When A.I. Meets DRR:
What it means for gender and sexual minority communities

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Why this matters

Artificial intelligence is increasingly shaping how disaster risk is understood and managed [1]. It supports early warning systems, response coordination, and decisions about where resources are allocated [2]. The potential is clear. AI can improve speed, scale, and targeting in ways that traditional systems cannot [3].

However, these benefits are not neutral. They depend on how systems are designed, what data they rely on, and who they are built for [4]. For gender and sexual minority communities, this is critical.

These are groups already facing higher levels of disaster risk, not because of inherent vulnerability, but because of exclusion from policy, services, and decision-making [5]. Across disaster contexts, evidence shows consistent barriers to shelter, healthcare, and receiving aid [6]. Emergency systems often rely on binary gender categories, formal identification, and legally recognised family structures. These assumptions can exclude people at the point they most need support [7].

Health impacts are also significant. Disruptions to care, including gender-affirming services, and stigma within healthcare systems can limit access during crises [8]. These issues are well documented and reflect broader structural inequalities.

A key part of this problem is visibility. Sexual orientation and gender identity are rarely captured in disaster data [9]. Where data does not exist, communities are absent from risk assessments, planning processes, and response decisions [7, 10]. This shapes how risk is defined and whose needs are prioritised.

This is the context into which AI is being introduced.

What AI changes in disaster risk reduction

AI systems rely on data to identify patterns, predict outcomes, and support decisions [9, 11]. In disaster risk reduction, this includes forecasting hazards, identifying at-risk populations, allocating resources, and shaping communication strategies [12].

Used well, AI has the potential to improve inclusion. It can help identify gaps in service provision, support more targeted communication, and strengthen continuity of care in disrupted environments [7, 13]. It may also help recognise informal support systems, including chosen families and community networks that are often overlooked in formal planning [14].

However, these outcomes are not automatic. They depend on how systems are designed and governed [15]. AI does not create new inequalities in isolation. It reflects and amplifies existing ones [16]. Where data is incomplete or biased, AI systems will reproduce those gaps [14, 17]. Where systems are designed around majority populations, those outside those assumptions remain underserved.

This makes the use of AI in disaster contexts a policy issue as much as a technical one [10, 18].

Where the risks sit

There are several areas where the use of AI in disaster risk reduction creates specific risks for gender and sexual minority communities. These risks are not separate from existing challenges in DRR. They are an extension of them, shaped by how data is collected, how systems are designed, and how decisions are made.

The first is bias and exclusion in data. AI systems rely on large datasets to identify patterns and inform decisions [10, 19]. In disaster contexts, this often includes historical records of impacts, response actions, and recovery outcomes. These datasets rarely include information on sexual orientation or gender identity [9, 20]. In many cases, this data is not collected at all. In others, it is actively avoided due to political, cultural, or ethical sensitivities.

The result is that gender and sexual minority communities are either underrepresented or entirely absent from the data used to train AI systems [10, 21]. Where they do appear, it is often through indirect or proxy indicators that fail to capture the diversity within these communities. This creates a situation where AI systems are making decisions based on incomplete representations of the population. For example, a model designed to identify "at-risk households" may rely on assumptions about family structure that exclude same-sex couples or chosen families [9, 22]. Over time, this leads to systematic gaps in how need is identified and addressed.

The second is structural invisibility. This goes beyond individual data gaps. It reflects the way entire groups can be excluded from how risk is defined and measured [23]. In disaster risk reduction, risk is often quantified using indicators such as income, housing type, or geographic exposure. While these are important, they do not capture the social and institutional barriers that shape how different groups experience disasters [10, 24].

For gender and sexual minority communities, these barriers include discrimination in accessing services, lack of legal recognition, and exclusion from formal support systems [25]. When AI systems rely on standard indicators of vulnerability, these factors are often missed. This means that even where data exists, it may not reflect the actual drivers of risk. The outcome is that resources are allocated based on a partial understanding of need, reinforcing existing patterns of exclusion [26].

The third is privacy and safety. AI systems used in disaster contexts often rely on real-time or near real-time data. This can include mobile phone data, social media activity, geolocation tracking, and other forms of behavioural information [27]. While this data can improve situational awareness and response speed, it also raises significant risks.

In many parts of the world, gender and sexual minorities face legal or social penalties if their identities are disclosed [28]. In these contexts, the collection, storage, and use of personal data can create direct risks to safety [29]. Even anonymised datasets can sometimes be re-identified, particularly when combined with other data sources. There is also the risk that data collected for humanitarian purposes could be accessed or repurposed by state or non-state actors [30]. Without strong safeguards, systems designed to support disaster response could unintentionally expose individuals to harm.

The fourth is digital exclusion. Many AI-enabled systems assume a level of access to technology that cannot be taken for granted [31]. Early warning systems may rely on smartphone alerts. Communication platforms may require internet access. Service delivery tools may depend on digital registration or verification processes.

These systems can improve efficiency, but they also risk excluding those who cannot access them [32]. Gender and sexual minority communities are often overrepresented in groups facing economic marginalisation, unstable housing, or social isolation [5, 33]. This can limit access to devices, connectivity, and digital literacy [34]. In disaster settings, these challenges can be compounded by displacement or loss of resources. As a result, those most in need of support may be the least able to benefit from AI-enabled services.

The final issue is accountability and decision-making. Many AI systems operate in ways that are not easily understood by those using them [9, 10, 35]. Complex models can produce outputs without clear explanations of how decisions were reached. In disaster contexts, where decisions often need to be made quickly, there is a risk that these outputs are taken at face value.

This creates challenges for accountability. If an AI system prioritises one area over another for resource allocation, it may not be clear why [36]. If certain groups are consistently underserved, it may be difficult to identify whether this is due to bias in the data, the model, or the way the system is being used [37]. For gender and sexual minority communities, who are already less visible in formal systems, this lack of transparency makes it harder to challenge or correct inequitable outcomes [38].

Taken together, these risks highlight a common issue. AI systems are often presented as objective or data-driven, but they are shaped by human choices at every stage [39]. Without deliberate attention to inclusion, those choices are likely to reflect existing inequalities. In disaster risk reduction, this means that the use of AI has the potential not just to replicate exclusion, but to embed it more deeply within systems that are increasingly relied upon for decision-making [10, 40].

Policy gaps and entry points

The risks outlined above do not sit outside existing policy frameworks. In many cases, they fall directly within areas that disaster risk reduction policy already claims to address, particularly around inclusion, data, and governance. The issue is that these commitments have not yet been translated into practice in a way that engages with how AI systems operate.

The Sendai Framework establishes a clear principle of inclusion and a commitment to leave no one behind [41]. In practice, however, its treatment of gender remains largely binary. This limits its ability to engage with the realities of gender and sexual minority communities and, by extension, the risks they face within AI-enabled systems [20]. Where these groups are not explicitly recognised, they are unlikely to be considered in national implementation, data collection, or monitoring processes.

This gap is not only conceptual. It has direct implications for how risk is measured and managed. If national disaster risk assessments do not capture the social and institutional barriers faced by gender and sexual minorities, these factors will not be reflected in the datasets used to train AI systems [42]. The result is a continuation of the same structural invisibility identified earlier, now embedded within digital tools.

More recent policy developments begin to address this. The addendum to the gender action plan explicitly recognises sexual orientation, gender identity, gender expression, and sex characteristics as relevant to disaster risk [5]. It also highlights the importance of intersectionality, participatory approaches to data, and the recognition of non-traditional family structures [10, 43]. These are not abstract principles. They speak directly to the issues raised by AI, particularly in relation to data inclusion, representation, and the design of systems that reflect lived realities.

However, there remains a disconnect between these inclusion-focused developments and the rapid expansion of AI in disaster contexts. Emerging AI governance frameworks, whether at national or international level, tend to focus on issues such as safety, transparency, and accountability in general terms [44]. They rarely engage with the specific ways in which marginalised groups, including gender and sexual minorities, may be affected [17].

This creates a gap at the point where two agendas intersect. On one side, there is a growing recognition of the need for more inclusive disaster risk reduction. On the other, there is increasing reliance on AI to inform decisions within that system. Without deliberate alignment, there is a risk that progress made in one area is undermined by neglect in the other [14].

This gap also presents a clear entry point. The principles already exist within DRR policy. The task now is to apply them to the design, procurement, and governance of AI systems in a way that is specific, measurable, and enforceable [4, 21].

What needs to change in practice

Addressing these issues requires more than high-level commitments. It requires changes in how systems are designed, how decisions are made, and how accountability is exercised across different actors [15, 21].

For governments and emergency management agencies, the starting point is procurement and oversight. AI systems are increasingly being integrated into public decision-making, often through partnerships with private sector providers [14, 18]. At present, requirements for these systems tend to focus on performance, cost, and technical functionality. Inclusion is rarely treated as a core criterion.

This needs to change. Any AI system used in disaster contexts should be subject to a structured assessment of its potential impacts on different population groups, including gender and sexual minorities [45]. This is not only about identifying risks, but about understanding how those risks arise. For example, if a system relies on household-level data, what assumptions does it make about family structure? If it uses mobility data, whose movements are captured and whose are not?

Data governance is equally important. Expanding the inclusion of gender and sexual minorities within data systems requires careful consideration [29]. In some contexts, collecting this data may create risks rather than reduce them. This places greater emphasis on voluntary, consent-based approaches, and on ensuring that communities have a say in how data is collected and used [10, 14, 27]. The principle of community-led data, as set out in the gender action plan addendum, is particularly relevant here [5].

Legal safeguards also need to be strengthened. Data collected during disaster response should not be used for purposes that could harm individuals, including law enforcement actions in contexts where identities are criminalised [46]. Without clear boundaries, the risks associated with data collection and AI use are likely to outweigh the benefits for some communities.

For those developing AI systems, the key issue is design. Many of the risks identified earlier are the result of design choices, rather than unavoidable technical limitations [47]. This includes decisions about what data is used, how categories are defined, and what outcomes are prioritised.

Addressing bias requires moving beyond general statements about fairness and engaging with the specific contexts in which systems are used [48]. This may involve testing systems against scenarios that reflect the realities of gender and sexual minority communities, rather than relying solely on aggregate performance metrics. It also requires greater transparency. Users of AI systems, particularly in high-stakes contexts such as disaster response, need to understand how decisions are being made and where limitations exist [49].

Privacy needs to be treated as a central design issue [50]. This includes minimising the collection of sensitive data where possible, ensuring strong protections where it is necessary, and considering how data could be misused in different contexts. In some cases, the most appropriate approach may be to avoid collecting certain types of data altogether.

Accessibility is another key consideration. Designing systems that assume high levels of connectivity or digital literacy will inevitably exclude some users [31]. This is not simply a technical issue. It reflects broader inequalities in access to resources and services. Ensuring that AI-enabled tools can function in low-connectivity environments, or are complemented by non-digital approaches, is essential to avoid reinforcing these divides [51].

International organisations have a role in bridging the gap between policy and practice. This includes developing clearer guidance on how inclusive principles should be applied to AI in disaster risk reduction, as well as supporting the development of standards that can be applied across contexts [52]. There is also a need to invest in capacity building. Many organisations working with gender and sexual minority communities do not have the resources to engage with AI governance, yet they are often best placed to identify risks and propose solutions.

Civil society organisations remain central to this process. Much of the existing understanding of how disasters affect gender and sexual minorities comes from community-led work [5]. As AI becomes more prominent, there is a need to extend this work to include the impacts of digital systems. This includes documenting where systems fail, as well as where they work, and using this evidence to inform policy and practice.

For researchers, the priority is to move from abstract discussions of risk to detailed analysis of how systems operate in practice [13]. This includes examining the full lifecycle of AI systems, from data collection to decision-making and implementation. Participatory approaches are particularly important, ensuring that research is grounded in lived experience rather than external assumptions.

Across all of these areas, a common theme emerges. Inclusion cannot be treated as an add-on. It needs to be built into the core of how AI systems are developed and used within disaster risk reduction [53].

Conclusion

The integration of AI into disaster risk reduction is accelerating [12]. These systems are becoming part of how risk is defined, how decisions are made, and how resources are allocated.

For gender and sexual minority communities, this creates both risk and opportunity. The risks are clear. Without deliberate action, AI systems are likely to reproduce and reinforce existing patterns of exclusion [21]. These patterns are already visible within disaster policy and practice. AI has the potential to embed them more deeply.

At the same time, there is an opportunity to take a different approach. The principles needed to support more inclusive disaster risk reduction already exist [20]. What is required now is to apply them in a way that reflects how systems are changing.

This includes recognising that data is not neutral [11], that technology reflects the assumptions built into it [54], and that inclusion needs to be actively designed and maintained. It also requires acknowledging that decisions about AI are not only technical. They are political, institutional, and ethical [4].

There is a window of opportunity to shape how these systems develop. Policy frameworks are evolving, and approaches to AI governance are still being defined [44]. Decisions made now will influence how these systems operate in practice.

Disaster risk reduction is only effective when it reflects the realities of the populations it serves [41]. The same applies to AI. If these systems are to improve outcomes, they need to be built on a more complete understanding of risk, one that includes those who have historically been excluded from both data and decision-making [14].

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