Collective crisis intelligence for frontline humanitarian response

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This report is based on the insights and experiences of a whole range of projects and researchers working at the forefront of exploring CI and AI for humanitarian crisis management and response.

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Executive summary

Photo: NASA at unsplash.com

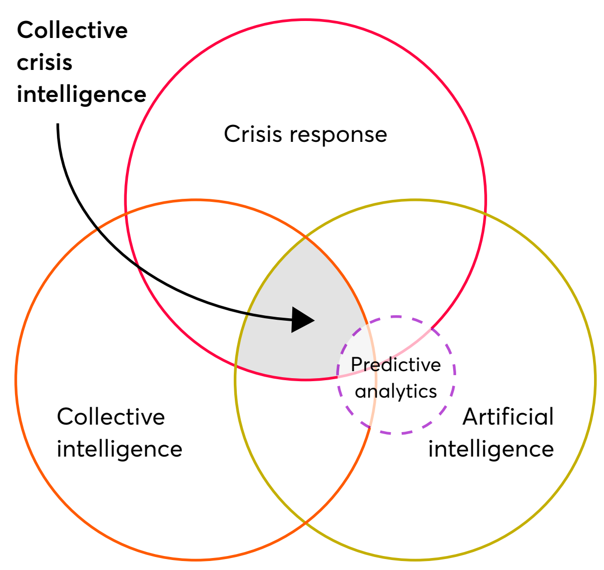
This report provides the first analysis of how an emerging innovation approach, 'collective crisis intelligence' (CCI), is being used to improve anticipation, management and response in the humanitarian sector. It sets out the conceptual and technical landscape for a UKHIH funded 'Accelerated Innovation Collaboration' (AIC) which is delivered by Nesta and the International Federation of Red Cross and Red Crescent Societies (IFRC) Solferino Academy.

Collective crisis intelligence (CCI) combines methods that gather intelligence from affected communities and frontline responders with artificial intelligence (AI) for more effective crisis mitigation, response or recovery.

CCI is a subset of a wider field known as collective intelligence design

Collective intelligence design is an approach which brings together diverse groups of people, new sources of data and digital technologies to tackle complex problems.

In CCI, collective intelligence methods (including crowdsourcing, crowdmapping or web scraping from social media) are primarily used as a means to generate more timely or localised data about a crisis. These are combined with AI techniques to process and analyse local insights more quickly. The research in this report is particularly focused on exploring the intersection between the use of collective frontline intelligence and predictive analytics – a suite of AI methods that rely on algorithms to make predictions about the future or otherwise unknown events.



Collective crisis intelligence is predominantly used for early warning of crises and real-time information for effective response

Our review identified and analysed 28 examples of CCI in lower- and middle-income country settings or with global coverage. The vast majority (68 per cent, *n*19) of current CCI are being used to improve capacity for early warning of a crisis, or to provide real-time situational information for more effective crisis response. Almost half (46 per cent, *n*13) of all cases are improving preparedness and response capabilities during rapid onset natural disasters, such as floods, earthquakes and hurricanes. These are followed by complex emergencies and conflict, which account for 14 per cent (*n*4) of cases, respectively.

Examples of CCI: established use cases

- **Dataminr** uses natural language processing, computer vision and machine learning to analyse multiple online data streams for early warnings of natural disasters, which are then used to generate reports for emergency responders and decision makers.
- **Sentry Syria** combines sensor data and reports generated by volunteer 'plane spotters' who live near air bases and in conflict zones in Syria to predict when air strikes will occur and provide early warning alerts.
- The **eBayanihan/Agos** platform collects needs assessment reports generated by local residents to help frontline workers understand what to prioritise during response efforts.

Collective crisis intelligence is a nascent field

Of the 28 CCI case studies, 42 per cent (*n*12) had a broad geographical coverage, spanning either multiple countries or covering a global scale. Twenty-one per cent (*n*6) of the case studies in our sample focused on applications developed for countries in Africa, while 18 per cent (*n*5) were developed for countries in Asia.

Academic organisations are central to early stage CCI innovation but are rarely involved in taking CCI solutions to market. Most CCI solutions that have managed to operationalise or scale to multiple markets were private-sector-led (seven of the 13 solutions that are operational in one market or scaling to other markets have been developed by private organisations). Local or national governments make up 36 per cent (*n*10) of users for more mature CCI solutions. Only eight examples were actively used by citizens or local communities.

In general, there is a U-shaped distribution for solution readiness. Many of the CCI solutions analysed were at an early stage of development (seven cases in concept/idea; four cases in prototype). There are mixed levels of integration into humanitarian workflows or systems, with 50 per cent (*n*14) having not been integrated at all, and the same number having been integrated either directly or indirectly (e.g. through reporting to humanitarian organisations). We only identified one example of peer-reviewed evaluation among our case studies.[a, 1] None of the CCI solutions analysed as part of the research are currently evaluating their own performance in line with the OECD DAC Network on Development Evaluation criteria.

a. The Africa's Voices project carried out an evaluation of the interactive SMS methodology in comparison with other methods.

Collective crisis intelligence could help strengthen localisation, anticipatory action and a more human-centred AI

A unique element of CCI solutions is their reliance on the intelligence of affected communities and frontline actors, including both frontline emergency workers employed by humanitarian organisations and on-the-ground volunteers.[b, 2] They have the potential to support humanitarian action that is both locally led, and more inclusive – rooted in the insights of those closest to the crisis.

By drawing on novel data sources, including from responders and communities on the frontline, CCI solutions can build a richer local and social understanding of crises. Combining these with the processing power of AI technologies, such as predictive analytics, means humanitarians can have access to more timely and contextual data – which can be used for anticipatory action, effective response or sustainable recovery.

CCI and the related 'Participatory AI' approach[c] offer the potential to mitigate the risks of applying AI and predictive analytics in a humanitarian setting – through co-design of solutions, the production of less biased data that reflects the experiences of the most affected populations, and community-based assessment of model efficacy. However, this is not a given and requires careful design.[3]

Emerging applications of collective crisis intelligence include modelling of interventions for more effective programme planning

Based on our analyses, we categorised existing CCI solutions and potential future applications into five categories of 'use cases': 1) Situational awareness, 2) Assessing community needs, assets and priorities, 3) Resource planning and management, 4) Programme planning and operations, 5) Monitoring and evaluation. 'Established' use cases (green) are where we see the most existing solutions, the 'emerging' category (amber), where we have seen ≤3 examples of CCI solutions, and 'speculative' use cases (red) where CCI solutions don't currently exist but could bring a lot of value. The relevance or prioritisation of each of these use cases will of course change in different contexts.

Photo: NOAA at unsplash.com

b. For example, the IFRC has a vast network of volunteers totalling around 13.7 million active volunteers globally, highlighting a wealth of experience and knowledge.

c. Participatory AI refers to the involvement of a wider range of stakeholders than just technology developers in the creation of an AI system, model, tool or application. As a field, it sits within the broader category of participatory design of technology.

Overview of existing, emerging and speculative 'use cases' for CCI solutions

	Before a crisis		Immediate aftermath of a crisis	After a crisis	
Use case categories	**Mitigation**	**Preparedness**	**Response**	**Recovery**	**Value added by CCI**
Situational awareness	Predicting a crisis before it happens Example case studies: AIME, Premise	Providing early warning of a crisis Example case studies: Dataminr, Flood Management EWS, Sentry Syria, Project Jetson, Community Water Watch	Providing real-time situational information for more effective response Example case studies: Ebayanihan, RapidID, Haze Gazer, HERMES, PetaBencana.id	Providing real-time situational information for more effective recovery	Improving timeliness, spatial coverage and contextual relevance of data Most relevant for: rapid onset natural disasters
Assessing community needs, assets and priorities	Predicting vulnerability to a crisis	Identifying most vulnerable families/properties and identifying existing assets for emergency response	Peer exchange – matching of needs and resources in affected communities	Soliciting ideas and priorities from communities for post-crisis rebuilding Example case studies: CSAP, Remesh	More contextually relevant data, mobilisation of local resources and more inclusive decisions Most relevant for: all crisis types
Resource planning and management	Predicting resources needed to mitigate crises	Predicting resources needed to respond to a crisis	Enhanced coordination for funding distribution	Predicting resources needed for recovery efforts Example case studies: Targeting the Ultra-Poor in Afghanistan	More effective use and targeting of resources for anticipatory action and/or financing. Most relevant for: all crisis types
Programme planning and operations	Modelling behaviours and interventions for crisis mitigation Example case studies: Sequía Companion Modelling	Modelling behaviours and interventions for crisis planning Example case studies: Modelling humanitarian relief in Haiti, HOPE	Enhanced coordination for distributed response Example case studies: WeFly Portal	Modelling behaviours and interventions for crisis recovery Example case studies: Sequía Companion Modelling	More effective interventions, through collective understanding of impacts, dependencies, and emergent or unintended effects Most relevant for: complex emergencies, slow-onset disasters
Monitoring, accountability and evaluation	Monitoring of crisis mitigation efforts		Monitoring response efforts	Monitoring recovery efforts	Enhancing accountability and legitimacy through community feedback and oversight Most relevant for: all crisis types

TEN R&D OPPORTUNITIES FOR COLLECTIVE CRISIS INTELLIGENCE

Building on the use cases and our technical analysis we identified ten key research and development (R&D) opportunities. We have grouped these into three categories of action: two opportunities related to the types of users of CCI solutions, four that push CCI methods to respond to particular issues in crisis management, and three that seek to leverage and integrate new technologies in CCI solutions. We outline these ten areas for investment below.

Expanding CCI solutions to new users

1. **Develop CCI solutions with and for frontline responders and affected communities**

   Only one CCI case study analysed appears to have been designed or prototyped from the outset with the involvement of frontline responders. While just eight solutions are directly being used by local civil society organisations or affected communities. Creating solutions that both draw insight from those on the frontline, and enables them to take more effective local action remains a major innovation opportunity.

2. **Use collective intelligence methods to deepen community participation in crisis management**

   The majority of CCI solutions at present use passive data collection methods (i.e. data that is collected without asking the user for it – such as through social media scraping) rather than active data collection methods, where the user is aware that they are contributing data. There is an opportunity to deepen community participation by using collective intelligence methods to allow people to actively contribute. Citizen science is one such currently under-utilised CI method, which helps build community awareness and action through monitoring environmental conditions and health/wellbeing. At present CI methods that crowdsource opinions and ideas, or that allow people to deliberate on decisions are rarely applied (11 per cent, *n*3). Advances in NLP are now making it easier for organisations to cluster and make sense of qualitative data generated from these methods, and this offers new opportunities to understand and respond to local community priorities.

Applying CCI solutions to new issues in crisis management

3. **Expand situational awareness of misinformation and disinformation**

   The scale and spread of misinformation and disinformation is a growing challenge for humanitarian organisations – with documented examples on the rise.[4] A number of humanitarian agencies including MSF, IFRC and UN Global Pulse are already developing tools to address this problem. CCI methods can play an important role in enabling early identification of misinformation. Using crowdsourcing or community reporting to identify and verify rumours in real time can help humanitarian agencies address misinformation in a timely manner and adapt their interventions accordingly.

4. **Predict the resources needed for crisis mitigation, response and recovery**

   Efforts are growing to predict where a crisis will happen, who will be affected, how big the impact will be and when it will strike. However, none of the CCI or predictive analytics solutions we studied were attempting to predict the resources needed to mitigate or respond to a crisis. There is an opportunity to better utilise 'Who Does What and Where' (3Ws) data in predictive analytics, and to train models on historical data of previous crisis management efforts. The adoption of anticipatory initiatives – such as forecast-based financing – could be greatly accelerated by the development of such resourcing forecasts. And perhaps resourcing predictions could help improve operational efficiency, mobilise new resources or partnerships to close the current funding gap for humanitarian response.

5. **Monitor humanitarian response and recovery efforts**

   We did not find any CCI solutions which involved communities in real-time monitoring and evaluation of humanitarian response or recovery efforts, despite the increasing focus on real-time evaluations (RTEs) and adaptive management approaches in the last decade.

   Although also rare outside of the humanitarian sector, there have been some efforts to use CI approaches to involve citizens in monitoring the implementation of programmes or policies. Existing CI-only examples have relied on citizen-generated data (often using GIS systems, plus citizen reports and images) to provide 'ground truthed' evidence.

6. **Leverage CCI to facilitate distributed intelligent actions for crisis response**

   The majority of CCI solutions analysed currently help facilitate centralised control and coordination of crisis response activities. A significant opportunity for future CCI solutions is to create solutions that allow for more distributed intelligent actions for crisis preparedness and response – between community members, civil society organisations and between non-traditional/traditional actors. A key feature of the COVID-19 response has been the emergent volunteering efforts enabled by peer-to-peer matching of resources, skills, assets and needs between affected communities. Greater proactive innovation and investment now could help overcome some of the limitations of these initiatives and help accelerate localisation efforts in the future.

Leveraging new technologies in CCI solutions

7. **Leverage unsupervised or semi-supervised machine learning techniques for improved situational awareness**

   The majority of existing CCI solutions that combine predictive analytics use supervised machine learning methods. However, these methods require large amounts of labelled data which has practical limitations and is often challenging in a humanitarian crisis context. The application of weakly-supervised and semi-supervised learning enables solutions to overcome modelling challenges from limited labelled data points.[5] Future CCI solutions could also draw on these techniques to extract insight from diverse unlabelled datasets, such as on-the-ground reports, remote sensing data and news and social media data, all of which are becoming more readily available through open channels.

8. **Model the complexity of crises and the effects of humanitarian challenges and actions**

   There is a significant R&D opportunity to model crisis co-dependence and network effects of humanitarian interventions or population behaviours. Agent based modelling (ABM) techniques have not been widely used to date in CCI solutions (2/28), neither have bottom-up mathematical modelling methods (e.g. Cliodynamics) (0/28). But with greater focus on anticipatory action and finance, and with the sector facing intersecting crises (e.g., COVID and climate), simulations and causal effect models are likely to become increasingly valuable as tools to support programme planning and policy.

9. **Participatory modelling for improved multi-stakeholder decision making**

   A specific innovation opportunity to ensure the relevance and application of ABM to local communities and frontline responders is the method of companion modelling. This participatory approach uses the collective intelligence of a wide range of stakeholders to design and implement ABM, and features interactive simulations enabling participating stakeholders to test different scenarios and outcomes. This could help strengthen the ability of frontline responders and communities to understand the impact of different actions and deploy resources most effectively.

10. **Use CI to bridge the gap between human reasoning and AI predictions**

    There is an opportunity to better quantitative models of qualitative human reasoning.[6] Collective intelligence could be used to capture human hypotheses for the drivers of humanitarian crises, which can then be converted into quantitative variables to be used as inputs into an AI or predictive analytics system. None of the case studies that we explored explicitly capture human reasoning for why events have taken place. However, future R&D opportunities for CCI could be to construct mathematical representations of human reasoning via equations to then provide insight and make predictions.

Examples of CCI: emerging use cases

- **Africa's Voices** and the **Remesh** platform for Inclusive Peacebuilding are two CCI solutions that crowdsource opinions to stimulate debate about policy issues in post-crisis environments and track the diversity of local perspectives, as well as dominant themes.
- **Modelling humanitarian relief in Haiti** uses Agent Based Modelling (ABM) to understand the behaviour of local populations, use of relief facilities and the spread of information after a crisis occurs.
- **Sequía** used participatory design to develop an ABM of the local environment together with local cattle farmers in drought-affected Uruguay. Farmers who helped to design the model, used it to identify land management options that could help them alleviate the impacts of drought.

Sustaining participation and the inability of predictive algorithms to transfer between contexts are two particular challenges for collective crisis intelligence solutions

Risks and challenges related to CCI solutions are similar to those posed more generally by the adoption of AI and other digital technologies in humanitarian action. They include privacy and exploitation concerns, as well as replicating or exacerbating existing inequalities by unequal representation and access. However, CCI solutions may face particular challenges with generating or sustaining active participation during crises, given the need to prioritise speed of response, difficulties with connectivity or accessing affected locations and the importance of considering the mental health of affected populations.

Technical barriers to scaling include the inability of predictive algorithms to easily transfer between contexts, and the paucity of high-quality, labelled datasets that these approaches require. In addition, few low- or middle-income countries have the technical infrastructure to support the latest developments in AI methods. Organisational barriers include the considerable data literacy and digital skills gap among volunteers, emergency responders, humanitarian staff, as well as coordination failures within and between humanitarian organisations.

Conclusion and next steps

CCI offers a potential alternative to the trajectory of AI development in the humanitarian sector. This project is one of the first attempts to develop and test new methods for involving affected populations and frontline responders in the development, evaluation and utilisation of new predictive AI models. We hope to demonstrate how CCI solutions would enable these communities to benefit directly from advances in AI and predictive analytics, through early warning, early action, enhanced response and better recovery.

Introduction

This report provides the first analysis of how an emerging innovation method, 'collective crisis intelligence', is being used to improve anticipation, management and response in the humanitarian sector.

It sets out the background conceptual, technical and solutions landscape for a UK Humanitarian Innovation Hub-funded 'Accelerated Innovation Collaboration' (AIC) which is delivered by Nesta and the International Federation of the Red Cross and Crescent Societies (IFRC). It provides an overview of the current state of practice, identifies future potential opportunities and new approaches to be tested. The research was primarily intended to help inform the practical prototyping and testing phase of our collaboration with Red Cross and Crescent Societies in Nepal and Cameroon. We are publishing this for the benefit of the wider community of humanitarian innovators and innovation funders, whom we hope will use the findings to spur further R&D efforts in this emerging area.

Methodology

The report details the findings from research conducted between April and July 2021.

The key objective of this landscape analysis was to identify practical applications, future opportunities and gaps in CCI for localised emergency response. To explore this we adopted a mixed methods research approach comprising:

CCI case study analysis: To understand the current state of the CCI landscape

We identified and analysed 28 CCI case studies,[d] looking at a range of dimensions, including data sources, technology types, collective intelligence methods, artificial intelligence (AI) methods, type of crisis, and stage of innovation. All case studies were from lower- and middle-income country settings or with global coverage and included contributions from local populations and/or frontline responders. The case study analysis was supplemented by telephone interviews with some of the CCI solution developers. It is difficult to be comprehensive in any case study analysis of an emerging innovation field and so there may be other CCI solutions we didn't capture.

d. These case studies were drawn from Nesta's existing repositories and publications of collective intelligence case studies, expert interviews, and a rapid review of the academic and grey literature on humanitarian crises, emergency response and disaster risk reduction.

Predictive analytics analysis: To understand the application of predictive analytics for collective crisis intelligence

We analysed 33 case studies that applied predictive analytics to challenges in the humanitarian sector. Sixteen of these case studies were taken from the longlist of 28 CCI solutions. These were selected based on our ability to access detailed technical information through publicly available channels or interviews. An additional 17 case studies involving predictive analytics were sourced to enable a more comprehensive review. Supplementary interviews were conducted with technical experts working at the organisations developing CCI solutions involving predictive analytics. This subset of case studies was used for the analysis in Section 1.4.2 and parts of Section 1.5.

Analysis of humanitarian trends: To understand the trends shaping the sector (including the use of technology), and how the tasks and 'workflows' of frontline responders are changing in response

A wide range of literature related to trends shaping the humanitarian sector was reviewed, including official reports published by international institutions and humanitarian actors (e.g. World Economic Forum, OCHA, IFRC), as well as grey literature. This was supplemented by five telephone in-depth telephone interviews with humanitarian experts.

We also conducted four telephone in-depth interviews, a survey and a focus group with frontline responders and volunteers working for National Societies within IFRC and wider IFRC staff to understand their views on the types of crises growing in importance, the key tasks in their role and how these are changing, as well as the solutions and technologies they commonly employ in their work. Trends around the use of technology in the humanitarian sector were explored with additional interviews with technical experts.

Gaps and Opportunities workshop: To share findings

Following completion of the exploratory research outlined above, a workshop was held on 24 June 2021 to share findings identified in the research and fill remaining knowledge gaps. Using interactive activities, the workshop also generated ideas about existing and future priorities that future CCI solutions should respond to. Attendees included technical and humanitarian experts and IFRC frontline responders/volunteers who had participated in interviews, as well as representatives from IFRC and members of the CCI project Advisory Group.

A limitation of this report is that affected communities were not consulted/included in this initial phase of research. The views of volunteers and frontline responders working for National Societies within IFRC have been included in the analysis.

Figure 1: Summary of the research programme conducted between April – July 2021

CCI case study analysis

- 28 case studies
- All lower- and middle-income country settings or with global coverage
- All feature contributions from local populations and/or frontline responders

Predictive analytics case study analysis

- 33 case studies that applied predictive analytics to challenges in the humanitarian sector
- Included 16 examples from the CCI case study analysis

Humanitarian trends and tasks analysis

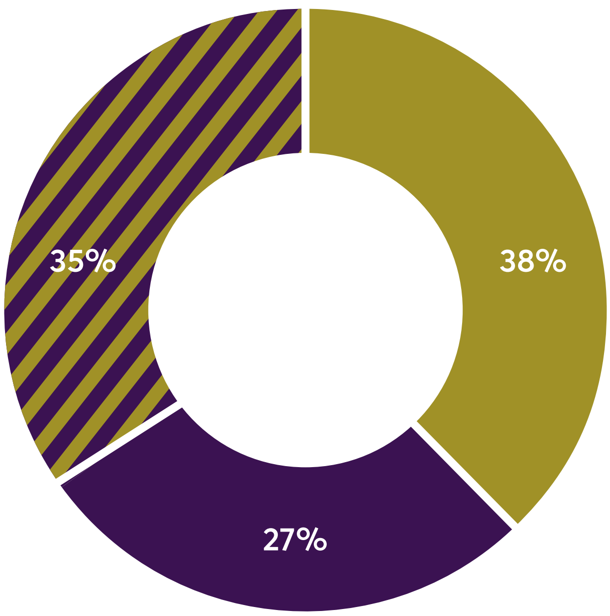
- Literature review
- Five interviews with humanitarian experts
- Four interviews with IFRC frontline responders and volunteers
- Survey with wider IFRC staff
- Focus group with wider IFRC staff

- Five interviews with technical experts (i.e. in predictive analytics)
- Four interviews with CCI solution teams

Gaps and Opportunities workshop 24 June 2021

A three-hour workshop with individuals who had participated in the exploratory research and members of the Advisory Group to share findings and fill in knowledge gaps

Figure 2: Summary of the 45 CCI and predictive analytics case studies analysed



Used in predictive analytics analysis

Used in CCI analysis

Used in CCI and predictive analytics analysis

Of the 45 case studies analysed:
16 were CCI and predictive analytics, 12 were CCI only and 17 were predictive analytics only

01

Collective crisis intelligence

Photo: Hanna Morris at unsplash.com

What is collective crisis intelligence?

Collective crisis intelligence (CCI) combines methods that gather intelligence from affected communities and frontline responders with artificial intelligence (AI) for more effective crisis mitigation, response or recovery.

CCI is a subset of a wider field known as **collective intelligence design** – an approach which brings together diverse groups of people, new sources of data and digital technologies to tackle complex problems. Traditionally, collective intelligence has drawn from a variety of methods many of which are already familiar to the humanitarian sector such as crowdsourcing, crowdmapping, and open innovation. Increasingly, artificial intelligence methods, such as machine learning algorithms, are being used in combination with collective intelligence methods. This is making it easier to gather large amounts of human-generated content like text, images and videos and to extract patterns from it (see the Appendix for a glossary of collective intelligence and AI methods).

At the same time, a suite of AI methods known as predictive analytics is also growing in use in the humanitarian sector. It encompasses a variety of statistical techniques that enable a computer to analyse structured data using numeric and machine-readable data. It typically relies on algorithms from classical machine learning to make predictions about the future or otherwise unknown events.

This research particularly focuses on exploring the intersection between localised collective intelligence from affected communities and frontline responders, and predictive analytics (see Figure 3) – where the combination has been used deliberately to support crisis management at any phase in the crisis management cycle (see Figure 4). This aligns with the IFRC's model of Preparedness for Effective Response (PER) which aims to strengthen local preparedness capacities to ensure timely and effective humanitarian assistance.[7]

Figure 3: Defining collective crisis intelligence

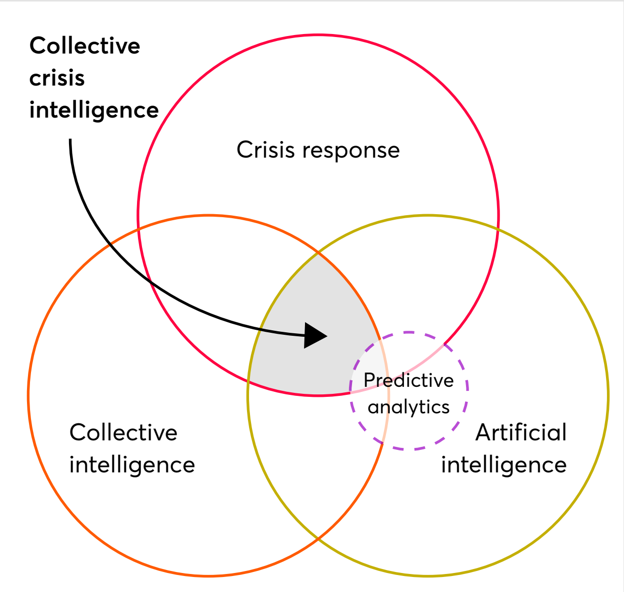
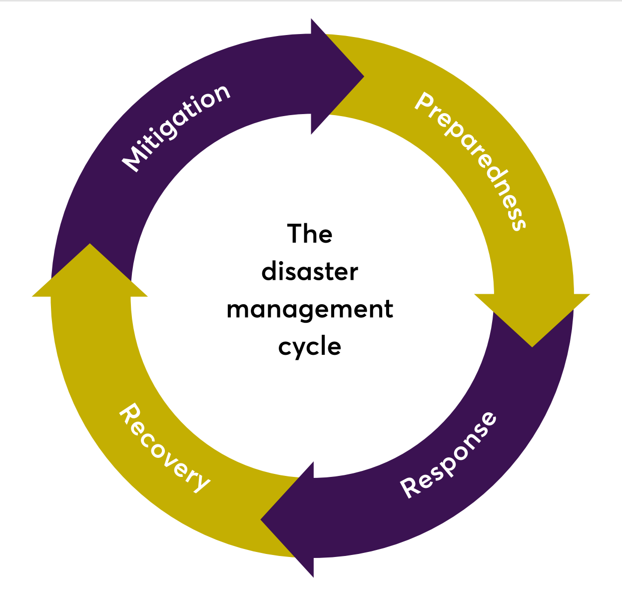


Figure 4: The four phases of the crisis disaster management cycle



CCI and the key design principles

Collective intelligence design is a design philosophy that can be applied at any stage in a typical innovation, product development, policy design or service design process. It is underpinned by four key principles:[8]

1. Increase diversity of the people you involve and the opinions you listen to.
2. Enable people to contribute views and ideas independently and freely.
3. Integrate different types of data to unlock fresh insights.
4. Be citizen-centred: data empowerment, not data extraction.

The CI design principles are guiding considerations to take into account when designing a project. In contrast, CCI is a specific methodological innovation opportunity to apply CI design in the context of localised crisis response. There is an opportunity for CCI to play a niche role in the existing data and tech ecosystem of humanitarian action by bridging community derived local insights with the computational power of AI. CCI also has the potential to improve the contextual grounding and accountability of tools and solutions applied in the sector.

1.1 CCI for rapid onset emergencies

Is CCI particularly relevant for rapid onset emergencies?

Rapid onset emergencies occur quickly and often unexpectedly, usually linked to sudden natural events such as earthquakes. Due to the speed at which they unfold, they are more difficult to predict compared to slow onset disasters, like droughts, that unfold over months or even years. Given the sectoral focus on anticipatory action and prediction, there is a risk that efforts may be focused on crises that can be more easily predicted (i.e. slow-onset crises). A 2020 review of the most common applications of predictive analytics in the humanitarian sector by Hernandez and Roberts demonstrated a focus on disease outbreak, migration and conflict, or slower-onset complex emergencies.[9]

The limiting condition for developing AI and predictive analytics applications is often the availability of data of sufficient relevance, scale and quality. Data collection and management in rapid onset emergencies is particularly challenging because of the speed at which a crisis unfolds, obstructive physical environments, and difficulties in coordinating humanitarian actors and organisations.[10] By drawing on novel data sources, including from responders and communities on the frontline of a crisis, alongside technologies to process vast quantities of data quickly, CCI may help to overcome information, data and implementation gaps in rapid onset emergencies. CCI solutions offer a pathway towards more ethical, equitable and sustainable ways of working with humanitarian data and local actors. Grounding CCI solutions in the communities they serve will ensure that future developments in anticipatory action and predictive capabilities reflect the sector's localisation agenda, and enhance accountability and legitimacy.

In this research we explored CCI applications across a broad range of crises, not just rapid onset emergencies. This helped us to understand the widest range of current and future 'use cases' (or applications) of CCI, and the extent to which combining localised collective intelligence methods with predictive analytics could contribute to more effective decision making in disasters.

The role of frontline responders

A unique element of CCI solutions is their reliance on the intelligence of affected communities and frontline actors, including both frontline emergency workers employed by humanitarian organisations and on-the-ground volunteers. Many humanitarian organisations rely on local volunteers to deliver basic services during crisis response.[11] The ability of these individuals to access affected locations and understand the contextual needs of communities experiencing a crisis places them in a unique position to contribute to CCI. This research also sought to understand the extent of their current involvement in CCI solutions or if frontline responders could be better integrated in future CCI innovations.

1.2 Mapping CCI for community-based and first-line crisis response

1.2.1 PREVALENCE AND GEOGRAPHY

Key findings

- We identified and analysed 28 current applications of CCI.
- Forty-two per cent (*n*12) of the case studies had either been applied in multiple regions or covered a global scale.
- Asia and Africa were the regions with the highest number of CCI solutions.

We focused our analysis on case studies that demonstrate the use of CCI approaches in humanitarian settings in low- and middle-income countries. To meet the selection criteria, case studies had to combine multiple data sources e.g. crowdsourced observations, social media scraping; use collective intelligence methods to gather insights from frontline responders and affected communities e.g. crowdmapping local infrastructure, social media posts gathered through web scraping, crowdsourcing impact reports; and include some use of AI, including but not limited to predictive analytics. e.g. crowdmapping with computer vision for analysis of satellite imagery, or automated chatbots to improve the coordination of drone pilots during disaster response. In total, we analysed 28 case studies that fit these criteria.[e]

e. We do not claim that this list is comprehensive, particularly for early stage innovations, many of which may not have publicly available information online.

Figure 5: The 28 CCI case studies

	Case study/tool		Case study/tool
1	Artificial Intelligence in Medical Epidemiology (AIME)	15	Modelling humanitarian relief in Haiti
2	Common Social Accountability Platform (CSAP)	16	Monitoring of the Venezuelan exodus through Facebook's advertising platform
3	Community Water Watch (FloodTags)	17	Open Cities AI Challenge for Disaster Reduction
4	Companion Modelling – Sequía	18	PetaBencana.id: Risk Map
5	Dataminr for humanitarian response	19	Project Jetson
6	eBayanihan/Agos	20	RapiD (MapWithAI)
7	Flood Management EWS India	21	Safe Water Optimization Tool (SWOT)
8	Haze Gazer	22	Sentry Syria
9	Hybrid sensing for EmeRgency ManagEment System (HERMES)	23	Targeting the Ultra-Poor Program (TUP)
10	Humanitarian Operations Planning Environment (HOPE)	24	Text Analytics for Resilience-Enabled Extreme Events Reconnaissance
11	Humanitarian Tracker	25	Translators without Borders
12	Remesh: Inclusive Peacebuilding through Dialogue	26	Artificial Intelligence for Digital Response (AIDR)/ Human-annotated Twitter Corpora for NLP of Crisis-related Messages
13	Internal Displacement Event Tagging Extraction and Clustering Tool (IDETECT)	27	WeFly Portal
14	Managing Information in Natural Disasters (MIND)	28	Zika mitigation with Premise

Geographical focus

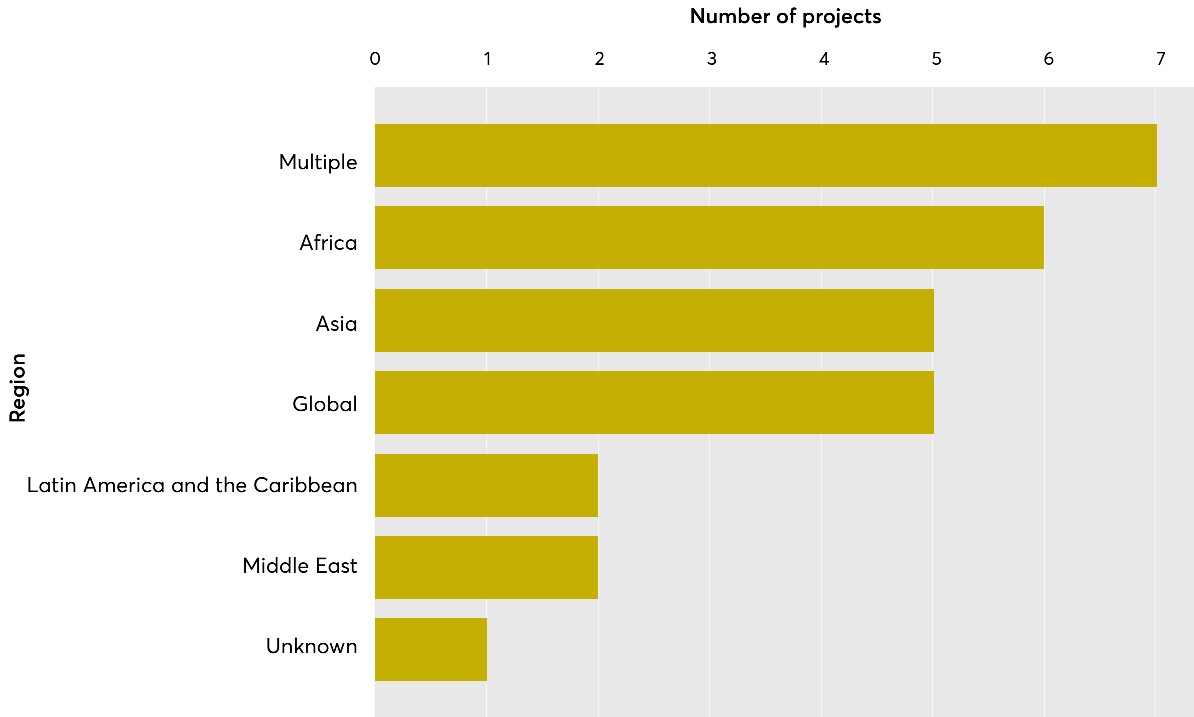
Of the 28 case studies analysed, 42 per cent (*n*12) had a broad geographical coverage, spanning either multiple countries or covering a global scale. For example the **Artificial Intelligence for Digital Response (AIDR)** platform developed by the Qatar Computing Research Institute (QCRI),[f] covers disasters across the world using openly available online data sources. The **HERMES** system and **Managing Information about Natural Disasters (MIND)** platform from Pulse Lab Jakarta also track emerging disasters at the global scale (see Case study 1).

Twenty-one per cent (*n*6) of the case studies in our sample focused on applications developed for countries in Africa, while 18 per cent (*n*5) were developed for countries in Asia. In 2020, Asia experienced 41 per cent of disaster events and 64 per cent of total people affected, which highlights the importance of developing new solutions that can be applied in this regional context.[12] Examples applied on the African continent include *Project Jetson* that predicts the numbers of people who will be displaced and where in Somalia, and the **Common Social Accountability Platform** (see Case study 3) which enhances the inclusion of citizens in decision making across governance, humanitarian and development programmes in Somalia. We found just two case studies in Latin America and the Caribbean and the Middle East respectively.

f. QCRI operates as part of Hamad Bin Khalifa University.

Photo: Fahrul Azmi at unsplash.com

Figure 6: The regional distribution of CCI solutions



By 'Multiple' we mean applications that have been tested or applied in more than one region. The 'Unknown' category corresponds to the HOPE case study by Humanitarian Data Systems which is in very early stages of development.

1.2.2 ORGANISATIONS DEVELOPING AND USING CCI SOLUTIONS

Key findings

- Academic organisations are central to early stage CCI innovation but are rarely involved in taking CCI solutions to market. Fifty-four per cent (*n*15) of the CCI solutions were at early stage development, either as an initial proof of concept, prototype or pilot.
- Most operational CCI solutions are private sector led.
- Local or national governments make up 36 per cent (*n*10) of users of more mature CCI solutions. Only eight examples were actively used by citizens/public or local communities.
- CCI proof of concepts are usually supported by academic research funding while mature CCI solutions transition to a mixed funding portfolio made up of both public and private sector organisations.

Who is developing and using the CCI solutions?

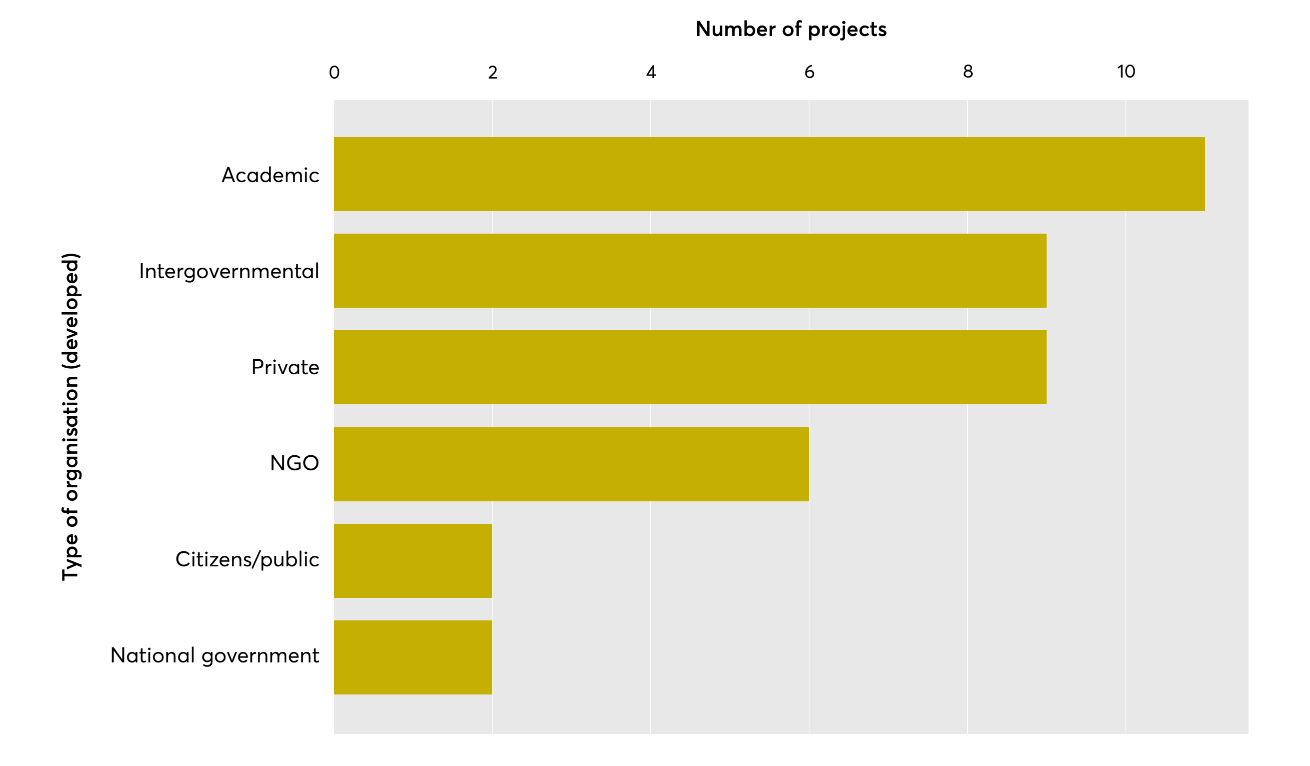
Thirty-nine per cent (*n*11) of the CCI examples in our sample had been developed by researchers in academic institutions, sometimes with the involvement of researchers from intergovernmental institutions. The majority of early stage innovation (concept/idea, prototype or pilot) was carried out by these partnerships. However, academic organisations were rarely involved in taking CCI solutions to market and most CCI solutions that have managed to operationalise or scale to multiple markets were private-sector-led; out of the 13 solutions that were operational in one market or scaling to other markets, academic institutions were only involved in the development of three solutions, while seven involved private sector organisations. Possible drivers of the lack of academic-humanitarian technology partnerships are speculative but tend to focus on conflicting funding requirements (e.g. academic funding for experimental projects that doesn't fulfil humanitarian organisation requirements) and divergent goals around academic excellence and on-the-ground impact.[13] For 36 per cent (*n*10) of case studies in the earliest stages of innovation, it was not clear whether they were being used and by whom (see Figure 8). This may indicate the absence of a pathway to impact for projects that are research-led even in cases that involve multilateral organisations such as the World Bank and UNICEF.[g] Two notable exceptions are the **PetaBencana.id** platform, and the **CSAP from Africa's Voices** (see Case study 3). Both organisations successfully transitioned from a research prototype originally developed by universities to operational technologies maintained by standalone organisations, a foundation in the case of the former and the latter, a social enterprise. PetaBencana.id has also secured an ongoing implementation partnership with the city government of Jakarta and the Indonesian National Disaster Management Agency.

Project Jetson was the only case study in our sample that was developed in-house by a humanitarian organisation. Two other CCI solutions were created in partnership or with the support of individual National Societies within the IFRC, or subsequently integrated into existing workflows. For example the **Community Water Watch** project, a partnership between the Tanzanian Red Cross Society and

g. The challenge of scaling beyond prototype and early stage concepts was also voiced by multiple experts during interviews. We explore this further in Section 3.1.

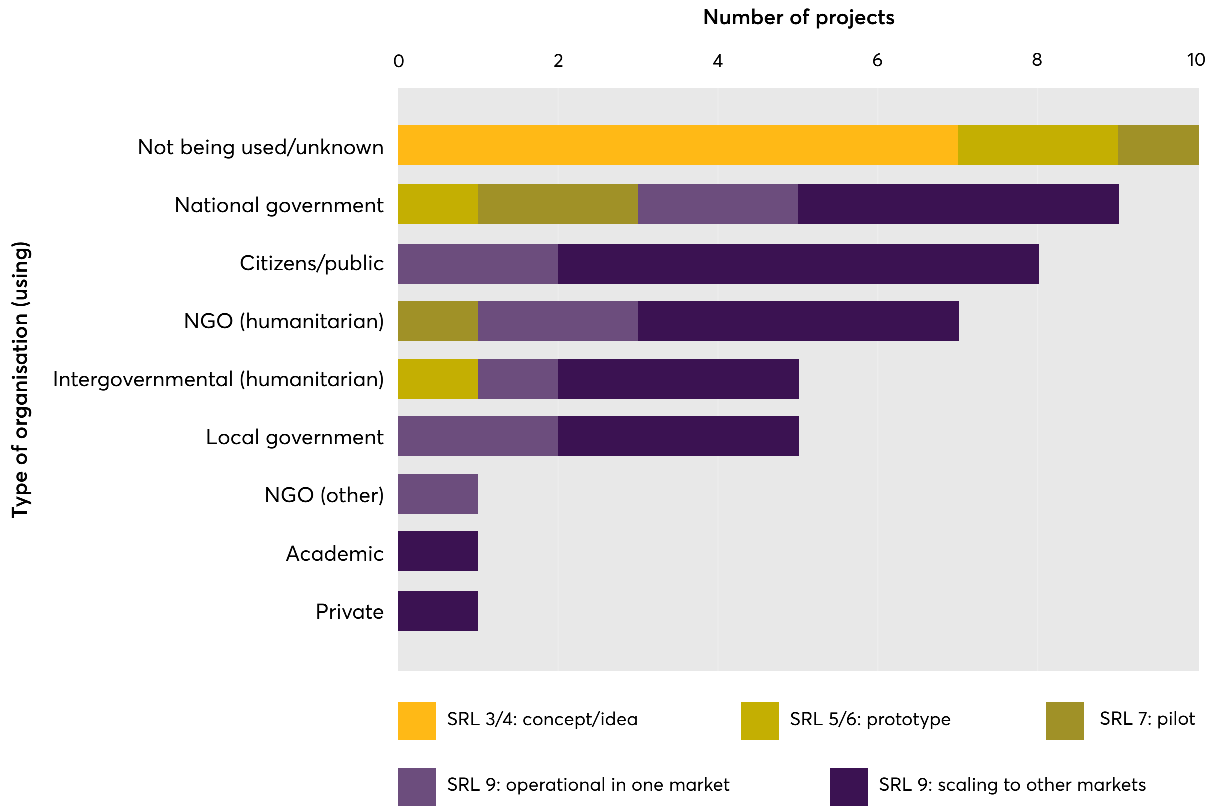
Flood Tags, a private company based in the Netherlands, combines direct messages from Red Cross volunteers with sensor data and web-scraped data to provide early warnings of flooding in Dar Es Salaam. **RapiD Editor**, an AI-enabled mapping tool for OpenStreetMap, was developed by Facebook and can be used within the Humanitarian OpenStreetMap Team community mapping platform (see Case study 2). Government agencies and decision makers at national and local level were the most common users of CCI solutions, either as part of their emergency response operations or as an input to policy (see Figure 8). Only 29 per cent (*n*8) of our case studies were being used by citizens/public, including affected communities. We further explore the impact, solution readiness and integration into workflows with a broader set of case studies in Section 1.5.2.

Figure 7: The organisations/groups developing CCI solutions



Citizens/public covers different informal professional groups or individuals from local and affected communities. We found only two CCI solutions, the WeFly portal and Companion Modelling, that were actively designed and developed with the involvement of these groups. e.g. local drone pilots, farmers.

Figure 8: The organisations/groups using CCI solutions



Citizens/public covers different informal groups or individuals from local and affected communities, e.g. teachers, farmers, residents affected by flooding.

Funders of CCI solutions

The majority of projects that tested out new concepts or ideas for CCI[h] were funded by academic institutions or research funding bodies supporting the work of research groups who specialise in humanitarian response or disaster management. It is likely that the development costs for these projects were relatively low as many of them relied on existing open source tools, for example open APIs. In contrast, the projects that have had to develop new tools or platforms are typically funded by private investment, international organisations, national governments (often in the context of foreign aid programmes) or some combination of these. For example the two prototype dashboards developed by Pulse Lab Jakarta, **Haze Gazer** and **MIND** (see Case study 1), were funded by the Australian Government. Many private-sector-led solutions have also been funded by national governments, which has allowed them to adapt their tools for implementation across multiple markets where countries have similar vulnerabilities to crises. For example, **AIME** (see Case study 6), a company that has developed multiple AI-enabled tools to predict disease outbreaks, was funded by the national governments of Brazil and Malaysia to enhance their ability to predict outbreaks of Zika and Dengue. Several CCI projects have had to develop a mixed funding model to sustain themselves over the long term. Both the **PetaBencana.id platform** and **Africa's Voices** (see Case study 3) were created with the help of academic funders but have subsequently been supported by a combination of awards and grants from international governments, private foundations, NGOs and the private sector, such as the technology companies Twilio and Twitter.

h. Classified as the earliest stage of innovation: proof-of-concept (SRL 3/4) or prototype (SRL 5/6).

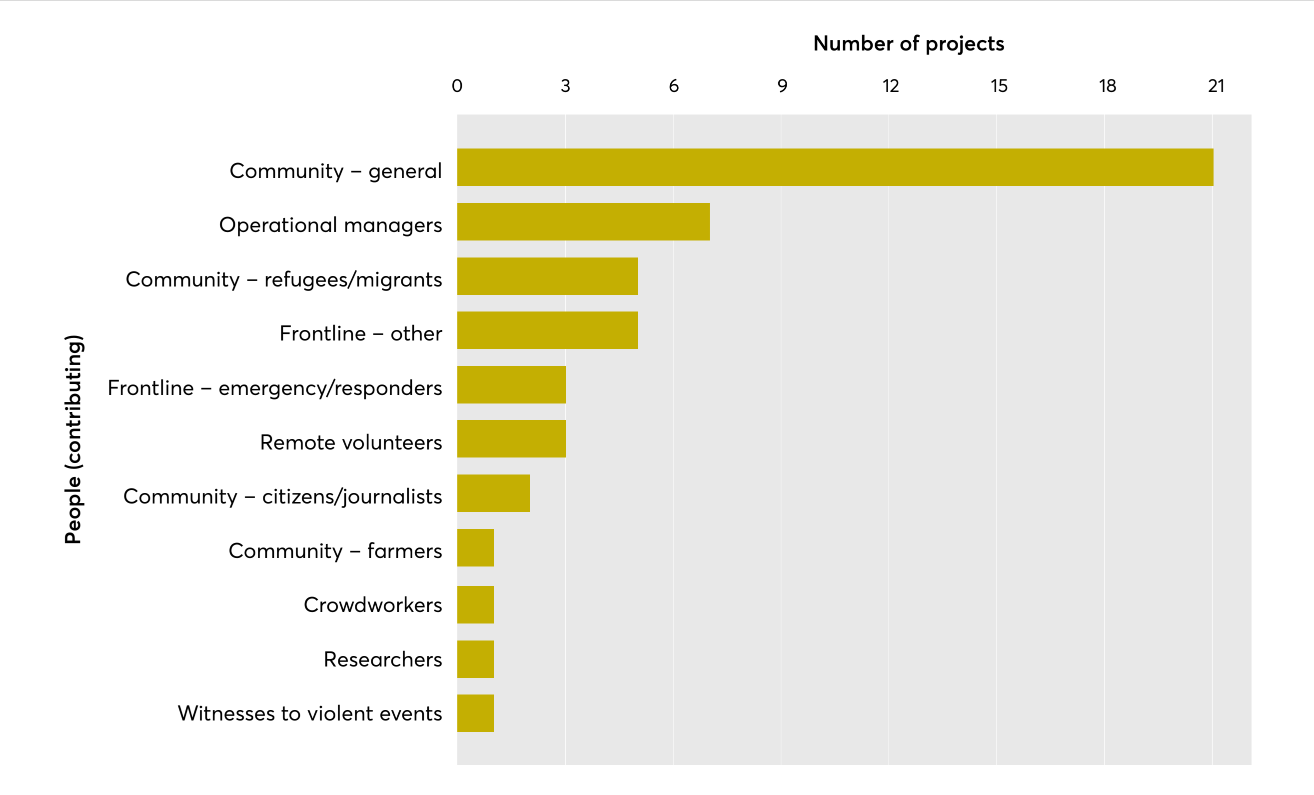
1.2.3 CONTRIBUTORS TO CCI SOLUTIONS

Key findings

- Frontline workers and volunteers are underused as a source of specialised local intelligence in current CCI solutions.
- Contributions from affected communities are only rarely sourced from sub-groups with distinct lived experience or skills, e.g. farmers or refugees.
- Even though affected communities were the primary contributors of data for CCI solutions, they were rarely the end-users of the resulting tools.

Although many different actors are involved in the crisis management cycle, including policy makers, operational managers and strategic decision makers at humanitarian organisations, the proximity of local residents and frontline workers to the crisis environment gives them a unique perspective. They are familiar with the underlying cultural, social and political conditions, and the needs of local communities and their firsthand experience of the impact gives the ability to assess the effectiveness of crisis management.[14] For our analysis, we focused on the contributions to CCI made by the groups closest to the crisis environment – frontline workers (including local volunteers, official emergency responders, healthcare workers, etc.) and those living in crisis-affected regions (see Figure 9).

Figure 9: The types of people contributing to CCI solutions



We have split affected communities and frontline workers into subcategories defined by specific expertise or lived experience.

Photo: Gyan Shahane at unsplash.com

Contributions from affected communities

Our analysis revealed that 75 per cent (*n*21) of CCI case studies gathered contributions from the general local population rather than specific groups, particularly during crisis response. Notably, even though affected communities were the primary contributors of data for CCI solutions, they were rarely the end-users of the resulting tools (8/28 case studies,[i] see Figure 8 where affected communities are included in 'citizens/public' category).

Only 29 per cent (*n*8) of the reviewed case studies focused on gathering more specialised community intelligence. Of these, two examples identified citizen journalists as unique contributors and one used crowdsourced observations from farmers to model different ecosystem management interventions in a drought-affected region in Uruguay. The remaining five projects worked with refugee or migrant communities. For example, **Project Jetson** used ethnographic methods to engage Somali refugees in developing a new tool that predicts displacement.

Contributions from frontline workers

Although it is difficult to disambiguate the contributions made by community members and frontline workers in the case of data contributed through online sources, our analysis identified eight case studies with distinct contributions by frontline workers separate from general insights gathered on social media. The contributions ranged from the collection of water samples to test for appropriate chlorination levels in refugee camps by frontline healthcare staff in the S**afe Water Optimisation Tool** case study, to the localised reports of water levels by Red Cross volunteers in Tanzania as part of the **Community Water Watch** project. Even though rapid onset emergencies are likely to stimulate 'emergent' or spontaneously self-organising voluntary groups, none of the examples we found explicitly mentioned these groups.[15] In general, it appears that frontline workers and local volunteers (both those affiliated with humanitarian organisations and informal groups) are underused as a distinct source of intelligence across current CCI solutions. This may be due to data literacy or skills gaps amongst frontline staff, the lack of tools developed for use with local languages or reluctance to engage in data collection due to privacy concerns (this is explored further in Section 3.1).

i. The 'citizens/public' category covers use by local residents.

1.3 'Use cases' for CCI in humanitarian response

Key findings

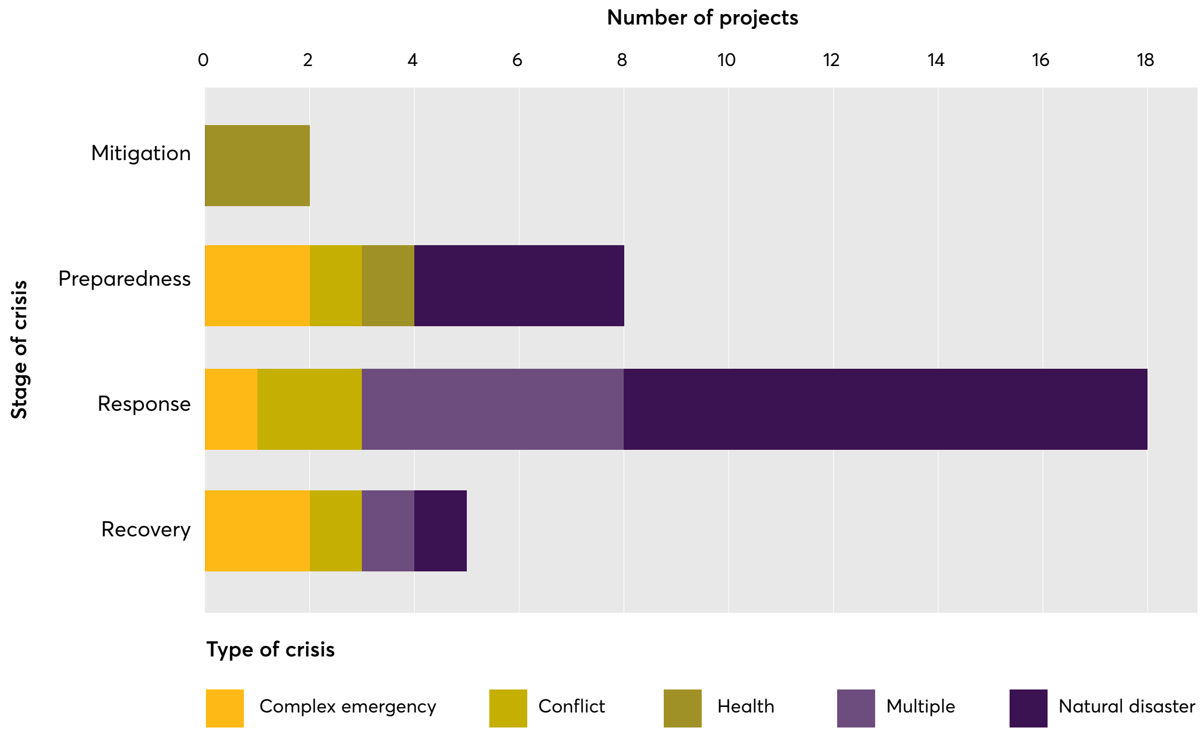
- Forty-six per cent (*n*13) of all CCI solutions in our sample are used during preparedness and response for rapid onset natural disasters, especially flooding and earthquakes.
- Only a small subset of current CCI solutions (2/28 cases) focus on crisis mitigation or prevention. Both examples use collective intelligence for on-the-ground environmental surveillance to predict disease outbreaks.
- Sixty-eight per cent (*n*19) of CCI solutions are currently most applied in two key 'use cases':
  - **Providing early warning of a crisis**, with most solutions focusing on rapid onset emergencies
  - **Providing real-time situational information to assess impact and needs**, again these also focused predominantly on rapid onset emergencies
- There are other emerging 'use cases' that show promise for future investment in CCI solutions:
  - Predicting a crisis before it happens
  - Soliciting ideas and priorities from communities for post-crisis rebuilding
  - Modelling behaviours and interventions for crisis mitigation or planning or recovery
  - Enhanced coordination for distributed response

A wide range of CCI are currently being used to improve capacity for early warning, and response, with a much smaller proportion being used for the mitigation and recovery phases of crisis management. Forty-six per cent (*n*13) of all CCI solutions are improving preparedness and response capabilities during rapid onset natural disasters, such as floods, earthquakes and hurricanes. These are followed by complex emergencies and conflict, which account for 14 per cent (*n*4) of cases respectively. This contrasts with our expanded analysis of predictive analytics without collective intelligence of affected communities or frontline staff (Section 1.4.2), which had a smaller proportion of cases for rapid onset disasters. We only identified two cases related to health crises but these were also the examples where CCI was being used for mitigation, namely to prevent or reduce the likelihood of a disease outbreak.

Photo: Piyush Priyank at unsplash.com

Photo: Barbara Zandoval at unsplash.com

Figure 10: The application of CCI solutions across the crisis management cycle



Natural disasters cover sudden-onset geophysical and climate-related crises and the multiple category refers to CCI solutions that cover different types of crises. Numerous CCI solutions covered multiple stages of the crisis management cycle, therefore the total number of case studies displayed in the charts exceeds 28.

As part of our analysis of existing CCI solutions, we identified six 'use cases' with at least two case studies. These provide a high-level description of a specific task in the crisis management cycle for which the solution is used.

Figure 11: Summary of the existing CCI 'use cases'

	Before a crisis		Immediate aftermath of a crisis	After a crisis
Use case categories	**Preparedness**	**Preparedness**	**Response**	**Recovery**
Situational awareness	Predicting a crisis before it happens **Example case studies:** AIME, Premise	Providing early warning of a crisis **Example case studies:** Dataminr, Flood Management EWS, Sentry Syria, Project Jetson, Community Water Watch	Providing real-time situational information for more effective response **Example case studies:** Ebayanihan, RapiD, Haze Gazer, HERMES, PetaBencana.id	
Assessing community needs, assets and priorities				Soliciting ideas and priorities from communities for post-crisis rebuilding **Example case studies:** CSAP, Remesh
Programme planning and operations	Modelling behaviours and interventions for crisis mitigation **Example case studies:** Sequía Companion Modelling	Modelling behaviours and interventions for crisis planning **Example case studies:** Modelling humanitarian relief in Haiti, HOPE	Enhanced coordination for distributed response **Example case studies:** WeFly Portal	Modelling behaviours and interventions for crisis recovery **Example case studies:** Sequía Companion Modelling

1.3.1 ESTABLISHED 'USE CASES' FOR CCI SOLUTIONS

The majority of solutions analysed (19 examples)[j] fell into two distinct use cases. We have categorised these as 'established' use cases (green boxes in Figure 11). They focus on developing situational awareness just before or in the immediate aftermath of a crisis.

Providing early warning of a crisis

Early warning systems based on forecasting and/or predictive analytics are increasingly recognised by the humanitarian sector as vital for promoting early action.[16] To be effective, early warnings must be able to access, parse and isolate relevant information about a crisis in a temporally and spatially precise way, which is especially difficult for sudden-onset disasters which have reduced time-windows for early warning. CCI expands the range of available data sources that can be used by predictive machine learning algorithms to spot early signals of a crisis. We found six CCI case studies that were being applied in this way. The most common methods for this use case

j. Readers will note that we reference 21, then six and two case studies for the three categories in this section which exceeds our total case study count. Some CCI solutions cover more than one purpose, and were assigned to multiple categories in our analysis.

include combining web scraping with machine learning to accelerate the ability to access and process local insights. For example, **Dataminr** (see Case study 5) which uses natural language processing, computer vision and machine learning to analyse multiple online data streams for early warnings of natural disasters. These are compiled into situational reports for emergency responders and decision makers. **Sentry Syria** (see Case study 9) combines sensor data and reports generated by volunteer 'plane spotters' who live near air bases and in conflict zones in Syria to predict when air strikes will occur and disseminate warnings to civilians. Before Sentry was introduced, warnings of air strikes lacked speed and accuracy.[17] Both **Dataminr** and **Sentry Syria** use CI and AI to combine the intelligence of people on-the-ground with novel data sources. This approach improves timeliness, spatial coverage and contextual relevance of data enabling civilians to seek safety, and supports emergency personnel to prepare and respond quickly and confidently.

Providing real-time situational information for more effective crisis response

After a crisis hits, assessing the impact, allows frontline responders to plan and prioritise resources effectively. Existing CCI case studies (13 in total) are helping to address this challenge by integrating data from multiple sources, including real-time on-the-ground accounts of the impact of a crisis through crowdsourcing on mobile or web-based platforms. This is especially relevant for rapid onset disasters, which are more difficult to predict, crises with restricted on-the-ground access and when crisis intelligence is scattered between multiple platforms and actors. Citizen-generated data gathered through CCI are often georeferenced so that emergency responders know both what has happened and where. For example, **Haze Gazer** provides near real-time information on fire outbreaks and at-risk communities in Indonesia to coordinate and focus government response. **Haze Gazer**, originally developed by Pulse Labs Jakarta, was handed over to the Executive Office of the President of the Republic of Indonesia and integrated into the Indonesian Government's Early Warning System (EWS) for crises. Prior to this, the EWS lacked the integration of multiple data sources in near real time and visualisation elements.[18] The **eBayanihan/ Agos** platform (see Case study 12) collects needs assessment reports generated by local residents to help frontline workers understand what to prioritise during response efforts. The **MIND** platform (see Case study 1) mines online sources for up-to-date information. It uses an automated data pipeline that scrapes data from relevant Wikipedia entries and the International Aid Transparency Initiative, as well as OpenStreetMap edits, to understand the existing development initiatives and networks in affected areas. These solutions provide a more accurate and granular understanding of real-time on-the-ground experience and needs, enabling responders to better target support.

Photo: Marcus Kauffman at unsplash.com

1.3.2 EMERGING 'USE CASES' FOR CCI SOLUTIONS

Four additional use cases use methods that allow for the longer-term planning and decision making that underpin crisis mitigation or recovery efforts. These are categorised as 'emerging' use cases as the number of current examples we found for each was typically less than three.

Predicting a crisis before it happens

Improving the predictive capability of humanitarian organisations and local communities offers opportunities to take actions to either prevent or mitigate crises from occurring. Although we only identified two existing case examples of CCI for this purpose, there is clear potential to further develop this use case particularly for the prevention of sudden-onset disease outbreaks. For example, since the 2016 Zika outbreak, public health authorities in Cali, Colombia have been working with the company Premise and a local network of volunteers to monitor the location of mosquito breeding sites as well as mosquito density. This allows city officials to target their larvicide programmes effectively, helping to avoid outbreaks of diseases carried by the insect (see Case study 4). Another example, **Artificial Intelligence for Medical Epidemiology (AIME)**, predicts the likelihood of outbreaks for mosquito-borne diseases up to three months in advance using a combination of crowdsourced reports from doctors, epidemiological data and data about variables that influence mosquito breeding, such as weather (see Case study 6). In field tests in Malaysia, the system predicted localised outbreaks of dengue fever up to 30 days in advance with more than 80 per cent accuracy. CCI can support more accurate crisis forecasting by combining unique insights of different actors with on-the-ground experience and a wide range of novel data sources. Being able to access and analyse these diverse datasets makes it more likely that machine learning algorithms will be able to pick up a weak early signal that a crisis is likely to occur, enabling timely action that can prevent or mitigate the impact.

Modelling behaviours and interventions for crisis planning

Two additional case studies used agent based modelling (ABM) or other computational modelling with simulations to improve crisis preparedness. **Modelling humanitarian relief in Haiti** (see Case study 10) used ABM to understand the behaviour of local populations, use of relief facilities and the spread of information after a crisis occurs. Although this example was not developed beyond a proof of concept, it demonstrates an alternative use of CCI for forward planning of humanitarian interventions. The **Humanitarian Operations Planning Environment (HOPE)** being developed by the company Humanity Data Systems, is likewise very early in its development. Their ambition is to create an integrated system that brings together machine learning and modelling alongside project and stakeholder management capabilities to create a complex-event planning environment for crisis preparedness and response. By modelling behaviours in this way, CCI aims to enhance the understanding of impact, dependencies, and emergent or unintended effects within a specific context or locality; this could support appropriate, localised crisis planning.

Modelling behaviours and interventions for crisis mitigation or recovery

Modelling processes that allow different stakeholder groups to explore options for resource allocation, while surfacing different priorities can be a valuable input to formal decision making, as well as grassroots action.[19] One case study in our sample used collective intelligence methods in this way. The Sequía case study used participatory design to develop an agent based model of the local environment together with local cattle farmers in drought-affected Uruguay. Farmers who helped to design the model, used it to identify land management options that could help them alleviate the impacts of drought but there is no evidence they could continue using the tool beyond the initial engagement with the research team (see Case study 7). This type of CCI solution offers significant potential for democratising and improving adaptive strategies during recovery and mitigation of crises brought on by the changing climate, although more investment will be needed to advance them beyond proof-of-concept. CCI solutions that use participatory modelling approaches, as described here, have the potential to enhance collaboration and build trust between stakeholder groups (including those that may have competing interests).

Soliciting ideas and priorities from communities for post-crisis rebuilding

Each crisis is different and impacts different groups in the affected region in distinct ways. Long-term recovery is only possible if rebuilding processes respond to the needs of these different groups and are appropriate for the local sociocultural context.[20] Two (2/28) CCI projects are helping to address this challenge by allowing institutions to tap into and understand the diversity of local perspectives or ideas about different topics. **Africa's Voices** and the **Remesh platform for Inclusive Peacebuilding** are two CCI solutions that crowdsource opinions to stimulate debate about policy issues in post-crisis environments and track the diversity of local perspectives, as well as dominant themes. Both projects rely on an interactive system that brings affected groups into dialogue with local politicians or policymakers. **Africa's Voices** uses interactive radio shows to connect decision makers to questions and topics raised by listeners who message the show using unique SMS codes. **Remesh** has used an online platform to allow up to 1,000 people to contribute to live discussions, while politicians respond in real time using television broadcasts. **Remesh** and **Africa's Voices** have both expanded their approaches to cover a range of local dialects and languages, as well as working with local actors to attract contributions from diverse groups. Despite these efforts, both approaches still suffer from sampling biases due to the self-selection of their participation mechanisms. The sector's localisation agenda has placed increased emphasis on the importance of community engagement, and eliciting community perspectives and needs. CCI solutions offer a means of delivering engagement at scale, while capturing contextually relevant data. This can improve the inclusiveness and legitimacy of decision making, and support community resilience and empowerment.

Photo: Sam Mann at unsplash.com

1.4 Case study analysis of CCI solutions

1.4.1 DATA SOURCES AND CI LANDSCAPE

Key findings

- All CCI solutions rely on combining existing official (government) data and newly created citizen-generated or geospatial data. Private sector data is rarely used.
- A key input to the majority of cases (64 per cent, *n*18) is open data, most of which is in the form of unstructured text or images, gathered from social media platforms. Open APIs are a key enabler of passively contributed local insights gathered in this way.
- Actively crowdsourced data is normally gathered through dedicated apps or online platforms which allow for more structured data entry.
- Data generated through collective intelligence methods is verified for accuracy using either peer validation mechanisms or AI. Several initiatives also offer optional or compulsory training for volunteers to ensure data quality.
- Very few cases in our sample include crowdsourcing of opinions and ideas (11 per cent (*n*3) of cases) or used CI to allow participants to build on each other's contributions or interact, e.g. through deliberation or peer-to-peer exchange of skills and resources.

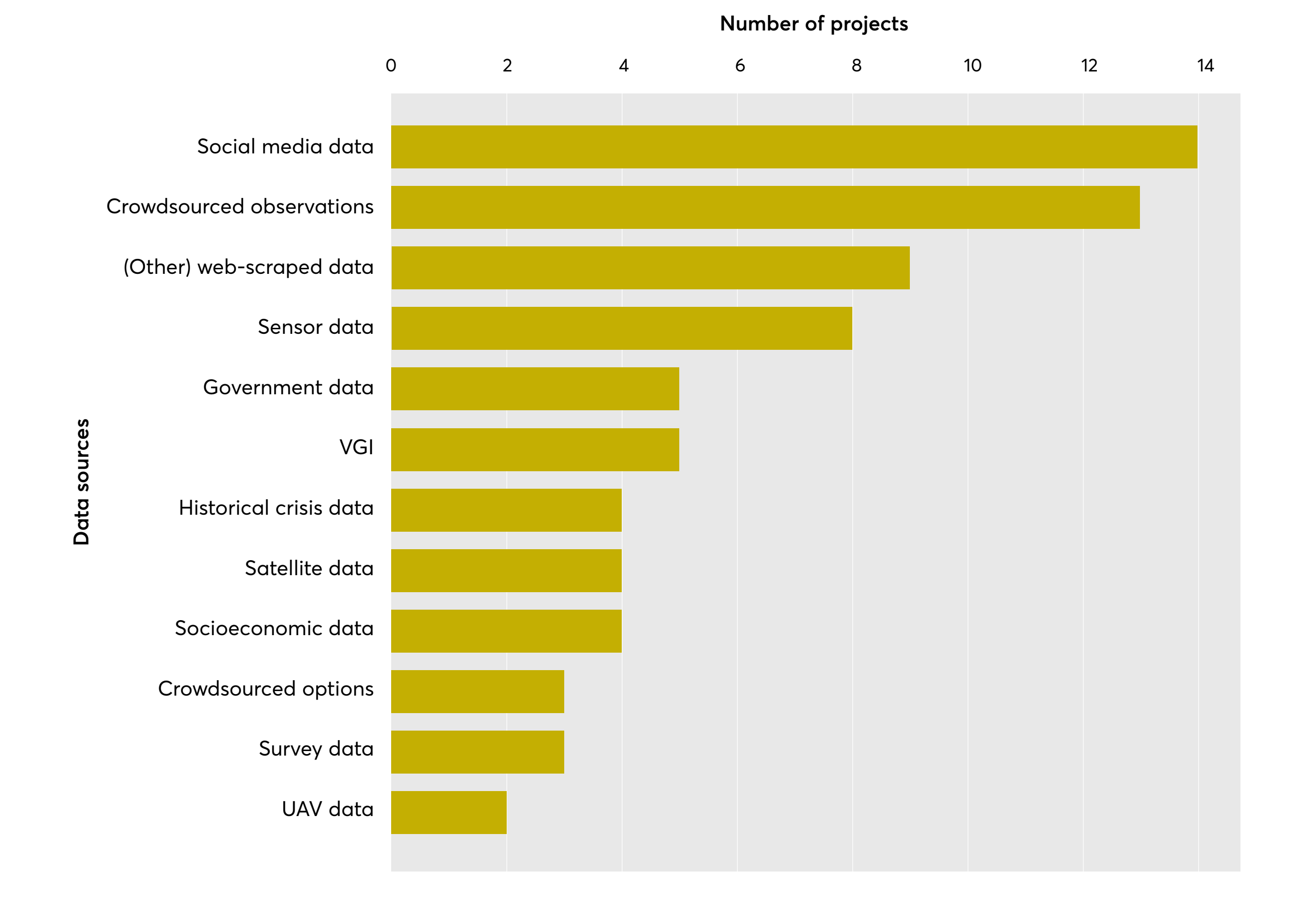
Open data is a key enabler of CCI solutions

Our analysis shows that CCI solutions draw on a combination of existing data sources, primarily official statistics, historical crisis data and geospatial data, as well as creating new citizen-generated data (see Figure 12) through collective intelligence methods such as crowdsourcing, web scraping and crowdmapping (see Figure 13 for the most commonly used CI methods).

A key input to many of the case studies is open data (64 per cent of cases, *n*18), most of which is unstructured. The term unstructured is used to describe data that do not follow a predefined consistent format, making them more difficult to store and analyse. Fifty per cent (*n*14) of case studies use either text or image based unstructured data. Common sources for this data include social media, news reports, on ground reports from volunteers, and satellite data from Google Earth Engine.

Half of the cases we reviewed used 'passively' generated data from locals gathered through social media platforms, primarily Twitter (data from Instagram and YouTube are used less frequently). Social media data was gathered using web scraping and open-APIs filtered for relevant content with computer vision or natural language processing algorithms, e.g. image or text data to assess damage caused by a disaster (see Section 1.4.1). The most commonly used sources of geospatial data among CCI solutions were sensors (*n*8), volunteered geographic information (VGI) (*n*5) and satellites (*n*4), but UAV data was relatively underused. Only two of the cases we found used private sector data, namely call detail records and market price data.

Figure 12: Data sources being used by CCI solutions



Most CCI solutions gather 'passively' generated local intelligence through social media and other web-scraped data. Crowdsourced observations were the most popular data type that required an active contribution.

Gathering citizen-generated data with crowdsourcing

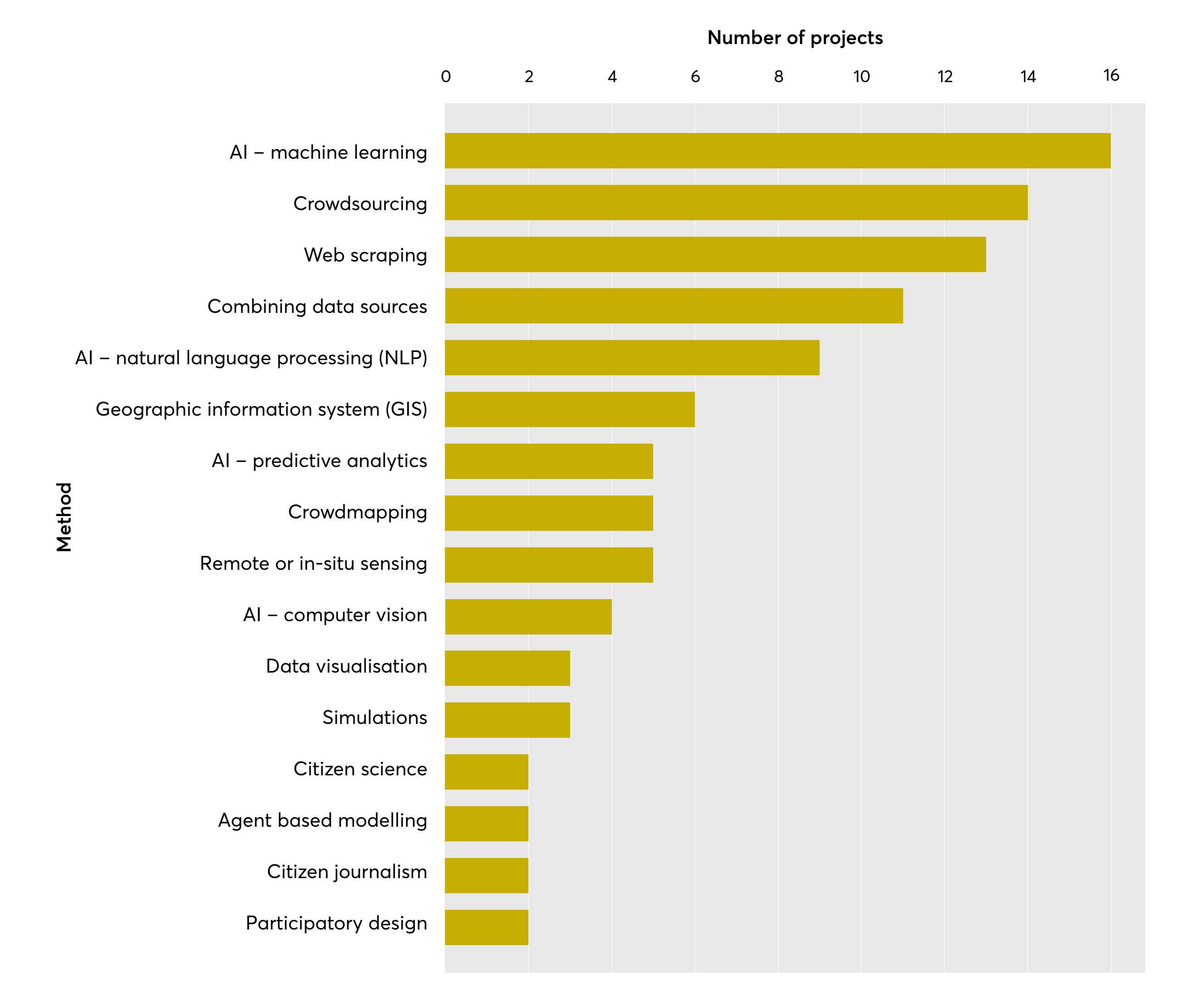
In CCI, collective intelligence methods are primarily used as a means for generating novel data about a crisis. Forty-six per cent (*n*13) case studies actively solicit real-time observations using crowdsourcing, either through pre-vetted volunteer networks or from any witnesses to a crisis. In the case of **Sentry Syria**, the team from Hala Systems collect on-the-ground reports of plane sightings from vetted volunteers, which when combined with remote sensing and open media data are used as inputs into an airstrike early warning system[21] (see Case study 9). Several cases used collective intelligence methods to generate georeferenced or spatial data to track the impact of the crisis on local infrastructure and localised environmental conditions, using either crowdmapping or remote sensing. The case studies in our sample that relied on active crowdsourcing of observations or citizen-generated reports typically gathered data in a structured way using dedicated mobile apps, SMS/messenger technology or web platforms.

Infrequently used CI methods

Very few cases in our sample include crowdsourcing of opinions and ideas (*n*3) or citizen science (*n*2).[22] One of these is the **Africa's Voices** project, which sends questions directly to migrant populations to collect their ideas and opinions on specific policy issues, using SMS and interactive radio programming (see Case study 3). During their most popular broadcasts, they have managed to generate up to 4000 responses from participants each week.

Current CCI solutions also typically rely on independent contributions from participants, which are then aggregated. Of the existing solutions, only the **Remesh** platform created opportunities for interaction between participants.[k] This online deliberation tool is being used by the UN during peacekeeping operations in regions experiencing or recovering from conflict. It uses AI to cluster contributions into themes and participants can vote on the statements they agree with. During field tests in Yemen and Libya, the tool has been used to engage a local population of up to 1,000 in discussions with politicians and organisations involved in peacebuilding.

Figure 13: The types of methods being used by CCI solutions



k. This case study is referred to as Inclusive Peacebuilding through Dialogue in the Appendix.

Photo: NASA at unsplash.com

Participant training and data validation help to ensure quality

Ensuring high quality data is a key design consideration for any collective intelligence or data-led initiative.[23] Several CCI projects helped to ensure data quality through optional or compulsory training of volunteers. The **Zika Premise** project in Cali, Colombia hosted training sessions for local participants before recruiting them for data gathering. The Premise platform also uses AI to check for duplicate entries or query contributions. This AI-enabled approach was also used by **eBayanihan/Agos**, a multi-platform application that sources citizen reports about the priorities and needs of affected populations in the immediate aftermath of a crisis. Other CCI projects rely on peer verification mechanisms to check the accuracy of information. For example, the HOT Tasking Manager platform has a community-led process for validating the mapping efforts of volunteers. Although edits are made by a combination of remote and local mappers, it is local OSM communities who are at the centre of the work. These local participants also often verify the contributions of beginners, alongside more experienced remote mappers.[24]

Other technology being used by CCI solutions

A number of core digital and mobile technologies underpin CCI solutions, in addition to the AI component. The most commonly used technologies were online data or visualisation platforms and open-APIs. Several case studies also deployed AI-enabled chatbots to interact with participants in order to solicit more relevant information. For example, the **WeFly Portal** platform (see Case study 8) uses an automated bot based on natural language processing to simplify the drone registration process for pilots responding to natural disasters while the **HERMES** tool (see Case study 11) uses chatbots to gather more detailed information in the immediate aftermath of a crisis by replying to social media entries posted by local witnesses.

1.4.2 PREDICTIVE ANALYTICS LANDSCAPE

Key findings

- Most solutions in our sample are framed as supervised learning problems (23 case studies). Further to this, many of the supervised learning problems analysed are also framed as classification problems (14/23).
- The prevalence of open text data sourced from on-the-ground accounts or social media has meant Natural Language Processing (NLP) techniques are used in eight case studies, with Convolutional Neural Network algorithms (CNNs) frequently used to gain insight from text and images.
- Deep learning algorithms were also applied in eight case studies (including four that also used NLP techniques such as CNNs). While these algorithms are helpful to form predictions from large volumes of unstructured data and are useful for modelling complexity, they can carry ethical challenges due to being less interpretable.
- CI can enrich findings from predictive analytics models, particularly in contributing greater local and social context to model input data. One example of this is CI to better capture ethnolinguistic characteristics.
- First principle mathematical models are rarely used to make predictions on humanitarian challenges, however they may model the complexity of crises better than applying existing machine learning algorithms. They also benefit from being more interpretable than deep neural networks.

To better understand current and potential future applications of predictive analytics for CCI we expanded our case study analysis to include a deep dive of 33 predictive analytics solutions, 16 of which also met our definition of a CCI solution (see Methodology section).[I] Expanding our case study analysis in this way enabled us to explore the differences between predictive-analytics-only and CCI solutions, and identify the unique value gained from combining collective intelligence and predictive analytics.

What are they predicting?

The case study sample covers a wide range of humanitarian challenges, with complex emergencies and natural disasters being the most common (30 per cent each, *n*10). Many case studies were also anticipatory AI solutions that make predictions over a broad range of timescales. Almost half of the case studies explored focus on informing anticipatory action for crisis mitigation and early warning, especially for solutions concerned with displacement. For example, **Project Jetson** predicts the movement of displaced people in Somalia one month in advance, while **Mixed Migration Foresight** predicts total forced migration in Myanmar and Afghanistan one to three years in advance. This kind of anticipatory insight enables humanitarian actors to act on the probability of a crisis rather than the certainty of one, which can in turn inform strategies to protect development gains and potentially reduce long run costs.[25]

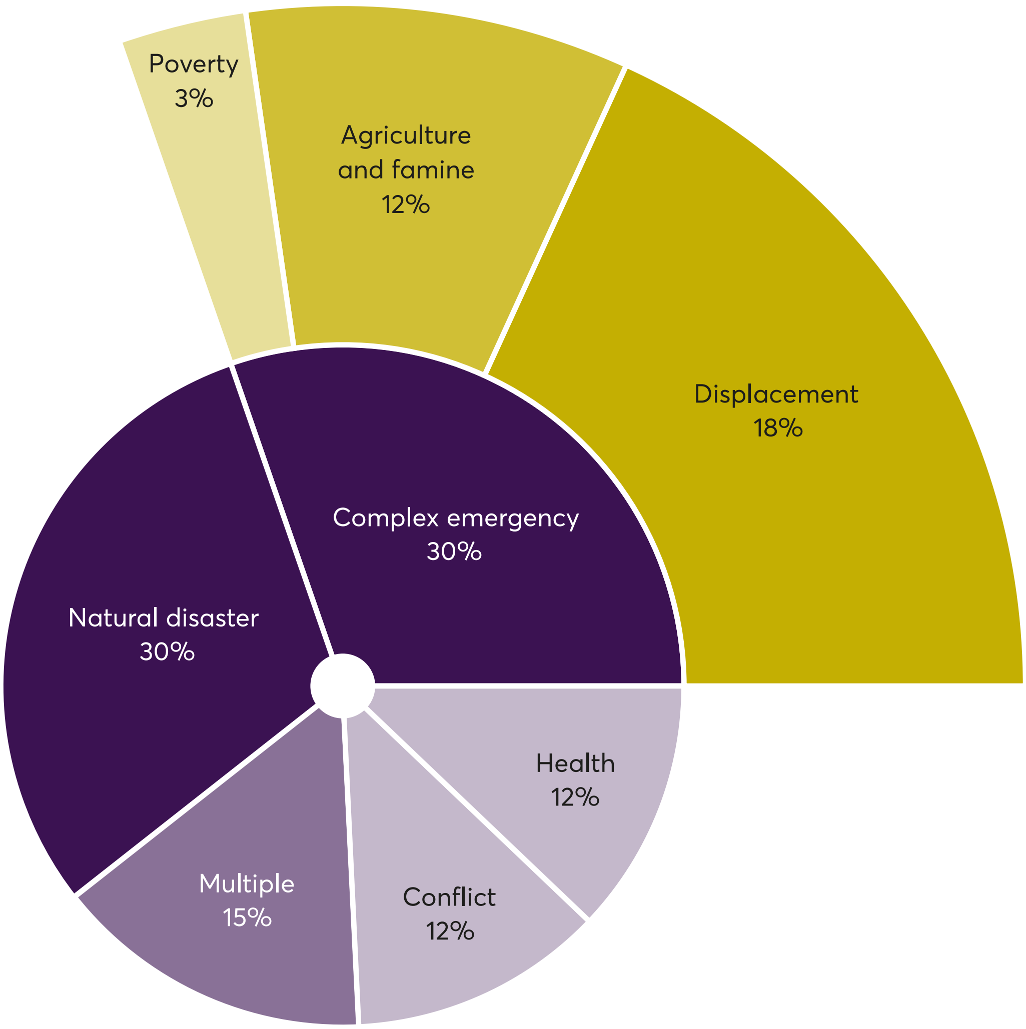
How do predictive-analytics-only solutions differ from CCI solutions?

In this analysis complex emergencies and natural disasters contribute to the largest share of case studies (30 per cent each), with displacement being the largest subgroup. This differs from the CCI case studies from Section 1.2, where complex emergencies are less

I. See Methodology for full description and Appendix for the full list of case studies as well as a Technical Glossary containing definitions for the terminology used in this section.

prevalent. Many of the complex emergencies examined here are predictive-analytics-only case studies that pertain to slower onset crises. As the crises are slower onset they allow for the generation and collection of large volumes of data, that are then used to form predictions. For example the **Identifying Children at High Risk of Defaulting From Immunisation** case study uses historical vaccine enrolment data and demographic data, such as gender, age, and language to predict immunisation default risk in Karachi and Muzaffargarh. Furthermore, many of the predictive-analytics-only slower onset crises rely on longitudinal humanitarian datasets such as World Bank development indicators, ACLED data and UN agency data rather than data from frontline communities. In our sample, challenges around displacement as a consequence of prolonged political instability, in particular, frequently use this type of data. For example, the **Kimetrica**, **Mixed Migration Foresight** and **Flee** case studies consider UNHCR refugee counts, population data and Word Bank development indicators when making predictions on displacement.

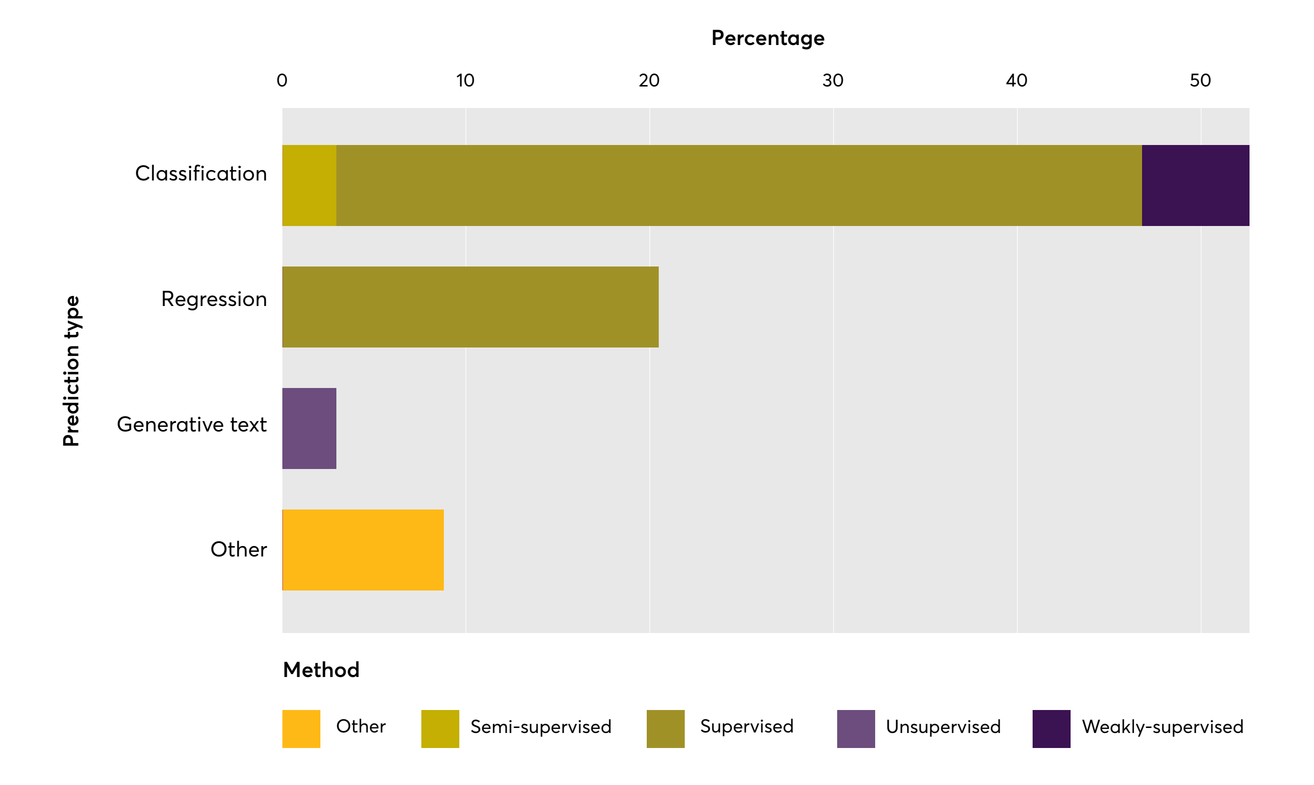
Figure 14: Summary of predictive analytics case studies by crisis type



Frequently used methods, techniques and algorithms

The majority of case studies examined (70 per cent, *n*23) are framed as supervised learning problems and most of these use predictive analytics for classification (61 per cent, 14/23) to assign data into categories. Supervised approaches rely on large volumes of labelled data as examples to train algorithms to form predictions. An example of a supervised classification solution is the **Violence Early-Warning System (ViEWS)**, which uses classification algorithms such as Logistic Regression and Random Forest to predict the probability of three types of political violence. The predictions are then presented as a probabilistic risk scoring.[26] The **HERMES** system also uses supervised learning for classification, in this case a crisis witness detection classifier is trained using features from the text and user metadata to identify key social media users to request more information from (see Case study 11).

Figure 15: The distribution of prediction type, split by method



Diving more deeply into the techniques applied in our case study sample, the prevalence of open text data through on-the-ground accounts or social media has meant Natural Language Processing (NLP) techniques are used in a significant number of cases (24 per cent, *n*8). An example of this is the **Internal Displacement Event Tagging Extraction and Clustering Tool (IDETECT)** which uses NLP to extract displacement information, including type of displacement, cause of displacement and location from news and UN and NGO reports. **Artificial Intelligence for Digital Response (AIDR)** also uses NLP, in this case it is used to classify tweets related to humanitarian crises, creating an open annotated data repository for humanitarian actors and researchers.

Common use of text and image data has also informed algorithm selection, with Convolutional Neural Network algorithms (CNNs), which are often applied to text or images, being the most commonly applied algorithms in our sample. The **Assessing Post-Disaster Damage from Satellite Imagery** case study uses a CNN to identify 'Damaged' and 'Undamaged' buildings from satellite images following the Santa Rosa wildfire, Haiti earthquake and conflict in Aleppo. The **Text Analytics for Extreme Events Reconnaissance** case study also uses a CNN, in this case the algorithm is used to classify news articles related to an earthquake event into four categories, 'building', 'infrastructure', 'resilience' and 'other', before summarising the article under those categories for a machine generated reconnaissance report. The common framing of problems as classification problems also means that algorithms such as Support Vector machines, XGBoost, Random Forest Classifiers, Logistic Regressions and general Deep Neural Networks were applied frequently in our sample (see Technical Glossary for definitions).

In the case studies explored, there is a dichotomy between the use of more interpretable statistical machine learning models and their application to structured data, and the use of less interpretable deep learning algorithms, such as CNNs, to derive insight from unstructured data. Due to the prevalence of unstructured open text and image data (e.g. from social media) deep learning algorithms were applied in 24 per cent (*n*8) of cases. The use of this approach in high stakes settings may pose ethical challenges as these models are known to be less interpretable than other algorithms (explored further in Section 3.2).

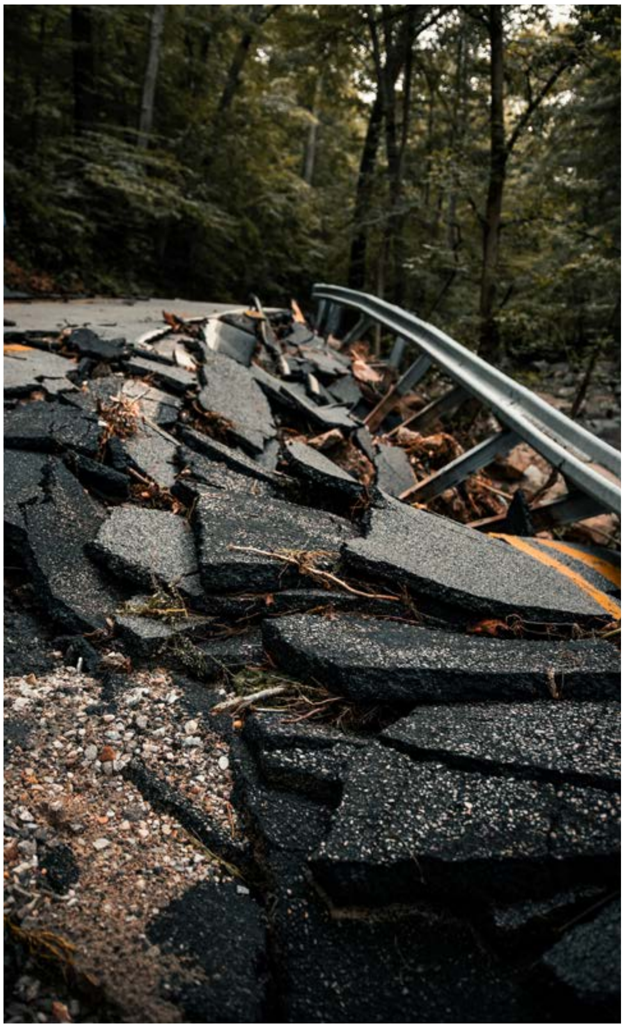
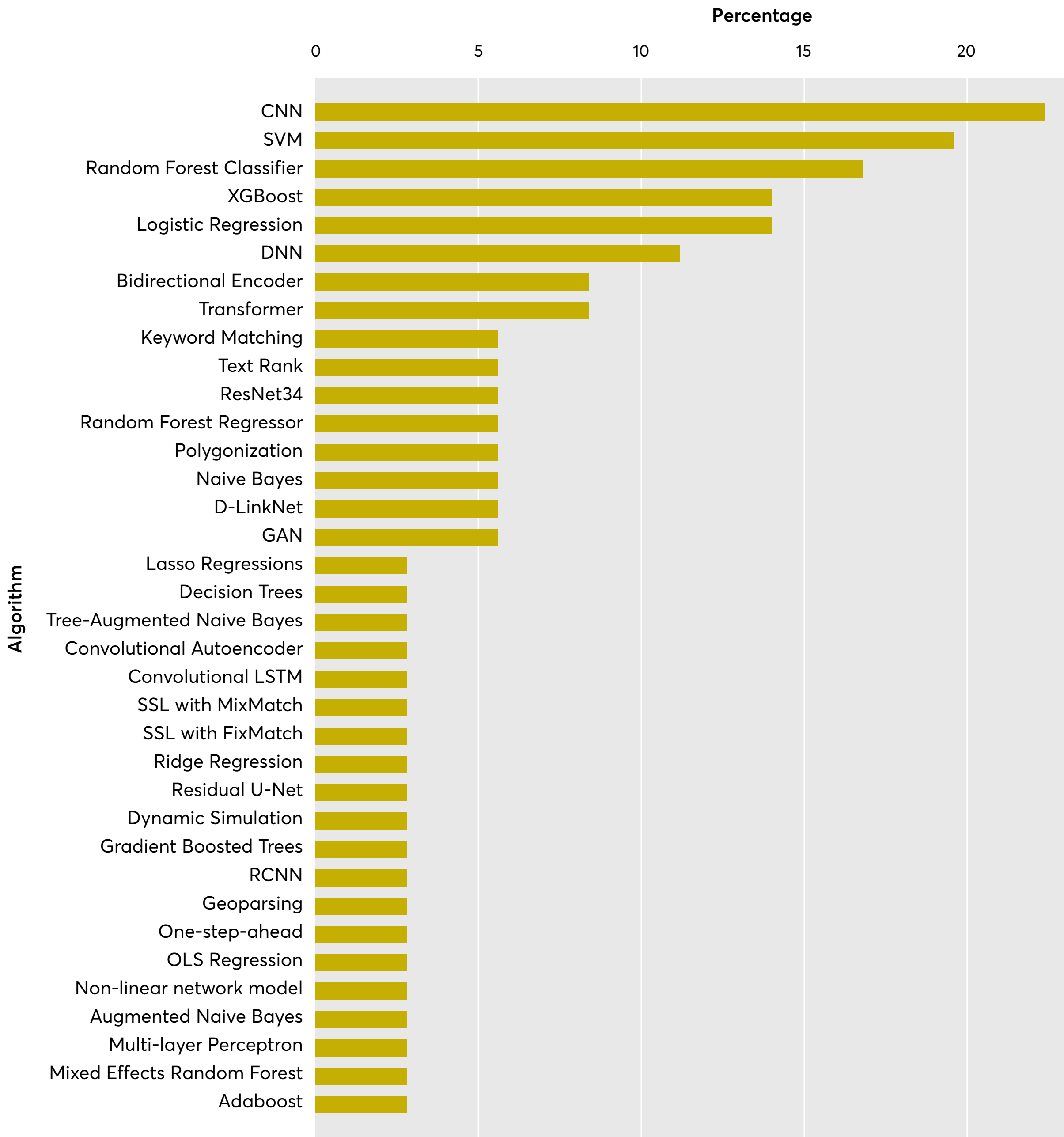


Photo: Colin Lloyd at unsplash.com

Figure 16: The distribution of algorithm type



Emerging use of satellite imagery

Growing availability of open satellite data, together with growth in open source deep learning frameworks, such as Tensorflow and Microsoft CNTK, has led to more frequent use of computer vision for satellite imagery to solve humanitarian challenges. Satellite constellations such as MODIS, Landsat and Sentinel offer free access to their datasets,[27] while open platforms such as Google Earth Engine provide a user friendly interface to analyse that data.[28] Case study examples that utilise computer vision for satellite imagery include, **RapiD** and **Mapping New Informal**

Settlements. **RapiD** uses deep learning to predict road locations, while Mapping New Informal Settlements predicts the location of informal settlements of Venezuelan refugees in Colombia. Each case study analyses satellite imagery in a different context and applies different techniques, demonstrating the diverse insight that can be gained. Satellite imagery will become increasingly valuable as the quality of these images continues to improve and computational costs reduce.

Infrequently used methods

As noted above, case studies from our sample were often framed as supervised classification problems. Alternative approaches, such as unsupervised, semi-supervised and weakly-supervised learning methods, and Agent Based Modelling (ABM) have been used relatively infrequently, with only 18 per cent (*n*6) of case studies applying these techniques. This may, in part, be due to the difficulty in evaluating the success of these approaches given the absence of labelled data. However, being able to make predictions without labelled data can also be beneficial, particularly in a humanitarian setting where many datasets at the onset of a crisis are unlabelled.

Similarly, we identified limited examples of predictive analytics or CCI case studies that apply first principles mathematical modelling. **Global Urban Analytics for Resilient Defence (GUARD)** is one of the few case studies explored that combines mathematical modelling, developed using logic and established domain knowledge, and AI to make predictions on conflict and peace. Guo[29] highlights that traditional machine learning approaches are often linear in nature, making them less appropriate for modelling the complexity often found in humanitarian challenges, and while neural networks may be better suited to this, they are less interpretable. Building models from the ground up using mathematical first principles could enable more interpretable outputs that better reflect societal interconnectedness. This approach is further explored in Section 2.3.

The approach taken by **GUARD** overlaps with aspects of Cliodynamics, a relatively new discipline that uses first principles mathematical modelling and data to translate historical theories from economics, socio-economics and sociology into empirical models that make predictions. Despite being applicable to many societal and political humanitarian challenges, we have seen little use of Cliodynamics[30] in the sector and even less so outside of a research setting.

The value add of CI to predictive analytics

Collective intelligence methods help to build rich local and social data which can then be used as inputs into predictive analytics models. The case studies that relied on predictive analytics without the input of collective intelligence were often missing this dimension, and instead predictions relied on numerical measures of economic, socioeconomic and climate performance at country and regional levels. For example, **Hunger Map Live**, the World Food Programme's global hunger monitoring system, combines data on food security, weather, population size, and macro-economic data to predict hunger risk. Another predictive-analytics-only case study, **ViEWS: Violence Early-Warning System**, uses GDP data, population sizes and other demographic measures to forecast political violence. While these data sources, which are often made available through established humanitarian agents such as the World Bank, UNHCR and WFP, are hugely valuable for analytics, (particularly due to their longitudinal history which is essential for training machine learning models), local context and social sentiment is sometimes missing. Several CCI case studies on the other hand capture this through social media data (e.g. **Dataminr** and **HERMES**) and on-the-ground reports (e.g. **eBayanihan** and **Sentry Syria**). Collective intelligence can therefore be used to enrich predictive analytics models with greater local and social context.

Social sentiment in crisis response and management can also be informed by ethnolinguistic analysis, however many lowerand middle-income countries have high degrees of ethnolinguistic diversity making predictive analytics in this space challenging. This is particularly true in the case of under-resourced languages where data and NLP dictionaries are limited. In these cases, the analytics gap can again be filled with collective intelligence through crowdsourcing methods or establishing communities of practice such as the Masakhane network that is creating libraries and datasets for under-resourced African languages.[31] Guo et al. (2019)[32] discuss how crowdsourced sentiment analysis can be used to label situational or environmental sentiment for under-resourced languages to identify early signs of conflict. Crowdsourcing for under-resourced languages can, in some cases, more accurately capture sentiment than translations from English defined NLP resources such as lexicon dictionaries. In our interview with Africa's Voices on the **Common Social Accountability Platform**, the team highlights the importance of being able to analyse responses from different regional languages for the Somali community and communicate back to participants in those languages.

While non-CI datasets are hugely valuable, often readily available, and can contain the significant history necessary for machine learning, there are gaps that can be filled through new collective intelligence datasets. Exactly how collective intelligence can be used to further the value from predictive analytics will however depend on individual use cases. In our case study analysis in Section 1.4, we highlight the CI methods used and the additional data collected through these methods.

In addition, the ethics of AI and predictive analytics has been widely documented and increasingly scrutinised due to concerns around privacy, exploitation, a growing digital divide, and the potential harm of societal biases becoming hardwired into AI systems (see Section 3.2). Collective intelligence and related participatory approaches offer the potential to mitigate some of the risks of AI and predictive analytics through co-design and creating new, more diverse datasets that are relevant to the local context.

Photo: Barbara Zandoval at unsplash.com

1.5 Maturity of CCI approaches

1.5.1 SOLUTION READINESS OF EXISTING CCI AND PREDICTIVE ANALYTICS SOLUTIONS

Key findings

- In general, there is a U-shaped distribution for CCI and predictive analytics solution readiness, with most solutions either in proof of concept or scaling phases, and few in 'middle' phases of prototype, pilot or operational in one market.
- Predictive-analytics-only and CCI case studies have a similar distribution for solution maturity as they face many of the same barriers to adoption and scaling.
- Many early stage solutions use more novel techniques and methods such as semi-supervised learning and Agent Based Modelling.

CCI and predictive analytics have been applied to a range of humanitarian challenges, however the maturity of solutions varies widely. In general, there is a U-shaped distribution for solution readiness, with 15 and three case studies, respectively, either in proof of concept or scaling phases (see Figure 18). To assess solution readiness we used the Solution Readiness Framework from Nesta's Collective Intelligence Design Playbook, which is adapted from NASA's technology readiness levels.[33] The framework includes nine degrees of solution maturity, which were simplified into five categories for our analysis. The categories are: Concept/Idea (SRL 3 and 4), Prototype (SRL 5 and 6), Pilot (SRL 7), Operational in one market (SRL 9), Scaling to other markets (SRL 9). Bridging the gap between a concept/idea and operational products depends on a range of factors including feasibility, replicability of required inputs and having a viable resourcing model; which will determine whether a solution reaches SRL 9.

Despite expanding our analysis to include predictive-analytics-only case studies, we did not identify a significant difference in deployment likelihood compared to the CCI case studies. The scaling requirements for predictive analytics and CCI solutions overlap, which likely explains why they have a similar solution readiness distribution. Scaling requirements are explored in more detail in Section 3.1.

Figure 17: Solution Readiness definition from Nesta CI Playbook

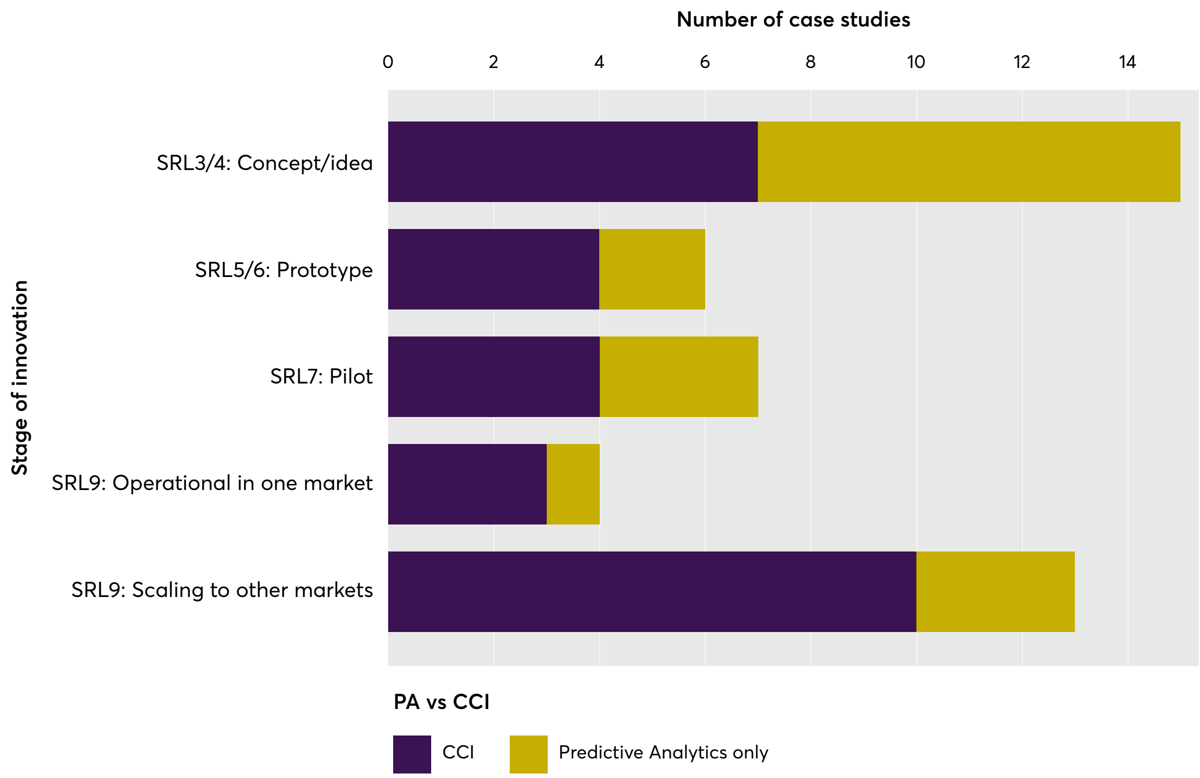
The left-most rotated text reads 'SRL1 – Research of basic principles for a solution'. The right-most rotated text reads 'SRL9 – Proven implementation of product, service or process at scale'.

Examples of more mature solutions from our case study review include **Sentry Syria** and the **Early Warning Project**.[34] **Sentry Syria** has been deployed in Idlib Governorate and Rif Damascus in Syria, where air raid sirens and social media alerts are sent to residents to provide an early warning of an air strike. Meanwhile, the Early Warning Project (EWP) utilises a deployed Logistic Regression model to provide genocide risk scoring for all countries with populations greater than 500,000. The risk assessment for EWP is then published annually.

Case study examples of early stage solutions include **Assessing Post-Disaster Damage**[35] and **Modelling Humanitarian Relief in Haiti**[36] (see Case study 10). Assessing Post-Disaster Damage uses novel machine learning techniques to assess damage caused by the Santa Rosa wildfire, the Haiti earthquake, and violence in Aleppo. **Modelling Humanitarian Relief in Haiti** also applies novel techniques, using Spatial Agent Based Modelling to understand how agents respond to aid distribution following an earthquake event.

A common thread through many early stage solutions is the use of novel machine learning techniques and data sources. For example, **Assessing Post-Disaster Damage** applies computer vision to satellite imagery and uses semi-supervised learning. In this case, the high resource cost of computer vision together with the cost of high resolution imagery can be prohibitive to deployment,[37] particularly in low-resource settings. Nonetheless, these more nascent techniques offer a means to extract new and valuable insights and should continue to be explored for new CCI solutions.

Figure 18: Solution Readiness distribution for CCI and predictive analytics solutions



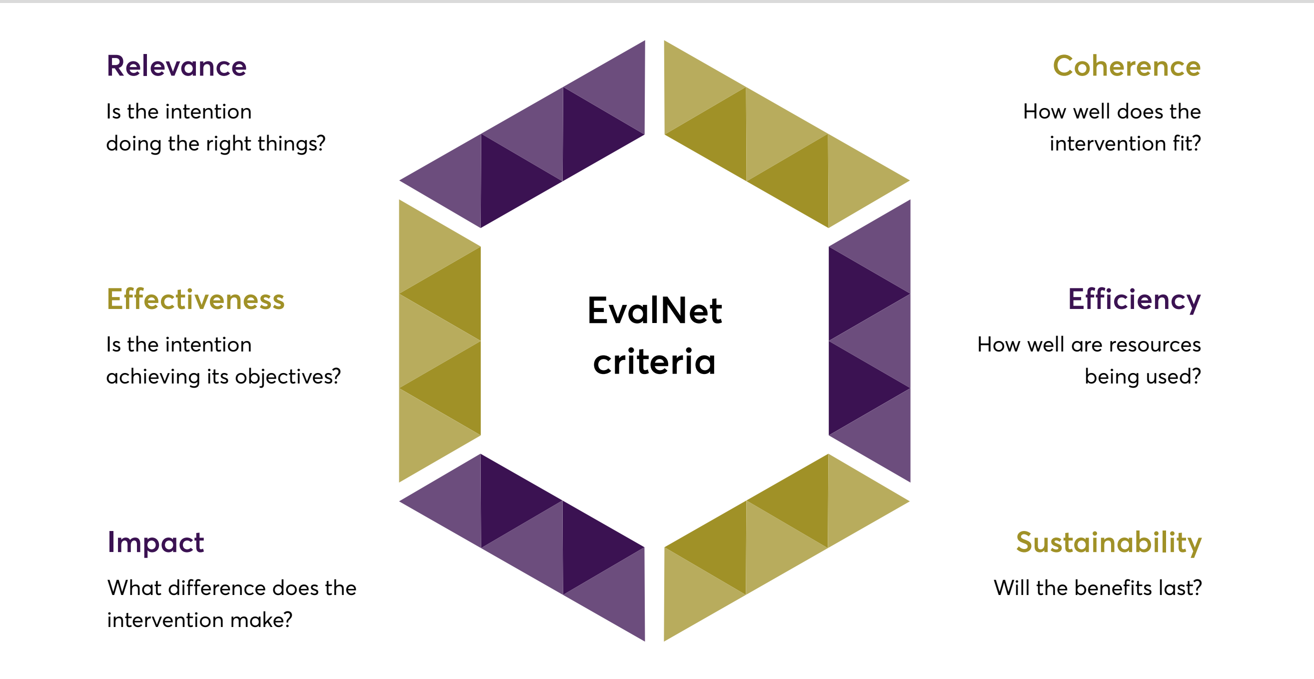
1.5.2 ASSESSING THE IMPACT OF CCI SOLUTIONS

Key findings

- Scope to conduct a rigorous impact evaluation of CCI solutions is very limited. None of the CCI solutions included in this research are currently evaluating their own performance in line with the criteria set out by the OECD DAC Network on Development Evaluation (EvalNet), and there is a paucity of data or information to support attempts to evaluate performance.
- We focused on the three aspects of the EvalNet evaluation criteria – (wider) impact of the solution, the effectiveness of the solution (i.e. achieving positive closely attributable results) and solution coherence (coordination of the solution with other solutions and/or actors).
- Solutions where information/data was available related to their wider impact (43 per cent, *n*12) or the accuracy/effectiveness of the solution (25 per cent, *n*7) demonstrated promising results.
- Solution coherence appears to be limited. The early stage of many CCI and predictive analytics case studies means few have been integrated into humanitarian workflows or systems. This finding was supported by the survey where very few respondents reported using any predictive analytics, artificial intelligence and/or techniques that use algorithms in their work.

We explored the extent to which CCI solutions have been evaluated according to the EvalNet criteria outlined by the OECD to understand their alignment to broader development objectives.

Figure 19: OECD DAC Network on Development Evaluation – Evaluation Criteria



Scope to comprehensively evaluate CCI solutions is currently very limited due to the absence of information and data on solution performance, and the availability of independently produced results. For 32 per cent (*n*9) of the CCI solutions analysed as part of this research, there was no available data or information to support attempts to evaluate performance. In addition, many of the CCI solutions analysed are at an early stage of development (seven cases in concept/ idea; four cases in prototype). This means that opportunities to analyse solutions according to certain elements of the criteria are restricted (i.e. efficiency and sustainability). Finally, none of the CCI solutions analysed as part of the research are currently evaluating their own performance in line with the criteria set out. We only identified one example of peer-reviewed evaluation among our case studies.[38] This raises questions around how best to evaluate innovative, emerging and novel solutions in the sector, and integrate this into solution development. Developing a recognised evaluation process could contribute to the body of evidence on the benefits of localisation (and localised solutions) for the quality and impact of humanitarian responses, which is currently known to be lacking.[39]

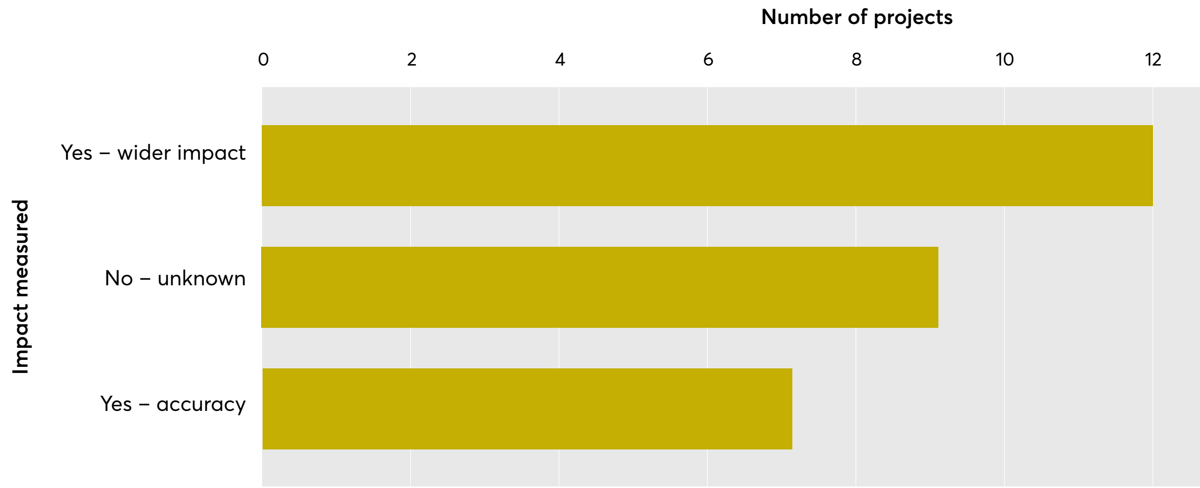
We have focused on three aspects of the EvalNet criteria – impact, effectiveness and coherence – that were possible to assess based on publicly available information and a small number of interviews with solutions developers. Due to the early stage of many of the CCI solutions analysed, efficiency, sustainability and relevance are particularly hard to assess. Evaluating efficiency and sustainability require further information around cost-savings and the longer-term impact of solutions. In addition, to critically appraise how sustainable solutions are, more up-to-date information is needed to understand whether the net benefits of the intervention have continued. Evaluating relevance requires analysing how solutions respond to contextual changes to assess the extent to which they can (or have been) adapted to remain relevant. Some of the CCI solutions analysed have not yet been deployed or have not been implemented over a sufficient time frame to allow for contextual changes that would support an evaluation of this element.

The following section is not intended as a comprehensive evaluation of existing CCI solutions but outlines some of the existing relevant trends among the projects we analysed.

Impact

Impact refers to the extent to which the intervention achieves significant ‘higher-level’ effects (i.e. meaningful or important changes). In contrast, effectiveness is concerned with more closely attributable results. For the purpose of this evaluative exercise, we are using impact and effectiveness to differentiate between the real-world impact of a CCI solution and the effectiveness of a CCI solution at achieving accurate results (i.e. results not achieved through application in real-world scenarios). The chart below indicates the number of CCI solutions that had been evaluated in terms of their wider impact (43 per cent, *n*12) or in terms of the solution accuracy/ effectiveness (25 per cent, *n*7).

Figure 20: Impact and accuracy/effectiveness of CCI solutions



Solutions where the wider impact was evaluated demonstrated promising results. These solutions tended to be at a later stage in development, including operating in one market or scaling to other markets. Available information on the impact of these solutions looked at a range of measures including levels of community engagement, feedback from users, number of partnerships with government agencies, as well as estimates of casualty reduction. A number of the solutions achieved widespread community engagement, for example **Africa's Voices** has engaged more than 18,000 displaced people in Somalia since 2018. Feedback from those who have engaged with these solutions is positive; 78 per cent of participants in Africa's Voices stated that the process made them feel involved in decision making (see Case study 3). Where relevant, estimates of casualty reduction also offer encouraging results about the potential for CCI solutions to save lives. **Sentry Syria** by Hala Systems disseminated over 680,000 warnings to civilians over seven distinct channels during airstrikes in 2018 leading to an estimated 20-30 per cent reduction in casualty rates in several areas under heavy bombardment (see Case study 9).

It is important to note that evaluating the wider impact of CCI solutions depends on the country context in which the solution is applied. For example, the wider impact of **Dataminr's First Alert** system has predominantly been assessed in a US context, and not in other countries (see Case study 5). As noted in Section 3.1, predictive models tend not to generalise well between different settings or crises, highlighting the importance of country or crisis-specific evaluations to assess wider impact.

Effectiveness

CCI solutions in the concept or prototype phases of development have tended to focus on model accuracy/effectiveness (i.e. achieving positive closely attributable results), due to the absence of application in real-world scenarios. For example, predictive algorithms were evaluated on their ability to anticipate past crises using historical data. Where solution accuracy was tested, the findings also indicate promising results. **Artificial Intelligence for Digital Response (AIDR)** collects crisis-related messages from Twitter, asks a crowd to label a subset of those messages, and trains an automatic classifier based on the labels. The accuracy of the tool has been successfully tested to classify informative vs. non-informative tweets posted during the 2013 Pakistan Earthquake which achieved a classification quality of 80 per cent.[m] However, the tool has not been deployed in large scale emergencies hindering the ability to evaluate the tool's wider impact. It should also be noted that robust evaluation of emerging approaches such as semi-, weakly- and un-supervised machine learning models may be difficult due to the lack of labelled data, which will challenge their wider uptake.

Coherence

Coherence refers to the compatibility of the intervention with other interventions in a country, sector or institution, and seeks to capture the complementarity, harmonisation and coordination of the solution with other solutions and/or actors. Due to the early stage of development of many of the CCI solutions analysed (39 per cent, *n*11, are in the proof-of-concept or prototype stages), there is limited evidence of integration or 'coherence' with other aspects of humanitarian crisis management and response.

We have also assessed coherence through the integration of CCI solutions into existing humanitarian workflows. We take a broad definition of humanitarian workflows and systems, including decentralised information that goes directly to communities, as well as institutional channels through humanitarian organisations. Based on our sample, there was mixed integration of solutions into humanitarian workflows and systems. Fifty per cent (*n*14) of solutions have not been integrated at all, 32 per cent (*n*9) have been used directly in humanitarian workflows or systems, and 18 per cent (*n*5) have been partially integrated. The degree to which solutions have been integrated into workflows is also strongly correlated with solution maturity. Unsurprisingly, we found that deployed solutions that had been validated outside of a test environment were more likely to be adopted than research or proofs of concept.

Defining coherence

Humanitarian workflows and systems are defined here as processes or systems that lead to a humanitarian response. This can be at various levels of centralisation:

- At an institutional level, e.g. through international or humanitarian organisations, or through policymakers
- At the volunteer level, with volunteers independently delivering the humanitarian response
- At the community level, with humanitarian interventions delivered directly to the community

In the context of the above definition, the extent to which our case studies have been integrated into humanitarian workflows and systems is then measured on a **1 – 3 scale** (see Figure 27 in the Appendix)

1. Not at all integrated
2. Used indirectly in humanitarian workflows and systems (e.g. through reporting to humanitarian organisations)
3. Used directly in humanitarian workflows or systems

m. Accuracy was evaluated using the Area Under Curve method.

Examples of solutions that have been integrated include **Haze Gazer** (directly) and **Sentry Syria** (indirectly). **Haze Gazer**, an analysis and visualisation tool for forest fires in Indonesia, is a rare example of a CCI solution that has been directly integrated into official workflows. Originally developed by Pulse Lab Jakarta, the tool has now been fully subsumed into a larger Early Warning System (EWS) housed in the President's situation room.[40] The EWS enables the Government of Indonesia to predict and monitor fires as they unfold and to evaluate how effectively the government responds.[41]

"The first time I saw Haze Gazer, I said we should use it. We now use it in the President's situation room, so that we can have more accurate predictions. It helps us to use our limited budget to prevent forest fires."

Representative from Executive Office of the President of the Republic of Indonesia

"These platforms are instruments to be used for government business processes. We have tweaked the functions and use these for political means – as evidence to engage with different line ministries. Our Early Warning System is confirming the beginning of a hypothesis on funds being poorly allocated, less than optimal coordination, etc."

Representative from Executive Office of the President of the Republic of Indonesia[42]

Sentry Syria is a decentralised solution that provides early warnings of airstrikes directly to the affected communities using social media bots, local sirens, TV and radio, as well as to hospitals and schools. Warnings, as well as insight and trend reports on war crimes, aircraft activity and ceasefire violations are also shared with global stakeholders, including governments, NGOs, and the United Nations.[43]

Our survey of IFRC staff and volunteers confirmed the lack of solution integration with broader humanitarian workflows. Very few respondents reported using any predictive analytics, artificial intelligence and/or techniques that use algorithms in their work. Those who were using AI techniques only did so occasionally, despite being optimistic about wider integration and application in the future.

"We rarely use it [predictive analytics, AI, techniques that use algorithms], but wish/intend to use it more in several research programmes and through our 510 Global team."

Netherlands Red Cross

"There is a lot of potential, but we need to improve the breadth and depth of data sets that we currently have."

IFRC Secretariat (Switzerland)

02

Gaps and opportunities for CCI in humanitarian response

Photo: Yosh Ginsu unsplash.com

2.1 Trends and tasks facing the sector

Key findings

- The increasing complexity of crises and worsening societal conditions that compound the impact of crises point to an urgent need for new solutions to support better crisis management and response.
- In particular, trends around decentralisation, localisation and the mobilisation of non-traditional actors demonstrate the appetite for and necessity of involving local communities and affected populations more in crisis response and management.
- The growing prominence of the private sector (both as a source of funding and provider of technological solutions), and broader technological transformation shaping the sector, create new risks around responsible data use, fetishisation of technology, and highlight the need for monitoring and evaluation.
- Community engagement and participatory design or evaluation of interventions could help to mitigate some of the concerns about technology use in the sector.

The following section provides a summary of prominent trends shaping the humanitarian sector and how the nature of humanitarian work, tasks and workflows performed by those involved in crisis management are changing in response.

Increasing complexity of crises and weakening societal foundations

Trends related to the changing nature of crises are well documented, and tend to highlight an increased focus on protracted conflicts, mass displacement, climate change and health crises. Although there are fewer large-scale interstate conflicts, conflicts are becoming more protracted and destructive; the average length of conflicts increased from four to seven years between 2005 and 2017.[44, 45] Climate change and related weather events are increasing in frequency, reach and impact, leading to direct casualties and indirect deaths mediated through the environment, such as water-borne diseases following a flood. Global health crises are also increasing in likelihood due to globalisation and increased levels of trade and travel leading to rapid disease transmission, as observed with COVID-19. This effect is being felt by humanitarian staff who reported in our survey that both climate and health crises were becoming more important in their work, and that they are increasingly responding to multiple types of crises (rather than single issues).[46] In addition, mass migration and forced displacement have become a by-product of the evolving nature of crises, posing new challenges for crisis management and response. Displacement from conflict reached a record 68.5 million people in 2017.[47]

In addition to shifts in the types of crises that occur, crisis response and management are also being made more complex due to weakening societal foundations and the rise of new 'online' threats that undermine stability. Rising inequality, stagnating economic growth in developing countries, and extreme poverty increasing in developed countries compound the challenges posed by crises. Worsening health and wellbeing (i.e. the rise of mental health conditions and non-communicable diseases) as well as new threats to social cohesion (i.e. the rise of xenophobia) are creating adverse conditions for establishing an equitable and therefore resilient society.[48] Worsening societal conditions are also affecting donor countries, threatening international solidarity due to an increased focus on domestic issues, and compromising access to sufficient, long-term funding for the sector.

Social cohesion and stability are being further undermined by the rise of mis- and dis-information, which surfaced as notable challenges in our research with frontline staff and experts working in the sector. Social media is an essential communication tool for affected populations during a crisis by facilitating the circulation of a large amount of information in a short period of time, often faster than official sources.[49] However, resultant mis-information harms communities, while information overload also increases the likelihood of fake news spreading.

Implications for tasks and workflows

With these trends set to continue, there has been much emphasis put on the concept of the humanitarian-development-peace nexus. The UN and World Bank have set out a New Ways of Working which aims to deliver closer cooperation and collaboration between humanitarian, security and development actors to decrease vulnerability in the long term.[50] The shift to anticipatory action and much closer working with grassroot organisations on-the-ground as well as affected communities is also a response to these two 'mega trends'.

Rise of early and anticipatory action

In response to the increasing frequency, length, impact, and cost of crises, and the threat of climate crises in particular, there is a growing focus on anticipatory action.[51] At the UN Secretary General's Climate Action Summit in 2019, the Risk-informed Early Action Partnership (REAP) was formed and set a target to cover one billion more people through financing and delivery mechanisms connected to effective early action plans by 2025.[52] However, the sector's emphasis on anticipatory action introduces new risks as efforts may be focused on the low-hanging fruit (i.e. crises that can be more easily predicted, such as slow-onset crises) and neglect less predictable crises.[53] The IFRC is already innovating in the area of anticipatory action, including in relation to harder to predict crises. For example The Philippine Red Cross team used impact-based forecasting models and automated maps to understand the impact of Typhoon Kammuri/Tisoy before landfall, enabling aid workers on-the-ground to act and warn potentially affected districts.[54]

Implications for tasks and workflows

Accelerating anticipatory action requires increased forecasting capacity, drawing on input from different actors in the sector. This will require gaps in data management to be addressed, including improved data collection as well as better integration of available data.[55]

To support the application of anticipatory action for harder to predict crises, increased data gathering involving collaboration with communities will be necessary for capturing weak and early signals across a range of contextual, social, and environmental variables.

Decentralisation and localisation

Over the last decade, many humanitarian organisations have focused on decentralisation and localisation as a way to enable bottom-up resilience and to empower the communities they support. This has been driven by a push for anti-racism and decolonisation of the sector and increasing scrutiny of the legitimacy gap of INGOs, as well as strong arguments based around effectiveness, efficiency, and sustainability.[56] In addition, the deteriorating security situation for international organisations operating in politically challenging crisis contexts has necessitated increasing reliance on local organisations; COVID-19 has accelerated this trend by inhibiting travel. In response, efforts have been focused on boosting the role of locally based organisations in crisis response.

Country Based Pooled Funds (CBPFs) have been a key mechanism for facilitating decentralisation. Although international donations to CBPFs rose by 17 per cent in 2017, contributions are lagging behind targets.[57] This slow progress is underpinned by the sector's risk aversion and lack of trust in smaller, local organisations, who may not be able to meet strict due diligence criteria. International funding administrators pose additional challenges for decentralisation and localisation by dictating how funds should be allocated, which may not be in line with the needs of a community.

> *"Risk tolerance for community-led innovation is low – funders don't like to give money directly to the communities that don't have a legal relationship with them or policies and can pass due diligence."*
>
> **Humanitarian expert**

> *"When we secure funding, some donors can be flexible, they choose a methodology and let us decide how to run it, but some donors are more prescriptive and there is an allocated amount of funding for data collection and analysis – so this could mean the amount of resource allocated to it is limited."*
>
> **Red Cross frontline responder**

Implications for tasks and workflows

The sector is at a crossroads, trying to reimagine its role within communities. As affected populations often have limited voice in the direction, timing, or application of funding, participatory processes that engage communities will be central to this. This may also involve frontline workers sharing resources and training local, affected communities, in turn enabling them to lead crisis response. This emerged in the Gaps and Opportunities workshop with IFRC representatives based in Nepal who highlighted the importance of having strong local hubs to manage COVID-19 response in the context of travel restrictions inhibiting other humanitarian actors from being rapidly deployed in a region. CCI solutions offer a potential pathway to a new form of aid that takes community empowerment as its starting point by foregrounding the principles of collective intelligence design.[58]

Photo: Aladdin Hammami at unsplash.com

Mobilisation of non-traditional actors

Despite the challenges noted around decentralisation and localisation, the active role played by citizens and communities in leading social movements is increasingly recognised as essential to managing and responding to the crises they are facing. The mobilisation of non-traditional actors in humanitarian crises *"demonstrate[s] a shift in power and decision making"* across the sector, whereby crisis-affected communities and global volunteer networks are challenging how large, formal institutions have traditionally functioned.[59] Technology has been key to the establishment of citizen and community-led networks in crisis response. However, non-traditional actors have not yet been fully integrated into traditional crisis management and response. For example, emergent volunteer networks are often absent from emergency plans due to the top down approach of official actors.[60, 61]

> *"Historically the government is responsible for emergency response, but with Hurricane Dorian we saw how the community got involved. People were sporadically coming to assist. But that grassroots aid response wasn't coordinated."*
>
> **Red Cross frontline responder**

Implications for tasks and workflows

Future crisis management and response should seek to better leverage the growing regional, national and international networks of highly engaged local actors, communities and volunteers. In particular, localised crisis response requires better planning around how traditional and non-traditional actors can function most effectively together.[62]

Funding gaps, and the growing role of the private sector

The architecture of humanitarian systems is shifting and diversifying, involving the integration of non-traditional actors and local communities, as well as the private sector. The private sector is now being looked at to play a critical role in filling the sector's funding gap, especially as the international community is stepping away from its traditional donor role, mostly due to domestic pressures.[63] The growing needs of affected communities and dwindling support from traditional donor countries has resulted in a funding gap of $11 billion in 2019.[64] Private organisations are now facilitators of new funding models (e.g. new insurance-based models), and providers of tools and mechanisms for distributing funds (e.g. mobile money).[65]

Private sector organisations, including entrepreneurs, start-ups as well as multinationals, are also providers of technological solutions and innovation within the sector. However, humanitarian organisations are still behind in terms of working with private sector digital and data partners, with technological change often happening 'to them' rather than 'with them'. Improving humanitarian-private partnerships has been identified as central to driving digital transformation in the sector in the IFRC's Digital Transformation Strategy.[66] However increased collaboration also requires greater scrutiny and monitoring, with particular attention paid to the risks this may pose for affected and vulnerable populations (i.e. in relation to data ownership and responsible data use).[67]

"There is scepticism of the private sector, but there are connections to be made. We need to be better consumers of private sector services. However, there are obviously the dangers of big tech – particularly in countries with less regulation. There's a risk they could use crises as test beds for new projects."

Humanitarian expert

Implications for tasks and workflows

Increased collaboration with the private sector will require new skills and approaches, including brokering and regulating new public-private partnerships. Attention will need to be paid to ensure the private sector maintains responsible data use and to scrutinising (and mitigating) the risk of new concentrations of power underpinned by geographical ownership of AI technology, particularly if AI solutions in humanitarian contexts are predominantly developed by US companies.

Technological transformation

As demonstrated by our review of CCI solutions, technological transformation across the sector is changing how humanitarian organisations take action, from driving the cost-effectiveness of response to predicting and preventing crises. The adoption of new technologies has been accompanied by the increased use of data in the humanitarian sector, to aid monitoring, decision making and evaluation. As a result, traditional business 'functions' are growing within humanitarian organisations to provide the necessary infrastructure to support technological operations and data management needs.

Despite the tech-solutionism in the sector, there is a strong sense among experts that technologies have not scaled in practice. This broadly aligns with our finding that the integration of CCI solutions into humanitarian workflows has been limited. There is a growing appetite for further technological transformation accompanied by responsible and appropriate scaling of solutions. This, alongside the emerging availability of novel data in the field is a positive sign for CCI, but it needs to be accompanied by investment in capacity building to mitigate the growing data and digital skills gap within the sector, particularly for volunteers who are on the frontline of data collection (see Section 3).[68]

There are also concerns that digital transformation is not doing enough to be 'intentionally inclusive', to avoid excluding groups who may already be left out and overcome in-built biases and power imbalances, while also managing risks around forced inclusion. This attention to the digital divide has primarily focused on issues of data access and equality, which has exacerbated divisions along key demographics (e.g. gender, geographical, economic, age) while disproportionately impacting the most vulnerable. Affected communities are rarely involved in owning and managing their own personal data, and despite assurances around protection and intentional sharing, security may be low and result in data breaches.[69]

> *"There is a lot of hype around technologies where they're untested…and there's a risk of fetishising technology – Who doesn't have a mobile phone? Who doesn't have access?"*
>
> **Humanitarian expert**

Implications for tasks and workflows

Using new technologies and data responsibly requires capacity building and training of humanitarian actors. This may involve new approaches to support humanitarian actors to manage training around existing responsibilities and workloads (such as the IFRC's Data Playbook Toolkit[70]). In addition, new technologies require critical evaluation of the usefulness and appropriateness of their application (particularly in relation to AI due to potential associated risks, as explored in Section 3.2). There is a considerable need for improved data literacy, as well as responsible data collection and management at a local level, as one barrier to greater use of data and technology is a paucity of timely, high quality and reliable data in crisis contexts.[71] Solutions such as the DEEP data management platform[72, n] are designed to support humanitarian groups to create more robust data storage and data analysis by leveraging a wider range of narrative and news reporting for situational assessment. As noted in Section 3.1, building trust with communities, such as through participatory approaches, is essential for meaningful and sustainable participation, particularly when data is involved. Community engagement and participatory design or evaluation of interventions could also help to mitigate some of the concerns about technology use in the sector.

n. DEEP data management platform is a multi-partner initiative with Data Friendly Space serving as the technology developer.

Figure 21: Summary of key trends and changes in humanitarian response

Key challenges and changes	How the humanitarian sector is responding	How tasks and workflows are changing
Complexity of crises Crises are becoming 'more common, more costly, more complex, and more concentrated' **Protracted conflicts** Conflicts are becoming increasingly protracted and destructive to affected communities. The average length of conflicts increased from four to seven years between 2005 and 2017 **Climate change** Climate change and its related events are increasing in frequency, reach and impact	**Anticipatory action** In response to the increasing frequency, impact, and cost of crises (and particularly the threat of climate crises) there is a growing focus on early warning and anticipatory action to avoid loss and damage and ultimately save lives. Anticipatory action pilots have been implemented, however there is a need to scale these and increase geographical coverage	**Progressing anticipatory action by:** • Increased forecasting capacity by improving models • Strengthening disaster risk management systems • Addressing gaps in data management • Better integration of data on climate, environment, and violence, and in conflict contexts • Establishing a better understanding of community needs and behaviours to inform anticipatory action
Technological change Technological transformation across the sector is changing how humanitarian organisations support crises, from driving cost-effectiveness of response to predicting and preventing the impact of a crisis	**Digital transformation** Where funding has been made available, traditional business 'functions' are growing within humanitarian organisations to provide the infrastructure to support technological operations and data management needs Increased scepticism about 'techno solutionism' and the value proposition of AI due to concerns around the risks for affected communities, and marginalised and vulnerable groups	**Embedding technological transformation, and ensuring it aligns with localised and decentralised approaches by:** • Training and management on how to use and apply new tools • Critical evaluation of the usefulness and appropriateness of their application • Greater (responsible) data collection and management (including inclusive and community-based approaches to data collection) • Improving data literacy • Participatory and people-centred design of solutions/tools/interventions
Growing funding gap Growing needs of affected communities and dwindling support from traditional donor countries with growing needs of affected communities has resulted in a funding gap of $11 billion in 2019	**Diversification of the funding landscape** Bridging the growing funding gap requires diversification of the funding landscape, including through the private sector playing a more prominent role alongside traditional international actors that have led the sector historically	**Increasing collaboration with the private sector responsibly by:** • Brokering public-private partnerships, including with non-financial contributors • Regulating new financial actors in the space • Monitoring increasingly varied sources of funding • Managing funding distribution • Monitoring the impact of funding initiatives • Community engagement/ participatory process to ensure funding changes account for the needs of affected communities

Figure 21: 'Summary of key trends and changes in humanitarian response (continued)

Key challenges and changes	How the humanitarian sector is responding	How tasks and workflows are changing
Decolonisation and legitimacy gap for INGOs A push for anti-racism and decolonisation of the sector and increasing scrutiny of the de facto power, legitimacy and accountability of INGOs	**Decentralisation and localisation** Many humanitarian organisations have focused on decentralisation as a way to enable bottom-up resilience and empower the communities they support. Increasing reliance on local organisations has also been driven by worsening safety and security conditions for international humanitarian organisations and personnel in some crisis contexts. This has been accelerated by COVID-19 In addition, there is increasing focus on involving affected communities, and particularly on the promotion of marginalised voices **Citizens and communities taking action** Citizens and communities are playing an increasingly active role in leading social movements, including managing and responding to the challenges and crises they are facing	**Driving community participation and citizen-led action by:** • Building relationships and contacts with local community members • Establishing open channels for communication (so communities can monitor and respond directly) • Follow-up with community members who have participated • Disseminating community feedback to relevant stakeholders • Training communities in advance of crises and then providing resources so they manage response themselves • Staying abreast of 'emergent volunteers' and how they can work alongside 'traditional' agency responses
Worsening societal foundations Inequality is increasing, economic growth is stagnating in some developing countries, and extreme poverty is increasing in many developed countries Health and wellbeing of many communities is worsening (i.e. mental health), and this is amplified by new threats such as COVID-19 New threats of mis- and dis-information, and declining international solidarity due to increasing focus on domestic issues	**Increased convergence on humanitarian–development–peace nexus** Increasing emphasis on the integration of humanitarian, development and peacebuilding programmes to deliver coordinated and ongoing relief, challenging the status quo of the aid system[73] **Improving access to healthcare** Efforts to reduce healthcare access barriers particularly in light of the increasing costs of healthcare and challenges around reaching healthcare facilities[74]	**Providing wider community support and responding to emerging societal issues by:** • Increasing volunteer and frontline responder training in mental health support • Adapting existing humanitarian infrastructures (e.g. hotlines and community engagement actions) to providing mental health support • Proving training for existing volunteers/ frontline responders and/or creating new volunteer roles for volunteers in recognising and dispelling misinformation, especially through social media groups and WhatsApp channels (as referenced in the Gaps and Opportunities workshop)

2.2 'Use cases' for CCI – Gaps and Opportunities

Key findings

- CCI solutions are currently most applied in 1) providing early warning of a crisis, 2) providing real-time situational information for more effective response efforts.
- However, there is still significant potential to innovate further in these 'use cases'. For example:
  - › Emerging methodological advances in unsupervised or semi-supervised machine learning approaches can overcome the lack of labelled data typically required for classical machine learning techniques.
  - › There are also opportunities to expand situational awareness beyond the traditional information of disaster impact assessment – for example, to include monitoring of mis-information/disinformation, and mental health of affected communities.
- R&D investment is needed for tools that solicit the opinions or priorities of communities for post-crisis recovery. Our analysis found few (2/28) examples of CCI solutions in this solution space, but advances in NLP are increasingly offering enhanced ability to analyse large amounts of unstructured qualitative data generated by people.
- There is a significant R&D opportunity to model crisis co-dependence and network effects of humanitarian interventions or population behaviours. Agent based modelling techniques have not been widely used to date in CCI solutions, but with greater focus on anticipatory action and with intersecting crises (e.g., COVID-19 and climate), simulations are likely to become increasingly valuable as tools to support programme planning.
- New frontiers for CCI R&D include facilitating distributed intelligent actions for crisis response; both peer-to-peer matching of resources/skills/assets/needs between affected communities, and coordination between traditional and non-traditional frontline actors.
- CCI is not currently being used to predict the resources needed for crisis mitigation, response and recovery; or to generate real-time granular monitoring of humanitarian response and recovery efforts.

Our CCI case study review and technical deep dive both highlighted many commonly used methods. They also pointed to the emergence of new datasets, new open source modelling frameworks, and an evolving attitude towards AI from policymakers and humanitarian organisations which is shaping how the sector responds to different methodological approaches and key opportunities for the future. Alongside this, our analysis of the changing humanitarian landscape and interviews and workshops with a range of experts and frontline responders suggested the emerging needs and problems that are growing in importance across the sector.

Based on these analyses, we have categorised existing CCI solutions and potential future ones into a range of 'use cases', grouped into five categories:

1. Situational awareness
2. Assessing community needs, assets and priorities
3. Resource planning and management
4. Programme planning and operations
5. Monitoring and evaluation

The use cases have been colour coded according to how established they are in current applications of CCI (see Section 1.3). The 'established' (green) represent use cases that correspond to most existing solutions, the 'emerging' category (amber), where we have seen ≤3 examples of CCI solutions, and 'speculative' use cases (red) where we are yet to see CCI solutions applied in this field. This final category was derived from our analysis of needs surfaced through interviews and workshops with practitioners and frontline workers, as well as a literature review of existing CI solutions in related fields. Many existing use cases have been applied in the context of rapid onset natural disasters such as floods and earthquakes. The added value of CCI in these cases lies in the improved timeliness and granularity of insights. Emerging and speculative uses of CCI may have wider applicability. For example, we see modelling of behaviour and interventions to inform planning and operations as having particular relevance for slower-onset crises and complex emergencies. In this case, CCI can help humanitarian actors to navigate complexity and improve buy-in for policies and actions.

The relevance or prioritisation of each of these use cases will change in different contexts, determined by local vulnerabilities, as well as the existing capacity and information ecosystem for a particular crisis type. The use cases are summarised below (Figure 22) and further elaborated in the next section as key opportunities for R&D.

Photo: Talha Nair at unsplash.com

Figure 22: Overview of existing, emerging and speculative 'use cases' for CCI solutions

	Before a crisis		Immediate aftermath of a crisis	After a crisis	
Use case categories	**Mitigation**	**Preparedness**	**Response**	**Recovery**	**Value added by CCI**
Situational awareness	Predicting a crisis before it happens Example case studies: AIME, Premise	Providing early warning of a crisis Example case studies: Dataminr, Flood Management EWS, Sentry Syria, Project Jetson, Community Water Watch	Providing real-time situational information for more effective response Example case studies: Ebayanihan, RapiD, Haze Gazer, HERMES, PetaBencana.id	Providing real-time situational information for more effective recovery	Improving timeliness, spatial coverage and contextual relevance of data Most relevant for: rapid onset natural disasters
Assessing community needs, assets and priorities	Predicting vulnerability to a crisis	Identifying most vulnerable families/properties and identifying existing assets for emergency response	Peer exchange – matching of needs and resources in affected communities	Soliciting ideas and priorities from communities for post-crisis rebuilding Example case studies: CSAP, Remesh	More contextually relevant data, mobilisation of local resources and more inclusive decisions Most relevant for: all crisis types
Resource planning and management	Predicting resources needed to mitigate crises	Predicting resources needed to respond to a crisis	Enhanced coordination for funding distribution	Predicting resources needed for recovery efforts Example case studies: Targeting the Ultra-Poor in Afghanistan	More effective use and targeting of resources for anticipatory action and/or financing Most relevant for: all crisis types
Programme planning and operations	Modelling behaviours and interventions for crisis mitigation Example case studies: Sequía Companion Modelling	Modelling behaviours and interventions for crisis planning Example case studies: Modelling humanitarian relief in Haiti, HOPE	Enhanced coordination for distributed response Example case studies: WeFly Portal	Modelling behaviours and interventions for crisis recovery Example case studies: Sequía Companion Modelling	More effective interventions, through collective understanding of impacts, dependencies, and emergent or unintended effects Most relevant for: complex emergencies, slow-onset disasters
Monitoring, accountability and evaluation	Monitoring of crisis mitigation efforts		Monitoring response efforts	Monitoring recovery efforts	Enhancing accountability and legitimacy through community feedback and oversight Most relevant for: all crisis types

2.3 Ten key R&D opportunities for CCI solutions

Our analysis points to ten key opportunities for further investment by humanitarian funders, humanitarian agencies and the AI or technology communities to get the most out of CCI. We have grouped these into three categories of action: two opportunities related to the types of users of CCI solutions, four that push CCI methods to respond to particular issues in crisis management, and three that seek to leverage and integrate new technologies into CCI solutions. We outline these ten areas for investment below, relating them to the main sectoral trends and CCI use cases.

Given the nascent nature of CCI, pursuing these opportunities will rely on a commitment to experimentation as well as generating an evidence base for what works and assessing the impact of these interventions in a more holistic manner.

Beyond the ten R&D opportunities, there is considerable potential to adapt existing CI-only solutions (that do not currently have an AI element) or AI-only solutions into CCI; leveraging these low-hanging fruit would be a 'quick win' for the field. We identified a wide range of humanitarian crisis solutions with CI and AI elements that could be adapted in this way.

Figure 23: Overview of ten R&D opportunities for CCI solutions

Expanding CCI solutions to new users	Applying CCI solutions to new issues in crisis management	Leveraging new technologies in CCI solutions
Develop CCI solutions with and for frontline responders and affected communities	Expand situational awareness to include misinformation and disinformation	Leverage unsupervised or semi-supervised machine learning techniques and increasing availability of open data
Use collective intelligence methods to deepen community participation in crisis management	Predict the resources needed for crisis mitigation, response and recovery	Model the complexity of crises and the network effects of humanitarian actions for better anticipation
	Monitor humanitarian response and recovery efforts	Participatory modelling for improved multi-stakeholder decision making
	Leverage CCI to facilitate distributed intelligent actions for crisis response	Use CI to bridge the gap between human reasoning and AI predictions

Expanding CCI solutions to new users

1. **Develop CCI solutions with and for frontline responders and affected communities**

   Of the 28 CCI case studies analysed, all drew on the collective intelligence of affected communities and frontline responders in a variety of ways – either through direct contributions (e.g. reporting mechanisms) or indirectly (e.g. through web scraping or using APIs and search results to access relevant data).

   Some of these case studies have gone further and resulted in solutions that are directly used by civil society organisations and affected communities (29 per cent, *n*8) or integrated into localised frontline response by government actors (39 per cent, *n*11). But just one case study (WeFly) appears to have been designed or prototyped from the outset with the involvement of any of these groups. Creating solutions that both draw insight from those on the frontline, and empower them to take more effective local action remains a major innovation opportunity that is at the heart of this UKHIH-funded Accelerated Innovation Collaboration on CCI. Using Participatory AI methods throughout the design and development process will help to ensure solutions are relevant to and owned by communities and frontline responders (see the accompanying report Participatory AI for humanitarian innovation).

Alongside participation, CCI solutions should also aim to reflect the diversity of the affected communities they represent, including ethnolinguistic diversity. However, despite many crises involving linguistically diverse communities, only one of the CCI case studies examined, the Common Social Accountability Platform (CSAP), analyses diverse regional languages. This may be due to limitations surrounding NLP on linguistically diverse datasets such as the bias of models towards the morphology and word order of English language.[75] Furthermore, language drift and evolution makes modelling diverse languages more complex, as already limited resources and dictionaries become out of date. However, while there are challenges, greater language inclusivity of CCI solutions can enable them to more effectively access insight from affected communities across the crisis management cycle. An example of this was explored by researchers in 2019, where novel NLP techniques were used to analyse sentiment in linguistically diverse social media posts relating to ongoing conflict between Russia and Ukraine.[76]

Most relevant for:	All CCI use cases
Link to trends:	Enabling localisation and community-led action

2. **Use collective intelligence methods to deepen community participation in crisis management**

Our analysis highlighted that the majority of CCI solutions at present use passive data collection methods (i.e. data that is collected without asking the user for it – such as through social media scraping) rather than active data collection methods (i.e. the user is aware that they are contributing data).

There is an opportunity to deepen community participation by using collective intelligence methods to allow people to actively contribute. **eBayanihan** and **Sentra Syria** are examples of CCI in which citizens play an active role in collecting data through crowdsourced reporting mechanisms. One key CI method which is currently under-utilised in crisis management is citizen science. This usually involves groups of volunteers working with scientists to generate or analyse data. In addition to generating important research insights, it also helps to build community awareness and action.[77] The **Community Water Watch** and **Zika Premise** case studies demonstrate the potential citizen science methods have to contribute to crisis prediction and early warning for rapid onset emergencies and pandemics, and this has been borne out during the COVID-19 pandemic too.[78] A recent systematic review of the contribution of citizen science to the SDGs, showed the wider potential of citizen science to monitor environmental conditions and provide information on health and wellbeing-related issues.[79]

Another emerging 'use case' for CCI is in tools that use SMS, radio and web platforms to solicit the opinions or priorities of communities for post-crisis recovery (two case studies). At present CI methods that crowdsource opinions and ideas, or that allow people to deliberate on decisions are rarely applied. Meanwhile, advances in NLP are making it easier for organisations to cluster and make sense of the large amounts of unstructured qualitative data that can be generated through these approaches. This combination of methods offers humanitarian organisations and frontline workers new opportunities to understand and respond to local community priorities.

Most relevant for:	'Situational awareness' and 'Assessing community needs, assets and priorities' CCI use cases
Link to trends:	Enabling localisation and community-led action

Applying CCI solutions to new issues in crisis management

3. Expand situational awareness of misinformation and disinformation

The scale and spread of misinformation and disinformation is a growing challenge for humanitarian organisations – with documented examples on the rise.[80] It can contribute to new humanitarian crises, exacerbate existing ones or hinder humanitarian response – as visibly highlighted during the COVID-19 pandemic.[81] Humanitarian organisations recognise that they need to be better at recognising trends in misinformation/disinformation and taking early action to combat them. This area is seeing significant investment from both humanitarian and development actors,[82] and tools to monitor and combat misinformation are increasing in the sector. For example, as part of the COVID-19 response, the IFRC and its national societies in sub-Saharan Africa developed a system to collate and analyse unstructured community feedback in order to identify and address rumours and misinformation early.[83]

CCI methods can play an important role in enabling early identification of misinformation. Using crowdsourcing or community reporting to identify and verify rumours in real time could help humanitarian agencies address misinformation in a timely manner and adapt their interventions accordingly. MSF's **WikiRumours** (see supplementary case studies in the Appendix[o]) project crowdsources health-related rumours from the community (inputted through SMS or an online portal, or via a proxy community liaison officer). Interventions are planned to address rumours that are spreading fast within the community or have a big impact on MSF operations. This tool does not currently use AI but has looked at integrating it into the platform in the future. Parallel efforts by UN Global Pulse as part of the WHO's Infodemic Response Alliance will soon be using artificial intelligence to analyse radio coverage for trends in misinformation such as rumours around vaccines, promotions of false cures, and discussions about financial hardships.[84]

o. WikiRumours does not currently use AI so does not fit the strict CCI criteria. We consider it an interesting example in response to the trend on misinformation and have included it as a case study in the Appendix.

Translators without Borders (TWB) have used AI-enabled technology to combat the rise of misinformation during the COVID-19 pandemic. They developed chatbots that use natural language processing to respond to questions posted through popular messenger apps WhatsApp and Telegram in both the DRC and north-east Nigeria.

The chatbots provide actionable advice in local languages, as well as generating data about common sources of dis- and mis-information. TWB plans to develop a dashboard based on this data to help local humanitarian agencies adapt their communication in response.[85]

Most relevant for:	'Situational awareness' CCI use cases, especially providing real-time information for more effective response
Link to trends:	Increased complexity and weakening societal foundations

4. Predict the resources needed for crisis mitigation, response and recovery

Efforts are growing to predict where a crisis will happen, who will be affected, how big the impact will be and when it will strike. However, none of the CCI or predictive analytics solutions we studied were attempting to predict the resources needed to mitigate or respond to a crisis.

There is an opportunity to better utilise 'Who Does What and Where' (3Ws) data in predictive analytics, and to train models on historical data for previous crisis management efforts. As discussed in Section 3.1, many humanitarian datasets continue to be stored in disparate files, including 3Ws datasets that contain crucial information on aid distribution. Consolidating these datasets in more robust data pipelines could help to generate new insight.[86] The Humanitarian Data Exchange (HDX)[87] is contributing to sharing compiled 3Ws datasets and analysis. HDX have also published visualisations of 3W data that highlight local and sector (e.g. health, wash, nutrition) activity. This information can be used to identify underserved areas during humanitarian crises and recommend resource reallocation based on impact predictions, such as those generated by the **InaSAFE – Flood impact**[88] case study.

The adoption of anticipatory initiatives – such as forecast-based financing – could be greatly accelerated by the development of such resourcing forecasts. And perhaps resourcing predictions could help mobilise new resources or partnerships to close the current funding gap for humanitarian response.

Most relevant for:	'Resource planning and management' CCI use cases
Link to trends:	Anticipatory action, growing funding gap

5. **Monitoring of humanitarian response and recovery efforts**

We did not find any CCI solutions which involved communities in real-time monitoring and evaluation of humanitarian response or recovery efforts, despite the increasing focus on real-time evaluations (RTEs) and adaptive management approaches in the last decade. The move towards localisation across the sector is partly based on the assumption that it will improve impact and accountability to local populations, but the evidence for this remains piecemeal and anecdotal.[89] Future CCI solutions could help to address this gap by building perceptions of local communities into assessment of localisation programmes and the evaluation of their outcomes, as well as traditional humanitarian operations. Although also rare outside of the humanitarian sector, there have been some efforts to use CI approaches to involve citizens in monitoring the implementation of programmes or policies. In those examples, citizen-generated data (often using GIS systems, plus citizen reports and images) to provide 'ground truthed' evidence has been key.

The ¿Qué Pasa Riachuelo? was an online platform and social monitoring tool, allowing citizens and NGOs to follow the execution of the legally mandated clean-up plan and report breaches or problems.[90] TransGov in Ghana, also uses a digital platform and app to enable the public to monitor policy implementation by allowing citizens to 'audit' and report on the completion of development infrastructure projects in their neighbourhoods. Its aim was to increase citizen engagement and advance public accountability.[91] Initiatives that follow this model help to build trust between local communities and institutions, which is vital for long-term post-crisis recovery.

The continuing security and access issues for humanitarian actors, combined with new types of crises, like the COVID-19 pandemic, may be making it even harder for traditional monitoring and evaluation techniques to be carried out in the field. Yet these activities are critical to connecting with affected communities and frontline responders, and enabling faster learning and adaptation for more effective use of strained resources. Technology and frontline volunteers can help to improve access to hard-to-reach communities but every solution needs to be localised to tap into the most popular communication channels. An existing early-stage CI solution in this space is Loop, an online global platform where individuals upload stories to give feedback on humanitarian and development services in their communities.[92] The Loop platform is accessible via SMS and popular messenger services like WhatsApp and Facebook, as well as a web platform, making it appropriate for a wide range of humanitarian settings. Loop may benefit from integrating AI-enabled recommendation systems to complement human moderators and streamline the connections between organisations and participants.

While humanitarian actors and organisations are increasingly collecting feedback, progress on actioning and responding to feedback and 'closing the feedback loop' is lagging behind.[93] Future CCI solutions should focus on helping humanitarian organisations to effectively understand, manage and respond to the feedback they receive; this is where AI algorithms that cluster and categorise large volumes of text can help expand organisational capacity to manage a deluge of feedback.

Most relevant for:	'Monitoring and evaluation' CCI use cases
Link to trends:	Localisation, growing funding gap

6. **Leverage CCI to facilitate distributed intelligent actions for crisis response**

The majority of CCI solutions analysed help facilitate centralised control and coordination of crisis response activities. For example, **WeFly** helps authorities coordinate drone permission approvals. A notable exception to this, however, is **PetaBencana.id** which crowdsources information from Jakarta residents on flooding across the city and combines it with official and sensor data. The result is a real-time flood map that is used by residents to help them make smarter decisions about how to avoid affected areas – allowing people to act independently in a more intelligent way. It is also used by municipal authorities to coordinate and prioritise its flood response efforts.

In our analysis, there were few case studies that allowed communities or local actors to connect to one another, or build on each other's contributions. **PetaBencana.id** does mobilise its contributors to verify reports of flooding made by others, and **Humanitarian Tracker** verifies reports from citizen journalists against other reports as well as official sources though it doesn't connect citizens. There is a missed opportunity for CCI solutions to coordinate and influence the activities of people and organisations in a complex system in new ways by integrating different types of available data and facilitating interaction. Atma Connect is one example of a tool facilitating distributed problem solving in the humanitarian sector (though it did not qualify for inclusion in the case study analysis due to the absence of an established AI element). Atma Connect is a free website and mobile app that enables local community members to post and respond to comments (i.e. emergency alerts to crises, community problems, potential solutions) and connect with each other to coordinate response. In addition, there are examples of this outside crisis response. One of those examples is Breadline, a collective intelligence platform that enables local food rescue volunteers from NGOs in Hong Kong to see quantities of leftover bread at different bakeries across the city in real time. It allows the volunteers to choose their own collection routes, removing bakeries from the list when volunteers indicate that they intended to pick up from a particular store. The increased transparency enabled volunteers to act in a decentralised way that also let them draw on their tacit knowledge of the fastest way to get round the city and led to a fourfold increase in bread collected.[94] How might these approaches be applied to enable more effective local distribution of resources either immediately before or after a crisis?

A potential untapped opportunity for future CCI solutions is to create solutions that allow for more distributed intelligent actions for crisis preparedness and response – between community members, civil society organisations and between non-traditional/traditional actors. A key feature of the COVID-19 response has been the emergent volunteering efforts enabled by peer-to-peer matching of resources, skills, assets and needs between affected communities. It has ranged from WhatsApp groups to local makers creating PPE for struggling hospitals, and communities in India and Nepal tracking oxygen supplies and hospital bed availability. Greater proactive investment now, could help overcome some of the limitations of these initiatives – such as difficulty connecting into institutions, privacy issues, or potential exploitation by fraudsters.[95]

Most relevant for:	'Assessing community needs, assets and priorities' and 'Resource planning and management' CCI use cases
Link to trends:	Enabling community-led action and contribution of non-traditional actors

Leveraging new technologies in CCI solutions

7. **Leverage unsupervised or semi-supervised machine learning techniques and increasing availability of open data**

Our case study analysis highlighted the frequent use of supervised learning methods in CCI and predictive analytics solutions (Section 1.4.2). However, these methods require large amounts of labelled data which has practical limitations and is often challenging in a humanitarian crisis context. The application of weakly-supervised and semi-supervised learning enables solutions to overcome modelling challenges from limited labelled data points.[96] Current applications in the humanitarian sector include **RapiD**, which uses weakly-supervised learning to validate geographic predictions made using a limited number of labelled data points, and **Mapping New Informal Settlements** which uses semi-supervised learning to create pseudo labels. Future CCI solutions could also draw on these techniques to extract insight from diverse unlabelled datasets, such as on-the-ground reports, remote sensing data and news and social media data, all of which are becoming more readily available through open channels.

Another emerging area of development is the use of remote sensing and in particular satellite imagery in making predictions pertaining to humanitarian crises. There is growing availability of high quality open satellite data together with ongoing development of open source deep learning frameworks, such as Tensorflow and Microsoft CNTK, which is reducing barriers to access. Computational barriers are also reducing with growing availability of resources via cloud and other platforms such as Google Earth Engine which contains MODIS and Landsat data. While our case study analysis identified the emerging application of satellite imagery in humanitarian predictive analytics, there were only two examples that combined this data with collective intelligence from affected communities, **RapiD** and **Haze Gazer**. There is therefore an opportunity to incorporate insight from satellite imagery in new CCI solutions.

Alongside satellite imagery there has been general growth in the availability of unstructured open data. This has led to novel approaches to generating insight from multiple unstructured sources in parallel. For example, **Dataminr**, in their humanitarian response tool, collects image-text pairs from citizen generated data (e.g. from social media), which are then processed and fused. While we have seen few examples of this kind of parallel analysis of multiple unstructured data sources, this approach provides greater contextual information and the opportunity to derive new insights across the crisis management cycle.

Concern surrounding the interpretability and explainability of deep learning methods that currently dominate the space (see Section 1.4.2) highlights a need to invest in other forms of supervised machine learning techniques (as proposed in this R&D opportunity) which build on complementarity of human and machine intelligence.

Most relevant for:	'Situational awareness' CCI use cases, with immediate opportunities to enhance crisis prediction and early warning
Link to trends:	Enabling anticipatory action

8. Model the complexity of crises and the network effects of humanitarian challenges and actions for better anticipation

With humanitarian crises becoming more protracted and overlapping (Section 2.1), new CCI solutions must begin to incorporate datasets and methods that account for the growing interconnectedness of crises.[97] However, in our examination of case studies, humanitarian challenges were often considered in a silo. Modelling the network effect of crises could improve the accuracy and efficacy of both anticipatory predictive analytics and interventions across the crisis management cycle. A recent example of a co-dependent healthcare crisis is the suspension of vaccines campaigns while nations focus on dealing with COVID-19. This has led to growth in infections for preventable diseases, such as measles.[98] Better modelling of crisis co-dependence, along with social and causal factors, would enable AI solutions to support humanitarian planning cycles.[99] Collective intelligence can support modelling through the collection of new datasets, and can enable a deeper understanding of crisis complexity particularly in relation to exploring community behaviour, network relationships, and the impact of humanitarian actions (including unintended consequences).

As discussed in Section 1.4.2, modelling societal complexity for prediction making can be difficult to achieve using some AI methods alone due to the nonlinear relationship of social and economic dynamics.[100] **GUARD** is an example that attempts to overcome this by building a ground up mathematical model rather than relying on existing machine learning algorithms. It also dissects the potential causes of predictions made by the system through a multilayer network model that helps to uncover causal links by sequentially removing layers. Bottom-up modelling through Cliodynamics (see Section 1.4.2), similar to that explored with GUARD, may also be a useful approach for complex crisis CCI solutions.

Most relevant for:	'Programme planning' and 'Resource planning and management' CCI use cases
Link to trends:	Complexity and interconnectedness of crises, enables anticipatory action and localisation, growing funding gap

9. Participatory modelling for improved multi-stakeholder decision making

Agent Based Modelling (ABM) is another computational approach that is growing in relevance for the humanitarian sector. Greater focus on anticipatory actions, forecast based financing and early action has meant simulations and scenario analysis are increasingly valuable. For example, the predictive-analytics-only case study **Flee** uses ABM to simulate the movement of refugees after the 2012 Mali civil war.[101] With greater focus on anticipatory response, there is an opportunity to further explore the application of ABM and other approaches in distributed AI such as multi-agent systems and swarm intelligence.[102]

A specific innovation opportunity to ensure the relevance and application of ABM to local communities and frontline responders is the method of companion modelling (see Case study 7, Sequía). This participatory modelling approach uses the collective intelligence of a wide range of stakeholders to design and implement ABMs, and features interactive simulations enabling participating stakeholders to test different scenarios and outcomes. In particular, exploring community behaviour with the participation of affected communities (and connecting this with analysis of behavioural insights and economics) may also help to better understand the impact choices and trade-offs of individuals within systems for improved multi-stakeholder decision making. Overall, this could help strengthen the ability of frontline responders and communities to understand the impact of different actions and deploy resources most effectively across the crisis management cycle.

Most relevant for:	'Programme planning' and 'Resource planning and management' CCI use cases
Link to trends:	Complexity and interconnectedness of crises, enables anticipatory action and localisation, growing funding gap

10. Use CI to bridge the gap between human reasoning and AI predictions

There is an opportunity to better model qualitative human reasoning quantitatively.[103] Collective intelligence could be used to capture human hypotheses for the drivers of humanitarian crises, which can then be converted into quantitative variables to be used as inputs into an AI or predictive analytics system. None of the case studies that we explored explicitly capture human argumentation in the data. **Africa's Voices' Common Social Accountability Platform** comes closest to this by crowdsourcing opinions from the Somali community, but stops short at explicitly capturing reasoning for why events have taken place. Methods from Cliodynamics, as detailed in other parts of this report, can be used to construct mathematical representations of human reasoning via equations to then provide insight and make predictions.

Most relevant for:	'Assessing community needs, assets and priorities' and 'Resource planning and management' CCI use cases
Link to trends:	Enabling community-led action and contribution of non-traditional actors

03

Challenges and barriers for existing CCI approaches

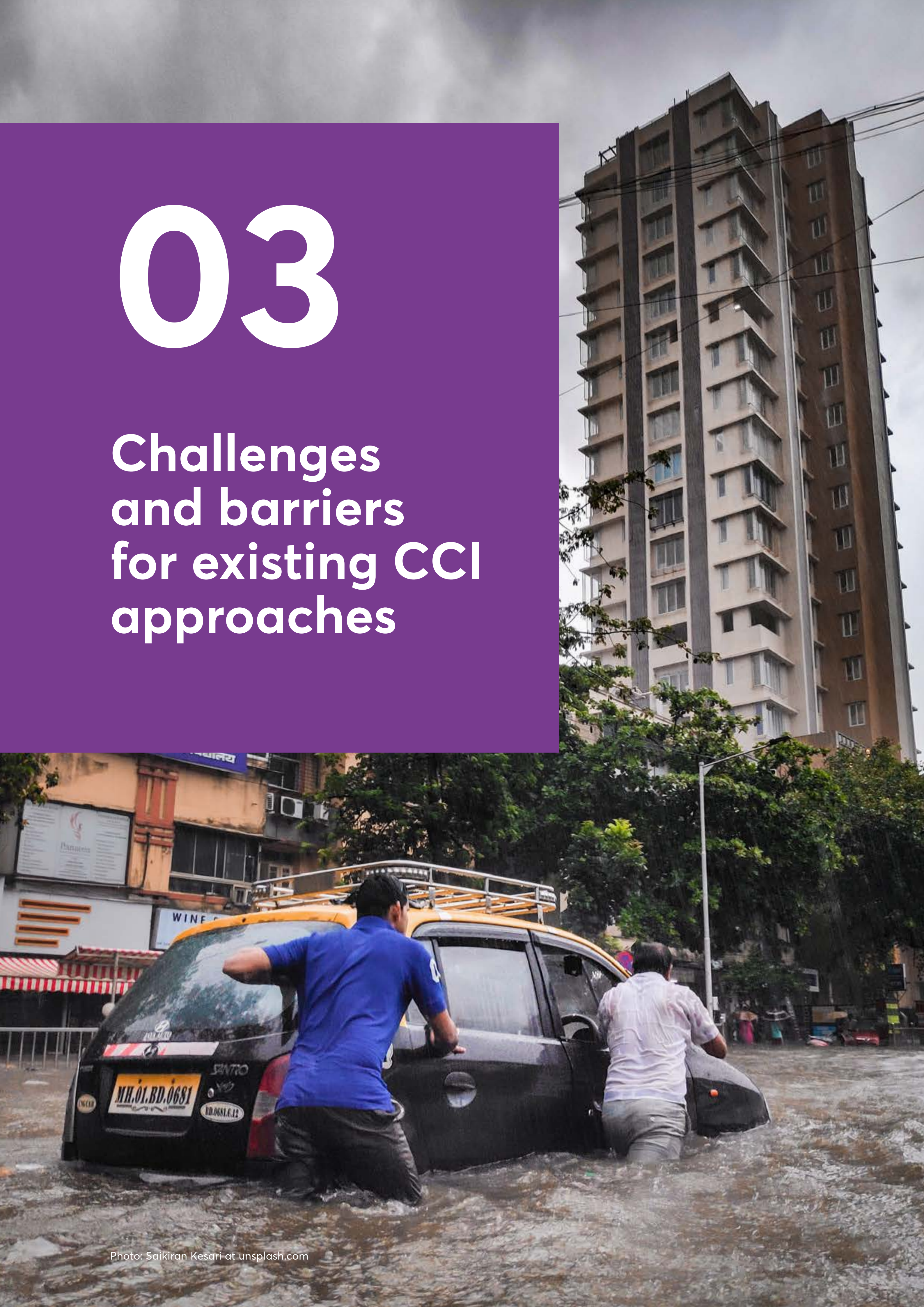


Photo: Saikiran Kesari at unsplash.com

Key findings

- There are three key technological barriers to scaling CCI solutions:
  - Predictive algorithms cannot easily transfer between contexts without loss of accuracy.
  - Predictive analytics approaches need high quality, labelled datasets tailored to each specific location and setting.
  - Few low- or middle-income countries have the technical infrastructure to support the latest developments in AI methods.
- The two core organisational barriers standing in the way of implementation are:
  - A data literacy and digital skills gap among volunteers, emergency responders and humanitarian staff.
  - Coordination failures within and between humanitarian organisations stand in contrast to the agility that will be required for CCI methods to succeed at scale. In the absence of senior advocacy it is unlikely this will shift.
- CCI projects may also face challenges with active participation in humanitarian settings. During crises the need to prioritise speed of response, difficulties accessing affected locations and the mental health support of crisis-affected populations place strain on maintaining participatory processes.
- Developers of CCI solutions need to follow the principles of CI design to ensure they tailor the initiative to the motivations of the groups who are expected to contribute using context-appropriate incentives.

3.1 Barriers to scaling and adoption

Despite the examples of impactful CCI applications, our interviews with experts, innovators and frontline workers suggested that the pace of adoption for new technologies has been piecemeal and hindered by a range of technical, organisational and sectoral challenges. This section outlines some of the key barriers to scaling CCI solutions within the humanitarian sector, focusing on systemic challenges related to technology, organisational culture and participation. The focused R&D efforts for CCI described in the previous section will need to be implemented alongside investment that helps to address these systemic challenges in order to succeed.

> *"When it comes to tech, most changes seen in the sector are really playing around the edges (e.g. drones); new ways of doing things are yet to be embedded and scaled."*
>
> **Expert interview**

Technical and data barriers to adoption

Inability to generalise to new settings

One of the primary technical challenges for scaling approaches that rely on predictive models is their inability to generalise well to new settings. Model features need to be adapted to incorporate the relevant contextual variables for different geographies and the availability or quality of data sources may also vary. Hala Systems experienced this challenge while working to generalise the **Sentry Syria** solution to new regions.[104] Furthermore, models developed with underlying sampling bias will also struggle to generalise. In the **Targeting the Ultra-Poor Program** case study, ultra low income populations in Afghanistan were predicted using mobile phone call records.[105] As only members of the population who own a mobile phone were included in the analysis, the model, as is, would be unable to scale to include the broader population.

Issues with data availability, quality and labels

Data quality issues can also impact model generalisation and performance. This is particularly true in a humanitarian context, with data quality issues being prevalent in Low Income Developing Countries (LDCs) where data is more likely to be incomplete or inaccurate.[106] Contributing factors include, infrequent national and regional data collection[107] and collection of inaccurate and biased survey data due to improper interview training.[108] A data quality assessment of the humanitarian response in Iraq and Bangladesh showed that more than 61 per cent and 55 per cent of people, respectively, felt unsatisfied or only somewhat satisfied with the quality of data available.[109]

As demonstrated by our analysis, the majority of predictive methods currently make use of supervised techniques. This algorithmic approach relies on the availability of labelled datasets. Many of the datasets relevant for humanitarian settings are unlabelled and require significant human effort to label them. This is particularly challenging during the onset of a humanitarian crisis where labelled data is limited.[110] Emerging AI techniques such as semi-supervised learning, as applied in the **Assessing Post-Disaster Damage** case study, can help overcome this.

Private sector data, which is currently underused in CCI (see Section 1.4.1) may help the sector address challenges around data availability. For example, during the COVID-19 pandemic numerous private sector organisations, including Apple and Google, made mobility data available to support research on virus transmission.[111] This is far from the norm and there are many barriers around negotiating access to private sector data. Smaller humanitarian organisations and solution developers, such as start-ups, are unlikely to have the resources and in-house expertise to secure data sharing agreements. Large, established humanitarian organisations may have more power to negotiate on behalf of their members or networks but even they may be hampered by internal bureaucracy and inflexible organisational processes.

Insufficient computational resources and technical infrastructure

As well as human resource challenges with labelling, there are also computational resource challenges that can impede scaling. Despite improvements, some datasets, such as remote sensing data are expensive to attain and require significant computational processing power. IT infrastructure limitations in humanitarian organisations is a further challenge for developing and scaling AI solutions. Humanitarian organisations often act as a key data source for model development, however many humanitarian datasets are stored in disparate Excel files making it difficult to consolidate and process data in an efficient way. This problem is exacerbated when attempting to scale, as robust data pipelines are required.[112] Solutions such as the DEEP data management platform[p] are designed to

p. DEEP data management platform is a multi-partner initiative with Data Friendly Space serving as the technology developer.

support humanitarian groups to create more robust data storage. Frontline responders and volunteers have noted that data collection and storage are particularly challenging in contexts where internet and electricity is intermittent.[113] The Humanitarian OpenStreetMap Team is one of the few CCI solution users that has accounted for this challenge. They have incorporated the Field Papers[q] tool into their workflows for paper-based data entry in low-bandwidth settings, while the Portable OpenStreetMap can be used for offline OSM editing.[114]

Organisational and sectoral barriers to adoption

Technical and research skills gap to use and maintain tools

To embed and scale new tools and technologies within humanitarian operations, the sector will need to evolve its current methods and invest in building digital skills across all levels, from data entry to data-led decision making.[115] A number of survey respondents noted the lack of individuals or teams with relevant or specialised skills and tool complexity (requiring specialised skill sets and training) as key barriers to widespread use of new tools and technologies within their organisations.[116] Tools should be created with intended users for their contexts and understanding, to ensure their use and uptake. This applies at all levels of responsibility, as one frontline responder interviewee noted a skills gap among volunteers on-the-ground.

> *"We have a lot of senior citizens volunteering. Many were retirees, including military retirees, they just want to use pen and paper. People are older and they're not familiar with the systems."*
>
> **Red Cross volunteer interview**

This is a significant barrier to the successful integration of CCI tools, many of which rely on the collection of new data (see below), which will require resource-limited frontline workers to develop new research skills.

Frontline workers and humanitarian staff can also be reluctant to collect the data that is crucial to understanding a specific crisis context (see Section 1.4), which may help tailor AI systems to new uses and locations.[117] Security and access issues may also mean that volunteers or frontline personnel may not be allowed to collect data due to restrictions. Further challenges that emerged around data collection during emergency response include staff not having the time nor adequate training to collect data.[118] Where possible, CCI solutions should make use of established data collection tools and build on existing technical infrastructures, particularly when these have already been integrated into humanitarian workflows. For example, the Red Cross and Red Crescent societies have established partnerships with Open Data Kit[119] and KoBo Toolbox[120] which are both open source and can be adapted to serve a variety of data collection needs. This will simplify training and accessibility of these tools for frontline workers and communities.

q. The Field Papers tool was developed by Stamen Design for the OpenStreetMap (OSM) editing community. http://fieldpapers.org/

Even with good performance and availability of data, scaling requires the solution to be adopted by a product owner willing to deploy, monitor and maintain the solution. Ownership of AI systems still largely requires specialist technical knowledge and there is a limited number of democratised AI development tools. With an AI skills gap, it can be challenging for non-profit and humanitarian organisations, for which many AI proof of concepts are built, to later scale those solutions.

Organisational inertia and lack of leadership buy-in

Slow adoption of new tools and innovative methods is often a result of a lack of senior advocacy within major humanitarian organisations.[121] Many of these organisations have traditional structures and approaches that have been ingrained through decades of practice, often resulting in 'organisational inertia'.[122] Persistent scepticism about the value of community or frontline derived knowledge and data has resulted in top-down preference for traditional data sources and a lack of process shift and/or willingness to include participatory approaches into the workflows. This lack of advocacy can stunt investment in CCI and mainstreaming new tools, ultimately preventing tools from scaling within organisations. Even for organisations that do advocate for CCI methods, competition between humanitarian organisations can limit sharing of data and insights to maintain competitive advantage and secure funding.[123] Our interviews with frontline responders revealed poor coordination of data collection among organisations during emergency response, often leading to data collection duplication. Some also noted challenges around data sharing due to data security and privacy barriers between organisations. For CCI to be most effective in the sector, cross organisational and community agreements should be established before a crisis to create a common infrastructure and open environment for the collection and sharing of data.

"During the Beirut blast, there was the Red Cross response, and the response from the army and other organisations too. Each organisation was collecting information on affected communities – each organisation was collecting the same data, but there was no appropriate coordination of data collection."

Red Cross frontline responder interview

Photo: Mark Chaves at unsplash.com

> *"There is the wrong notion that we 'know it all', we have an inward-looking attitude. In addition, inflexible organisational structures mean we're not able to foster innovation."*
>
> **Red Cross survey respondent**

> *"Another humanitarian actor. already had the data, but they said it was confidential so they wouldn't share it with us. This led to a duplication of tasks to get the same information from the same source. Organisations involved aren't trusting and transparent with each other."*
>
> **Red Cross volunteer interview**

Funding challenges

Broader sectoral issues are also inhibiting scaling and adoption of CCI solutions and tools. Alongside the growing funding gap in the humanitarian sector, there is a lack of long-term funding and, specifically, spending on R&D;[124] both are key to driving the development, implementation and scaling of sustainable CCI solutions and tools. Humanitarian spending on R&D and innovation is poorly reported, though known to be lagging behind other sectors. In addition, budgets from donors are prescriptive and tend to be dedicated to key services of providing relief, leaving limited opportunity for innovation. While donors are making more funds available for innovation, more funding is needed to support long-term sustainable and impactful innovation. In addition, long-term funding across the sector is needed to free up staff time from administering small grants, and reallocated resource to digital and data training to close the skills gap; this will be particularly important for scaling CCI solutions that may require more technical skill sets, as well as sustaining ongoing data collection and management necessary for sustainable CCI solutions.

Participation in humanitarian settings

Perhaps the most significant barrier to the successful adoption of CCI solutions, lies in the difficulty of meaningfully engaging with affected local populations and sustaining participation as a crisis unfolds. The latest mapping and prioritisation exercise conducted by Elhra, reported that only 33 per cent of all innovation projects and 57 per cent of all research projects consulted with members of affected communities during the development of the output.[125] This stands in stark contrast to the localisation agenda (see Section 2.1) and the emphasis placed on understanding the needs of affected communities in the OECD DAC evaluation criteria (see Section 1.5.2).

The speed and scale of humanitarian response determine the extent of coherent participation, especially in very large-scale emergencies that need to be dealt with immediately in whatever way possible, such as the events in Pakistan and Haiti in 2010.[126] Difficulty of local access and risk of potential danger to volunteers also have a significant impact on the level of participation. In environments such as South-Central Somalia, international organisations must rely on 'remote management' and can only connect to local communities through third-party actors,[127] while Yemen Data Project volunteers must remain anonymous while collecting data on the ongoing conflict.[128] In addition, language barriers and digital or data literacy gaps are key challenges to participation among affected communities.

Crises are marked by trauma and significant upheaval in the lives of local populations, whether they are caused by war, a big shock, or a natural disaster. This may limit the uptake of collective intelligence processes that rely on crowdsourcing active contributions from affected populations.[129] The increased need to offer mental health and wellbeing support for affected communities was also highlighted as an emerging task in our interview with frontline responders.

Overcoming participation barriers

Investing in dedicated training for volunteers, frontline workers or local leaders as mediators of CCI solutions may help to overcome this participation gap. As highlighted in Section 1.4.1 several CCI solutions already offer dedicated training to support new volunteers. As with any collective intelligence project, developers of CCI solutions need to consider the appropriate incentives for local participation by working closely with communities during the design of new tools. Offering financial rewards to participants can be a powerful motivator – the Premise tool, a data collection platform deployed widely across numerous development programmes, uses micropayments to encourage local uptake (see Case study 4). Using a hybrid approach which integrates both passive and active data collection from local populations may also help to address participation challenges. For example, the **HERMES** solution uses social media chatbots to request further information from users who have already posted about a disaster, after they are initially identified using web-scraping and AI-enabled filtering (see Case study 11). Beyond training and incentives, building trust with communities and frontline workers is essential for meaningful and sustainable participation, particularly when data is involved. Overcoming language barriers requires appropriate resources and tools to support multilingual capabilities, and engage with communities and local responders in a language they understand. For example, **Translators without Borders** is an organisation offering language and translation support for humanitarian and development agencies. In partnership with Mercy Corps, **Translators without Borders** developed a chatbot in three languages to improve COVID-19 understanding in northeast Nigeria by allowing people to message questions in their language and receive answers immediately and conversationally.[130]

Motivations are rarely static over the course of a project.[131] For example, the creators of the platform **eBayanihan**, which collects citizen-generated reports of local needs and impact assessment during disasters have noted the challenge of maintaining participation (see Case study 12). Any CCI solution that relies on ongoing active contributions from local stakeholders will need to keep track of how motivations change over time and adapt their incentive structures and platform features accordingly.[132] This is particularly true for newly created tools or platforms, which need to work harder to build a dedicated community or participant base.

Photo: USGS at unsplash.com

Photo: Ismail Salad Hajji at unsplash.com

Should CCI solutions scale to new contexts?

The challenges outlined in this section lead us to question the use of 'scaling' as a measure of success or impact with respect to CCI solutions. For predictive analytics models to work effectively they must first be tested and validated in an embedded context. Every new deployment will require tailoring of data sources and model parameters to meet the specific needs of users in that context. Participatory design approaches should likewise ensure CCI solutions are adapted to local needs, taking into account the access that communities and frontline staff have to different types of technology, their motivations and ability for contributing. There is an obvious tension between the desire for solution generalisability to enable scaling (inhibited by the technical limitations described here), and the need for solution specificity that is grounded in localised intelligence and embedded for localised response. Scalability and localisation are seemingly at odds with each other.

Instead of focusing only on scaling specific solutions, we propose that innovation funders and donors should take a longer-view, investing in i) scaling open data and open model infrastructures; and ii) scaling the local capabilities needed to design, test and deploy locally relevant CCI solutions.

Placing the emphasis on scaling digital and social infrastructure that allows tools and solutions to be used more widely will help support the global commons knowledge; creating usable and useful open data, open science and open innovations that are available to everyone. In particular, open data standards, open access technology (including open data collection tools) are critical infrastructures for CCI, enabling faster experimentation and adoption by disparate communities, scaling across geographies and more rapid learning about what works.[133]

3.2 Risks and ethical challenges of CCI

Key findings

- The risks and challenges related to CCI solutions are similar to those posed by the adoption of AI and other digital technologies in humanitarian action. They include privacy and exploitation concerns, as well as replicating or exacerbating existing inequalities by unequal representation, access and digital exclusion.
- Participatory AI approaches which involve affected communities and frontline responders in designing, developing and testing CCI solutions may offer practical ways of addressing these risks, and go beyond the sector's current emphasis on voluntary codes or principles.

This report details a wide range of opportunities for the application of CCI methods during crisis management. Many of the emerging methods and tools that enable CCI may raise ethical concerns that require careful examination by actors in the sector, as well as ongoing oversight of potential harms.

Threats to privacy and exploitation

The divide of those who have access to, or literacy of, digital technologies is widening both locally within countries and globally between countries.[134]

Regardless of access to technology, humanitarian work is generating a considerable amount of personal data that could be mishandled, hacked, or used with malicious intent.[135] Personal Identifiable Information (PII) can range from biometric data of refugees to the movement of communities escaping a conflict,[136] each of which could be used to exploit or threaten the people whose data it is. As a result, the collection and management of personal data must only be done when necessary, with relevant security measures in place and consideration of the unintended consequences of collecting this data. Investing in data literacy initiatives to ensure that communities and frontline workers are able to understand and give meaningful consent for data sharing will require a sector-wide effort.[137] Although taking this more responsible approach to developing data pipelines and AI systems may introduce friction and delay implementation of CCI solutions, it will ultimately help to build trust between humanitarian organisations and the communities they serve, as well as making the technology more robust.

Widening the digital divide and power imbalances

This unequal access to technology and widening digital divide is driving social and economic inequality,[138] while also limiting the reach and effectiveness of CCI tools. Research shows that collective intelligence activities are improved by diversity of contributions.[139] Unless the inequality of access is acknowledged and factored into design, there is a danger that CCI solutions will underrepresent certain communities, potentially amplifying inequalities through the application of CCI tools. However, meaningful access is not simply about being online; it requires regular internet access, an appropriate device, enough data and a fast connection.[140] Conversely, some communities have become so reliant on digital technologies and reliable and affordable internet access that traditional relationship networks have been weakened and communities have become less resilient as a result.[141]

Another potential harm is that the widespread biases and power structures in society become embedded within data and hardcoded into AI systems. This will amplify existing inequalities and vulnerabilities. For example, the coding or interpretation of data by humanitarian experts can be the result of a misunderstanding of local context, which can be adopted by machine learning algorithms that then industrialise this bias in data collected. As a result, many organisations are favouring manual coding of data to ensure the models are representative of the communities that are generating the data.[142] Some CCI tools and AI also favour data that can only be generated by communities with access to mobile phones or the internet,[143] which may focus response to more advantaged communities and further isolate others. Social media data also allows for a near real-time overview of a crisis and as a result, enables a more rapid response. However, this can also distort models to focus on immediacy of issues rather than considering long-term implications and mitigation.[144]

The impact of these risks around data and AI could be catastrophic for humanitarian operations and the communities they serve. The cost of both false negatives and false positives in predictive models could be significant, from wasting resources to the loss of life. As described in Section 3.1, models that are developed without adequate contextual input, or have been developed for one geography or context and are applied to another, are particularly at risk of producing inaccurate or unrepresentative results that can drive unintended consequences. We explore the potential harms of AI and how participatory design might help to address some of these limitations in an accompanying publication, Participatory AI for humanitarian innovation. NetHope have also recently released a toolkit to build capacity in the social impact sector to design, deploy and use AI responsibly and ethically.[145]

Photo: Ovinuchi Ejiohuo at unsplash.com

Pushback on 'tech solutionism'

The humanitarian sector has not been immune to techno-solutionism (or techno-optimism) that has taken hold across much of wider society – the enticing view that technology solutions will solve major challenges.[146] For the humanitarian sector, with a growing funding gap, technological solutions and digital tools have been embraced for their perceived efficiency and cost-effectiveness. However, there is growing concern and push-back within the sector around an over-reliance on technology and digital solutions, and that technology adopted in the name of progress may in fact exacerbate, entrench, or even create new problems in the sector. For example, Human Rights Watch recently reported that the UN may have put hundreds of thousands of Rohingya refugees at risk of persecution after improperly collecting and sharing personal information.[147] These instances of error (rightly) sow distrust for the potential of 'big data' and technological solutions and tools.

So far, affected communities have rarely been involved in solution design or in owning and managing their own personal data. Therefore, participatory design (with affected communities) and improvements to data literacy across the sector are key to mitigating the risks of technological transformation, as well as for garnering the support of sceptics of new digital tools and solutions in the humanitarian sector. Alongside this, efforts must be made to prevent forced inclusion or participation, and to protect the rights of affected communities, and particularly vulnerable groups, to privacy and anonymity.

Addressing the risks and challenges of CCI through Participatory AI approaches

AI systems, in their ability to learn, anticipate, and in some cases make decisions, are increasingly shaping humanitarian interventions. As we have outlined throughout this report, they can be powerful tools for the humanitarian sector to draw on, helping to enhance the speed, scale and processing capabilities of anticipation and response to crises. But they also pose new risks to the rights and freedoms of the communities who are the recipients of humanitarian aid. Despite the plethora of frameworks that detail ethical frameworks and principles for working with AI systems across different sectors, there are few examples that try to operationalise this theoretical guidance in real world settings. In an accompanying report (Participatory AI for humanitarian innovation) we have mapped out the current approaches to participatory design of AI systems from the nascent field of Participatory AI,[148] and explored how these approaches may be adapted to a humanitarian setting to design new CCI solutions.

Participation alone will not be enough to address these concerns. It should be developed alongside other complementary measures, such as sector-wide regulation, new approaches for sharing and governing data (e.g. data trusts) and investment connectivity and robust technical infrastructure.

04

Conclusions

Photo: Mohit Kumar at unsplash.com

This report provides the first analysis of how an emerging innovation approach, 'collective crisis intelligence' (CCI), is being used to improve crisis anticipation, management and response. CCI combines methods that gather intelligence from affected communities and frontline responders with artificial intelligence (AI) for more effective crisis mitigation, response or recovery.

There are promising examples of CCI for early warning and more effective response to crises, particularly in relation to rapid onset crises. These have been enabled by the growth in open source data, software and models. There are also emerging opportunities to expand the role for CCI solutions, for example predicting crises before they occur to prevent and minimise their impact, or modelling interventions for more effective planning.

Overall, the field is still at an early stage of maturity, and few solutions have been integrated into humanitarian operations. At present affected communities and frontline responders are rarely involved in designing, testing or managing these tools, but CCI could help the humanitarian sector develop a more human-centred approach to AI. Likewise, CCI offers a route to support anticipatory action and greater localisation. It has the potential to enable crisis affected communities to benefit directly from advances in AI and predictive analytics, through early warning, early action, enhanced response and better recovery. This requires concerted R&D investment of the kind initiated by the UK Humanitarian Innovation Hub, and a focus on creating the open digital infrastructures that underpin these innovations.

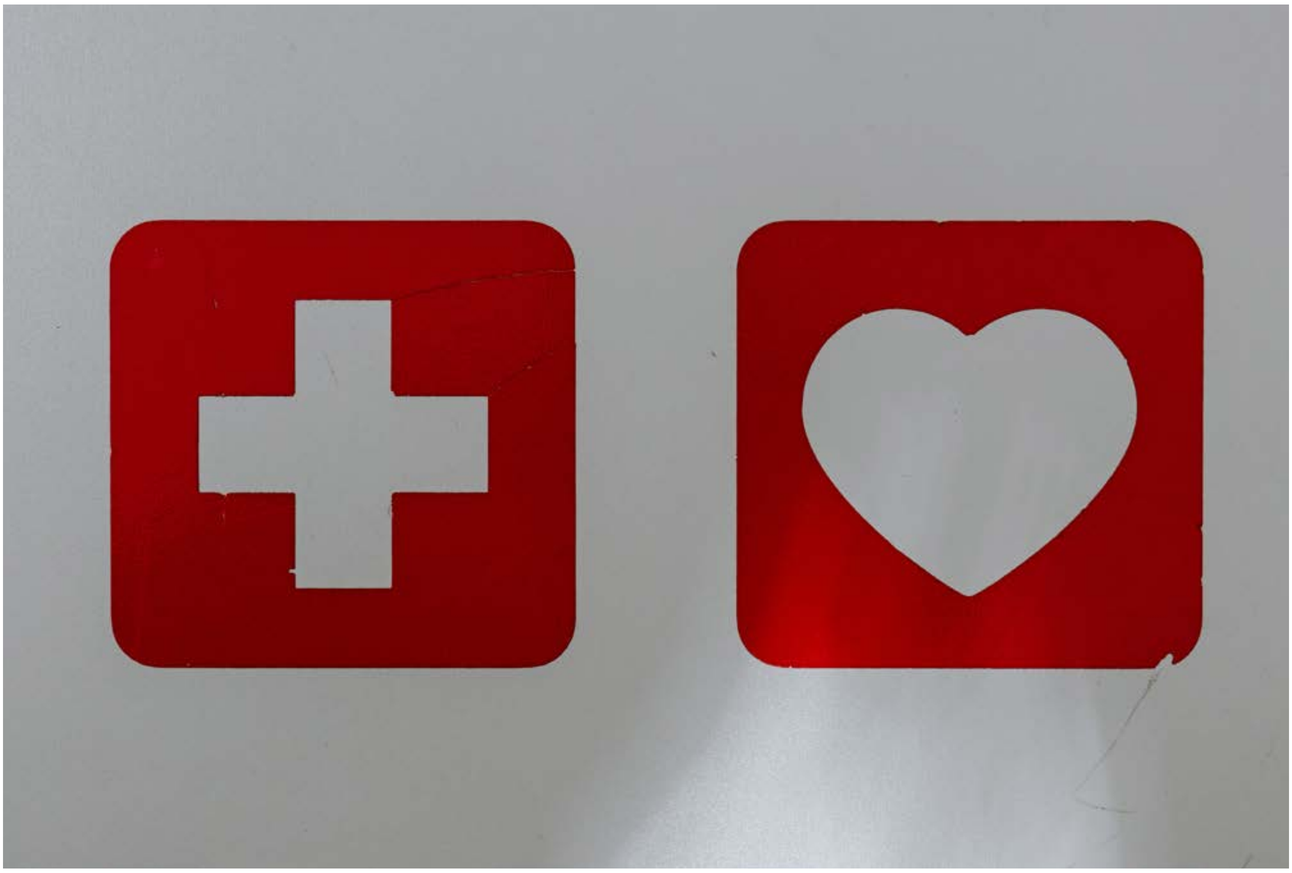


Photo: Claudio Schwarz at unsplash.com

05

CCI case studies

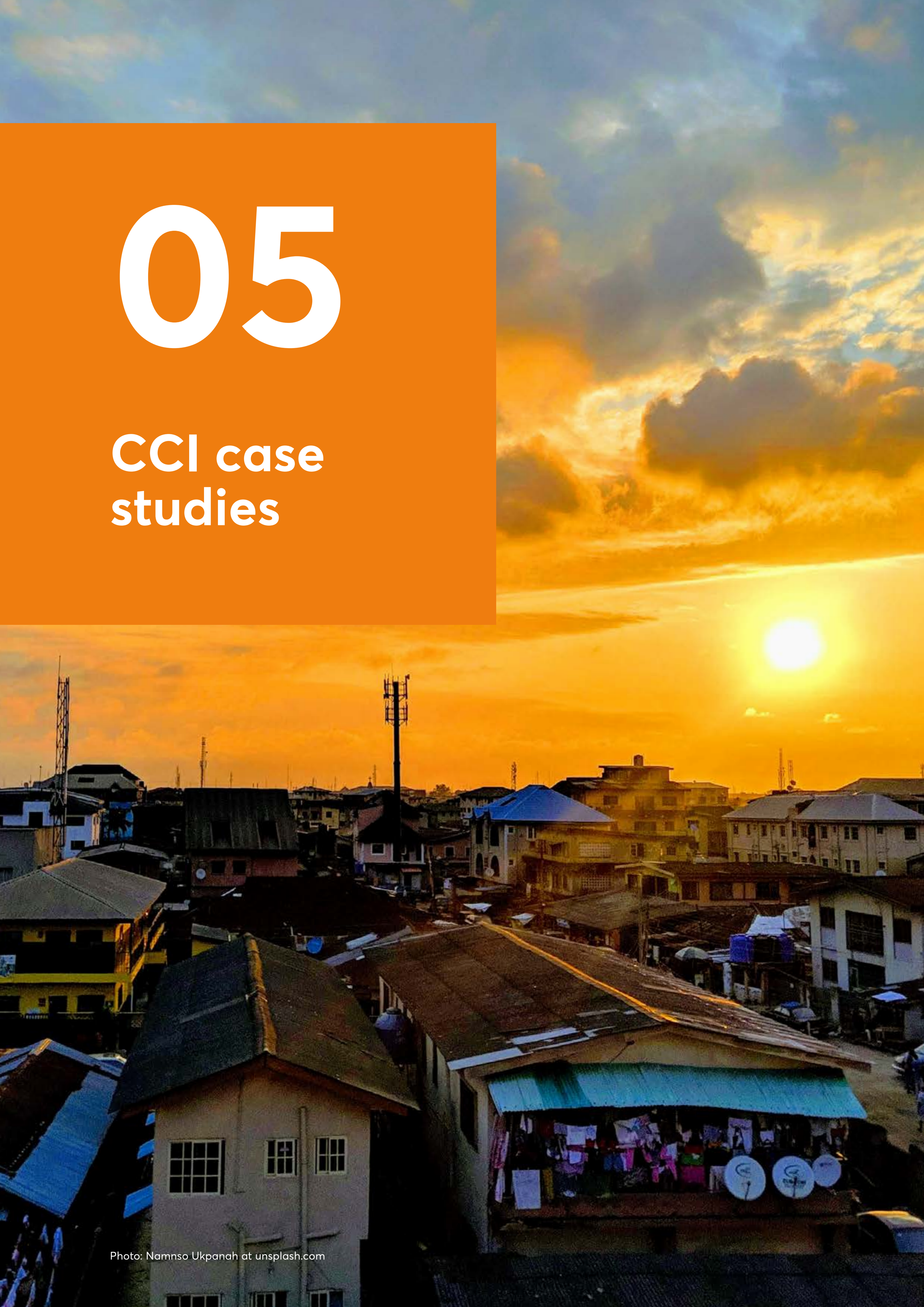


Photo: Namnso Ukpanah at unsplash.com

CASE STUDY 1

Managing Information in Natural Disasters (MIND)

STAGE OF CRISIS: Response

TYPE OF CRISIS: Natural

USE CASE: Providing real-time situational information for more effective response

CI METHODS: Web scraping, Combining data sources, Natural Learning Processing (NLP), Data visualisation, Machine learning

PEOPLE CONTRIBUTING: Community (general)

DATA: Social media data, Web-scraped data, GIS data

TECHNOLOGY: Data Platform, Open source, APIs

AI: Web Scraping, NLP, Machine Learning

TYPE OF ORGANISATION USING: Not being used/unknown

What is the problem?

During a natural disaster, access to accurate, consistent and timely information can be limited. This can slow, and sometimes prevent, responders from acting and collaborating in a crisis. As a result, different response efforts may be using different datasets and information, and therefore not supporting the communities most in need.

What is the CCI solution?

MIND is an automated open source platform created by UN Global Pulse that collects and processes data from a range of sources and presents this data through a single aggregated platform that all responders can use when coordinating response to a natural disaster.

How is it being done?

The platform is built on an automated data pipeline (using a number of APIs), allowing it to stream and analyse several non-traditional data sets all in one place. This includes data generated by affected communities local to the incident taking place and scraped from Twitter and Google searches, as well as information from Wikipedia and OpenStreetMap about the location, casualty reports from news sources, and data from the International Aid Transparency Initiative, showing details about projects and organisations in the affected areas. The automated collection and processing of the data is triggered based on disaster alerts received from the Global Disaster Alert and Coordination System (GDACS), which is a global system aimed at closing information and coordination gaps.

So what? *(What is the impact? Why is this better than other approaches?)*

MIND is in the prototyping phase of development and is openly available for user testing. Ultimately, the MIND platform has been designed to create a single source of data that can be used by first responders on-the-ground during a natural disaster, increasing the speed and focus of the response to a crisis to save lives and support affected communities.

VALUE ADD: The CCI approach leveraged in MIND improves the timeliness, spatial coverage and contextual relevance of data for better response. In addition, the tool supports data coordination and access during a crisis.

CASE STUDY 2

RapiD (Map with AI)

STAGE OF CRISIS: Preparedness, Response

TYPE OF CRISIS: Natural

USE CASE: Providing real-time situational information for more effective response

CI METHODS: Crowdmapping, Computer vision, Remote or in-situ sensing, GIS, Predictive analytics, Machine learning

PEOPLE CONTRIBUTING: Remote volunteers, Community (general), Operational managers

DATA: Satellite data, VGI

TECHNOLOGY: Open source, Annotation platform, Cartographic platform

AI: Computer vision, Predictive analytics, Machine learning

TYPE OF ORGANISATION USING: NGO, Civil society

What is the problem?

For 15 years, thousands of volunteers have used OpenStreetMap (OSM) to create a free and open map of the world. The community of mappers help build OSM by adding manually captured data, importing and reviewing open public data or official data (such as satellite images) and annotating features like roads, highways and bridges. While mappers may be remote, local communities can also use the tool to map their local neighbourhoods.

Despite the popularity of OSM, many areas remain unmapped, unvalidated or incorrectly labelled. This is mostly because crowd annotation of maps is time- and labour-intensive for volunteers and finding an equivalent number of real-life validators is difficult. Maps are not static – particularly in vulnerable regions affected by conflict (such as where borders may be disputed) and environmental crises – so they may require remapping if an area experiences rapid changes in infrastructure. These areas need constant monitoring, which is difficult to achieve manually.

Accurate maps play an essential role in crisis situations by supporting the response efforts of frontline workers, aid organisations, national and international government bodies by helping them to understand the scale of impact, and effectively target and coordinate relief.

What is the CCI solution?

The Humanitarian OpenStreetMap Team (HOT) is a dedicated community that uses OSM to support responses to crises, such as urban floods and migration, by mapping vulnerable regions. In 2018, HOT launched the MapWithAI initiative (in partnership with Facebook) which elevates the collective intelligence of volunteers by using artificial intelligence (AI) to drive the speed, efficiency and scale of mapping efforts.

How is it being done?

MapWithAI uses computer vision to detect roads and terrain features of the streets on high-resolution satellite imagery. Trained using years of volunteer-labelled satellite data, complex patterns in images are identified by an algorithm known as a deep neural network segmentation model. This model estimates the probability that each pixel is part of a road, predicts and draws potential roads, and generates an enhanced image for the volunteer community through an editing tool called RapiD. Using RapiD, volunteers verify the AI generated roads, helping to identify errors in the model and contribute to its improvement.

The project initially focused on the response to flooding in Kerala, India, but has since been integrated into the HOT volunteer-management platform for deployment on other projects. Project managers and volunteers can opt-in to use the tool or continue mapping without it. Using RapiD, volunteers are able to create maps of disaster affected regions more quickly. Projects carried out through the HOT task manager platform draw on contributions from a wide range of participants including local volunteers and frontline responders, particularly for validation of remote mapping efforts.

So what? *(What is the impact? Why is this better than other approaches?)*

The new tool helps the OSM community to prioritise mapping efforts and respond more efficiently. Volunteers are still vital to the effort, as the algorithm can make mistakes. The combination of AI with crowdmapping has already led to impressive results. In Kerala, 21,500 roads were added to the map using the tool. A project in Thailand used the tool to catalogue more than 300,000 miles of roads in only 18 months, which may have taken another three to five years to achieve through 'traditional' mapping. Since December 2019, MapWithAI has generated maps for almost every country.

VALUE ADD: Combining the input from the OSM community with AI generated maps improves the timeliness, spatial coverage and granularity of maps of crisis affected environments. The process also enhances the validity of the data and information communicated through maps.

CASE STUDY 3

Common Social Accountability Platform (CSAP)

STAGE OF CRISIS: **Response, Recovery**

TYPE OF CRISIS: **Multiple**

USE CASE: **Soliciting ideas and priorities from communities for post-crisis rebuilding**

CI METHODS: **Crowdsourcing**

PEOPLE CONTRIBUTING: **Community (general), Refugees/migrants**

DATA: **Crowdsourced opinions**

TECHNOLOGY: **SMS, Radio, Information platform**

AI: **Machine learning**

TYPE OF **ORGANISATION USING: NGO, National government, Local government, Humanitarian**

What is the problem?

Following decades of unrest, Somalia is starting to move towards recovery. However, government capacity to deliver services and respond to citizen needs remains limited. A lack of established accountability mechanisms not only prevents government decisions from being informed and guided by citizen input and feedback, but also reduces citizens' trust in government to respond to their needs. In addition, there are limited channels and opportunities for meaningful interaction between citizens and the numerous aid agencies delivering support in the country.

What is the CCI solution?

The charity Africa's Voices launched the Common Social Accountability Platform (CSAP) in Somalia in 2018 to increase the inclusion of citizens in decision making across governance, humanitarian and development programmes.

CSAP tackles the gap in connecting Somali citizens to decision making through a CI approach by maximising the scale and inclusivity of dialogue between citizens and authorities. In addition, CSAP provides a robust digital platform to gather and analyse evidence on citizen perspectives (including by using AI).

The charity partners with a wide range of aid-related organisations and national and international government bodies (including Somalia Stability Fund, Oxfam, European Union, UK Foreign, Commonwealth and Development Office) to deliver projects, and provide recommendations to external stakeholders (such as policymakers).

How is it being done?

CSAP adopts a collective intelligence approach by crowdsourcing opinions from affected communities, producing citizen-generated data, and conducting complex data analytics (including AI) to analyse feedback at scale.

The platform uses Africa's Voices' interactive radio method for building dialogue and gathering public opinion. Radio programming and SMS messaging create a platform that Somali citizens actively engage in, whilst simultaneously allowing for feedback received from citizen SMS messages to be robustly analysed, understood and ultimately, acted upon.

Their method gathers insights from conversations held in local languages, on a scale otherwise unattainable for qualitative methods. The data collected is interpreted by qualitative research techniques, data science and AI to analyse discussions in local languages.

The platform uses Coda 2, a software tool built in collaboration with the University of Cambridge, which allows interpretation and effective labelling of large volumes of textual data. The tool uses AI to augment the interpretive capacities of researchers rather than to automate data analysis, enabling them to listen to and interpret a larger set of conversations in local languages.

So what? *(What is the impact? Why is this better than other approaches?)*

Since 2018, Africa's Voices has engaged more than 18,000 displaced people in Somalia in policy discussions to help with post-crisis recovery. Seventy-eight per cent of participants in CSAP stated that the process made them feel involved in decision making, and 87.4 per cent of the participants reported that engaging with CSAP made them feel involved in decision making in their community. The platform offers a sustained channel for open conversation between citizens and decision-makers, such as local and national government actors, humanitarian agencies working in the field, and other international organisations.

The interactive radio methodology used by **Africa's Voices** has also helped humanitarian agencies responding to COVID-19 to understand the local beliefs about the virus and vaccines that shape community behaviours. Their report summarising the findings of this research was used to inform communications and interventions by local NGOs.[149]

VALUE ADD: Africa's Voices supports the collection of contextually relevant data and enables more inclusive decisions by ensuring diverse and hard-to-reach perspectives are accessed. This enhances the validity of data, drives greater use of community perspectives in decision making, and improves alignment of actions/decision making with community preferences.

CASE STUDY 4

Zika mitigation with Premise

STAGE OF CRISIS: **Mitigation**

TYPE OF CRISIS: **Health**

USE CASE: **Predicting a crisis before it happens**

CI METHODS: **Citizen science, Crowdsourcing, Crowdmapping, Combining data sources**

PEOPLE CONTRIBUTING: **Community (general), Operational managers**

DATA: **Survey data, VGI, Crowdsourced observations**

TECHNOLOGY: **Mobile app, Data platform, Data repository**

AI: **Machine learning**

TYPE OF ORGANISATION USING: **Local government, Civil society**

What is the problem?

Over one million people die a year from mosquito borne diseases, and in 2016, the city of Cali in Colombia suffered the second largest Zika virus outbreak in the world as a result of a lack of data and control on mosquito populations. To prevent and limit these outbreaks, a vast amount of data is required to identify and remove breeding grounds, such as standing water. Monitoring locations across a city or region is a laborious process that requires a large number of people to regularly collect data.

What is the CCI solution?

Utilising a citizen network in and around the city of Cali, the Premise platform provided a tool to allow affected communities to crowdsource data and monitor conditions in hard-to-reach geographies. Citizens are trained through the Premise app and offered micro-payments as incentives to collect data, which can then be visualised for authorities to monitor and respond to mosquito breeding sites. The platform also enables a collective mitigation response by informing citizens of best practice in vector surveillance and control.

How is it being done?

The Premise crowdsource platform relies on a four step process: configure, collect, quality control and visualise. First, the city authority and Premise community managers establish the questions that need to be asked to the citizen network to collect the data that is required for a targeted response. This is configured into the platform with appropriate instructions to ensure a consistency and quality to data collection. The citizen contributors' network then begin collecting data, incentivised through behavioural nudges and micro-payments, and upload the data to the Premise platform. Premise utilises AI to quality control the uploaded data and identify any false or duplicative entries. Finally, this data is visualised on the Premise platform for both the community and authorities to work together to identify and remove potential breeding grounds.

So what? *(What is the impact? Why is this better than other approaches?)*

The Premise platform was set up with a community network and used throughout 2018 resulting in 615,000 inspections crowdsourced and over 54,000 separate sewage openings regularly inspected. As a result of this citizen-led monitoring and response, there was a 27 per cent reduction in high risk 'hot spots' for the yellow fever mosquito, Aedas aegypti.

VALUE ADD: Premise improves the timeliness, spatial coverage and contextual relevance of insights for better response. In particular, it increases the representativeness of data by engaging affected communities, including those in hard-to-reach geographies.

CASE STUDY 5

Dataminr

STAGE OF CRISIS: **Response**

TYPE OF CRISIS: **Natural disaster**

USE CASE: **Providing early warning of a crisis**

CI METHODS: **Natural Language Processing (NLP), Machine learning, Predictive analytics, Web scraping, Computer vision**

PEOPLE CONTRIBUTING: **Frontline (emergency responders), Community (general)**

DATA: **Social media data, Web-scraped data, Sensor data, Socioeconomic data**

TECHNOLOGY: **Data platform, API, Mobile app**

AI: **NLP, Machine learning, Predictive analytics, Web scraping, Computer vision**

ORGANISATIONS USING: **Intergovernmental, Public sector, Local government**

What is the problem?

Social media platforms, blogs and forums are just some of the platforms that are being used by individuals to share their thoughts and experiences online in real time. During unexpected, breaking events, such as natural disasters, social media content can act as an early signal and provide up-to-date information of the dynamics of a situation. Publicly available data also offers a more accurate reflection of the situation on-the-ground than official data sources. However, the speed of turnover and vast amount of posted information make it difficult to separate useful material from noise, losing an opportunity for emergency responders to make use of these early signals to plan and coordinate.

What is the CCI solution?

Dataminr's CI solution analyses citizen-generated data from social media and the wider web using AI and NLP to detect the earliest signals of high-impact events and emerging risks. Dataminr's tool First Alert has been developed specifically for application in the public sector, including in humanitarian crisis events.

How is it being done?

Dataminr's First Alert system integrates numerous non-conventional data sources, such as citizen-generated content in the form of images and free text posted on social media (which tend to increase during unexpected crises), to isolate the early signals that anticipate emergency events. The platform combines this crowdsourced data with other data streams, such as audio broadcasts from first responders and sensor data (including data from the aviation industry).

Dataminr uses a hybrid AI approach to detect anomalies and events that could have widespread public impact in the data that it scrapes. The methods are a combination of natural language processing (NLP) for text classification, computer vision for identifying images and machine-learning for audio streams. Finally, the platform uses natural language generation to issue text summaries as alerts to public sector organisations that are tasked with responding in crises.

So what? *(What is the impact? Why is this better than other approaches?)*

Thanks to Dataminr, organisations can leverage and improve their abilities to manage risks. The AI speeds up response times and increases the capacity of teams to detect, classify and determine the significance of information generated by the crowd.

When the Category-4 Hurricane Harvey hit the American South, Dataminr was able to issue an advance warning to clients about the planned closure of Houston's port, so they could make arrangements to mitigate the impact on any of their logistics and supply chains. In 2019, Dataminr announced a partnership with UN Global Pulse – a UN initiative that aims to bring real-time monitoring and prediction to development and aid programmes. The partnership supports humanitarian response by enabling UN teams access real-time information in a crisis in order to help save lives and help keep UN staff safe.

In a crisis situation, Dataminr's First Alert service and outputs can be used by public sector clients who need to prioritise where to deploy aid in a crisis, as well as private companies who might need to make arrangements to keep their workforce and supply chains secure during environmental disasters.

VALUE ADD: Dataminr improves the timeliness, spatial coverage and context relevance of data and insights by integrating non-conventional data sources. The tool triangulates multiple data sources to generate a more comprehensive understanding of a crisis as it unfolds.

Photo: NOAA at unsplash.com

CASE STUDY 6

Artificial Intelligence in Medical Epidemiology (AIME)

STAGE OF CRISIS: **Preparedness, Mitigation**

TYPE OF CRISIS: **Health**

USE CASE: **Predicting a crisis before it happens**

CI METHODS: **Combining data sources, Predictive analytics, Machine learning**

PEOPLE CONTRIBUTING: **Frontline (other)**

DATA: **Epidemiological data, Government data, Crowdsourced observations, Sensor data, Historical crisis data**

TECHNOLOGY: **API, Back-end algorithm, Data platform, Dashboard**

AI: **Predictive analytics, Machine learning**

TYPE OF ORGANISATION USED BY: **National government**

What is the problem?

Dengue is a mosquito-borne infection and major international public health concern, with severe dengue affecting many Asian and Latin American countries and up to 2.5 billion people worldwide. A major challenge in many dengue endemic countries is that disease surveillance is often passive and reliant on case reporting by health workers, meaning it can be difficult to ensure completeness and timeliness of data. Often dengue outbreaks have occurred or even passed their peak before they are registered by systems. Time delays and poor predictive capability mean that public health officials are missing vital opportunities for disease control and to implement a timely localised response.

Predicting outbreaks is of paramount importance as there is no treatment to prevent or stop dengue, and the WHO recommends that the vaccine only be given to persons with confirmed prior dengue virus infection, thereby leaving large swathes of the population in disease endemic countries at risk.

What is the CCI solution?

Artificial intelligence in Medical Epidemiology (AIME) is an early warning system incorporating AI to identify and forecast dengue outbreaks with a high accuracy and spatial precision. AIME leverages the intelligence of local doctors and healthcare professionals and combines this with a wide range of data sources and machine learning to predict (and therefore prevent) disease outbreak.

How is it being done?

AIME uses real-time data generated by doctors, who send in notifications of dengue cases via AIME's subsystem (REDINT); this can be accessed by hospitals within a community/region, enabling them to immediately update and report dengue cases to the public health municipality. Case data is combined with existing datasets of variables that influence the spread of dengue – from local terrain and elevation to roofing types and thunderstorms, as well as official data about the local population and socioeconomic variables. The AIME platform combines data and uses a machine learning algorithm in order to predict, geo-locate and determine future outbreaks.

The platform enables surveillance of current disease outbreaks, by determining their exact location, and can forecast future outbreaks.

So what? *(What is the impact? Why is this better than other approaches?)*

The predictive accuracy of the AIME platform has been tested in Malaysia, Brazil and Philippines, and has been able to predict dengue outbreaks up to three months in advance and geo-locate them up to a 400 meter radius. In Malaysia, the platform predicted dengue outbreaks with an accuracy of 81 per cent. In Brazil and the Philippines the accuracy was 84 per cent.

AIME combines data sources with machine learning to improve disease surveillance and forecasting, in turn allowing clinical and public health services to move away from passive surveillance to proactive planning and response.

VALUE ADD: AIME improves the timeliness, spatial coverage and contextual relevance of data for better preparedness and to support crisis mitigation.

CASE STUDY 7

Companion Modelling: Sequía

STAGE OF CRISIS: **Preparedness, recovery**

TYPE OF CRISIS: **Complex emergency**

USE CASE: **Modelling behaviours and interventions for crisis mitigation, Modelling behaviours and interventions for crisis recovery**

CI METHODS: **Participatory design, Agent based modelling, Companion modelling, Simulations**

PEOPLE CONTRIBUTING: **Community (farmers), Researchers, Operational managers**

DATA: **Sensor data, Crowdsourced observations**

TECHNOLOGY: **Simulations, Digital models, Open source**

AI: **Agent based modelling**

TYPE OF ORGANISATIONS USED BY: **Civil society**

What is the problem?

Natural resource ecosystems (e.g. forest, agricultural, land-use management, water) are complex to model and understand because they are affected by a wide range of factors including both environmental and human behaviours. Knowledge related to ecosystems and the factors that impact them is distributed between numerous stakeholders, such as scientists, local residents and frontline managers, who often have distinct (and sometimes competing) interests. This makes it difficult to understand the short- and long-term' impacts of environment and resource management decisions, and to tackle resource issues that require collective decision making and agreement. In the case of the Sequía Project in Uruguay, local farmers were struggling to identify and plan adaptation strategies in the face of severe drought.

What is the CCI solution?

Companion modelling uses Agent Based Models (ABMs) and role-playing games to help represent and simulate socio-economic systems for natural resource management. This participatory approach uses the collective intelligence of a wide range of stakeholders to design and implement ABMs, and features interactive simulations enabling participating stakeholders to test different scenarios and outcomes.

How is it being done?

The underlying concept of companion modelling is to use role-playing games to enable stakeholders to interact with a model or simulation of a specified resource ecosystem, and to modify the behaviour of various agents in order to understand the impact of different uses of resources. Over a series of workshops with stakeholders, the model is specified and explored while participants discuss the implications of various management decisions.

A companion modelling approach is a participatory and iterative process whereby stakeholders are involved in the definition and design of the questions, models, simulations and outputs. In turn, it is possible to collectively explore scenarios to better understand how a desired situation may be reached.

The Sequía project used Cormas, a simulation computer programme that uses ABMs. It is an open-source platform used by environmental resource researchers internationally to facilitate the design, monitoring and analysis of simulation scenarios.

So what? *(What is the impact? Why is this better than other approaches?)*

In the Sequía project, Cormas has been used to help local farmers in Uruguay identify. adaptive strategies to improve the resilience of livestock producers. The livestock sector plays a central role in the economy of Uruguay, which has the world's highest number of cattle per capita. Due to severe droughts affecting the north Uruguayan region over recent decades, animals often die or are slaughtered prematurely. The companion modelling project sought to improve the adaptive capacities of livestock farmers, such as by testing different livestock breeding strategies. Many of the farmers and technicians who participated in the workshops continued using the model to find more effective management strategies under normal and drought periods.

A companion modelling approach draws on the collective intelligence of stakeholders and data to enhance collaboration and group decision making. Outputs can be used by ecosystem stakeholders and managers to anticipate and model changes to the environment based on the input of different individuals/groups, in turn strengthening the ability of communities to manage environmental and resource challenges in the future.

VALUE ADD: Sequía enables more effective interventions, through collective understanding of impacts, dependencies, and emergent or unintended effects. It supports buy-in from different stakeholder groups about decisions and plans. In particular, it enhances engagement with citizens and other local actors, and supports collaboration between stakeholder groups (including those that may have competing interests).

Photo: Jorge Marquez at unsplash.com

CASE STUDY 8

WeFly Portal

STAGE OF CRISIS: Response

TYPE OF CRISIS: Natural

USE CASE: Enhanced coordination for distributed response

CI METHODS: Participatory design, Remote or in-situ sensing, Crowdsourcing

PEOPLE CONTRIBUTING: Operational managers, Community (general), Frontline (other)

DATA: Crowdsourced observations, UAV data

TECHNOLOGY: SMS, Chatbot, Information platform, Drones, GIS, Cartographic platform

AI: AI chatbot, Machine learning, NLP

TYPE OF ORGANISATION USING: National government

What is the problem?

Small-and-lightweight drones are increasingly being used around the world in managing disaster response and relief operations during and after crisis events. They offer an opportunity to understand the level of damage caused, deliver resources, support search and rescue effects, and map affected areas. Drones are a particularly helpful tool during large scale natural disasters, such as earthquakes, but they need to be deployed in a timely and coordinated fashion in order to ensure they are used effectively.

Unmanned aerial vehicle (UAV) registration and flight authorisation in many countries (including countries that experience frequent earthquakes, such as Nepal) is a lengthy paper-based process, requiring individuals and organisations to visit multiple offices. This makes it challenging to quickly authorise drone flight when it's needed most, to understand who is operating drones in disasters, and ultimately slows down the relief response due to poor coordination and accountability amongst responders.

What is the CCI solution?

WeRobotics have developed a prototype SMS messaging platform, the WeFly Portal, to coordinate drone deployment during disaster response. The portal acts as a CI tool by bringing together data from drone pilots and flight authority officials. Through the tool, users can register drone pilots and approve flight permissions quickly, significantly reducing the risk of drone collisions while improving coordination and accelerating response efforts. The platform uses AI-enabled chatbots to solicit the relevant information from drone pilots. WeFly also integrates citizen-generated data (i.e. public complaints) to aid authority decision making around drone use.

How is it being done?

Drone pilots send requests for flight permission directly to relevant authorities through an online app. The app uses an interactive WhatsApp bot through which pilots can request flight permissions and quickly submit details from their phone in a user-friendly way, and the public can raise complaints or inquiries about drone flights.

In addition, the prototype includes a website with public information on registering a UAV in Nepal, including the rules, regulations, contact of authorities, and more. The site also includes a secure web platform for relevant authorities to review flight permission/extension requests (including pilot information, geolocation, flight and flight plans), complaints or inquiries raised by the public, and a view of nearby flights.

The prototype platform was developed and tested with national and international stakeholders from nine countries, including the Civil Aviation Authority of Nepal (CAAN), and was based around the UAV registration and flight authorisation process in Nepal.

So what? *(What is the impact? Why is this better than other approaches?)*

While the impact and effectiveness of the WeFly Portal hasn't yet been tested and measured, the platform will greatly help official authorities coordinate drone permission approvals, particularly in time-critical contexts such as disaster response.

VALUE ADD: WeFly Portal enables enhanced coordination of drone deployment for distributed response. It also facilitates a collective understanding of impacts, dependencies, and emergent or unintended effects of drone deployment.

CASE STUDY 9

Sentry Syria

STAGE OF CRISIS: Response

TYPE OF CRISIS: Conflict

USE CASE: Providing early warning of a crisis

CI METHODS: Machine learning, Web scraping, Crowdsourcing, Remote or in-situ sensing

PEOPLE CONTRIBUTING: Frontline (other), Community (general)

DATA: Other (web-scraped data), Social media data, Crowdsourced observations, Sensor data, Historical crisis data

TECHNOLOGY: Mobile app, API, Blockchain, Chatbot, Data platform, Sensors (in situ)

AI: Machine learning, Web scraping

TYPE OF ORGANISATION USED BY: Civil society

What is the problem?

In conflict zones airstrikes have devastating consequences – causing civilian deaths and injuries on a massive scale. Densely populated neighbourhoods, hospitals, schools or other locations with high levels of civilians are often targets for strikes. It is challenging to predict when strikes will occur, and to issue time-critical warnings enabling civilians to seek safety from imminent attacks.

What is the CCI solution?

Sentry, developed by social enterprise Hala Systems, is an indication and warning system that uses a multi-sensor network to generate a real-time awareness of threats and quickly disseminate warnings. Sentry uses acoustic sensor data, reports from people on-the-ground and open media 'scraping' to detect warplanes in flight. It then uses artificial intelligence (AI) to validate information from multiple sources, and issues warnings to civilians and global stakeholders. Combining the intelligence of local community actors with a wide range of additional data sources and AI enables Sentry to give accurate warnings to affected civilians and stakeholders.

How is it being done?

Sentry combines a number of 'sensing' data sources, including data captured by sensors that detect the sound of military aircraft and reports from volunteer "plane spotters" who live near air bases and in conflict zones to predict when and where air strikes will occur.

The volunteer "plane spotter" network was an early grassroot response to airstrikes in Syria made up of trusted civilian contacts (including teachers, engineers, doctors, farmers). Plane spotters work in shifts and watch for planes, recording information in a smartphone app. Sentry combines this with data from remote acoustic sensors hidden in trees and tall buildings and data scraped from social and local media (by a machine learning algorithm) to confirm information about the plane and flight path.

The 'sensing' data inputs are validated by an AI-based model trained on historical data; the software estimates the possible target and timing of the airstrike by comparing it to past cases of attacks.

Sentry then issues alerts to citizens in affected areas five to ten minutes in advance of an airstrike to give them time to escape. Warnings are disseminated through social media (including via chat bots), TV, radio and on-the-ground sirens, and direct messages are sent to local civil society organisations, hospitals and schools.

Sentry uses blockchain technology to immutably store war crime information and citizen reports collected through the tool.

So what? *(What is the impact? Why is this better than other approaches?)*

Sentry has taken the ad-hoc system of plane spotting and added analytical precision to save many more lives. During 2017-2018, Sentry covered an area of nine Syrian governorates with a reach of over 2.3 million people and led to an estimated 20-30 per cent reduction in casualty rates in areas under heavy bombardment.

This project demonstrates how a wide range of critical data sources can be combined in areas where data is scarce, such as war zones, and validated by AI to provide a reliable and accurate prediction of time-sensitive threats. In addition to providing targeted citizens with time to prepare for attack, Sentry supports a timely and coordinated response from other local, national and international actors (i.e. doctors, charities and government bodies) who can quickly deploy support and aid where it's needed most.

VALUE ADD: Sentry Syria improves the timeliness, spatial coverage and contextual relevance of data enabling (and improving) early warning.

CASE STUDY 10

Modelling humanitarian relief in Haiti

STAGE OF CRISIS: Preparedness

TYPE OF CRISIS: Natural

USE CASE: Modelling behaviours and interventions for crisis planning

CI METHODS: Agent based modelling, GIS, Crowdsourcing, Simulations

PEOPLE CONTRIBUTING: Operational managers, Community (general)

DATA: VGI, Crowdsourced observations, Socioeconomic data

TECHNOLOGY: Digital models, Simulations

AI: ABMs, Predictive analytics

TYPE OF ORGANISATIONS USING: Not being used/unknown

What is the problem?

During and following a crisis situation, decision making at both the individual and the collective level changes rapidly due to the severe disruption caused to people's daily lives. To manage and respond to a crisis effectively, and to aid humanitarian efforts during a crisis, it is important to understand and anticipate how different groups and individuals will react in a spatially and temporally precise way.

Challenges in understanding people's behaviour during a crisis are often compounded by a lack of spatial data in less developed countries. Even in cases where spatial data is available, it often lags behind what has changed on-the-ground – for instance when the physical landscape has altered due to a natural disaster.

What is the CCI solution?

This case study outlines a prototype of an agent-based model (ABM) integrating GIS, crowdsourced geographic information and other sources of publicly available data, which seeks to explore how aid might be distributed to better support affected communities. The model uses the devastating 2010 earthquake in Haiti which is estimated to have killed 230,000 people and left more than 1.6 million people homeless. The model explores how affected communities search for food following an earthquake and allows the user to explore different scenario options for aid distribution.

How is it being done?

The model uses a diverse range of crowdsourced data including geographic information about population density, relative level of devastation, existing transportation networks, location of aid centres, and environmental parameters. The researchers used publicly available (open) data to estimate population density and OpenStreetMap data.

The simulation produces a map showing the movement of individuals throughout the environment and the spread of information about aid (e.g. food) availability, as well as graphs tracking how individual agents use different aid centres over time.

Over time more and more agents become aware of their nearest food distribution point as well as other distribution points, as information spreads throughout the system. Agents then evaluate if it is worthwhile for them to go and get food. They do this by planning the shortest path to the food via the road network.

At the end of the simulation, the model reports a series of statistics, which capture the overall health of the population as well as the final status of the aid centres (e.g. food distribution points).

So what? *(What is the impact? Why is this better than other approaches?)*

The model demonstrates how GIS and ABMs can be used to enable better planning and preparedness for future crisis events, by helping to understand agent behaviour within an environment experiencing a crisis. There is a great potential for the use of GIS and ABM to assist first responders with logistical support in natural disasters by anticipating how affected communities will respond and behave in an environment experiencing a crisis.

VALUE ADD: The model has the potential to enable more effective interventions, through collective understanding of impacts, dependencies, and emergent or unintended effects.

CASE STUDY 11

HERMES

STAGE OF CRISIS: **Response**

TYPE OF CRISIS: **Natural**

USE CASE: **Providing real-time situational information for more effective response**

CI METHODS: **Web scraping, Natural Language Processing (NLP), Machine learning, Crowdsourcing**

PEOPLE CONTRIBUTING: **Community (general)**

DATA: **Social media data, Crowdsourced observations, Other (web-scraped data)**

TECHNOLOGY: **Data platform, Mobile app, Chatbot, Information platform**

AI: **Web scraping, Natural Language Processing (NLP), Machine learning**

TYPE OF ORGANISATIONS USING: **Not being used/unknown**

What is the problem?

The widespread use of mobile phones means that many people involved in disasters publish information-rich textual and multimedia messages on social media networks, often live and in situ. Following a crisis, both natural or man-made, this data can be used to generate a situational awareness of the event and aftermath, to help governments, aid agencies and other organisations to respond. However, relevant information from social media is typically unstructured, heterogeneous and fragmented over many messages, in such a way that it cannot be directly used. Extracting and processing vast volumes of data quickly and effectively is of paramount importance for supporting emergency crisis relief efforts.

What is the CCI solution?

HERMES is a CI tool developed by the Italian National Research Council which enriches available social media data in the aftermath of disasters by identifying relevant Tweets and automatically asking follow-up questions to garner more detailed information from the person who posted the message. It leverages the collective intelligence of affected populations and wider citizens by using social media data posted in crisis events, and applies AI to effectively process the data and maximise utility.

How is it being done?

HERMES automatically complements spontaneously published data (i.e. a Tweet) with targeted solicited data by asking the person who posted the Tweet specific questions to gather further detailed information. The system listens to the stream of social media messages related to a disaster. Then, it leverages AI techniques to select a subset of relevant social media users directly involved in the disaster, from which to solicit additional information. HERMES automatically asks targeted questions to selected users, and it collects answers to those questions in real-time.

Finally, relevant information obtained via message classification or information extraction is often leveraged to produce and update crisis maps, and shared with Emergency Operation Centers.

So what? *(What is the impact? Why is this better than other approaches?)*

Results show that HERMES was able to engage far more users than comparable well-established, institutional services that seek to engage witnesses and affected populations. When compared with the USGS service 'Did you feel it?' (a survey service that collects information from people who felt an earthquake), HERMES was capable of engaging remarkably larger numbers of contributors, particularly when considering earthquakes occurring outside of the US and those having little media coverage. Engaging witnesses directly through Twitter led to more responses than a previous similar system that took witnesses to a separate survey.

The rich information gathered in real-time by HERMES can be used to help a range of governments and organisations understand the scale and impact of disaster, and effectively support frontline emergency responders to target relief.

VALUE ADD: HERMES improves the timeliness, spatial coverage and context relevance of data for better response.

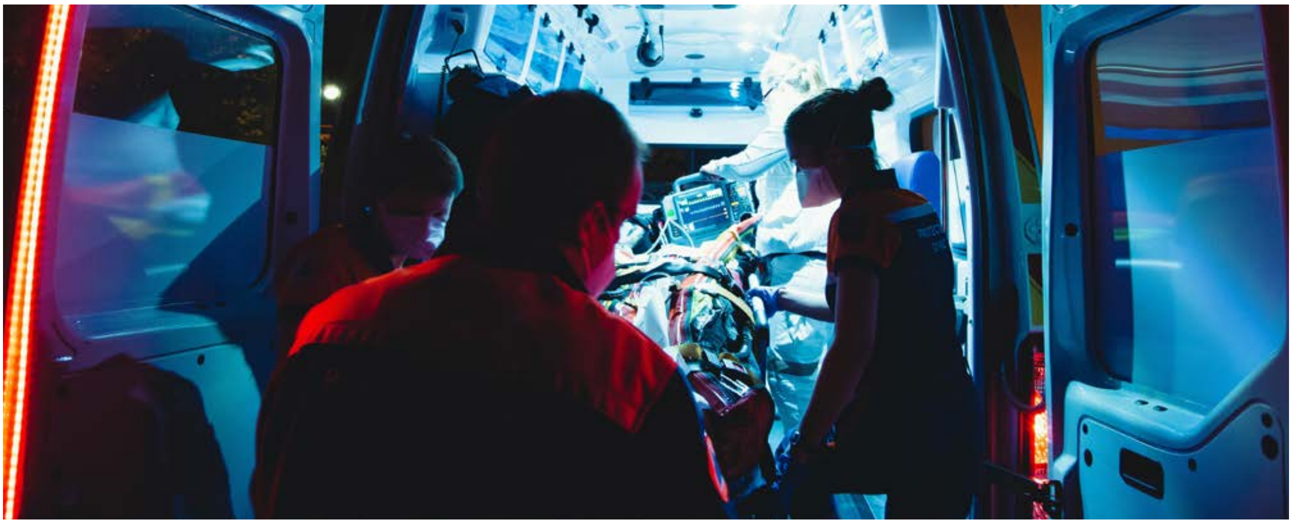


Photo: Mat Napo at unsplash.com

CASE STUDY 12

eBayanihan

STAGE OF CRISIS: **Response**

TYPE OF CRISIS: **Natural**

USE CASE: **Providing real-time situational information for more effective response**

CI METHODS: **Crowdsourcing, Crowdmapping, Machine Learning, GIS**

PEOPLE CONTRIBUTING: **Community (general), Frontline (emergency responders)**

DATA: **Social media data, Crowdsourced Observations, VGI**

TECHNOLOGY: **Mobile app, Data platform, SMS, GIS**

AI: **Machine learning**

ORGANISATIONS USED BY: **National government**

What is the problem?

When a natural disaster strikes, such as Typhoon Lando (Koppu) in the Philippines, it can be challenging for affected communities to communicate with first responders about the scale of the disaster and the support that is required. Equally, first responders, operational managers and government agencies often use a multitude of data sources to coordinate response that do not always reflect the support needs of affected groups.

What is the CCI solution?

eBayanihan is a muti-channel platform that enables citizens to view and upload reports of natural disasters and community needs, providing a direct link to first responders, operational managers and government agencies. Citizens are therefore able to express the support that is required in their affected communities, rather than responders focusing on the mapped impact of the natural disaster. First responders, operational managers and government agencies therefore have a single source of data that informs how to target their response, visualised through a dashboard and interactive map.

How is it being done?

Affected communities uploaded citizen reports (CitReports) that describe the damage caused by Typhoon Lando, as well as the needs of the community, such as shelter, food and water via multiple channels including SMS, web and an app. Machine learning algorithms help to model and validate these crowdsourced CitReports – categorising and visualising them for operational teams to respond to. These feed into a real-time dashboard visualising incidents and automating notifications to people managing, responding to or coordinating the response of natural disasters.

So what? *(What is the impact? Why is this better than other approaches?)*

At its launch, eBayanihan had 1,344 active users and during Typhoon Lando there were 299 reports made by users. Due to the infancy of the platform, this shows a relatively low level of participation during the event, however, increasing usage of the reporting tool and dashboard would build a vital connection between affected communities and those responding during future events.

VALUE ADD: eBayanihan improves the timeliness, spatial coverage and context relevance of data and insights for better response. It ensures alignment of response/ resource allocation with community needs and priorities.

Appendix

SUPPLEMENTARY FIGURES/ANALYSIS

Figure 24: Co-occurrence of different data types among CCI solutions (Section 1.4)

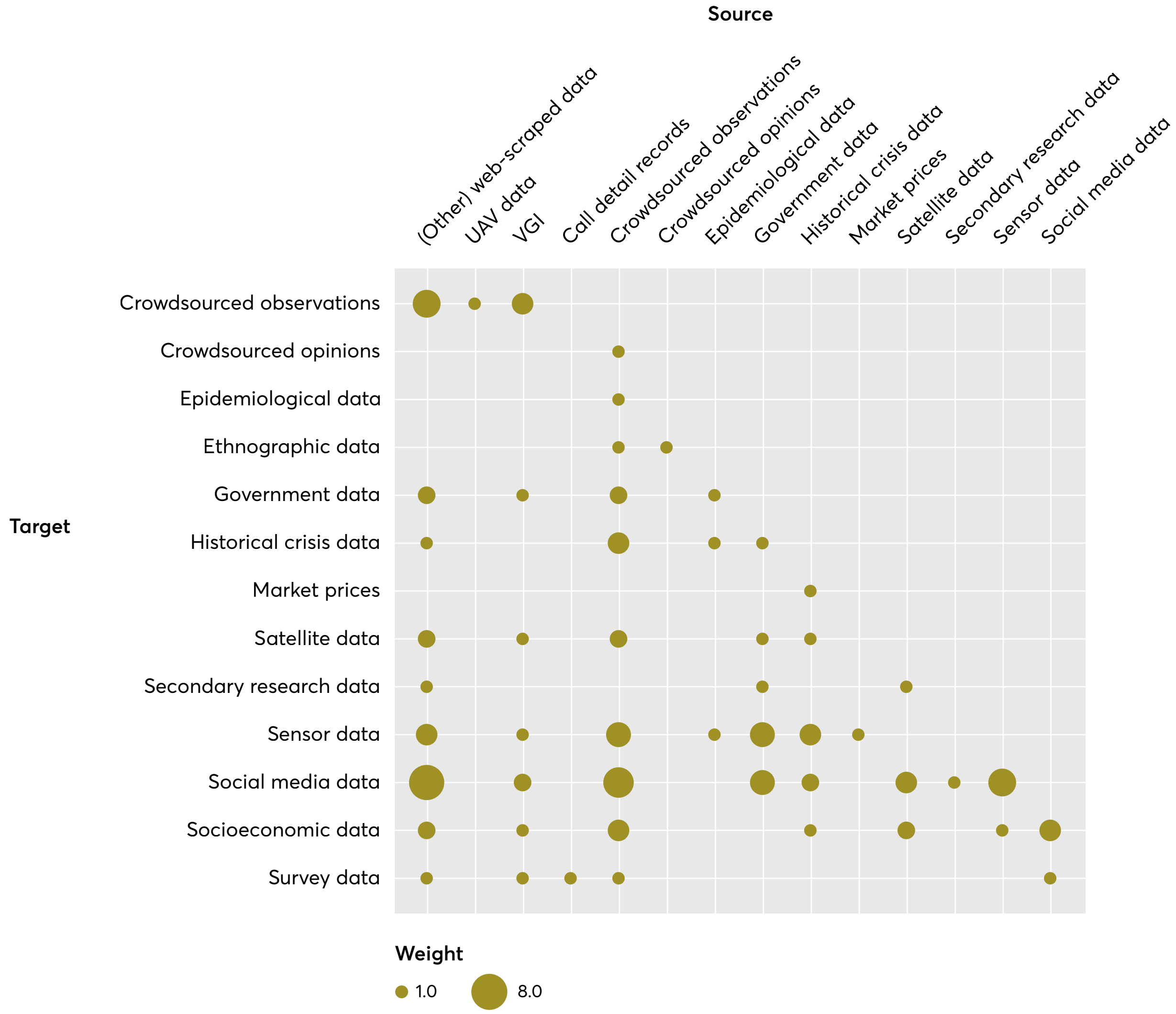


Figure 25: Types of technology used among CCI solutions (Section 1.4)

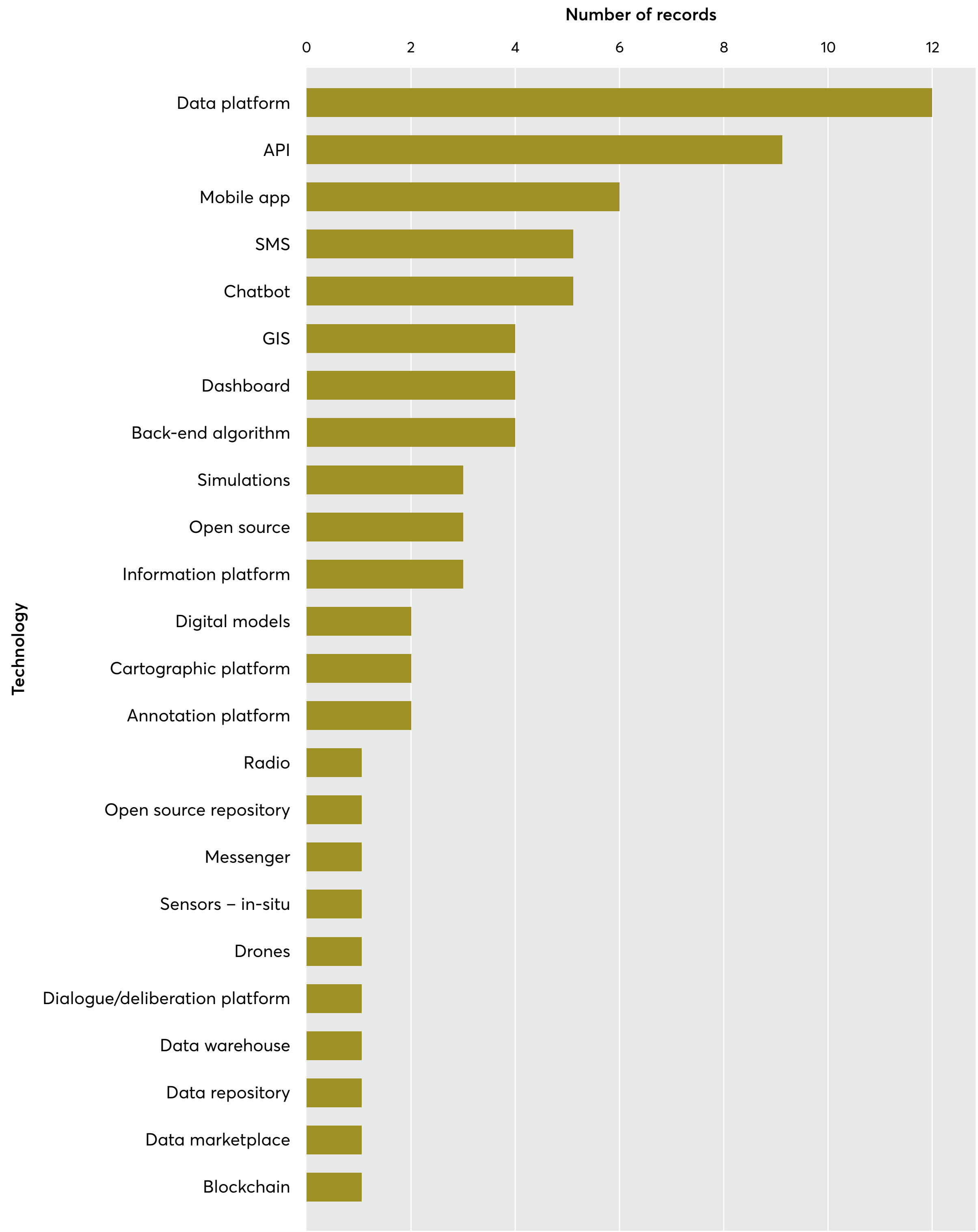


Figure 26: Co-occurrence of techniques and methods (Section 1.4)

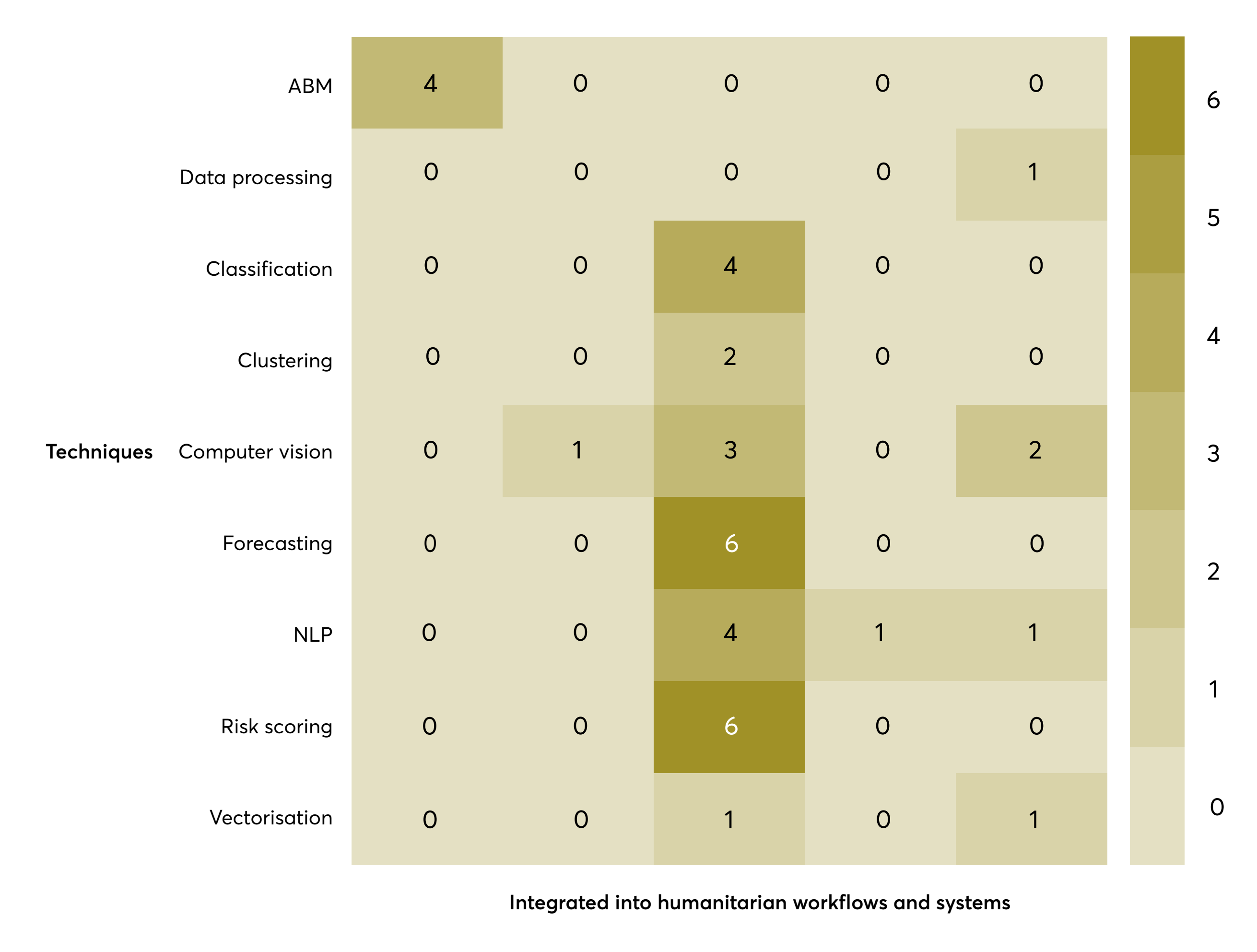


Figure 27: Algorithms applied by technique and method (Section 1.4.2)

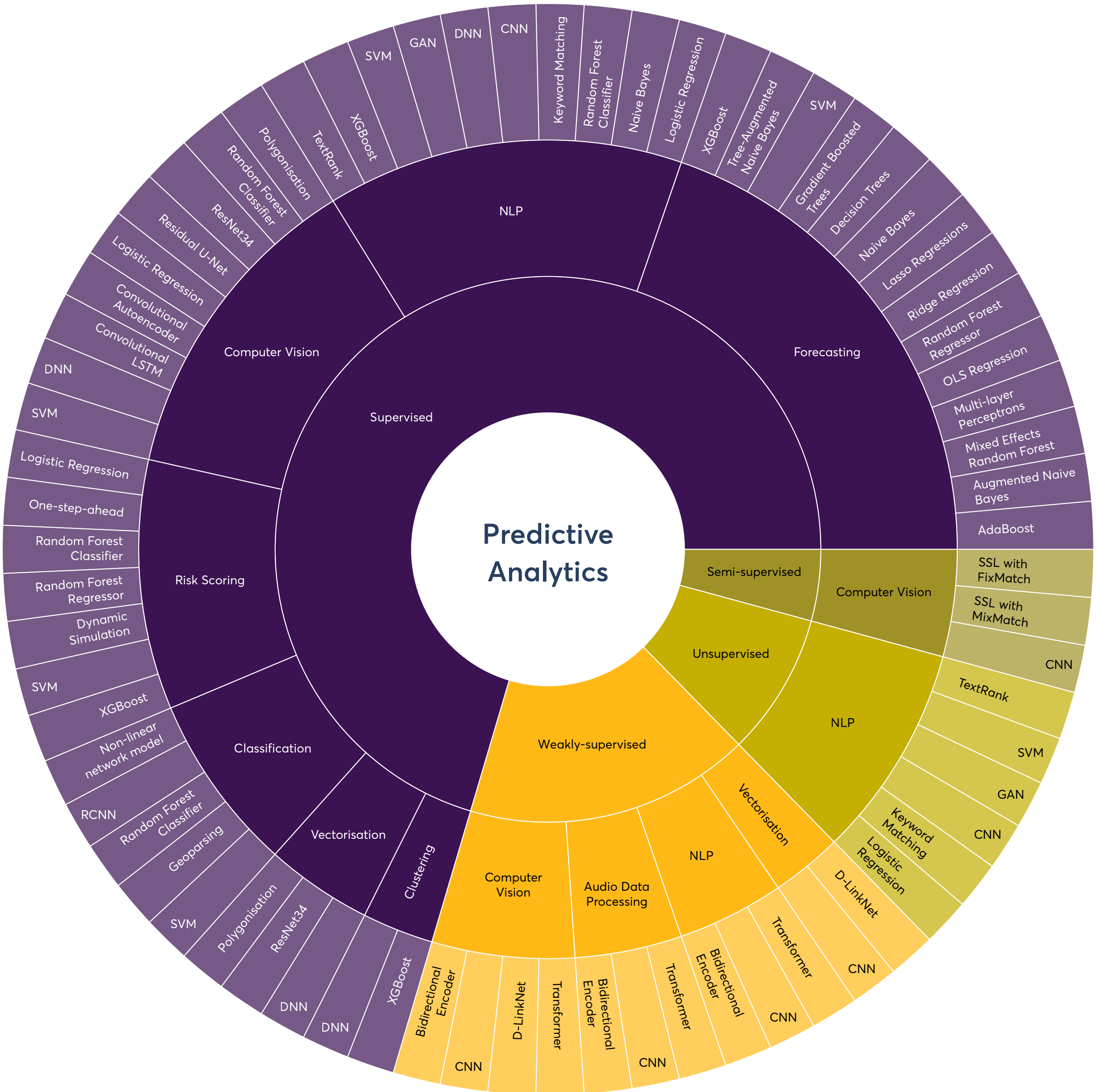
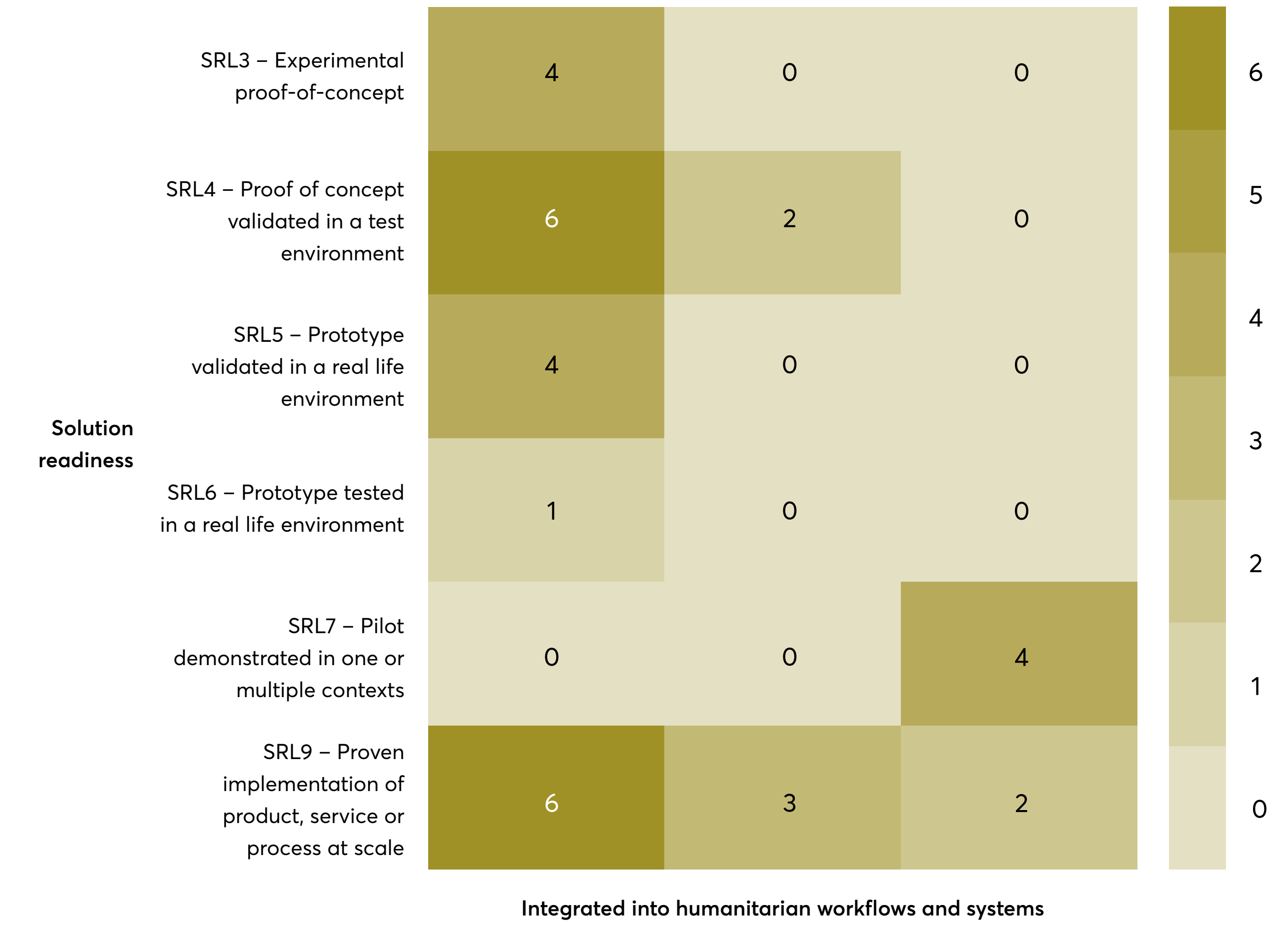


Figure 28: Correlation between Solution Readiness and integration in humanitarian systems (Section 1.5.1)



SUPPLEMENTARY CASE STUDIES

Supplementary case study 1

Early Warning Project (not CCI)

STAGE OF CRISIS: Preparedness

TYPE OF CRISIS: Conflict

USE CASE: Predicting a crisis before it happens

CI METHODS: Crowd forecasting, Predictive analytics, Machine learning, Combining data sources, Wiki survey

PEOPLE CONTRIBUTING: Frontline (other), Academics, Public

DATA: Crowd predictions, Socioeconomic data, Historical crisis data

TECHNOLOGY: Wiki survey, Crowd predictions platform

AI: Predictive analytics, Machine learning

ORGANISATIONS USED BY: Academic, NGO

This case study did not qualify under our definition of CCI as it doesn't draw on insights from affected communities or frontline workers.

What is the problem?

Triggers for humanitarian crises, such as mass genocide, are difficult to predict in advance due to their rare occurrence and the variety of contributing factors, some of which can change with little warning. The ability to accurately estimate the likelihood of genocide and mass atrocities could help better coordinate responses and prevent some of the trauma and devastation caused by these crimes.

What is the CCI solution?

The Early Warning Project (EWP) aims to address this challenge by leveraging the collective intelligence of crowds and experts, through crowd forecasting and ranking, and combines this with statistical modelling. The EWP seeks to identify countries where mass atrocities have not yet begun, but where the risk is high.

How is it being done?

The project was divided into three phases. During the first phase, EWP ran an annual comparison survey, which is open to the public for a month and is promoted to experts including policymakers, NGOs, and scholars in international affairs. Within the survey participants ranked pairs of countries by choosing which they perceived to be more likely to experience a new mass killing.

The results from the survey informed the selection of 17 'higher risk' countries, which the EWP then tracked in real time using 'crowd forecasting'. Crowd forecasts are calculated by aggregating many individual judgements about the likelihood of events, ranging from the outcomes of political elections to the winning teams for international sporting events. Participants can update their estimate over time depending on how different factors that influence the outcome evolve. In the EWP, crowd forecasting took place over the course of a year. Previous research on crowd forecasting has suggested that a non-specialist crowd made up of members of the general public can predict geopolitical events more accurately than individual intelligence analysts.

Alongside these human-based predictions, the EWP calculated a risk assessment score using statistical algorithms, one of which relies on a classical machine-learning method called 'random forest'. The algorithms generated their estimates based on more than 30 different variables from historical datasets, ranging from basic facts about the country, such as population size, to more specific measures of attitudes on human rights and civil liberties.

So what? *(What is the impact? Why is this better than other approaches?)*

The EWP produced a ranked list of more than 160 countries, based on their likelihood of experiencing a mass killing, in order to better target preventative action by governments and charities. Mass atrocities are rare events that have little historical precedent and so the EWP's approach ensures that weak signals from the crowd consensus predictions help address gaps in the statistical risk assessment and expert recommendations. The project is an example of combining different complementary capabilities of humans and AI to inform decision making.

Supplementary case study 2

WikiRumours (not CCI)

STAGE OF CRISIS: Response

TYPE OF CRISIS: Multiple

CI METHODS: Crowdsourcing

PEOPLE CONTRIBUTING: Frontline (other), Community (general), Community (refugees/migrants), Researchers

DATA: Citizen generated data

TECHNOLOGY: SMS, Data platform, Dashboard, API

ORGANISATIONS USED BY: NGOs

This case study did not qualify under our definition of CCI as it doesn't use AI.

What is the problem?

The Coronavirus pandemic has accelerated the scale and spread of misinformation and disinformation, which has a significant impact on humanitarian organisations' ability to work in affected communities, such as Médecins Sans Frontières (MSF) operating in Somalia and Afghanistan during the COVID-19 pandemic. Health misinformation and rumours often reduced trust in medical teams and limits health-seeking behaviour from the community, while disinformation can amplify these behaviours or even lead to attacks on health workers and institutions.

What is the solution?

WikiRumours is an open source web and mobile platform initially developed to prevent the spread of misinformation and disinformation, by involving members of the community in a 'debunking' process. The platform enables people to either directly identify and report misinformation and disinformation, or for a community representative to report directly to the tool. These instances of misinformation and disinformation can either be by word of mouth, or more frequently now, shared on social media. Once identified, a moderator triages the report based on severity and impact for MSF to respond to. If an intervention is required, MSF works with the communities to debunk the misinformation or disinformation.

How is it being done?

WikiRumours relies on data inputted either directly from the community through SMS or an online portal, or via a proxy community liaison within MSF who works with communities to identify any rumours circulating about health misinformation or disinformation. These rumours are then triaged by MSF officers to identify whether it is misinformation or disinformation, as well as the proliferation and impact of the report. For reports that are spreading fast within the community or have a big impact on MSF operations, an intervention is planned such as debunking the misinformation and disinformation with members of the community. This tool does not currently utilise AI, however, there are future use cases being considered such as automated identification of misinformation and disinformation spreading on social media.

So what? *(What is the impact? Why is this better than other approaches?)*

The project is in its infancy, however, the tool is already having a positive impact on MSF operations. Field teams are better prepared and able to respond to the rumours circulating in the communities they are operating in, and misinformation and disinformation can be identified promptly with interventions devised to limit the spread and impact of the incident.

Photo: Ryan Wilson at unsplash.com

TABLE OF ALL CASE STUDIES ANALYSED

These case studies were drawn from Nesta's existing repositories and publications of collective intelligence case studies, expert interviews, and a rapid review of the academic and grey literature on humanitarian crises, emergency response and disaster risk reduction.

	Title	Source	CCI case study	Part of 33 PA case studies	Solution description
1	**Sentry Syria**	aiforsocialgood.github.io/neurips2019/accepted/track1/pdfs/73_aisg_neurips2019.pdf	Y	Y	Sentry Syria is an early warning system that alerts Syrian citizens of a possible airstrike. Sentry is an AI solution that uses CI, such as social media, news reports and on-the-ground reports, as well as remote sensing to make predictions.
2	**Dataminr for humanitarian response**	www.dataminr.com/blog/multi-modal-fusion-ai-for-real-time-event-detection	Y	Y	Dataminr is an AI platform that uses techniques such as Computer Vision, Natural Language Processing and Audio Processing to detect risks and events. The Dataminr First Alert tool has been used in humanitarian crisis events.
3	**RapiD (MapWithAI)**	ai.facebook.com/blog/mapping-roads-through-deep-learning-and-weakly-supervised-training	Y	Y	RapiD is a collaboration between the Humanitarian OpenStreetMap Team (HOT) and Facebook to use computer vision on satellite imagery to predict road locations in under mapped areas.
4	**Targeting the Ultra-Poor Program (TUP)**	www.jblumenstock.com/files/papers/jblumenstock_ultra-poor.pdf	Y	Y	Research applying machine learning to mobile phone call records and household survey data to predict the probability of households having 'ultra-poor' status.
5	**Project Jetson**	jetson.unhcr.org/index.html	Y	Y	Project Jetson uses a range of machine learning techniques to predict the numbers of people who will be displaced and where in Somalia. Data considered for the model include market prices for basic commodities, rainfall and incidents of violent conflict.
6	**eBayanihan/Agos**	ebayanihan.ateneo.edu	Y	Y	eBayanihan is a disaster management system which crowdsources information from citizens. The system uses machine learning algorithms to validate crowd sourced reports.
7	**Monitoring of the Venezuelan exodus through Facebook's advertising platform**	journals.plos.org/plosone/article?id=10.1371/journal.pone.0229175	Y	Y	Research that uses Facebook advertising data from the Facebook API to estimate the number of displaced Venezuelans.

Table of all case studies analysed (continued 1)

	Title	Source	CCI case study	Part of 33 PA case studies	Solution description
8	**Hybrid sensing for EmeRgency ManagEment System (HERMES)**	www.sciencedirect.com/science/article/abs/pii/S157411922030081X	Y	Y	HERMES is a CI tool that uses AI to scape and later enrich social media data in the aftermath of disasters. It leverages the collective intelligence of affected populations and wider citizens by using social media data.
9	**Artificial Intelligence in Medical Epidemiology (AIME)**	www.scitechnol.com/peer-review/utilizing-artificial-intelligence-as-a-dengue-surveillance-and-prediction-tool-P0vC.php?article_id=9445	Y	Y	AIME uses machine learning techniques to spatially forecast dengue outbreaks in Malaysia. The solution uses historical dengue data.
10	**Managing Information for Natural Disasters (MIND)**	medium.com/pulse-lab-jakarta/managing-relevant-information-in-the-aftermath-of-natural-disasters-launching-pljs-latest-data-de3b4cbae07b	Y	Y	MIND is an open source disaster management platform created by UN Global Pulse that processes humanitarian data into a data pipeline which is then presented on the platform. MIND uses AI and CI during processing.
11	**Modelling humanitarian relief in Haiti**	www.sciencedirect.com/science/article/pii/S0198971513000550	Y	Y	An Agent Based Model that uses GIS, crowdsourced geographic information and other sources of publicly available data to model aid distribution.
12	**Common Social Accountability Platform (CSAP)**	interactive.africasvoices.org/csap/index.html	Y	Y	CSAP collects citizen SMS messages from citizens in Somalia to better understand what they think about critical topics.
13	**Companion Modelling – Sequía**	jasss.soc.surrey.ac.uk/17/1/6.html	Y	Y	An Agent Based Model to understand the impact of pasture growth, herd dynamics and agent behaviour on livestock producers facing drought conditions in Uruguay.
14	**Text Analytics for Resilience-Enabled Extreme Events Reconnaissance**	arxiv.org/pdf/2011.13087.pdf	Y	Y	A research project that uses Natural Language Processing and CI (through news and social media data) to automatically generate disaster reconnaissance reports.

Table of all case studies analysed (continued 2)

	Title	Source	CCI case study	Part of 33 PA case studies	Solution description
15	**Internal Displacement Event Tagging Extraction and Clustering Tool (IDETECT)**	www.internal-displacement.org/monitoring-tools/monitoring-platform	Y	Y	IDETECT uses Natural Language Processing to extract displacement information from news and UN and NGO reports.
16	**Artificial Intelligence for Digital Response (AIDR) / Human-annotated Twitter Corpora for NLP of Crisis-related Messages**	aidr.qcri.org	Y	Y	Artificial Intelligence for Digital Response is an open source tool that collects and classifies social media data related to humanitarian crises. Natural Language Processing is used to classify the social media messages.
17	**Early Warning Project**	earlywarningproject.ushmm.org	N	Y	The Early Warning Project uses machine learning to predict the risk of mass atrocities in countries around the world.
18	**AI-detected open building**	www.hotosm.org/projects/ai-assisted-humanitarian-mapping	N	Y	The Humanitarian OpenStreetMap Team (HOT) and Microsoft collaborated to use computer vision on satellite imagery to predict building footprints in Uganda and Tanzania.
19	**Mixed Migration Foresight**	data.humdata.org/dataset/2048a947-5714-4220-905b-e662cbcd14c8/resource/be6ab2c8-f3c4-4045-9acf-529f6091c253/download/drc-model-card.pdf	N	Y	IBM and the Danish Refugee Council collaborated to use machine learning to predict total forced displacement. Open source data from the World Bank, ACLED, UN, etc. was used.
20	**510 Typhoon Model**	www.510.global/philippines-typhoon-haima-priority-index	N	Y	The project is an initiative of the Netherlands Red Cross. Machine learning techniques were used to predict building damage ahead of a typhoon in order to identify priority areas for humanitarian aid.
21	**Predicting Food Crises**	documents.worldbank.org/en/publication/documents-reports/documentdetail/304451600783424495/predicting-food-crises	N	Y	Research project that uses structural, environmental, violent conflict and food price data to predict countries at risk of a food crisis.

Table of all case studies analysed (continued 3)

	Title	Source	CCI case study	Part of 33 PA case studies	Solution description
22	**Cholera Artificial Learning Model (CALM)**	arxiv.org/abs/1902.06739	N	Y	CALM uses machine learning models to forecast the number of new cholera outbreaks in Yemen. CALM utilises epidemiological, rainfall and conflict data.
23	**Predicting Cholera Risk in Yemen**	earthobservatory.nasa.gov/images/147101/predicting-cholera-risk-in-yemen	N	Y	A team of NASA funded researchers used satellite and ground-based data to predict cholera risk in Yemen. The UK international development office and UNICEF have used the model's results.
24	**Flee**	bura.brunel.ac.uk/bitstream/2438/12519/1/Fulltext.pdf	N	Y	Flee is a research project that uses Agent Based Modelling to simulate the movement of refugees after the Mali civil war in 2012.
25	**Hunger Map Live**	hungermap.wfp.org	N	Y	Hunger Map is a global hunger monitoring system created by the World Food Programme. It uses several data sources, such as food security information, weather, conflict, etc. and machine learning to predict global hunger risk.
26	**InaSAFE – Flood impact model**	fba.inasafe.org	N	Y	InaSAFE is a tool that predicts the impact following an extreme event, such as flooding. It combines information about the event together with country vulnerabilities to make predictions.
27	**Predictive Analytics to Identify Children at High Risk of Defaulting From a Routine Immunisation Program**	pubmed.ncbi.nlm.nih.gov/30181112	N	Y	A research project that uses machine learning techniques and demographic data to predict the risk of children missing their follow-up immunisation visits.
28	**Violence Early-Warning System (ViEWS)**	www.pcr.uu.se/research/views	N	Y	Violence Early-Warning System (ViEWS) is a tool that uses machine learning techniques to forecast risk of political violence. ViEWS provides forecasts 36 months into the future.
29	**Predicting Wildfires from Historical Remote-Sensing Data**	arxiv.org/pdf/2010.07445.pdf	N	Y	Google Research and Stanford University collaborated on a research project to use deep learning techniques and satellite imagery to identify wildfires.

Table of all case studies analysed (continued 4)

	Title	Source	CCI case study	Part of 33 PA case studies	Solution description
30	**Mapping New Informal Settlements**	arxiv.org/pdf/2008.13583.pdf	N	Y	A research project that uses machine learning and satellite imagery to identify informal settlements of Venezuelan refugees in Colombia.
31	**Assessing Post-Disaster Damage from Satellite Imagery**	arxiv.org/pdf/2011.14004.pdf	N	Y	A research project that explores the use of semi-supervised learning (SSL) to train machine learning models to identify building damage from satellite imagery.
32	**Kimetrica – Forecasting forced displacement due to conflict**	kimetrica.com/our-projects	N	Y	Research by Kimetrica applying machine learning techniques and open source data to forecast displacement in Ethiopia.
33	**Global Urban Analytics for Resilient Defence (GUARD)**	www.turing.ac.uk/research/research-projects/global-urban-analytics-resilient-defence	N	Y	Research to predict if human settlements will be in states of peace or conflict one year in advance. The model used first principles mathematical modelling and AI to make predictions.
34	**WeFly Portal**	blog.werobotics.org/2020/12/07/launching-a-digital-solution-to-expedite-drone-flight-permissions-for-disaster-response	Y	N	Tool to coordinate drone deployment during crises for more efficient response. The platform uses SMS messages to register pilots and approve flight permissions.
35	**PetaBencana.id: Risk Map**	www.oecd.org/gov/innovative-government/embracing-innovation-in-government-indonesia.pdf	Y	N	PetaBencana.id combines citizen generated social media reports with official data to provide a real-time online flood map.
36	**Zika mitigation with Premise**	www.premise.com/fighting-zika-with-digital-vector-surveillance-cali-colombia	Y	N	Citizen collected data about mosquito breeding grounds is combined with AI (through the Premise tool) to provide quality control recommendations.
37	**Haze Gazer**	hazegazer.org	Y	N	Haze Gazer combines satellite, population and citizen-generated data to provide near real-time information on fire outbreaks.
38	**Humanitarian Operations Planning Environment (HOPE)**	humanitydatasystems.com/hope	Y	N	HOPE uses analytics and AI to create scenario simulations that inform aid delivery. Data used by the tool includes, social media data, GIS and data collected from local actors.

Table of all case studies analysed (continued 5)

	Title	Source	CCI case study	Part of 33 PA case studies	Solution description
39	**Flood Management EWS India**	darpg.gov.in/sites/default/files/70.%20Flood%20Early%20Warning%20SystemFLEWS-Documentation-Final.pdf	Y	N	Flood risk modelling and real-time sensing to generate advance warnings to citizens and government authorities.
40	**Safe Water Optimization Tool (SWOT)**	www.safeh2o.app	Y	N	SWOT generates site-specific chlorination recommendations using AI and frontline water samples. It generates a site-specific free residual chlorine (FRC) target.
41	**Community Water Watch (FloodTags)**	www.floodtags.com	Y	N	Sensor data, media data and direct messages from on-the-ground volunteers are used to generate hyperlocal updates on flooding.
42	**Open Cities AI Challenge for Disaster Reduction**	www.drivendata.org/competitions/60/building-segmentation-disaster-resilience	Y	N	Computer vision was applied to high-resolution drone imagery and local OpenStreetMap data to predict building footprints in African cities.
43	**Remesh: Inclusive Peacebuilding through Dialogue**	aiforsocialgood.github.io/neurips2019/accepted/track1/pdfs/105_aisg_neurips2019.pdf	Y	N	Large-scale polling and interactive question-answering to build up a view of consensus on issues to help with recovery.
44	**Translators without Borders**	translatorswithoutborders.org/chatbot-release-northeast-nigeria	Y	N	Chatbot developed to improve COVID-19 understanding in northeast Nigeria. The chatbot allows citizens and community members to message questions in their language and receive answers immediately.
45	**Humanitarian Tracker**	www.humanitariantracker.org	Y	N	Platform through which citizen journalists can share eye-witness reports worldwide, about human rights violations, disease spread, rape, conflicts, or disasters.

Glossary

Term	Definition
Stages of crisis response: Mitigation	The lessening or limitation of the adverse impacts of hazards and related disasters.
Stages of crisis response: Preparedness	The knowledge and capacities developed by governments, professional response and recovery organisations, communities and individuals to effectively anticipate, respond to, and recover from, the impacts of likely, imminent or current hazard events or conditions.
Stages of crisis response: Response	The provision of emergency services and public assistance during or immediately after a disaster in order to save lives, reduce health impacts, ensure public safety and meet the basic subsistence needs of the people affected.
Stages of crisis response: Recovery	The restoration, and improvement where appropriate, of facilities, livelihoods and living conditions of disaster-affected communities, including efforts to reduce disaster risk factors.
Rapid onset disasters	A rapid or sudden onset disaster is one triggered by a hazardous event that emerges quickly or unexpectedly. Rapid onset disasters could be associated with, e.g., earthquake, volcanic eruption, flash flood, chemical explosion, critical infrastructure failure, transport accident.
Collective intelligence	At its simplest, collective intelligence can be understood as the enhanced capacity that is created when people work together, often with the help of technology, to mobilise a wider range of information, ideas and insights. Collective intelligence emerges when these contributions are combined to become more than the sum of their parts.
Collective crisis intelligence	Solutions that bring together Artificial Intelligence (AI), novel data sources and the participation of affected communities and frontline emergency workers to anticipate or respond to humanitarian crises.
Artificial intelligence	Intelligent technology systems that react to inputs from the environment to take actions that can affect that environment. This includes everything from the back-end algorithms that power Google's search engines and voice assistants on smartphones to AI-powered hardware systems like robots and autonomous vehicles.
Citizen-generated data	Citizen-generated data is a broad category that includes any information that can be collected from people either by active involvement (e.g. videos, reports, ideas – usually using digital platforms) or passively (e.g. transactions data, call detail records, wearables).
Citizen science	Citizen science is any process where scientists and (usually unpaid) volunteers work together to collect or process scientific data or observations. Citizen science unlocks new resources for research, experimentation and analysis by opening the process to anyone.
Combining data sources	Collective intelligence depends on the trust and goodwill of participants. Organisations must prioritize people and purpose over technology – and ensure their projects promote data empowerment, not data extraction.
Computer vision	The ability of a computer to understand, analyse or generate images and/or videos. Frequently used to help classify drone or satellite images or user-generated images.
Crowd forecasting	Crowd forecasting is a method that asks small or large groups to make predictions about the future. Individual predictions are aggregated using statistics into a consensus crowd forecast. It's inspired by research which showed that small crowds of nonexperts can often forecast political events more successfully than individual experts.

Glossary (continued)

Term	Definition
Crowdmapping	Crowdmapping is a type of crowdsourcing which gathers data from different sources (including social media, text messages or geographic data) to provide real-time, interactive information about issues on-the-ground. Crowdmapping can create detailed almost real-time data in a way that a top-down, centrally-curated map may struggle to replicate.
Crowdsourcing	Crowdsourcing is an umbrella term for a variety of approaches that source data, information, opinions or ideas from large crowds of people, often by issuing open calls for contribution. It can help bring new ideas to light that hadn't previously been considered, or to gather expertise from people who have specialised knowledge or understanding of an issue.
Microsurveys	Microsurveys are a short, abbreviated form of surveying which typically take the respondent only a few minutes to complete. Microsurveys are often delivered by mobile phone, text message or a digital platform. Benefits include a much faster turnaround, and higher frequency of results, compared to traditional surveys.
Natural Language Processing	NLP allows computers to understand, interpret and extract key information from human language. NLP techniques can be used to carry out automated analysis of user-generated text from sources like social media, to better understand what issues matter to people, translate languages or simulate language.
Open data	Open data is the raw data that is gathered by people or organisations and published in an electronic format that machines can read. It's then shared online and allowed to be reused by others instead of keeping it private.
Open source repository	An open source repository is a digital repository where content (e.g. code, text or DIY designs) can be stored and freely downloaded with few restrictions on use. Many open source repositories aid collaboration by providing a space for uploading documentation, monitoring and version control.
Peer-to-peer exchange	Peer-to-peer exchange refers to the process of sharing information horizontally to build and maintain a community, to collect data, connect people or send alerts. Platforms for this vary, ranging from messaging platforms to online forums or collaborative platforms. Some rely on the internet but others do not (e.g. SMS or mesh networks).
Predictive analytics	Predictive analytics encompasses a variety of statistical techniques that enable a computer to analyse structured data using numeric and machine-readable data. It typically relies on algorithms from classical machine learning. It can be used to make predictions about the future or otherwise unknown events.
Remote or in-situ sensing	Collecting information from satellites or physical sensors recording actions and physical changes (e.g. traffic cameras, weather sensors, ambient sensors, wearables or drones). This data can provide cheap, real-time measurements of anything from pollution to crop yields.
Web scraping	Web scraping is a method for extracting unstructured data from across the web, such as company websites or social media. Where official datasets are costly to gather and infrequently updated, web scraping can provide more timely insights into social or economic trends.

Technical glossary

Term	Definition
Machine Learning	A branch of Artificial Intelligence that uses data to identify patterns.
Supervised Learning	A machine learning approach that uses abelled data to train a model to predict outcomes.
Unsupervised Learning	A machine learning approach that uses unlabelled data to recognise patterns and group together data points.
Weakly-supervised Learning	A machine learning approach that uses a limited number of labeled data points to make predictions that signal what the labels could be. These weak labels are then validated by domain experts to create labels suitable for supervised learning.
Semi-supervised Learning	A machine learning approach that uses unsupervised learning to create pseudo labels for data that can then be used in a supervised learning problem.
Deep Learning	A branch of machine learning that employs artificial neural network algorithms.
Artificial Neural Networks	A subset of machine learning algorithms that recognise patterns in data using a computational approach that is loosely modelled on the human brain.
Computer Vision	A branch of Artificial Intelligence that enables computers to process and extract information from images and video.
Natural Language Processing	A branch of Artificial Intelligence that enables computers to process and extract information from natural language.
Logistic Regression	A classification algorithm used in machine learning to make binary predictions.
Convolutional Neural Networks	A class of artificial neural networks often applied to image data.
XGBoost	Machine learning algorithms that use multiple decision trees to make predictions.
Random Forest	Machine learning algorithms that use multiple decision trees to make predictions. Not to be confused with XGBoost.
Support Vector Machines	Supervised machine learning algorithms that can be used for classification and regression.
Remote Sensing Data	Data acquired from a distance, e.g. satellite data.
Agent Based Modelling (ABM)	ABM is a simulated environment that consists of actors (the agents) whose response to external factors can be tested.

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Expert interviewees and contributors

Name	Category	Role	Organisation	Date interviewed
Matt Thomas	Expert (trends)	Head of Strategic Insight and Foresight	British Red Cross	20/05/21
Ian Gray	Expert (trends)	Freelance humanitarian consultant		20/05/21
Barnaby Willitts-King	Expert (trends)	Senior Research Fellow, Humanitarian Policy Group	ODI	26/05/21
Aarathi Krishnan	Expert (trends)	Strategic Foresight Advisor	UNDP	26/05/21
Christina Bennett	Expert (trends)	CEO	Start Network	07/06/21
Jamilee Al Doueihy	Frontline responder/ volunteer	WASH Regional Program Officer	IFRC MENA (Based in Lebanon)	26/05/21
Teo Ignacio Landoni	Frontline responder/ volunteer	Youth Volunteer	Argentine Red Cross	21/05/21
Volunteer*	Frontline responder/ volunteer	Mass Care Sheltering Service Associate	American Red Cross	02/06/21
Serhii Panasenko	Frontline responder/ volunteer	PMER Officer	Ukrainian Red Cross	21/05/21
Ewan Oglethorpe	Expert (technical)	Executive Director – Data Friendly Space	Data Friendly Space	11/05/2021
Leonardo Milano	Expert (technical)	Predictive Analytics Team Lead	The Centre for Humanitarian Data	25/05/2021
Robert Soden	Expert (technical)	Associate Professor, Member of World Bank Working Group on Responsible AI in the Humanitarian Sector	University of Toronto	18/05/2021
Zineb Bhaby	Expert (technical)	Chief Technology Officer	iMMAP	15/06/2021
John Jaeger, Bellamy Hanoian, Dan Henebery, Alba Topulli,	Case study	Sentry Syria Team	Hala Systems	17/05/2021

*This participant has requested to be anonymous in the final report.

Expert interviewees and contributors (continued)

Name	Category	Role	Organisation	Date interviewed
Anna Colom, Isaack Mwenda, Alexander Simpson	Case study	Common Social Accountability Platform (CSAP) Team	Africa's Voices	21/05/2021
Joseph Muhlhausen	Case study	Head of Drone Data & System – WeFly Team	WeRobotics	17/06/2021
Jeffrey Stulmaker, Gary Ellis	Case study	Remesh team	Remesh	05/08/2021
Weisi Guo	Expert (technical)	Chair of Human Machine Intelligence – Cranfield University; Visiting Fellow – Alan Turing Institute	Cranfield University Alan Turing Institute	30/06/2021
Edward Zvekic, Caliope Sandiford, Wendeline Feltz-Van-Der, Ian O'Donnell, Matt Thomas	IFRC contributors		IFRC	Focus group held: 27/05/21

IFRC survey responses

	English survey (n=8)	French survey (n=6)
National Societies within the IFRC	• The Bahamas • Myanmar • Liberia • Norway • UK • Netherlands • IFRC Secretariat	• Benin • Burkina Faso • Cameroon • Togo
Positions	• Information Management Officer • RCCE Officer • PMER Officer • NSD Coordinator • Innovation Manager • Business Development • Team Leader, Business Models and Scaling • Senior Officer, IM & Data Analysis	• Volunteer • Community Mobilisation • Assistant Disaster Manager • Head of the Disaster Relief and Management Department • Health Director • CEA Service Manager

Endnotes

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