IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 6 December 2025, accepted 26 December 2025, date of publication 6 January 2026, date of current version 23 January 2026.

Digital Object Identifier 10.1109/ACCESS.2026.3651368

PERSPECTIVE

Roadmap Toward Responsible AI in Crisis Resilience and Management

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ABSTRACT Using novel data and artificial intelligence (AI) technologies in crisis resilience and management is increasingly prominent. AI technologies have broad applications, from detecting damages to prioritizing assistance, and have increasingly supported human decision-making. Understanding how AI amplifies or diminishes specific values and how responsible AI practices and governance can mitigate harmful outcomes and protect vulnerable populations is critical. This study presents a responsible AI roadmap embedded in the Crisis Information Management Circle. Through three focus groups with participants from diverse organizations and sectors and a literature review, we develop six propositions addressing important challenges and considerations in crisis resilience and management. Our roadmap covers a broad spectrum of interwoven challenges and considerations on collecting, analyzing, sharing, and using information. We discuss principles including equity, fairness, explainability, transparency, accountability, privacy, security, inter-organizational coordination, and public engagement. Through examining issues around AI systems for crisis management, we dissect the inherent complexities of information management, governance, and decision-making in crises and highlight the urgency of responsible AI research and practice. The ideas presented in this paper are among the first attempts to establish a roadmap for actors, including researchers, governments, and practitioners, to address important considerations for responsible AI in crisis resilience and management.

INDEX TERMS Applied computing, crisis resilience, equity, human-centered computing, information management circle, information systems, responsible AI.

I. INTRODUCTION

Crises resulting from natural hazards, pandemics, and conflicts occur with increasing frequency and intensity. Crisis resilience and management (CRM) plays a vital role in preparing for, mitigating, responding to and accelerating recovery from crises. Crisis resilience is defined as the ability of systems (e.g., critical infrastructure, businesses) to absorb and recover from the effects of a hazard in a timely and efficient manner, thereby reducing the social, economic, physical, and well-being impacts of disasters [1]. Crisis management refers to the process of identifying, assessing, and responding to a crisis in a timely and effective manner [2]. Typically, crisis management refers to a four stage model of prevention, preparedness, response, and recovery. As such, resilience to and management of crises are closely intertwined. Furthermore, it is important to note that not all crises are alike. Natural disasters (e.g., earthquakes, hurricanes) typically involve infrastructure protection agencies and rely on sensors, satellite imagery, and crowdsourced data under urgent time constraints. Pandemics involve public health governance and medical data sharing across jurisdictions, while conflict crises engage military or humanitarian organizations handling sensitive intelligence and security data. Each crisis type, thus, features distinct governance structures and data dynamics.

An AI system in CRM refers to a system designed to improve situational awareness or to support decision-making,

The associate editor coordinating the review of this manuscript and approving it for publication was Derek Abbott.

composed of various components such as data, AI models and techniques, and interfaces. We understand AI in a broad sense, including data analytics and machine learning (ML) methods as well as simulation models based on intelligent agents. The rise of AI systems in CRM is facilitated by rapid advancements in sensing technologies, inexpensive data storage capacities, and increased computing speeds that enable unprecedented data collection, storage, and processing. Following the turn to innovation as a central vehicle for improving CRM, researchers and corporations have developed a broad range of applications that exploit data, such as high-resolution satellite imagery, cell phone movement patterns, and social media data. AI systems have been used to support decision-making at different crisis phases, such as (1) preparedness, e.g., predictive risk assessment [3], [4], [5], [6]; (2) response, e.g., rapid damage assessment [7], [8], [9], [10], [11] or population migration and evacuation [12], [13], [14], [15], or (3) recovery, e.g., recovery progress assessment [16], [17], [18].

Crisis information management and decision support have significantly advanced due to contemporary theoretical frameworks. Modern interpretations of bounded rationality, particularly the ecological rationality and fast-and-frugal heuristics framework developed by Gigerenzer and Gaissmaier [19], emphasize that decision-makers in uncertain environments rely on adaptive heuristics instead of exhaustive optimization—an assertion that is particularly relevant in time-sensitive crisis scenarios. This aligns with Naturalistic Decision Making (NDM), as discussed by Klein [20], which illustrates how professionals utilize experience-based pattern recognition to navigate complex, high-stakes scenarios intuitively. Weick, Sutcliffe, and Obstfeld [21] redefined sensemaking at the organizational level as an ongoing process of "organizing" narratives and interpretations to navigate ambiguity. The concurrent progression of information systems led to the updated DeLone and McLean Success Model [22], which expanded the assessment criteria to include service quality alongside system and information quality.

Integrating AI into CRM necessitates a comprehensive reevaluation of these antiquated systems. AI does not remove the limits of limited rationality; it only changes them, as shown in Table 1. AI makes systems faster, but it also makes them more "algorithmically constrained" because the training data isn't always clear and the models aren't always clear. The NDM's dependence on expert intuition encounters challenges, as AI pattern recognition lacks the nuance and tacit knowledge inherent in human expertise. "Closed box" AI can make it harder for groups to understand things, which is important when problems come up. Traditional metrics for assessing information systems focus on utility and usage, while overlooking the ethical aspects of fairness, equity, and accountability that are essential in automated crisis management systems. This paper does not dismiss these theories; instead, it calls for substantial enhancements: shifting from human-centric limitations to hybrid human-AI governance, guaranteeing explainability that links algorithmic results with expert assessment, and expanding success criteria to incorporate responsible AI principles into crisis response frameworks.

Along with the increasing prominence of AI across domains, principles and standards have been established to guide the design, development, and use of AI, commonly referred to as responsible AI principles [23]. These principles have been applied in areas such as health care, security, finance, hiring, and news media [24]. The need for contextualization—particularly in automated decision-making—is increasingly recognized [25]. Several prior works have outlined responsible AI frameworks and systematic reviews in broader contexts [26], [27], [28], yet crisis-specific guidance remains limited. For instance, Papagiannidis et al. [26] synthesize responsible AI governance principles in general settings, while Song et al. [29] demonstrate the risks of unchecked AI outputs, such as hallucinations, in high-stakes self-rescue scenarios. Building on these insights, our roadmap differentiates itself by explicitly addressing the crisis resilience and management domain, translating established responsible AI principles into crisis-specific challenges and maintaining a critical view of AI's role in disaster decision-making. Importantly, crises differ significantly in governance structures, data environments, and operational demands, ranging from natural hazards that depend on real-time sensing and emergency agencies, to pandemics governed by public health institutions, to conflict-related crises involving humanitarian and security actors handling highly sensitive information. As a result, AI cannot be treated as a universal or default solution. Responsible AI integration requires recognizing the limits of AI technologies—particularly when data are unreliable, when automated decisions may erode trust, or when human-centered or low-tech approaches remain more effective—and aligning with societal, ethical, and contextual boundaries emphasized in recent analyses of AI and AGI development pathways [30], [31]. Despite the rapid growth of AI systems in CRM, key responsible AI issues remain insufficiently addressed [32], and persistent calls for actionable and operationally relevant guidance have only been partially met.

Applications in CRM raise specific challenges to responsible AI. Crises, by their very nature, create novel situations and emergent organizational arrangements that respond to them [33]. There is often a quickly changing situation, an overwhelming number of actors, with evolving responsibilities and tasks that are supported by a broad array of tools. This emergence poses challenges for data collection, data sharing, and data standards, as well as for data analysis via AI systems [34], [35]. It remains unclear, which decisions can or should be taken or informed by an AI, under which circumstances, and how this human-AI collaboration should be orchestrated.

Further, decisions in crises often cause moral dilemmas and are driven by values [36], [37]. Some actors might be guided by rights-based frameworks such as the capabilities

TABLE 1. Bridging traditional theory and responsible AI in crisis management.

Traditional Theory	AI-Era Gap & Challenge	Proposed Extension (This Roadmap)
Ecological Rationality [19]	AI expands processing capacity but introduces new "bounds" via training data limits and algorithmic opacity.	**Prop 2:** Mitigation strategies must address hybrid biases (human cognitive + AI algorithmic) rather than human constraints alone.
Naturalistic Decision Making [20]	AI pattern matching lacks the contextual nuance and tacit knowledge inherent in expert human recognition.	**Prop 3:** Explainability features must serve as a bridge between statistical AI outputs and expert human intuition.
Organizing & Sensemaking [21]	"Black box" AI outputs can disrupt the collective narrative and interpretation processes essential during chaos.	**Props 3, 4:** Transparency and accountability mechanisms are essential for maintaining organizational sensemaking capability.
Updated IS Success Model [22]	Standard metrics (system/info quality) fail to capture high-stakes safety, fairness, and ethical risks in crises.	**Props 1–6:** Success criteria must be expanded to include equity, fairness, explainability, accountability, coordination, and privacy.

approach, adopted by many development organizations [38], [39] while others focus on the crisis standards of care [40] enacted by MSF, an international and independent medical humanitarian organization. The UN Office for Coordination of Humanitarian Affairs (UN-OCHA) accordingly has put forward principles to guide information management [41] specifically during crises. However, the humanitarian principles such as humanity, neutrality, or reciprocity are not conventionally considered in the generic responsible AI literature.

The examples of AI use in CRM above highlight the importance of addressing responsible AI issues in CRM. Various reports and guidelines aim to point out the benefits and perils of using AI such as the UN-OCHA Data responsibility guidelines [42] primarily concern data acquisition and sharing. A recent report by the Global Facility for Disaster Reduction and Recovery [32] highlights the importance of deploying AI and machine learning in an effective and responsible manner. While the reports provide guidance for practitioners working in crisis response and address key concerns such as bias and privacy, they do not offer a systematic way of scrutinizing these concerns, nor do they provide a comprehensive research agenda. In the absence of a comprehensive research agenda for addressing responsible AI issues, the design and use of technologies may incur consequences that deteriorate CRM processes in the short- or long-term. Since in crises human behavior and values play a key role, we argue that the debate about how to measure and transform concepts and issues into policy or regulations has to take place at the intersection of AI, social science, and ethics. This paper is meant to initiate the debate and provide a concrete roadmap for responsible AI issues to be addressed and embedded into the design and development for the CRM field to take full advantage of AI systems.

In the following sections, we first present an overview of our research approach. Then, we discuss responsible AI principles for CRM that are framed as propositions to describe the key challenges of each field and specify research areas that need to be further addressed in the near future. For each proposition, we first provide a brief justification, followed by an elaboration of issues and challenges in the design, development and use of AI specific to crises based on a series of examples from recent crises. From there, we formulate a research agenda for each proposition. The paper concludes with a reflection and discussion.

II. RESEARCH APPROACH

To address the absence of a roadmap and research agenda toward responsible AI in CRM, the main research questions addressed in this paper are: (1) What are the core responsible AI challenges in the current state of the art and current practices related to CRM? and (2) What priority research areas for responsible AI in CRM need to be addressed over the next decade? To ensure that our agenda bridges academic research and current application, we designed a 2-stage approach, combining focus groups with a literature review. To capture insights, perspectives and challenges from various practitioners in CRM, we organized three thematic virtual focus groups to discuss diverse challenges and research questions related to responsible AI in CRM. The three themes for each focus group were: (1) AI-driven disaster management: opportunities and challenges, (2) Data governance: roles and responsibilities, and (3) Equity, privacy, and ethics. We invited a diverse group of subject-matter experts (SMEs) representing multiple sectors involved in crisis information management. The focus groups, conducted in June 2021, included 13 participants, each with more than 10 years of professional experience working with crisis data systems, decision-support tools, or AI-enabled CRM technologies. The group comprised 2 SMEs from international humanitarian organizations, 4 from international disaster management organizations, 3 from domestic emergency management agencies, 3 from private-sector "AI for good" programs developing disaster-related AI tools, and 1 academic expert specializing in humanitarian crises. Each session lasted approximately two hours. Because confidentiality agreements restrict disclosure of additional personal identifiers, organizational affiliations, or demographic attributes, participants are described at the sectoral level. Nonetheless, all participants held senior or technical roles requiring routine engagement with CRM data pipelines, model outputs, and operational decision-making. This depth of experience ensured that their contributions reflected real-world constraints, challenges, and expectations encountered in crisis information management practice.

We documented the ideas and perspectives shared during the focus groups and then analyzed this information using mind mapping techniques to identify emerging issues and challenges, as well as principles. To minimize the possibility of selection bias, for example, certain sectors or regions may not be fully represented among our participants, the findings from the focus groups are therefore interpreted as illustrative insights rather than an exhaustive survey of all stakeholder perspectives.

In addition to the focus groups, we applied title-based search on both Web of Science and Google Scholar platforms to conduct comprehensive literature reviews. We used the following keywords with combination of artificial intelligence or AI to search for the most relevant papers on the topic: (1) crisis (or disaster/natural hazard) management; (2) crisis (or disaster/natural hazard) resilience; (3) decision-making; (4) bias; (5) fairness; (6) explainable; (7) transparency; (8) accountability; (9) information system; (10) information management; (11) privacy. We then carefully reviewed the titles and abstracts of the found papers based on the search criteria and selected the representative works to conduct review. We used the principles put forward by the European Commission's High-Level Expert Group on Artificial Intelligence as a basis to analyze the literature. The principles include Human agency and oversight, Technical robustness and safety, Privacy and data governance, Transparency, Diversity, non-discrimination and fairness, Societal and environmental wellbeing, and Accountability [43]. We weighed these principles against the backdrop of requirements from the crisis management literature. The information gathered from the focus groups and the literature review was synthesized iteratively to establish the research roadmap. A substantial portion of the themes identified across both sources were aligned and directly informed the development of our six propositions: (1) Fairness, (2) Non-discrimination and bias in data, analysis, and decisions, (3) Transparency and explainability, (4) Accountability and credibility, (5) Inter-organizational coordination and public engagement, and (6) Information privacy and security. In several instances where the insights did not fully converge, these divergences were acknowledged rather than forced into agreement and were discussed in the later section.

III. PRINCIPLES FOR RESPONSIBLE AI IN CRM

In this section, we present the six propositions identified for responsible AI in CRM.

A. CRM AI SYSTEMS MUST PROMOTE EQUITY AND FAIRNESS CONSIDERING DIVERSE STAKEHOLDER VALUES

A critical aspect of creating AI systems for CRM is the consideration of fairness and equity [44]. Generally, a fair AI system is defined as an AI system whose results are independent of a given variable, especially sensitive attributes such as race and income [45]. We argue that in the context of crises fairness needs to be complemented by equity: reducing the disproportionate impacts of crises on vulnerable populations [46]. The current lack of consideration of various fairness criteria (such as group, individual, and causal fairness) in AI models in CRM can be greatly problematic and contribute to a lack of equity. Research has shown that inequality in a community reduces social resilience [47], and a perceived lack of fairness reduces trust in authorities [48], [49]. That implies that if AI-driven responses amplify inequality or inequity in a crisis, they hinder the crisis response they are designed to support.

1) CHALLENGES AND REQUIREMENTS

AI systems are increasingly used for decisions that have important distributive implications, ranging from forecast-based finance or anticipatory action [50] to assessments for prioritization of disaster-affected regions or sectors [51], or models for rapid disaster relief logistics [52]. While the crisis decisions that the AI seeks to automate should be guided by considerations of equity and fairness [41], there is still a lack of a formalization of these principles, which prevents them from being translated into AI models. Instead, current models are designed to maximize efficiency and effectiveness for crisis managers and the organizations for which they work [53]. Thus, the challenge is for AI developers and researchers to translate moral and normative concepts into formal methods and develop tools to support decision makers facing critical trade-offs among fairness, effectiveness, and efficiency. Where feasible, fairness can be assessed using measurable indicators, such as disparities in resource allocation outcomes across demographic or geographic groups. At the same time, not all aspects can be fully quantified. These measurable and non-measurable elements together shape responsible fairness assessment in CRM contexts.

A part of the challenge is that what is perceived as 'fair' represents a normative choice. While in the design of AI systems, it is virtually impossible to include the preferences and values of all possible and future stakeholders. For instance, during the COVID-19 pandemic, decisions were informed by epidemiological models that predicted the direct impact of the pandemic in terms of the number of people infected or the strain on the public health system. However, research has shown that the most vulnerable people were most exposed to the spread of the disease [54], gender gaps were widened [55], and the poorest households experienced the highest losses of household income [56]. In addition, school closures impeded learning and disproportionately affected disadvantaged children [57]. This clearly shows that data-driven pandemic models did not fully account for equity considerations, nor did they integrate the preferences and values of different stakeholders. Therefore, it is critical that the inclusivity and representation of all stakeholder groups is ensured so that AI systems can be designed to balance competing interests.

2) RESEARCH AGENDA

To address the considerations of equity and fairness, it is essential to understand the theoretical basis of equity and fairness and to identify conceptual analyses and components of fairness necessary for responsible AI systems in CRM. The understanding of equity and fairness might vary amongst groups and resist being codified. An equity-aware approach is more likely to be trusted and used by residents and community members if AI developers successfully improve community engagement. Moreover, the benefits of fairness-aware AI systems for CRM are multifold. In addition to more equitable decisions and actions that fairness-aware CRM AI systems could enable, they could enhance the much-needed equity awareness and compassion in public officials, emergency managers, and responders who use the AI.

We appeal to (1) focus on the impact of AI systems on the most vulnerable and marginalized groups; (2) define and formalize equity and fairness criteria for CRM AI systems; (3) formalize and integrate trade-offs between norms and criteria based on the values of diverse stakeholders. The most vulnerable need to take center stage because of moral and equity considerations, but may also harbor distrust of crisis management authorities, as these institutions may be perceived to not act in their interest. Defining equity/fairness criteria will require mapping stakeholder values in relation to the decision problem for which the AI system is being developed and specify accordingly proper equity/fairness criteria. Also, issues of data justice and fairness often come to the fore when we productively move away from ideas of a universal "person" to be specific about whom we are talking. The challenges here are ones that face many institutions and have no easy solutions but turning a blind eye to the problems is not a responsible approach. AI developers can collaborate with social scientists focused on participatory action research or with ethicists who can elucidate moral concepts.

B. CRM AI SYSTEMS SHOULD FACILITATE BIAS MITIGATION IN DATA, ANALYSES, AND DECISION-MAKING

Crises have been shown to induce or amplify a range of cognitive and data biases in human decisions because of the typical combination of time pressure, uncertainty and high stakes [58], [59], [60]. While AI has been promoted as a technology to make decisions more 'data driven' and 'objective'-potentially mitigating human bias, there is a range of algorithmic and data biases, to which AI is prone. Suresh & Guttag [61] further categorize AI biases into two stages: (a) data generation (such as historical bias, representation bias, and measurement bias), and (b) model building and implementation (such as learning bias, aggregation bias, and evaluation bias). What is not yet understood is the interplay of cognitive biases in human decisions, and data or algorithmic biases in an AI, and how they amplify or can counter each other.

1) CHALLENGES AND REQUIREMENTS

On the side of data and algorithms, recent studies have shown issues related to the underrepresentation of certain populations (e.g., low-income and racial minorities) in location-based and crowdsourced datasets cause group fairness issues [62], [63]. Imbalanced and underrepresented data and biased algorithms exacerbate the issues of inequalities caused by power differentials. Power is not distributed evenly throughout a population. In the US context and elsewhere, race, ethnicity, language, nationality, financial resources, location, religion, gender, sexuality, ability, and other dynamics are intimately involved with the assignment of power. But these are all macro-dynamics: within particular organizations, families, societies, and localities, there are wildly different organizations of power. AI systems in the context of CRM can create inequities when they rely on algorithms or datasets that obscure or reify power relations among groups of people. People or groups may be entirely unrepresented in datasets, leading to biased crisis response.

Sometimes, the management of a crisis occurs from a distance, which may hinder understanding or awareness of the nuances of local relations and introduce biases [64]. The source of risk or suffering might not be under the control of a local population, but the paradigm of resilience requires people who are suffering to live with risks [65], [66], [67]. This can be exacerbated when implementing AI to support decision making with biases. Several scholars warn that the introduction of remote, AI-based management may disenfranchise communities and local efforts [68]. The introduction of AI and remote management, especially if combined with data or algorithmic bias, can make it easier to overlook, neglect or discard specific groups, and thus further widens the power differentials between different groups who are impacted by a crisis, or between crisis managers/researchers and the people affected. These biases negatively impact fairness, creating double disasters as those who are already marginalized are disproportionately affected by the disaster and then ignored in the response [69], [70].

Besides the data and algorithmic biases, the complex and stressful decision-making situations in crises induce a range of cognitive biases that an AI may amplify. Decision makers in crises are confronted with tremendous time pressure, stress, and uncertainty. While there are hopes that an AI may help to make decisions in crises more 'objective', research has shown that in crisis conditions, decision makers tend to neglect biases in datasets and AI algorithms [60].

2) RESEARCH AGENDA

Technologies developed for CRM can have profound effects on those who receive or depend on aid and assistance. Recent research has shown that biased datasets and algorithms create path dependencies, from which decision makers are unable to adjust their initial decisions, even though they know that the initial data was flawed [60]. Yet, there remains a widespread belief in crisis management that decisions made based on biased data or algorithms will be corrected and adjusted as more information becomes available [71]. Therefore, it is incumbent on responsible AI developers to acknowledge that their technologies may create lasting bias. It is paramount that responsible AI attends to power differences using participatory or other approaches to ensure democratic processes are incorporated and to identify biases introduced during data collection and model development.

Developers of AI models need to understand how and why data was collected to identify gaps and biases that may affect model behavior. In addition, implementing debiasing techniques during data processing and model development is essential. These may include dataset audits (e.g., imbalance ratios, missingness patterns), bias detection tests (e.g., error disparities across groups), and mitigation strategies such as rebalancing, adversarial validation, or fairness-aware model adjustments. These practices align with established recommendations for mitigating bias in AI systems [72]. While several bias indicators can be quantified, some forms of bias—particularly those rooted in institutional practices or historical inequalities—require contextual interpretation and cannot be fully measured through technical metrics alone. Hence, bias mitigation must combine quantitative tools with domain expertise and qualitative review. Future research should (1) develop a comprehensive bias identification framework and metrics that can be applied to current and emerging data and algorithms; (2) track how different types of biases propagate from data through AI to sequential and interdependent decisions in human-AI collectives; and (3) propose debiasing pipelines that attend to power differences to augment responsible AI in CRM.

C. CRM AI SYSTEMS SHOULD BE EXPLAINABLE AND TRANSPARENT TO GAIN BROADER TRUST

Advanced AI algorithms can be useful in the context of CRM. For example, deep learning models can inform disaster response by using satellite imagery to detect areas that have been affected by a crisis [73]. However, many machine learning techniques, especially those relying on neural networks, create stochastic outputs that cannot easily be explained to decision makers and are often considered to be closed boxes. Many have argued that transparency is crucial to ensure that stakeholders trust machines. In the high-stake decisions typical for CRM, the inability to explain the outputs produced by machines can influence decision makers' and users' trust in AI systems [74], [75], [76].

1) CHALLENGES AND REQUIREMENTS

Generally, the purpose of explainable AI is to make the behavior of an algorithm more intelligible by providing explanations [77]. With the rise of automated decision-making, there is increasing attention for explainability, and the UN Secretary General's 2020 Roadmap for Digital Cooperation [78] explicitly links explainability to accountability (see next Section).

One approach to explainability is to increase the transparency into an AI system and ensure that AI systems that inform CRM decisions are explainable. However, while many papers postulate a link between explainability and trust in CRM, there is research that has shown that trust in the authorities and understanding of the rationale behind the decisions are vital to achieve compliance [79]. The mechanisms behind trust in or compliance to an AI are not yet understood.

Explainable models that can reveal feature interaction and feature importance provide information for decision makers who understand how to implement AI algorithms. However, models with less explainability due to their complexity often provide better accuracy compared to more explainable models [80]. Hence, during the early stages of AI system development, users and stakeholders should understand trade-offs between explainability and accuracy and have a clear definition of the desired level of accuracy and explainability. In crisis contexts, transparency requirements must match the pace of decision-making. During fast-onset events, decision makers often only have time for lightweight explanations, such as high-level feature importance, confidence scores, or basic data quality alerts. More detailed explainability analyses are typically feasible only during preparedness or recovery phases. Thus, transparency should align with the time sensitivity and information needs of each stage of a crisis.

Explainability and transparency can create opportunities for new knowledge to improve CRM processes, but researchers have also argued that there is little reason to be hopeful about the capacity of transparency to make for predetermined sets of goals such as fairness. Ananny and Crawford [81] described the limits of transparency in AI systems is not connected to systems of punishment or reward and so though transparency might reveal transgressions, there may be no changes as a result of the revelations; transparency can cause harm to vulnerable groups if it reveals secrets; transparency does not always produce something that is usable and may actually create more confusion; transparency doesn't necessarily build trust in systems because trust is a social concept that is experienced differently by different people; and transparency may not help people who lack technical knowledge, or as Ananny and Crawford put it, "seeing is not understanding" [81].

2) RESEARCH AGENDA

Although transparency and explainability do not address the existential question of whether some types of AI systems in CRM should exist at all, transparency and explainability are necessary for knowledge about how CRM processes work. Thus, transparency and explainability are keys to public oversight and public input, but require other institutional apparatus, such as measures of transparency and explainability of AI systems, to make them helpful to achieve goals of responsible AI. To support these goals, CRM practitioners may draw on established explainability tools such as feature-attribution methods (e.g., SHAP or permutation importance), saliency maps for image-based models, model documentation artifacts, and error-traceability logs that help reconstruct how outputs were generated. While these tools vary in granularity and usability, they provide practical avenues for enhancing explainability in both high-urgency and slower-moving crisis contexts. In addition, if an AI system is opened for investigation, there have to be real consequences for the system, including that development and use of the system ceases, to ensure trust in not only the AI, but the process of public accountability. Also, while the expertise to understand AI technologies lies with a few experts who understand both the domains of AI and crises, the investigation of AI systems has to include people who are supposed beneficiaries, as well as public employees and administrators. That is, diverse publics and societal actors need to be included in oversight [82].

Explainable models are more likely to facilitate relationship building and knowledge sharing among organizations and stakeholders. Hence, to move forward, it is essential for research to (1) explicitly define transparency and explainability for AI systems in CRM, including how to measure transparency and explainability of AI systems, what needs to be transparent in AI systems, and to what extent the explainability and transparency of AI systems is acceptable, desired or required; (2) understand the link between explainability, transparency, and trust; and (3) improve knowledge sharing and AI system understanding among diverse organizations to better cope with crises (something that we address further in Section III-E).

D. CRM AI SYSTEMS SHOULD YIELD CREDIBLE INSIGHTS FOR ACCOUNTABLE DECISION MAKING

When decisions are informed or even made by AI systems, there are important challenges related to accountability and credibility that need to be addressed. Accountability refers to the idea that certain people or organizations accept responsibility for the results of AI systems [83]. The problem of accountability in AI is challenging because it is difficult to determine who should be responsible for the impact of an AI, and how this responsibility should be implemented or enforced. A related concept, credibility, like trust, is a property of relations where an organization, people, or technology is held in high esteem [84].

Achieving accountability in practice will require institutional and legal mechanisms in addition to ethical intent. Clear liability frameworks should delineate who is accountable if an AI-driven decision leads to adverse outcomes in a crisis. Likewise, organizations might implement AI audit requirements or certification standards to enforce accountability; for example, requiring that crisis-management AI tools undergo regular third-party audits for fairness and reliability. Regulatory initiatives, such as national AI ethics guidelines or the proposed EU AI Act, can provide consequences for non-compliance and thus institutionalize responsibility. By embedding such enforcement mechanisms, we ensure that accountability is backed by concrete incentives and obligations, not left as an informal principle.

1) CHALLENGES AND REQUIREMENTS

Researchers, developers, and decision makers need a clear definition of responsibilities and accountability when an AI model is created and used for CRM. However, decision makers may expect ideal predictions and thus overestimate the capabilities of models, resulting in undesirable outcomes. For example, AI systems have been adopted to predict what areas and roads might be flooded. However, there is a risk of false-negative and false-positive predictions. Models wrongly predicting that a road will not be flooded could result in death or injury. A prediction of flooding on one road can lead to unnecessary bottlenecks elsewhere. In Indonesia, a false-negative prediction resulted in more than 1,200 people being killed due to a tsunami [85]: even though the earthquake that led to the tsunami was detected and felt, people did not evacuate because an early warning system failed to detect and warn of three tsunami waves. A crucial question is how AI systems can be held accountable for their actions during a crisis. If an AI system produces incorrect or harmful outputs, determining responsibility becomes complex, as it may involve developers, system operators, data providers, decision-makers, or regulatory bodies. To support accountability, crisis-relevant AI systems can incorporate measurable indicators such as model confidence scores, error tracking logs, incident reporting mechanisms, and documentation of decision rationale. These tools can help trace decision pathways and clarify responsibility.

Ignoring the results from AI models also can have dire consequences. The extent and magnitude of floods in Northwestern Europe in July 2021 were correctly predicted by the European meteorological services. But the warnings were discarded at the regional and local level in Germany as not credible, because the amounts of rain that had been predicted in a very short period were simply unimaginable to the decision makers [86]. This neglect led to delays in the order of evacuations, which resulted in dozens of casualties in the affected communities.

2) RESEARCH AGENDA

The burden of accountability can scare agencies and developers from adopting or creating AI systems. The issue of accountability requires a clear understanding among all entities involved and will likely change depending on the local laws. Importantly, research is needed to (1) co-create reference frameworks and standards for specific AI systems with AI developers, designers, and stakeholders to report chains of development for specific models to improve accountability; (2) educate developers, decision makers, and other model stakeholders about model limitations, underlying assumptions, possible areas for application, and model uncertainty with public documentation and innovative visualizations. For example, instead of a model predicting whether a road gets inundated or not, a model should/can provide the likelihood of road flooding. Decision makers then need training to interpret the results along with their own knowledge and risk threshold and communicate with residents. The decision makers and users should also be familiar with the way AI systems work and their inherent capabilities and limitations to avoid over- and underestimating the capabilities of models. Besides the agreed reference frameworks and standards, innovative research around visualizing uncertainty can help researchers communicate with different stakeholder groups.

E. INTER-ORGANIZATIONAL COORDINATION AND PUBLIC INVOLVEMENT ARE CRITICAL FOR CREATING RESPONSIBLE CRM AI SYSTEMS

Crisis Resilience Management includes diverse organizations and stakeholders. We have known for decades that information sharing amongst organizations is the backbone of effective coordination and crisis response [87]. However, the sharing of crisis data among groups of collaborators brings up issues of data ownership, confidentiality, data stewardship, and complex issues about metadata and interpretation [53]. Data sharing is a significant barrier to achieving integrated AI-based solutions developed upon different datasets owned by different organizations.

1) CHALLENGES AND REQUIREMENTS

Using AI systems in isolation could negatively affect collective sense making, information processing, and coordinated decision making, all of which are core elements for effective CRM [87]. Therefore, AI systems for CRM require the coordination of multiple organizations in sharing data. In practice, however, many organizations involved with CRM create and use their own AI systems in isolation because of the limitations on information sharing or organizational responsibilities and legal constraints [79], which can introduce errors into models, analyses, and interpretations. As a result, decision makers are confronted with a paradoxical situation of a deluge of uncertain, noisy, and conflicting information, while critical datasets may remain missing [35], [74].

One approach to address issues of inter-organization coordination is to create federated AI systems with human-centered AI (HCAI) frameworks. In the design, diverse CRM organizations need to coordinate, and stakeholders and publics influenced by an AI system need to be involved [88], [89]. However, identifying and engaging stakeholders is challenging due to the fragmented nature of CRM ecosystems, with limited coordination and cooperation among stakeholders. Integrating AI models created in isolation into a federated AI framework is also challenging without institutional connectedness. Here, a federated AI system is not fully integrated; instead, it means different AI systems interface with one another and share results. An important challenge here is that given the increasing importance of bottom-up initiatives in crisis response, CRM AI systems need to be designed to be adaptive to the emerging roles and information-sharing structures that are typical for today's crises [34].

Another important aspect of inter-organizational coordination is peer review and validation of methods and data underlying AI systems in CRM [90]. Including processes of peer review increases trust among organizations. However, some technologies may not be peer-reviewed or validated because of commercial and intellectual property interests. Prioritizing the protection of private interests could be problematic in CRM since the models may not be tested until a crisis strikes and the model results are not trusted by collaborating organizations. This issue can be addressed by implementing incentive mechanisms. Besides penalties for failing to conduct peer review and validation, official agencies can encourage inter-organizational coordination and public involvement with the Community of Practice in the field, including researchers, public, and private organizations to peer-review and validate AI systems through funding rewarding to augment responsible AI in CRM.

2) RESEARCH AGENDA

A collaborative ecosystem of researchers, developers, publics, crisis managers, humanitarian agencies, and other stakeholders should be formed to peer review and validate whether CRM AI systems are aligned with the required processes and standards. A federated AI system with human-centered AI frameworks could require incentive mechanisms and funding sources that provide incentives for coordination and facilitate open innovation. In addition, to improve organizational coordination and data sharing, data needs meta-data or stories about it to tell developers and users about its provenance and any quirks or intricacies that they should note when interpreting it. Researchers should attend to information quality requirements for crisis response organizations to improve the management of information [91]. To enhance inter-organizational data coordination and public involvement, future research should (1) develop a framework to facilitate federated AI systems and human-centered AI processes; (2) develop a standard to ensure data quality and its corresponding details (e.g., limitations) when sharing amongst various organizations; and (3) propose incentive mechanisms to encourage inter-organizational coordination and public involvement with peer-review and validation to augment responsible AI in CRM. It is important to note that inter-organizational silos have historically persisted in crisis management despite well-intentioned data-sharing initiatives. As such, even with federated AI architectures, long-standing institutional, cultural, and jurisdictional barriers must be addressed in parallel to realize meaningful coordination.

F. CRM AI SYSTEMS SHOULD ATTEND TO INFORMATION PRIVACY AND SECURITY

Major drivers of AI systems in CRM are the advancements in sensing technologies at a high resolution. While such highly granular data bring the advantages of greater precision and tailored decisions, they bear the risk of exposing personal data and other data that requires attention to information security and privacy. The massive collection of personal data about human behavior, ranging from mobility data collected via mobile phones to video footage from CCTV cameras or imagery collected via UAVs, inevitably has led to many questions about the ownership and the principles and protocols to deal with this data, and the requirements that guide their use.

1) CHALLENGES AND REQUIREMENTS

There are a range of ethical concerns about the use of data collected during or before disasters for crisis response purposes including whether individuals can have control of their information. In many cases, because of the scale and urgency of a crisis, data collection and use happen without informed consent. Parallels can be drawn to emergency medicine, whereby privacy can be violated and data about health status is shared if it serves the survival of the patient. Following this argument, for example, some may say that data collection via methods such as aerial imagery can only be justified only if it directly and immediately serves the population about which the data is collected.

Informed consent has to include the real possibility to opt out. Often, beneficiaries affected by a crisis or disaster are dependent on assistance, and they hardly have the free choice to opt out. In times of disaster, people may be at the worst moments of their lives — do AI system developers have the moral authority to make use of their social media in these moments [65]? This is amplified by the increasing use of biometric technologies to identify beneficiaries around the globe [92]; while one can abandon a cash voucher or ID card, this is impossible with fingerprints or iris scans. Further, there is the right to be forgotten, a feature of the GDPR in the EU, which implies that individuals can ask for the removal of their data. This may, however, be difficult if the data is published widely via dashboards or social media [93]. Moreover, individuals may not even be aware that their data are used for specific analyses or information products [94], [95]. Therefore, appropriate mechanisms need to be implemented that allow individuals to understand where and for which purposes their data is being used and to guarantee that the data can be withdrawn at any moment.

Besides privacy concerns, data sharing is subjected to important security considerations. Malicious actors might introduce fabricated and misleading data. While there are many advocates for open and public data sharing in crisis, there are important pitfalls to consider, especially in conflicts or human-made crises. Data in conflicts is especially sensitive since malicious actors can strategically exploit seemingly innocent data to target the most vital infrastructures of society, such as hospitals, schools, or humanitarian convoys. Datasets such as individual-level mobility data have sensitive information about populations and should not be shared. Therefore, even the collection, processing, and sharing of information that is considered "public" in a natural disaster have to be considered carefully in conflicts and should follow the idea of minimizing information flows, along with clear data standards, security levels, and data sharing protocols. Creations of accessible data archives that respect security and privacy interests are paramount, which ensures a chain of data stewardship that protects the integrity and quality of the data.

2) RESEARCH AGENDA

To address privacy and security concerns, in addition to creating an ethics framework to guide work, it is necessary to build upon coordination and cooperation across researchers, public, and private stakeholders, as discussed under Section III-E. Regulations and ethics frameworks are needed. In terms of data protection, the EU has developed the GDPR, which is widely regarded as the gold standard in data protection. It is legally required and critical to protect personal data or at least data which may identify individuals or specific ethnicities or groups in the context of CRM. It is important to recognize that privacy norms and regulations vary greatly across different regions and cultures. Crisis management often spans contexts where formal regulations may be looser or different values apply [96]. Therefore, responsible AI solutions must be culturally contextualized and adaptable to local expectations and legal frameworks. Future research can focus on two important directions: (1) creating datasets that respect users' rights and privacy regulations; and (2) addressing data provenance and stewardship in a way that respects security and privacy. Researchers can work with groups such as TrustedCI to develop strategies for ensuring information security and with archives such as Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan, the EU's Zenodo repository maintained by CERN, or other reputable public archives that have thoughtful data policies and stewards.

IV. DISCUSSION

A. REFLECTION ON THEORETICAL GAPS, FRAMEWORK, AND RESEARCH PROPOSITION DEVELOPMENT

The number of studies and tools related to AI in CRM has grown considerably over the past years; however, the majority of the literature is missing elements of responsible

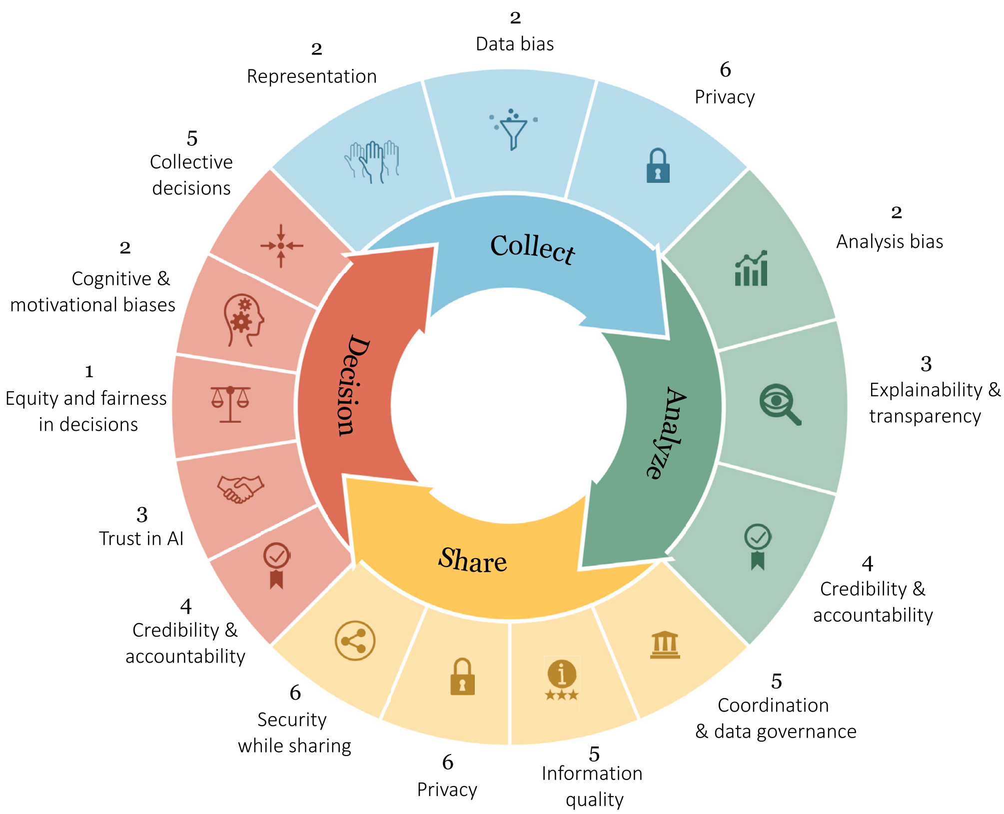

FIGURE 1. Responsible AI challenges in the crisis information management lifecycle. The numbers indicate the proposition we address regarding the responsible AI challenges.

AI. Several studies [24], [97] have discussed the role of AI in supporting decision-making or policy generally, yet the discussion of AI related to CRM is very limited. This is especially concerning since AI increasingly supports or even replaces human decisions [98]. Because decision-making in crises can significantly affect human life and create long-term impacts for our societies, AI used to support CRM must be especially carefully designed to maintain principles and considerations such as equity and fairness. In our view, the focus of using responsible AI in CRM should be on the affected populations and their needs. For example, even with agreement on an ethics framework to guide CRM, implementing ethical codes in AI systems is challenging if not impossible [99], [100], and there is no guarantee that an AI system will be ethical. Thus, AI system developers need to talk to different stakeholders to agree on an ethics approach that is grounded in shared, articulated principles, taking accountability into consideration.

In this paper, we presented a roadmap with six propositions to address responsible AI issues in CRM.

- Proposition 1 - CRM AI Systems must promote equity and fairness considering diverse stakeholder values: It is essential to define, theorize, and formalize criteria for incorporating equity and fairness in AI systems to support CRM. The most vulnerable populations should be considered when implementing AI to support decision-making in CRM.
- Proposition 2 - CRM AI systems should facilitate bias mitigation in data, analyses, and decision-making: Issues such as imbalanced datasets and biased algorithms are critical to CRM since they can result in undesirable outcomes, especially if they are amplified by a range of cognitive biases that are typical for crises. Since biases cannot be avoided in the urgency of crises, a comprehensive bias identification and mitigation framework is necessary for CRM AI systems to avoid detrimental results.
- Proposition 3 - CRM AI systems should be explainable and transparent to gain broader trust: The explainability and transparency of AI systems and their results can influence trust in AI systems. A key challenge in CRM is making complex problems explainable under time pressure. To this end, it is necessary to explicitly define and empirically measure transparency and explainability for AI systems in CRM, and understand how transparency and explainability propagate.
- Proposition 4 - CRM AI systems should yield credible insights for accountable decision making: Because decision-making during crises has enormous impacts, it is essential to clearly define the extent

of accountability of AI developers, researchers, and decision makers when an AI is created and used for CRM. Communications among all stakeholders regarding issues such as model limitations, assumptions and uncertainties are critical to ensure people do not over- or under-estimate the capability of AI systems.

- Proposition 5 - Inter-organizational coordination and public involvement are critical for creating responsible CRM AI systems: There are diverse organizations and stakeholders involved in CRM. Despite challenging, identifying and engaging stakeholders during AI design and development are critical to promote information sharing and coordination of plans and actions.
- Proposition 6 - CRM AI systems should attend to information privacy and security: Privacy and security should not be sacrificed due to the urgency and severity of crisis events; instead, rules and regulations are needed to encourage information privacy and security during data sharing and implementation. It is important to better analyse the trade-off between privacy and increased accuracy of an AI, and establish acceptable standards and thresholds. Also, it is important to establish suitable mechanisms that enable individuals to comprehend the intention and objectives of the usage of their data and ensure the right of revoking their data at any time.

B. CONTRIBUTIONS TO RESEARCH AND THEORETICAL IMPLICATIONS

Despite growing research related to AI in CRM, very limited attention has been paid to responsible AI practices. The crisis information management cycle consists of collecting, analyzing, sharing information, and making decisions based on information [41]. Through identifying challenges, specifying propositions, and mapping these onto existing models of crisis information management, the contribution of this study is to adapt and contextualize established responsible AI principles within the crisis information management domain, spanning the fields of information systems and AI design, cognition and information use, as well as ethics and normative questions. The six propositions for responsible AI in CRM, organized according to the Crisis Information Management Cycle, serve as a roadmap to fill this gap. We mapped the issues and considerations corresponding to these propositions to the different stages of the crisis information management cycle. In Figure 1, we show how the propositions for responsible AI in CRM map on to theoretical models of crisis information management focused on cycles of information collection, analysis, sharing, and decision-making.

Our intervention elaborates on the crisis information management processes and identifies normative sub-dimensions of how these responsible AI processes map onto these processes. For example, during the analysis phase of crisis information management, we show that responsible AI practices mean that this phase includes: preventing or mitigating analysis bias (Proposition 2), ensuring explainability and transparency of analysis for stakeholders (Proposition 3), and articulating chains of accountability for making use of AI analysis (Proposition 4). In addition, because of the cognitive, behavioral and moral dimensions of crisis information management, we stress that human-centered design is paramount across all phases of the cycles.

Figure 1 depicts the research challenges we put forward and need to be addressed to establish the foundations of responsible AI research in CRM. The roadmap and the propositions specified in this study serve as the first necessary step to bring responsible AI issues in CRM to the forefront of research agenda in this growing field. Further studies, discussed below in Section IV-D, are needed to establish frameworks and practices for incorporating responsible AI considerations in CRM and to implement the propositions we put forward in this paper.

C. IMPLICATIONS FOR PRACTICE

The propositions specified in this study are intended to promote responsible AI in CRM in practice and to improve AI systems in supporting CRM decision-making. This study has broad implications for AI in CRM practice, ranging from developers to emergency managers, humanitarian organizations, governments and public officials. A prerequisite to any implementation or formulation of standards and guidance is understanding the theoretical basis of responsible AI issues and collectively defining conceptual ideas related to responsible AI concerns. To bridge the gap between conceptual recommendations and practical implementation, Table 2 translates each proposition into CRM-specific actions for three primary stakeholder groups: AI developers, decision-makers, and public officials. These role-specific examples—ranging from bias audits on disaster datasets to implementing privacy-preserving AI in refugee operations—ensure that the roadmap is grounded in the realities of crisis contexts.

1) IMPLICATIONS FOR AI DEVELOPERS

The purpose of AI systems in CRM is to facilitate better informed decisions. To account for the much needed contextualisation, following the propositions specified in this study can facilitate more human-centered design of AI systems in CRM. For example, greater interpretability, transparency, and explainability can facilitate greater trust in AI systems, fostering, in turn, the integration of AI into the decision-making processes. In addition, including bias identification and mitigation frameworks and the consideration of equity and fairness in AI systems can avoid detrimental AI outcomes and subsequent decisions. The current lack of consideration of fairness and biases in CRM AI systems is greatly problematic since crises disproportionately impact vulnerable populations. The propositions specified in this study provide a roadmap that needs attention to promote responsible AI system design and development in CRM.

TABLE 2. contextualized practical implications for responsible AI propositions in crisis management.

Proposition	AI Developers	Decision Makers	Governments & Public Officials
1. Equity and Fairness	Implement fairness-aware algorithms and tools to detect demographic disparities in disaster impact prediction models.	Use allocation dashboards that visualize resource distribution equity during response.	Promote funding for inclusive data collection (e.g., local language data during pandemics).
2. Bias Mitigation	Apply bias audits and adversarial validation on crisis-related datasets (e.g., casualty estimates or infrastructure damage reports).	Flag suspected bias in AI-generated crisis alerts for human review before deployment.	Encourage development of cross-jurisdictional data-sharing standards to minimize institutional bias.
3. Explainability and Transparency	Integrate interpretable models (e.g., rule-based classifiers or SHAP values) in tools for early warning and damage forecasting.	Require confidence intervals and rationale for predictions used in decision dashboards.	Standardize explainability requirements for procurement of AI tools in public safety.
4. Accountability and Credibility	Embed audit logs and responsibility maps in AI pipelines used for rapid assessments.	Establish crisis-specific escalation paths for AI system failures or anomalies.	Define liability mechanisms for algorithmic decisions in public disaster response systems.
5. Inter-org. Coordination & Public Involvement	Design federated AI systems that allow data collaboration across emergency response agencies while preserving local control.	Engage communities in scenario-planning tools using participatory simulations.	Create legal frameworks supporting AI data exchange across municipal and national levels.
6. Privacy and Security	Employ privacy-preserving techniques (e.g., differential privacy, federated learning) when working with health or refugee data.	Ensure secure data pipelines in joint operations with NGOs and public health entities.	Draft data governance policies for ethical crisis data use under low-regulation contexts.

2) IMPLICATIONS FOR DECISION MAKERS

Making decisions under tremendous time pressure and uncertainty is known to induce cognitive biases, which may result in over- or under-estimating the capacity of AI systems and discarding biases in datasets and AI algorithms. To mitigate this effect, it is necessary to involve decision makers in AI design. This step will also draw attention to the chains of development, in turn enabling accountability and credibility. At the same time, co-design will help developers and decision makers understand and improve the AI systems they work with as a prerequisite for joint standards. Responsible AI system co-design has the potential to reveal the blind spots in CRM decisions, plans, and policies that lead to inequity in crisis impacts among vulnerable populations to support decision-making in CRM. The approach we proposed requires decision makers to collaborate with researchers, developers, and the public with different skill sets and perspectives to facilitate better coordination among different stakeholders.

3) IMPLICATIONS FOR GOVERNMENTS AND PUBLIC OFFICIALS

Since the issues and considerations discussed in this study correspond to different stages of the crisis information management lifecycle, it is necessary to (1) create ethics frameworks to guide the development of AI systems and (2) develop national and international standards, guidance, and regulations with incentive mechanisms and consequences for the AI system developers, AI users, and decision makers. With the ethics frameworks and regulations that provide guidance on issues such as data privacy, fairness, and transparency, AI system development might be reorganized such that AI systems address the responsible AI propositions discussed in this study. Although the frameworks and regulations may seem burdensome, they can guide the development and use of AI systems in CRM and ensure AI systems perform better with responsible AI considerations. In addition, proper incentive mechanisms can encourage the development of AI systems that address responsible AI considerations discussed in this study, while deterring the development of AI systems that do not take responsible AI into account. The propositions specified in this study are intended to initiate the discussion about the development of frameworks and regulations that include responsible AI considerations in creating AI systems for CRM.

D. LIMITATIONS AND FUTURE RESEARCH DIRECTION

The issues identified in this study are interwoven, as highlighted throughout the discussion. Table 3 summarizes the

TABLE 3. Summary of future research directions toward responsible AI in CRM.

Aspect of Responsible AI	Future Research Directions
Equity and Fairness	• Understand the theoretical basis of equity and fairness in the CRM context. • Define and formalize equity/fairness criteria for CRM AI systems. • Integrate trade-offs between fairness criteria based on diverse stakeholder values.
Bias Mitigation	• Develop a comprehensive bias identification framework and metrics applicable to current and emerging data and algorithms. • Track how biases propagate from data through AI tools to sequential and interdependent CRM decisions. • Propose debiasing pipelines that attend to power differences to augment responsible AI in CRM.
Explainability and Transparency	• Explicitly define transparency and explainability requirements for CRM-specific AI applications. • Understand how explainability and transparency influence user trust in crisis settings. • Improve inter-organizational knowledge sharing and system understanding to enhance crisis response coordination.
Accountability and Credible Insights	• Co-create development and reporting standards for specific AI systems with designers and stakeholders to improve accountability. • Develop educational frameworks for model stakeholders outlining assumptions, limitations, appropriate use cases, and model uncertainty through documentation and visualization.
Inter-organizational Coordination and Public Involvement	• Develop frameworks to facilitate federated AI systems and human-centered AI processes. • Develop standards to ensure data quality, including limitations and provenance, when sharing across organizations. • Propose incentive mechanisms for inter-organizational coordination and public involvement through peer-review and validation.
Privacy and Security	• Create datasets that include necessary crisis-relevant information while respecting user rights and privacy regulations. • Address data provenance and stewardship in ways that uphold privacy and security requirements.

recommended future research directions toward responsible AI in CRM. For instance, fairness concerns are connected to challenges of bias and transparency, and transparency influences coordination and accountability in crisis settings. Each of these themes may be explored further on its own and opens multiple lines of inquiry. While the focus group findings provide valuable practitioner insights, they could represent more exhaustive perspectives. Furthermore, the six propositions have not yet been empirically tested in real-world crisis environments. Future research should therefore examine their applicability and effectiveness through case studies, pilot implementations, and engagement with a broader and more diverse set of stakeholders. As also discussed earlier, the geographic distribution of participants and literature reflects where our contributors work, highlighting the need for expanded regional representation in future studies. Finally, future work may also explore how behavioral and socio-emotional factors—such as public trust, perception of AI, and emotional responses during crises—shape the adoption and impact of responsible AI practices in CRM. In addition, longer-term research may examine how responsible AI in CRM aligns with environmental, social, and institutional sustainability goals, providing a broader perspective on the long-term societal implications of AI-enabled crisis management.

V. CONCLUDING REMARKS

This paper brings the urgent issue of responsible AI in crisis response and management to the forefront of research and practice by formulating a clear set of propositions that highlight the most pressing challenges across technical, organizational, and ethical domains. The goal is to direct the attention of interdisciplinary communities—including data and information sciences, engineering, governance, social sciences, geography, and disaster science—and to raise awareness among governments and practitioners regarding the need for responsible AI approaches in complex and dynamic crisis environments. In synthesizing these insights, our six propositions collectively illuminate key trade-offs and synergies inherent in implementing responsible AI for CRM. For instance, enhancing model transparency and explainability can increase trust but may delay critical decisions under time pressure, while prioritizing fairness and equity must be balanced against operational efficiency during crises. Such cross-cutting tensions—such as privacy versus information sharing, or local autonomy versus inter-organizational coordination—demonstrate that responsible AI principles cannot be pursued in isolation. This integrated perspective offers a holistic understanding of how the propositions interact in practice and underscores the urgency of pursuing systematic and rigorous empirical studies to validate and refine the proposed roadmap for responsible AI in CRM.

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