes to data governance and the incorporation of AI. H8 emphasised: *“A lot of UN agencies don’t have a large AI engineer or data science capacity, so you see a lot of subcontracting. But I think it’s important that the agency asking for the solution owns*

*the problem and then brings in technical support.”* This highlights the importance of oversight to ensure that AI solutions align with humanitarian priorities, even when technical tasks are outsourced.

Policy experts emphasise that successful AI initiatives in humanitarian contexts depend on local engagement, co-creation, and inclusive governance. By involving people affected by crises from the outset, organisations can ensure that AI systems reflect the specific needs and challenges presented by different implementation environments. As P1 suggests, asking communities directly, *“What are your problems in your own words, and what features would you like baked into this model?”* helps to ensure the technology is grounded by lived realities rather than external assumptions. Similarly, P3 highlights the value of ground truthing and participatory design, explaining how these practices help validate data and enhance the accuracy of AI outputs: *“You wouldn’t know that until you went out with ground truthing teams to check and get complementary data to validate your big data or satellite imagery.”* Such collaborative approaches extend beyond technical fixes: they empower local actors to shape the design process, foster trust, and promote genuine ownership. In turn, this inclusive, community-driven methodology makes it more likely that AI solutions will remain relevant, effective, and sustainable after external support has ended.

**4.3.2 Ethical Considerations in Partnerships.** Collaborating on AI with external partners in the humanitarian space is ethically challenging, particularly when companies focus on technical performance over humanitarian goals. Employees of humanitarian organisations, like H7, highlight these differences in the ethical framing deployed by the tech and humanitarian sectors: *“For them, when we talked about ethics, they said, ‘My main concern is that the algorithm does what I say it’s supposed to do.’ So, they were more concerned with the metrics used to evaluate the algorithm, such as its accuracy.”* This reveals a tension between technical performance metrics and the ethical imperatives that govern humanitarian work, an ethical divide that must be navigated to ensure that partners develop solutions that do more than function technically but also uphold humanitarian principles and values.

Aligning with this sentiment, tech experts stress the importance of focusing on the practical value that AI brings to end users. T3 explains that tech partnerships should not be about selling technology but rather about ensuring that the tools developed address real-world concerns: *“The focus is on the value for the user, not on the technology because they don’t care about that.”* AI solutions must be designed in a way that is accessible and useful to the people they are intended to serve rather than focusing on technical complexity or cutting-edge innovation as an end unto itself.

However, policy experts focus on the risks of tokenistic participation, or what P2 refers to as “participatory washing”: *“Often, you’ll encounter participatory washing, where you want to be inclusive, but at the end of the day, it’s much more efficient for technologists who are steeped in their work just to get things done.”* This highlights the risk of superficial inclusion, where affected people and local communities are involved in name only, without having any real influence over the design or deployment of AI systems. Such tokenistic engagement undermines the foundations of ethical participation and can lead to solutions that are not aligned with local

needs. To avoid this, humanitarian organisations must prioritise genuine collaboration that respects the knowledge and agency of people affected by crises and other local actors.

Finally, there were significant concerns about power dynamics in AI collaborations, particularly regarding the Global North–South divide. P4 emphasises the need to value and integrate local expertise in AI projects rather than relying solely on external actors from the Global North: *“There’s also a strong need to emphasise the importance of tethering any university team from the Global North that’s swooping in to support with local expertise and contextual awareness.”* This underscores the importance of equal partnerships where affected people and local actors are not just recipients of technology but active participants in the design, deployment, and ongoing use of AI systems. Bridging this divide is critical to ensuring that AI solutions are ethically sound and culturally appropriate.

## 5 Thematic Intersections and the ECHO Framework

The three themes interact in complex ways, and the interconnections reveal underlying tensions and opportunities for the responsible integration of AI into humanitarian response. In the following section, we discuss the intersections between these themes to uncover broader implications for the adoption, management and governance of AI in humanitarian response.

### 5.1 AI Risks and Organisational Readiness

A major question at the intersection between ethical risks and organisational readiness is whether humanitarian organisations can govern AI responsibly. Across the three cohorts, there is agreement that AI requires robust governance frameworks. However, these may be difficult to implement without adequate organisational capacity. Regardless of the robustness of an ethical framework, it only be as effective as an organisation’s capacity to implement and enforce. Hence, the intersection of these two themes reveals a critical insight: *ethical AI adoption is inseparable from organisational readiness*. Building organisational capacity—spanning technical literacy, infrastructure, and leadership—must be viewed as an organisational imperative in pursuit of the ethical adoption and use of AI.

### 5.2 Collaboration and AI Risks

These two themes are closely linked, particularly around questions of ownership and control over AI systems. Given their internal capacity gaps, humanitarian organisations frequently rely on external tech partners to implement AI solutions. However, the outsourcing of technical expertise introduces ethical concerns. As H8 notes, organisations that do not own the AI systems they use may also lose control over the decision-making that dictates how those systems are used in practice. This dynamic creates tension in collaborations, concerning *who ultimately is accountable for the use of AI once deployed*. The intersection between collaboration and AI risks thus raises fundamental questions about accountability in AI governance. The attendant risks posed by AI cannot be delegated, and ideally, humanitarian organisations must maintain responsible ownership of their AI operations to ensure that ethical issues are identified and addressed in a timely and appropriate manner.

### 5.3 Organisational Readiness and Collaboration

The intersection between organisational readiness and collaboration also exposes the vulnerability of dependency on external partners due to capacity gaps. This intersection raises another fundamental challenge for humanitarian organisations concerning *how best to collaborate without fostering dependency on other sectors*. When organisations are dependent on external actors to manage AI tools, they are also less likely to develop the internal capacity needed for the sustainable, longer-term integration of AI. In many cases, external tech companies—still predominantly originating from the Global North—possess the tools, resources, and knowledge that humanitarian organisations in the Global South lack.

This can exacerbate existing inequalities and increase dependency. This reliance on external expertise risks not only loss of control over the governance of AI systems but also limits the ability of organisations to develop their own AI capabilities. By acknowledging these power dynamics, humanitarian organisations might advocate for open-source solutions, shared governance models, or capacity-exchange programmes that even the playing field and reduce the reliance on external suppliers and the risk of exploitative relationships.

### 5.4 The ECHO Framework: Educate, Co-create, Handhold and Optimise

We propose the ECHO framework, as informed by the findings of this research and the HCI principles of value-sensitive design, participatory approaches, explainability, and iterative refinement. The framework addresses these aforementioned intersecting considerations by providing a structured, adaptable roadmap.

**5.4.1 Educate.** In Educate, humanitarian staff gain a foundational understanding of AI’s ethical implications, data risks, and potential biases. Drawing from HCI’s user-centred design and explainable AI, scenario-based tutorials and intuitive interfaces can help staff recognise red flags—such as over-collection of sensitive data or the possibility of dual-use of AI tools—and understand their role in mitigating these risks. An example of such an interface is the Digital Dilemmas Experience [79]. This phase directly relates to the intersection of AI risks and organisational readiness; as staff become more AI-literate, they can engage critically with governance frameworks rather than treating them as abstract policies. From an HCI research perspective, this phase raises questions about how to design training interfaces, decision-support tools, and visualisation techniques that accommodate limited infrastructure and variable technical skills, enabling ethical decision-making despite resource constraints.

**5.4.2 Co-Create.** Co-Create brings together people affected by crises, humanitarian practitioners, policy experts, and technologists to collaboratively shape AI solutions that reflect contextual realities, local needs and priorities, and humanitarian values. By embracing participatory and value-sensitive design methods, this phase counters the tendency toward tokenistic engagement and strengthens readiness by embedding AI ethics and collaboration

into governance structures from the outset. The intersection between collaboration and AI risks can be reimagined as a productive space: ECHO's emphasis on co-creation ensures that ethical frameworks to mitigate risks are not imposed top-down by external partners but rather owned and understood locally. This raises HCI research questions about how to design negotiation interfaces, consensus-building workshop tools, and scenario planning simulations that help organisations agree on differing values and maintain ethical agency when working with external tech providers.

**5.4.3 Handhold.** Handhold focuses on transferring skills, decision-making authority, and system adaptability to the most relevant local organisations. By incrementally introducing AI features and providing modular learning supports, organisations reduce their long-term dependence on external actors. Here, the intersection between organisational readiness and collaboration becomes most apparent. ECHO's incremental approach addresses the challenge of how to collaborate without becoming permanently dependent on outsourced expertise. For HCI, this prompts inquiries into how to build interfaces and toolkits that are not just usable at one point in time but that foster ongoing capacity strengthening. This calls for the design of adaptive, explainable systems that communicate their logic and limitations, enabling staff with limited technical AI literacy and substantial time constraints to maintain control over decisions affecting the ethical application of AI and to ensure the sustainable integration of AI even as conditions evolve.

**5.4.4 Optimise.** Optimise institutionalises iterative refinement and continuous feedback loops so that AI systems remain ethically sound, accurate, and aligned with humanitarian principles over time. Regular audits, user feedback channels, and scenario testing respond to shifting crisis conditions, data challenges, and political landscapes. By embedding iterative evaluation, ECHO ensures that AI governance is not a static one-time deployment but a dynamic evolving process since maintaining relevance and accountability requires ongoing adaptation. For HCI researchers, Optimise highlights the need for longer-term evaluation methods, adaptive interfaces, and frameworks that facilitate sustained organisational learning, keeping pace with new ethical risks and ensuring that previously established collaborative models continue to serve local interests rather than external agendas.

## 6 Discussion

Despite the advantage AI provides for improved forecasting, resource allocation, and workload reduction, its integration is fraught with challenges. Our study began by asking what HCI can offer by way of a guide to the ethical and practical adoption of AI. Through the thematic analysis, we identified three themes that define challenges to the adoption of AI: AI risks in humanitarian work, organisational readiness, and collaboration. The clear and multiple intersections between these themes reveal intertwined complexities, allowing for the emergence of an HCI-informed framework that could assist the process of systematically addressing contextual challenges.

The aim of the framework presented here is not to provide a definitive “one-size-fits-all” solution but to articulate how insights from various corners of the HCI community—such as practitioners

involved in Information Communication Technology for Development (ICT4D), value-sensitive design scholars, user-experience professionals working in non-profit sectors, and human rights-focused technologists—can help humanitarian organisations navigate the complexities of AI adoption.

### 6.1 AI-related Challenges in Humanitarian Response

Prior studies in ICT4D and crisis informatics have long highlighted the risks posed by AI, such as data privacy breaches, inherent bias, and potential for misuse [38, 39]. Our findings corroborate these concerns by illustrating that such risks are not isolated but rather are markedly amplified in humanitarian contexts. Previous research has proposed Responsible AI frameworks that emphasise transparency, data protection, and human oversight [16, 23, 71]. However, our study reveals that the challenges posed by AI in humanitarian contexts are particularly dire in contexts affected by humanitarian crises [7, 30]. This raises questions of the sufficiency of Responsible AI frameworks, to which we suggest that there is an urgent need for systems that integrate real-time and continuous deliberation and contextual adaptation.

In parallel, literature on ICT4D has consistently pointed to gaps in digital infrastructure and literacy as significant barriers to technology adoption in lower-resource settings [6, 67]. Our results not only confirm these observations but also reveal that related organisational deficiencies are inseparable from the risks posed by AI. Our findings suggest that the lack of internal capacity exacerbates vulnerabilities, thereby undermining the reliability and sustainability of AI deployments. This integrated perspective extends earlier work that identified that the interplay between technical capacity and ethical oversight is critical in humanitarian contexts [7, 16, 82, 84].

Additionally, our findings echo and add complexity to insights from Computer-Supported Cooperative Work (CSCW) research, which has detailed the challenges of multi-stakeholder collaboration [43, 48]. Our findings indicate that such collaborations can introduce power imbalances and tokenistic engagements that diminish the commitment to meaningful accountability. For instance, participants described instances where external tech partners prioritised algorithmic performance over humanitarian imperatives, leading to solutions that did not fully align with local needs or values. This critique calls for a re-evaluation of existing collaboration models, suggesting that effective AI governance in humanitarian contexts must incorporate mechanisms for genuine local engagement and co-leadership.

By linking these dimensions, our study challenges the notion that ethical, organisational, and operational issues can be addressed in isolation. Instead, we argue that the interplay between these factors necessitates a holistic approach that can be fostered using an HCI-informed strategy that blends ethical reasoning with capacity building and participatory design.

### 6.2 Adaptation of HCI Principles

Much of the existing Responsible AI literature tends to emphasise top-down policy directives and static guidelines [16, 23, 71]. While these approaches have their merits, our findings indicate that the high-stakes and rapidly evolving nature of many humanitarian

contexts requires dynamic and evolving AI governance approaches. In this light, the HCI-informed ECHO framework offers a model that mitigates the intertwined challenges identified in our results and advanced ongoing conversations related to Responsible AI.

We first propose that building AI literacy and technical competence is crucial, not only to demystify AI but also to embed ethical considerations into the everyday practices of all practitioners. Existing studies have highlighted the benefits of scenario-based learning and explainable interfaces in enhancing user understanding [5, 13, 29], and upcoming training must be tailored to address both the technical deficiencies and the ethical challenges posed by humanitarian contexts.

Second, the imperative to ensure participatory design becomes evident when considering the need for local contextualisation, and Co-create draws on value-sensitive design and participatory methodologies—approaches well-documented in CSCW research [43, 48]. Unlike models that risk tokenistic inclusion, our approach calls for co-leadership from the outset, ensuring that the cultural, social, and situational nuances of each context are fully integrated into the AI design process. This not only enhances the relevance of AI tools but can also foster greater trust and accountability between stakeholders.

Third, many humanitarian organisations currently lack the internal capacity to sustain advances in AI systems, a gap that is exacerbated by over-reliance on external expertise [7, 84]. Drawing on literature from iterative capacity strengthening processes [40, 42, 70], Handhold advocates for the incremental transfer of skills and decision-making authority. HCI methods can facilitate this transition through modular training programmes and adaptive, accessible tools that evolve alongside an organisation's growing competencies. By doing so, we shift from a model of dependency toward one of sustainable autonomy, ensuring that the governance and use of AI are properly managed.

Finally, given the dynamic and often volatile nature of humanitarian crises, static AI systems are inadequate. Optimise leverages HCI's principle of iterative design and continuous improvement [58]. Through regular feedback loops, scenario testing, and iterative refinement, this phase ensures that AI systems remain aligned with the demands of humanitarian practice and the values and principles that shape humanitarian response over time.

Hence, an HCI-informed framework to work on ethical governance, capacity building, and participatory design has the potential to address the identified challenges through actionable strategies that are both context-sensitive and dynamically adaptive, ensuring that the implementation of AI in humanitarian contexts is operationally sustainable. This integrated perspective contributes to the literature by demonstrating that HCI fundamentally reshapes how ethical AI is co-created and managed in complex, real-world humanitarian contexts.

### 6.3 Call for Humanitarian HCI

ECHO aims to embed ethical values, inclusive governance, and continuous learning in the design, adoption and implementation of AI. In doing so, it also reveals that HCI must expand its toolkit and conceptual frameworks. Beyond enhancing usability or efficiency, we

call for HCI researchers to integrate ethics as a core design dimension, envision novel interaction paradigms for consensus-building and accountability, and foster organisational learning ecosystems that allow humanitarian staff to adapt, iterate, and ultimately own AI solutions. By innovating in these areas, we can ensure that humanitarian organisations evolve from passive technology adopters to active, informed leaders in the use of ethically aligned AI.

Our call to action holds relevance for humanitarian technology designers and implementers—including those in NGOs, UN agencies, and humanitarian tech start-ups—who can employ the ECHO framework to structure training modules, incorporate participatory sessions, and plan incremental skill transfer to local teams. HCI researchers specialising in ethics, value-sensitive design, and digital humanitarianism can further define ECHO's phases, test its applicability across diverse crisis environments, and develop new interaction techniques, such as scenario-planning simulations or negotiation interfaces, that enhance ethical decision-making and accountability. CSCW researchers, whose work centres on multi-stakeholder coordination, data governance, and transparency in non-profit or crisis-affected settings, can adapt insights from this study to better design collaborative platforms that uphold humanitarian values, foster meaningful community engagement, maintain trust and disrupt power asymmetries. Finally, policy experts and governance bodies can utilise the HCI-informed framework to translate Responsible AI principles into tangible guidelines, checklists, and protocols that humanitarian organisations can realistically implement, ensuring that ethical considerations remain front and centre in AI deployments.

In this light, the ECHO framework highlights new directions for HCI: designing tools and interfaces that help users reason ethically about AI outputs, developing collaboration platforms that uphold humanitarian values despite global power imbalances, and crafting participatory mechanisms that transfer knowledge and skills locally. These efforts will require multi-disciplinary collaboration, including working closely with humanitarian practitioners, people affected by crises, and policymakers to validate and refine approaches that do justice to the complexity of these contexts.

### 6.4 Limitations and Future Directions

Insights from this study are informed by extensive interview materials drawn from a diverse cohort of AI technology experts, humanitarian practitioners and humanitarian policy developers. While this breadth provides a rich understanding of the challenges to AI adoption in humanitarian contexts, several limitations must be acknowledged. First, our findings are shaped by the specific geographical, political, and organisational environments in which the interviewees operate. Differences in cultural norms, regulatory landscapes, and technological infrastructures may influence the applicability of our conclusions in other contexts. Future research could adopt a comparative approach, examining how variations in regional settings, particularly in regions with protracted crises, extreme weather conditions or organisational mandates, affect AI governance and capacity-building needs.

Second, our sample, while diverse, does not fully capture a fully representative cross-section of all relevant stakeholders, nor importantly those people affected by humanitarian crises or the use of

AI in such contexts. Project-level humanitarian workers, people receiving humanitarian services, and other local actors often face constraints that prevent them from fully participating in research interviews, leaving some perspectives chronically underrepresented. Future studies could use participatory action research methods, ethnographic fieldwork, or community workshops to engage more directly with those people who should be at the forefront of humanitarian research and subsequent design processes. Such approaches would yield a more nuanced and representative understanding of user experiences, cultural considerations, and social dynamics that might shape the adoption and impact of AI tools.

Additionally, the rapid evolution of AI technologies, policy debates, and humanitarian crises pose a temporal limitation. The conditions described here—both technological and geopolitical—will continue to shift rapidly. This temporal sensitivity calls for longitudinal studies that track how evolving AI capabilities, emerging regulatory frameworks, and changing donor priorities influence ethical governance and organisational readiness over multiple crisis cycles.

Fourth, our work primarily focused on high-level themes and conceptual frameworks rather than on conducting in-country interventions or experimental trials. Although ECHO and its associated principles were shaped by our empirical findings and the existing HCI literature, their practical relevance has yet to be tested. Subsequent research could involve pilot implementations of ECHO principles in specific humanitarian projects, tracking how the framework affects outcomes and overall, AI system sustainability over time.

Finally, while the ECHO framework aims to integrate HCI principles tailored to the realities of everyday humanitarian practice, further refinement and elaboration are needed. Future work could explore how to operationalise these guidelines into actionable toolkits, checklists, or software modules that humanitarian staff can readily use. Researchers and practitioners could collaborate to develop and test interactive decision-support systems, prototype interfaces for scenario-based ethical reflection, and context-sensitive dashboards that align with the four ECHO phases. Over time, iterative evaluations and user feedback will help distil best practices, adapt the framework to new challenges, and ensure that it remains relevant amid shifting humanitarian priorities and technological innovations.

In summary, while this study offers an initial framework, addressing its limitations and pursuing these proposed future directions for research will be essential if we are to transform conceptual insights into robust, context-sensitive, and ethically grounded AI adoption strategies that genuinely serve humanitarian objectives.

## 7 Conclusion

Our interviews with AI technology experts, humanitarian practitioners, and humanitarian policy developers revealed three inter-related themes that currently shape AI adoption in humanitarian contexts: the urgency of managing AI-related risks (including data misuse, bias, and dual-use scenarios); the critical importance of organisational readiness (from basic AI literacy to leadership buy-in and governance frameworks); and the necessity of equitable collaboration (ensuring local actors have meaningful influence and

are not sidelined by external technology partners). These findings reveal that the potential of AI to augment humanitarian crisis forecasting and response is tempered by serious ethical and operational constraints. To navigate these complexities, we proposed the ECHO framework (Educate, Co-Create, Handhold, Optimise). By embedding ethical reasoning into interfaces, fostering participatory design with people affected by humanitarian crises, incrementally building local and humanitarian organisational and sectoral capacity, and supporting iterative refinement, ECHO translates our interview findings into a practical HCI-informed roadmap for humanitarian organisations. It aligns the core humanitarian principles and user-centred methodologies with evolving AI tools, aiming to reduce dependencies, enhance trust, and maintain ethical accountability. While further empirical testing and refinement remain necessary, we hope this framework guides future collaborations, informing tangible design strategies, governance models, and capacity-building initiatives that ensure AI is applied to meet humanitarian objectives without compromising ethical imperatives or the dignity and safety of vulnerable people.

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