Double exclusion & AI in DRR

How marginalised groups are left behind in data, systems, and response

Kevin Blanchard

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Email - contact@drrdynnamics.com

Website - www.drrdynamics.com

BlueSky - @drrdynamics.bsky.social

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Understanding double exclusion

Double exclusion describes a structural problem that emerges at two connected points in the lifecycle of an AI system [1,2].

The first is data. AI systems in disaster risk reduction are trained on existing datasets, including historical records of hazard events, population data, infrastructure assessments, health information, and socioeconomic indicators [3]. These datasets have been built over time by institutions with their own priorities, limitations, and blind spots. Populations that have been systematically excluded from civil registration, administrative systems, and development programmes are therefore largely absent from the data that AI systems learn from. As a result, AI systems cannot generate reliable predictions or responses for people they have not been trained to recognise.

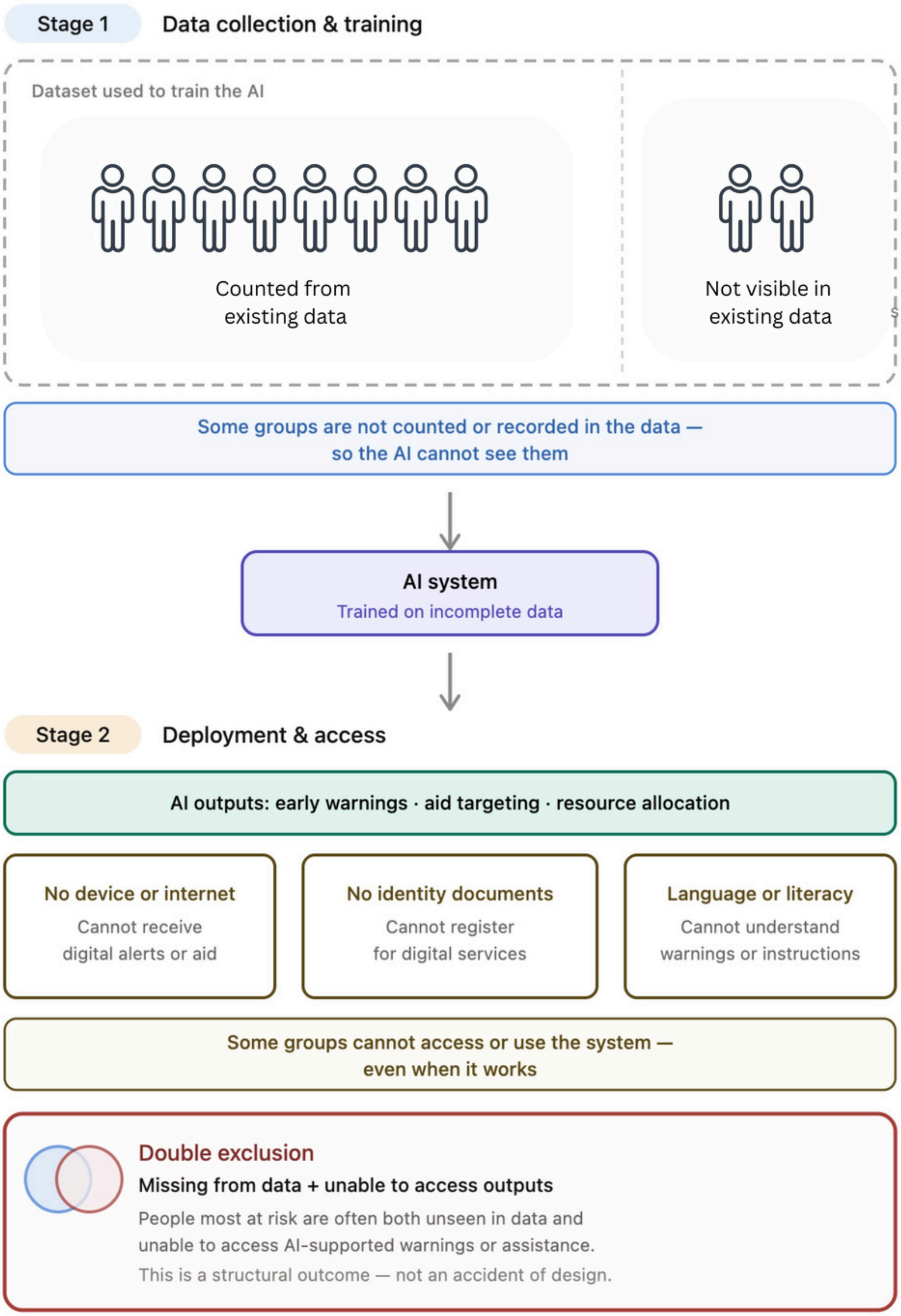
The second is deployment. Even where an AI system is technically sound, it can only reach those who have access to the channels through which it operates. Many AI-enabled tools rely on digital infrastructure, personal devices, connectivity, and, in some cases, formal identity documents. Access to these is uneven. In crisis settings, the gap between those who can use digital systems and those who cannot often widens rather than narrows.

Double exclusion is not simply a matter of poor design or weak intent. It is a structural outcome. It reflects how data has been collected and prioritised over time, and how digital infrastructure and access have developed unevenly across and within countries. When AI systems are built on these foundations, they tend to carry these patterns forward.

This matters because the groups most affected by double exclusion are often those already most at risk in disaster contexts: displaced populations, undocumented migrants, people living in informal settlements, women and girls facing gender-based violence, and communities in remote or poorly governed areas [4].

These are the groups that inclusive disaster risk reduction is intended to reach.

Double exclusion - diagram



Exclusion in data

AI systems used in disaster risk reduction draw on a wide range of datasets. Hazard modelling relies on satellite imagery, meteorological records, and seismic data. Risk assessments draw on population figures, poverty indicators, and infrastructure maps. Response planning uses historical impact data and post-disaster needs assessments. Each of these sources reflects decisions, made over time, about what was measured and who was counted.

The populations most exposed to disaster risk are often those least represented in these records. This is not incidental. It reflects consistent patterns.

Stateless populations and undocumented migrants are frequently invisible to civil registration and census systems. Without formal recognition by a state, they may not appear in the baseline data used to map population distribution or vulnerability. The United Nations High Commissioner for Refugees estimates that millions of people worldwide remain stateless, with many more living outside formal documentation systems [5]. For AI tools designed to identify at-risk populations or target assistance, this creates a clear and persistent blind spot [2].

Residents of informal settlements face a related issue. Informal or unplanned urban areas are often poorly represented in official maps and infrastructure data. They may be classified as uninhabited or omitted from administrative boundaries altogether [5,6]. This has direct implications in disaster contexts. Such settlements are often located in higher-risk areas, including floodplains or unstable slopes, and residents typically have fewer resources to draw on in recovery. If an AI risk model does not include these areas, the people living there are unlikely to be prioritised in preparedness or response planning [2].

Pastoralist and nomadic communities present a different challenge. Most administrative data systems assume fixed locations. People who move across regions, whether seasonally or in response to environmental pressures, are difficult to capture in static datasets [7]. This movement can be a form of adaptation, but it places these communities outside the scope of most data collection systems [3]. As a result, they are consistently undercounted in national statistics and in the datasets that inform AI models.

Gendered risks are another significant gap. Standard disaster datasets tend to focus on physical damage and often aggregate mortality [1]. They are less consistent in capturing the specific risks faced by women and girls in crisis settings, including gender-based violence, sexual exploitation, disruption to maternal and reproductive healthcare, and the burden of caregiving, which shapes mobility and access to assistance [8]. Whilst these risks are well documented in humanitarian practice, they are rarely structured into the datasets used to train or validate AI systems [1,2].

Disability data presents similar challenges. Global evidence shows that people with disabilities face higher risks in disasters, including higher mortality rates [9], yet disability disaggregation remains inconsistent across most national and humanitarian datasets [10].

These are not marginal gaps. They are systematic absences affecting entire population groups. When AI systems are trained on data that reflects these gaps, the outputs they produce will reflect them [1,2]. Predictions, risk rankings, and resource allocation decisions may appear technically sound while presenting a partial and uneven picture of who is at risk and where.

Exclusion in deployment

Even where an AI system is built on representative, high-quality data, it may still fail to reach the people it is intended to serve if the channels it relies on are not accessible [2]. In practice, most AI-enabled tools in disaster risk reduction and humanitarian response depend on conditions that are not universally met.

These conditions typically include access to a digital device, a functioning mobile or internet connection, basic literacy, and, in many cases, digital literacy, as well as some form of recognised identity to register with or access a system. Each of these can act as a barrier. Taken together, they can exclude large parts of the population in low- and middle-income countries, and even more so in crisis-affected areas [11].

Digital cash transfer programmes illustrate this clearly. These systems have expanded rapidly in recent years, and many now include AI components such as fraud detection and needs-scoring tools. In principle, digital transfers are faster, more transparent, and less vulnerable to certain forms of corruption than cash-in-hand distributions. In practice, systems that require biometric verification or formal identification can exclude those most in need [12,13]. Newly displaced people who have lost documentation, stateless individuals, or communities with low levels of SIM card registration may be unable to access support at the point they need it most.

Early warning systems present a similar tension. AI-powered models now underpin many national and regional alerts for floods, cyclones, and droughts [13]. Where they function well, they can provide valuable lead time. But their reach depends on the infrastructure and literacy that supports them. A warning sent by SMS reaches those with mobile phones, it does not reach those without [11]. A message issued in a dominant national language may not be understood by communities that use minority languages or none of the official ones [2].

These gaps are present in stable conditions. In crisis settings, they become more pronounced [1]. Disasters often damage or disrupt the very infrastructure that digital systems depend on [11]. Mobile networks fail, power supplies are interrupted, and displacement breaks access to services. People may lose phones, documentation, and connectivity at the same time. Those with the least reliable access to begin with are often the most affected [11].

The result is that AI-enabled tools can work effectively for some groups while excluding others in the same area and facing similar or greater need. This creates not only an efficiency gap, but an equity gap, where access to support follows existing patterns of advantage rather than actual levels of risk [3].

Less visible dynamics shaping exclusion

Beyond gaps in data and deployment, there are less visible dynamics that shape how exclusion is produced and sustained in AI-enabled disaster risk systems. These are harder to identify and, as a result, harder to address.

Hidden bias in data
AI systems used in risk assessment, targeting, and resource allocation rarely include sensitive attributes such as ethnicity, religion, gender identity beyond the binary or disability as direct inputs [15]. In many cases, they are designed not to. However, the variables they do rely on often act as proxies for those characteristics [16,17].

Where a person lives is closely linked to factors such as ethnicity, income level, or migration status, reflecting long-standing patterns of segregation, discrimination, or displacement. Housing type, mobile phone ownership, and patterns of use can also reflect income, gender, and age [15]. When these variables are used to inform predictions or allocation decisions, they can reproduce existing inequalities without explicitly identifying them [18]. The bias sits within the structure of the model rather than in any explicit decision to exclude.

In humanitarian contexts, this has been observed in targeting systems that disadvantage populations living in areas with poor infrastructure or low registration rates, both of which are often the result of prior marginalisation rather than lower need [19].

Participation gaps in system design
Community engagement is a core principle in disaster risk reduction and humanitarian work, and most organisations have formal commitments to participatory design and accountability to affected populations [20]. In practice, there is often a gap between those who are consulted and those who are most marginalised [1,2].

Engagement processes tend to reach communities that are easier to access, organised through recognised structures, and able to participate in the formats used [21]. More marginalised groups, including those living outside formal settlements, people without documentation, or those facing protection risks that restrict movement, are consistently underrepresented [,1,2,21].

This has direct implications for AI systems. Design flaws and bias can be identified and addressed through engagement, but only if the people most likely to be affected are involved. When they are not, issues that would be apparent to those communities remain invisible to developers and decision-makers until systems are already in use, when changes are more difficult and more costly [21].

Compound crises accelerating inequality
Much of the discussion around AI in disaster risk reduction assumes a relatively contained event within an otherwise functioning system [22]. In these conditions, some services remain operational, baseline data is broadly reliable, and institutions retain the capacity to respond.

Compound crises do not follow this pattern. When hazards overlap, such as drought combined with conflict, or flooding alongside a public health emergency, multiple systems come under pressure at the same time [23]. Health services become harder to access, markets are disrupted, and governance structures weaken [2]. The data used to train AI systems becomes less reliable as conditions move beyond what the model has previously encountered.

In these settings, inequalities do not remain stable. They deepen quickly [19,24]. Those most likely to be left behind are those who were already least visible to formal systems. AI tools trained on more stable conditions, and designed to operate through infrastructure that may no longer function, can produce increasingly unreliable outputs while appearing to operate as intended [2]. The gap between who the system assumes it is serving and who it actually reaches can widen without any clear signal.

This dynamic is likely to become more significant as climate change increases the frequency and severity of compound and cascading events, particularly in regions already facing high levels of vulnerability [25].

Accountability and governance gaps

The issues outlined in earlier sections are reinforced by gaps in the accountability and governance frameworks surrounding the use of AI in disaster risk reduction and humanitarian response [2].

Where AI systems are used to inform decisions about who receives assistance, who is considered high risk, or how resources are allocated, there are limited ways for affected populations to understand those decisions, identify errors, or challenge outcomes [1,3]. Those most likely to be affected by AI-driven exclusion are also those with the least political representation, the least access to complaints mechanisms, and the least capacity to question how decisions are made [1].

The wider governance landscape remains fragmented. There is no binding international framework governing the use of AI in disaster response [3]. National regulations, where they exist, vary widely and rarely address humanitarian contexts in detail. Voluntary guidance, including that developed by United Nations agencies and humanitarian bodies, such as the UNESCO Recommendation on the Ethics of Artificial Intelligence [26] and the UN Secretary-General’s Roadmap for Digital Cooperation [27], is applied inconsistently.

In practice, this leaves organisations deploying AI tools in crisis settings largely responsible for regulating themselves [28]. Internal ethics reviews and technical audits vary in quality and independence. Procurement processes do not consistently require transparency, explainability, or testing for bias [28]. At the same time, the pace of adoption, often driven by donor interest in innovation, can move faster than the systems needed to oversee it [28].

For marginalised populations already affected by double exclusion, this creates a clear accountability gap. Harms are less likely to be identified, and even less likely to be addressed in a systematic way [2].

Implications for policy and practice

Addressing double exclusion in AI for DRR does not mean rejecting AI entirely. It requires designing it differently, deploying it with greater care, and putting stronger governance around it [2,3]. The implications below focus on the actors who shape how these systems are developed and used in practice.

Governments

National governments set the conditions under which AI is used in disaster management. This includes establishing and enforcing data standards that require disaggregation by gender, disability status, and displacement status, consistent with the commitments established under the Sendai Framework for Disaster Risk Reduction. It also requires AI governance frameworks that explicitly cover humanitarian and crisis settings, rather than focusing only on commercial or general public sector use.

Investment in civil registration systems and identification infrastructure is also critical. Where people remain outside these systems, they are unlikely to be reached by AI-enabled support built on top of them [30,31]. Reducing exclusion from administrative systems is therefore a necessary step towards reducing exclusion from AI.

Humanitarian and development organisations

Organisations using AI tools should assess data representativeness before relying on them for targeting or resource allocation [28]. In practice, this means identifying which populations are missing from the data and what that implies for the reliability of outputs in a given context.

Participation in system design needs to be meaningful rather than procedural. This includes finding ways to engage highly marginalised groups in the design and testing of AI-enabled tools, even where they are difficult to reach through standard consultation approaches [2,3]. Where this is not possible, it should prompt questions about whether the tool is appropriate for use in that context.

Accountability mechanisms, including feedback and complaints systems, should also extend to decisions informed by algorithms [28]. People affected by these systems should be able to understand how decisions are made and have a clear route to raise concerns about errors or bias.

Donors
Donors shape both the pace and direction of AI adoption in the humanitarian and disaster risk reduction sector. Funding for innovation should be matched with funding for independent evaluation, including work that examines how different groups are affected by AI systems in practice [32].

Procurement and grant conditions should set minimum standards for transparency, bias testing, and accountability. Funding models should not create pressure to move quickly at the expense of safeguards [32].

Donors also have a role in supporting the underlying data and digital infrastructure that inclusive AI depends on, particularly in contexts where existing data is limited or unreliable [2].

Technology developers
Organisations developing AI tools for disaster risk reduction and humanitarian response should, as a starting point, document the datasets used to train their systems, including known gaps and potential sources of bias [19]. This information should be available to those deploying the tools and, where appropriate, to affected communities.

Where systems are used to support targeting or resource allocation, developers should assess how performance varies across different population groups, particularly those most likely to be marginalised. Guidance for deployment should also be clear about where a system is suitable for use, where it is not, and what conditions need to be in place for it to function in a fair and reliable way [19].

Conclusion

The integration of AI into disaster risk reduction presents a clear opportunity. These tools can support faster, more accurate, and better coordinated responses to increasingly complex and frequent crises linked to climate change. That potential is real.

At the same time, double exclusion highlights a fundamental risk in how AI is currently being developed and used in this sector. The populations most exposed to disaster risk are often those least represented in the data used to train AI systems, and least able to access the tools those systems support. This is not an unintended feature of individual systems. It is a structural outcome, reflecting long-standing inequalities in data collection, digital access, and institutional reach.

Addressing this requires more than incremental improvements to individual tools. It requires a more deliberate approach to data inclusion from the earliest stages of design. It requires addressing the access barriers that shape who can and cannot benefit from AI-enabled support. It requires accountability mechanisms that allow affected populations to understand and challenge decisions that affect them. And it requires governance frameworks that keep pace with the speed of AI adoption in crisis settings.

Without this, there is a risk that AI will not reduce inequality in disaster risk reduction, but deepen it. The sector has spent decades working to ensure that the most marginalised communities are not left behind. That commitment needs to extend to the technologies now being used to support it.

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