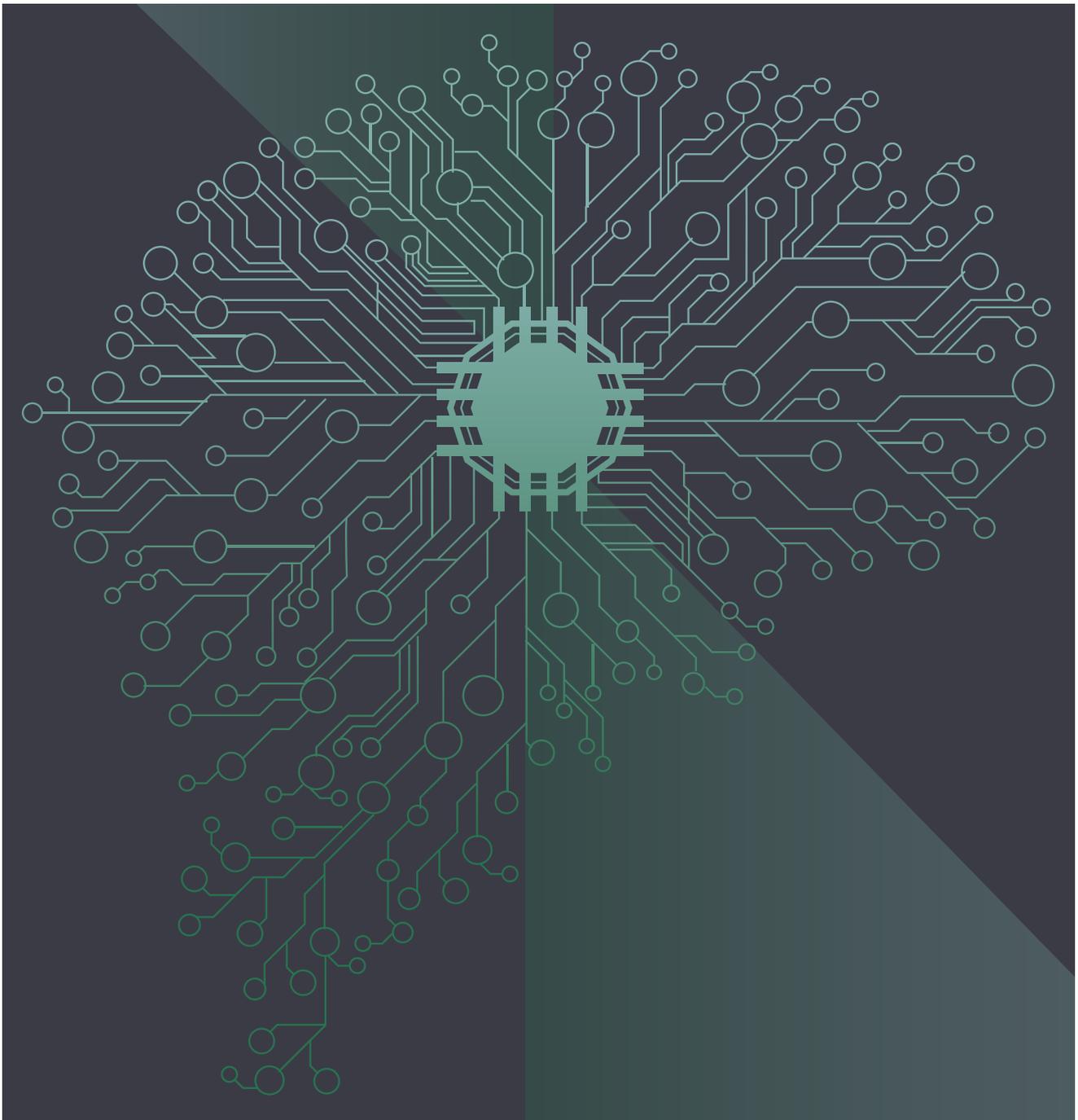


## The hype, the hope and the future

## Network Paper

Sarah W. Spencer



### **About the author**

Sarah W. Spencer is an independent consultant specialising in humanitarian action and development, public policy and technology for good. She is currently on sabbatical from the British government. The views expressed in this article are wholly her own and do not represent the official policies or positions of the UK government.

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### **Humanitarian Practice Network (HPN)**

ODI  
203 Blackfriars Road  
London SE1 8NJ  
United Kingdom

Tel: +44 (0)20 7922 0330  
Fax: +44 (0)20 7922 0399  
Email: [hpn@odi.org.uk](mailto:hpn@odi.org.uk)  
Website: [www.odihpn.org](http://www.odihpn.org)

### **About HPN**

The Humanitarian Practice Network at ODI is an independent forum where field workers, managers and policy-makers in the humanitarian sector share information, analysis and experience. The views and opinions expressed in HPN's publications do not necessarily state or reflect those of the Humanitarian Policy Group or ODI.

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# Network Paper

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## Humanitarian AI: the hype, the hope and the future

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## Introduction

Killer robots and autonomous weapons. Global unemployment. Mass surveillance.

**Superintelligence.** The **Singularity.** There are a host of fears about artificial intelligence (AI) and related industries such as machine learning (ML). But what exactly are they? How are they being used? What, if anything, do they offer the humanitarian aid industry? Are we at the beginning of a fundamental transformation of a business model that, in many ways, is no longer fit for purpose? Will they trigger an industry-wide digital disruption that will challenge the dominance of the largest humanitarian aid organisations, or serve to exacerbate the North–South divide?

Humanitarian actors and their donors are only just beginning to explore the ways in which these technologies will impact humanitarian action.<sup>1</sup> This Network Paper attempts to explore the benefits, opportunities, risks and obstacles to using AI/ML in the humanitarian sector. It seeks to unpack the myths and rhetoric related to AI/ML and evaluate the range of arguments made in favour of or against their use, drawing on literature and interviews with scores of experts across the aid and technology industries. Lastly, the paper offers some conclusions and suggestions for how humanitarian actors, technologists and donors might engage with AI/ML in humanitarian contexts.

The paper is in five sections:

- **Chapter 1: Summary.** A review of the paper’s key findings, some emerging lessons and suggestions for future engagement.
- **Chapter 2: ‘Wake up and smell the technology’: the opportunities and benefits of AI/ML.** An overview of the opportunities and benefits that AI/ML offers the humanitarian sector.
- **Chapter 3: The harm and the hype: the risks of deploying AI/ML for humanitarian action.** An exploration of the risks and limitations of using AI/ML in the humanitarian sector.
- **Chapter 4: The runway to scale: enduring obstacles to deploying AI/ML.** An analysis of the factors that limit and enable the widescale use of AI/ML for humanitarian action.
- **Conclusions: What next for humanitarian AI?** Emerging conclusions on how humanitarian actors might think through ways to engage with these technologies.

Hyperlinks to additional resources have been provided throughout the paper.

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1 Where practical, the term ‘humanitarian action’ is used in place of humanitarian aid to expand analysis and discussion beyond the delivery of services and support and include work linked to identifying and understanding conflict drivers and dynamics. See Glossary.

## Box 1 Understanding AI and ML

While there is no universally accepted definition of AI, the term is often used to describe a machine or system that performs tasks that would ordinarily require human (or other biological) brainpower to accomplish, such as making sense of spoken language, learning behaviours or solving problems. There are a wide range of such systems, but broadly speaking they consist of computers running algorithms (a set of rules or a 'recipe' for a computer to follow), often drawing on a range of datasets. ML uses a range of methods to train computers to learn from existing data, where 'learning' amounts to making generalisations about existing data, detecting patterns or structures, and making predictions for new data. Experts offer conflicting views about the relationship between AI and ML. Throughout this paper, AI and ML are referred to as inter-related systems. See the Glossary of key terms and the 'Terminology and language' section in this chapter for more information.

## Audience and scope

This paper is written primarily for humanitarian practitioners and experts – including those funding, researching, regulating, designing, delivering and assessing the services and support provided to communities impacted by crises. It may also prove useful for technology and innovation enthusiasts exploring ways to use digital technologies to advance the **Sustainable Development Goals**. While a more thoughtful examination of this movement – sometimes referred to as 'technology for good' or tech-for-good – is beyond the scope of this paper, some preliminary analysis is included in Chapter 4.

This paper explores the use of several AI/ML-related technologies, including predictive analytics, computer vision, conversational AI, chatbots and virtual assistants, natural language processing (NLP), natural language understanding (NLU) and text analytics. It does *not* include any significant analysis of biometrics, digital identification systems, distributed ledger or blockchain, robotics, unmanned aerial vehicles (UAVs) or drones, remote-sensing tools and satellite imagery, social media or telecommunications tools, such as Global System for Mobile Communication (GSM), mobile phones and SMS. However, where these technologies are used alongside AI/ML to improve humanitarian action – for example, the use of remote-sensing and AI/ML to assess and predict population movements or natural hazard-related disasters – these are discussed in some detail.

In addition, the paper highlights a select number of AI/ML projects as a means of illustrating the opportunities and challenges in using AI/ML to support humanitarian action and provides a strategic overview of the more frequent forms of AI/ML currently in use to support humanitarian action. It does not attempt to provide a tutorial on AI/ML systems or provide extensive explanation on how these systems work. These subjects have been well-covered by experts across a range of

media. Nor does it attempt to catalogue the host of pilot projects or AI/ML-powered tools being trialled in humanitarian contexts around the world or list all the types of AI/ML systems and their potential applications for humanitarian action.

## Terminology and language

As in the aid world, technology experts often disagree about the definition of key concepts and capabilities and the inter-relations between them. For example, there is still no standard way of classifying the array of AI/ML systems currently in use. Technology experts offer conflicting views about the relationship between AI and ML, with some referring to ML as ‘a subset of AI’ and others characterising it as a separate field altogether. Some computer scientists and technologists claim that much of the AI in existence today is **not actually AI at all**. This paper takes no formal position in these debates. Throughout the document, AI and ML are referred to as inter-related systems and, where practical, the term ‘humanitarian action’ is used in place of humanitarian aid to expand analysis and discussion beyond the delivery of support and include broader work linked to understanding conflict drivers and dynamics.

Equally, both the technology and humanitarian aid industries have a near-compulsive predilection for acronyms and jargon which – more often than not – pre-emptively excludes those less fluent from important discussions and debates about AI/ML and humanitarian action. Yet, these debates require experts from *both* industries. To improve accessibility for all readers and be as inclusive as possible, this paper presents ideas in their simplest forms, providing plain-language definitions of specialist terms from both the humanitarian aid and technology industries.

## Methodology

Research for this paper was conducted between December 2020 and May 2021. This included a desk review of publications and articles from a variety of sources and an analysis of use cases. More than 70 experts were interviewed from a range of institutions and disciplines, including academia, think tanks, technology companies, humanitarian agencies, multilateral organisations, public agencies, the media and private sector firms. The paper draws on the views of humanitarian practitioners, computer scientists and technology experts, innovation enthusiasts, ethicists, policy-makers, journalists, donors and philanthropists, as well as their experiences designing, delivering and evaluating AI/ML-powered interventions.

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## Chapter 1 Summary

### 1.1 Context

Need is rising. The UN estimates that **235 million people will require humanitarian assistance** and protection in 2021, a near-40% increase from 2020. Conflict, instability, disasters and climate-related events, as well as widespread economic contraction and other effects linked to Covid-19, are forcing hundreds of millions of people from their homes. By 2050, climate change will have created an estimated **86 million migrants** in sub-Saharan Africa alone. Some agencies **estimate that a quarter of a billion people** could be forcibly displaced worldwide by 2030.

But resources are stretched. More than a year into the Covid-19 pandemic, **global economic prospects remain uncertain**, following a contraction of close to 5% in 2020. Although **official development assistance** (ODA) from the Organisation for Economic Co-operation and Development's Development Assistance Committee (OECD DAC) members rose to an all-time high of \$161.2 billion in 2020 – mobilised primarily in response to the pandemic – 13 DAC members saw their net development assistance decline, a reduction of almost \$5 billion in aid.

In this context, humanitarian actors are exploring ways to use new and emerging technologies to deliver more effective and efficient humanitarian action and do more with less. This includes AI and ML. AI/ML helps companies like Amazon and Netflix develop and deliver **personalised recommendations** to their consumers. It powers **the well-known voice assistants Siri and Alexa**. And it increasingly helps determine who gets a job, who gets benefits, who gets a loan, who gets parole or who gets a vaccine.

A decade ago, AI/ML was more likely to feature in science fiction films than conversations about economic growth, unemployment and humanitarian action. But it is now more accessible than ever, driven by advances in computing power and software, better infrastructure, improved ML algorithms – especially deep learning – and larger, more widely available datasets. And technologists and innovation enthusiasts around the world are increasingly exploring ways to use AI/ML and other frontier technologies to **solve humanity's greatest challenges**. The World Food Programme (WFP)'s own Chief Information Officer has said **the agency has a 'moral imperative'** to leverage technology to achieve efficiencies.

### 1.2 Opportunities...

Advocates of and enthusiasts for AI/ML note that the effective application of these systems could improve humanitarian action by doing less with more and ultimately save more lives. AI/ML present a range of opportunities and benefits to early warning and humanitarian preparedness,

assessments and monitoring, service delivery and support and operational and organisational efficiency. Broadly speaking, AI/ML systems can support humanitarian action in two discrete yet interrelated ways:

- offering new insights by collecting more information and identifying latent patterns in large, complex datasets otherwise unidentifiable to humans; and
- increasing efficiencies through automation.

A range of AI/ML tools are currently being used across the humanitarian aid industry to predict and analyse trends, improve organisational functioning, personalise service delivery and allocate resources more efficiently. AI/ML can allocate tasks more suited for machines – data analysis, inventory, record-keeping – and free up time for humans to address more complex or sensitive issues. By analysing millions of satellite images alongside other data, AI/ML is now producing maps at a speed, on a scale and of a quality not seen before in the aid industry. It can find latent patterns in large datasets, including images, videos and freeform text as well as numbers, to make predictions about hazards, population movements and food insecurity. And it can help deliver new and previously unimaginable products and tools, like [MSF's AntibioGo](#), a fully-offline, smartphone app that uses computer vision to help clinicians detect [antimicrobial resistance \(AMR\)](#) and prescribe the best course of treatment for patients.

### 1.3 ...and risks

While an increasing number of humanitarian agencies have demonstrated that it is *possible* to use AI/ML in humanitarian contexts, few have demonstrated that we *should* use these tools above others. There are enormous risks associated with using AI/ML for humanitarian action, many of which have yet to be properly interrogated and addressed.

**Effectiveness.** The impact and effectiveness of AI/ML in humanitarian settings, particularly predictive analytics, remain unclear. Few agencies are sharing the successes and shortcomings of pilot projects, particularly predictive analytics, and there is still not enough analysis on the costs and risks of deploying AI/ML in humanitarian contexts. Moreover, the current fixation on predictive analytics in humanitarian settings raises an important question about impact and effectiveness: what problem are we trying to solve, and is it the right one? Some of the biggest obstacles preventing effective humanitarian action, including adequate resourcing, are political. And, if they aren't used carefully, the outputs of predictive models can unintentionally generate a harmful response to humanitarian crises. Designing more effective AI/ML in humanitarian settings requires a change in the way we define the problems that need solving, and how we identify AI/ML use cases.

**Bias and discrimination.** Without the right quality and quantity of data, data-hungry AI/ML models could generate inaccurate results, perpetuate patterns of marginalisation and inequality

and increase harm for already vulnerable populations. Yet, there is currently no requirement for humanitarian actors to audit their AI/ML systems for bias or discrimination, nor is there any systematic regulation of how humanitarian actors use AI/ML.

**Localisation and community participation.** AI/ML seems more likely to undermine localisation and participatory approaches than not. An increased reliance on AI/ML may limit the extent to which agencies seek to incorporate the views and voices of the communities they serve into the design of their programmes. And, while AI/ML firms in low- and middle-income countries (LMICs) are increasing, humanitarian actors have a notoriously poor track record of procuring services, particularly tech services, from the Global South.

**Accountability, transparency and human oversight.** Until the yawning accountability gap across the aid industry is properly addressed, the effective use of AI/ML to support humanitarian action will be hindered. And despite broad commitments to keeping a human-in-the-loop, human oversight in the design and use of AI/ML systems is far from guaranteed.

**Regulation, data protection and privacy.** One of the most significant risks linked to the use of AI/ML for humanitarian action is the absence of industry-wide regulations to guide the use and protection of humanitarian data, as well as data-intensive technologies like AI/ML. Many humanitarian actors have now developed internal data protection guidelines and policies, but their quality is mixed and compliance and enforcement are weak.

**Safety and sustainability.** As AI/ML systems and their algorithms play an increasingly prominent role in everyday life, the magnitude and depth of the potential harm created by biased algorithms increases. AI/ML can perform in unexpected ways that cause unintended harm, generating inaccurate results or making poor recommendations. AI/ML systems can also unintentionally boost the surveillance capabilities of authoritarian regimes or other bad actors, compounding the vulnerability of the tens of millions of people who are forcibly displaced or targets of persecution.

While these risks are certainly not reason to completely discount the potential of AI/ML, in and of itself, they justify caution and the need to ask the right questions when designing and deploying these systems in humanitarian contexts.

## How can we scale AI/ML in humanitarian contexts?

Developing and deploying effective and ethical, humanitarian-focused AI/ML requires, at a minimum:

- A clearly defined problem.
- Data, including the policies and systems to safely and ethically manage it.
- Funding for both the technology elements and the humanitarian services and support linked to the tool.

- Technological tools and know-how to design and maintain the tool, including software, hardware and staff.
- Well-trained staff, the right organisational structures and committed leadership.
- Regulatory frameworks and policies to manage the data and software.

Data-hungry technologies like AI/ML require large amounts of data to make them effective, but while the quantity of humanitarian data is increasing, its integrity and quality is mixed. With high price points for technology services, limited access to unrestricted funding,<sup>2</sup> and few donors willing to invest in higher-risk ventures, many humanitarian agencies continue to lack the funds necessary to effectively pilot and scale AI/ML projects. The somewhat opaque market for tech-for-good services makes it difficult for aid agencies to get the tech expertise they need, unless they have the networks, reputation or operational reach to successfully broker pro-bono relationships with corporate entities. The organisational structure of some agencies and the low number of AI/ML experts or data scientists employed by aid organisations further inhibits the design and uptake of AI/ML.

#### 1.4 Humanitarian AI: the inevitable disruption?

The technological change and innovation of the **Fourth Industrial Revolution (4IR)** is of a speed, scale and complexity that is unprecedented. Some believe that this change is outpacing the evolution of our culture, our institutions and the way we interact as humans. The Founder and Executive Chairman of the **World Economic Forum**, Klaus Schwab, believes that ‘we stand on the brink of a technological revolution that will fundamentally alter the way we live, work, and relate to one another’. The move towards automation and AI-fuelled efficiency has only **accelerated because of Covid-19**.

Although the humanitarian aid industry is only just coming to grips with these technologies, AI/ML will undoubtedly change the landscape in which humanitarian aid is delivered, and may also impact the stability of societies and states. The lives of more and more people across the globe are becoming digital, making them increasingly vulnerable to social engineering, micro-targeting and other forms of manipulation. AI/ML will affect both how conflicts play out and how humanitarian actors are perceived within those conflicts. Parties to conflict and their supporters have cheaper and more reliable access to AI/ML tools which can be used to surveil and control populations both inside and well beyond their borders. In some cases, these tools are changing more quickly than we can keep up with.

AI/ML, however, is unlikely to fully **disrupt** the humanitarian aid industry any time soon. While tech-focused, social enterprises have emerged as more regular players in the aid world, offering new ways to provide aid more directly to intended recipients and slightly stiffening competition over donor funding, the high barriers to entry to the humanitarian ‘market’ remain. Larger aid

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2 Unrestricted funds are donations a charity or non-profit can use to fund any activity deemed fit by the organisation’s leadership, in that the funding is not restricted to a specific purpose. Unrestricted funds typically cover operating expenses and special projects, and rarely amount to more than 15% of an organisation’s annual operating budget.

agencies are beginning to experiment with AI/ML, leveraging their cachet or cash to establish and cultivate relationships with tech companies. While uptake across the industry will continue to be slow – hindered by poor-quality data, erratic investments and contradictory thought leadership – this limited use of AI/ML may be enough to stave off competition from new market entrants and preserve the status quo. However, agencies without access to affordable technologies and/or robust datasets may find it increasingly difficult to compete. This could undermine the localisation movement and prevent efforts to shift power towards humanitarian actors in the Global South.

Some humanitarian AI/ML projects have failed to deliver meaningful impact because they don't address the right problems. While technologists understand their tools in a way most aid experts do not, few understand the complexities of humanitarian action, its purpose, ethics and principles, and the operational and political challenges aid agencies face in supporting and partnering with communities in crisis. Using AI/ML in humanitarian contexts thus requires both technology and humanitarian experts working together to identify and solve these problems.

Data is the fuel that powers AI/ML, and has been referred to as the new oil. But, unlike oil, the supply of data is unlimited as long as humans keep producing it. Humanitarian agencies now collect and share more data than ever before, from service delivery data, including personally identifiable information (PII), to population-based data. And they are finally, though slowly, developing the strategies and plans necessary to transform that data and information into valuable assets. However, the tools and systems the aid industry uses to ethically and safely manage this data have not kept pace, threatening the safety and security of the people humanitarian action seeks to support. Humanitarian actors that fail to develop sound data strategies and data management tools increasingly risk obsolescence.

Addressing the threats of climate change and escalating humanitarian need means finding new ways to support the most vulnerable. Countless experts have spent decades trying to improve humanitarian action and protect the world's most vulnerable. 'AI for Good' advocates must ground their enthusiasm (and, in some cases, hubris) in this experience and learn from the graveyard of well-intended tech-for-good projects. Equally, however, humanitarians must acknowledge the limitations of a 'business as usual' approach and recognise the opportunities that emerging technologies present. While it remains unclear whether the current benefits afforded by AI/ML outweigh the costs and risks in all cases, as time goes on AI/ML will grow more affordable, and more risk management tools and better governance approaches will emerge. With the right data and design, some AI/ML could yield important savings and efficiency gains for humanitarian action.

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## Chapter 2 ‘Wake up and smell the technology’: the opportunities and benefits of AI/ML

Advocates of AI/ML claim that the effective application of these tools could make humanitarian action more efficient and effective, and ultimately save more lives. As one technologist put it, ‘It’s time for the aid world to wake up and smell the technology’. Broadly speaking, AI/ML systems can support humanitarian action in two, interrelated ways:<sup>3</sup>

- **Offering new insights** by collecting and analysing more data in less time or at less cost. AI/ML can identify latent patterns in large datasets that might otherwise be unidentifiable to humans due to the complexity of the patterns or the sheer size of the data. This could include analysing large amounts of historic and current data to predict future events such as population movements, disease outbreaks or an individual’s vulnerability to violence or abuse.
- **Increasing efficiencies** by automating tasks that are resource-intensive or repetitive, or developing approaches that can be scaled quickly and at lower cost. This can reduce the number of people, time and/or other resources required to deliver a task, arguably freeing up time for humans to focus on more important work. For example, AI/ML can be deployed to identify anomalous or outlier financial transactions, flagging suspected instances of financial mismanagement with greater accuracy and speed than humans. AI/ML can also improve cost-efficiencies by automating information provision through chatbots or conversational AI.

This chapter explores these benefits in more detail, highlighting ways in which AI/ML are already supporting humanitarian action as well as other applications that have yet to be used in humanitarian contexts, but show promise. The opportunities and benefits of AI/ML are presented against four themes central to humanitarian action: early warning and preparedness; assessment and monitoring; service delivery and support; and operational and organisational efficiency.

### 2.1 Early warning and preparedness

One of the biggest opportunities we have is to try to use data, and especially the tools of predictive analytics to get ahead, to be more anticipatory, to predict what is about to happen and to trigger the response earlier (Mark Lowcock, former UN Under-Secretary-General for Humanitarian Affairs).

Actors across the aid industry have developed predictive analytics and ML models to support crisis preparedness and early warning efforts. In fact, the development of these models has been

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<sup>3</sup> AI/ML can also improve humanitarian action by creating new products such as biotech commodities and food compounds to support nutrition programmes. As these efforts are still so new, this paper does not examine this work.

so significant over the last several years that discourse about AI/ML and humanitarian action has become virtually synonymous with predicting conflict and population displacement, to the exclusion of a vast range of other AI/ML use cases.

By analysing huge quantities of historic data, predictive analytics and ML models attempt to identify trends or characteristics of future events – including their probability, severity, magnitude and duration – such as disease outbreaks and epidemics, population movements, changes to food security or extreme climatic events and disasters. Advocates of predictive analytics argue that these tools can improve the efficiency and overall impact of humanitarian action. ‘By creating an early signal of need that is tied to pre-agreed financing and actions, the response has the potential to be faster, cheaper and better, with more lives saved and protected’ ([Centre for Humdata](#)).

A number of agencies are developing models to predict conflict and population displacement. [UNHCR’s Project Jetson](#) provides predictions on the movements of displaced people from Somalia, drawing on a range of datasets to ‘[discover, understand, and measure the specific factors that cause, indicate or exacerbate the forced displacement of Somalis](#)’. Save the Children has developed a [tool](#) that predicts the scale and duration of conflict-driven displacement. The hope is that, in the future, the model’s outputs will improve decisions about infrastructure and procurement as well as the design and delivery of services. For example, in instances where a model predicts a crisis will continue for years, this information could shape decisions around fundraising and the types of support to deliver, for example to provide cash transfers, which are sometimes seen as a shorter-term solution, or longer-term programmes to develop infrastructure or livelihoods. The [Danish Refugee Council’s Foresight Model](#) uses ML and open data from 18 sources to predict displacement one to three years ahead of an event. Last year, the model predicted [Covid-19 would displace more than one million people across the Sahel](#). DRC and their technology partner, IBM, anticipate that the results of the model [will help policy-makers, donors and humanitarian actors improve their response](#), particularly by prioritising funding and developing data-driven strategies to address displacement.

Some actors have developed AI/ML systems to predict the impact of potential disasters to inform decisions about procurement and the deployment of staff (see section 2.2). NASA’s [Global Landslide Hazard Assessment \(LHASA\) model](#) and mapping tool uses ML to estimate potential landslide activity in near-real time, down to the square kilometre. These results are then overlaid with district-level population data to better assess the potential impact of landslides. The extent to which operational humanitarian actors have used this information remains unknown.

Predictive models and ML are also being used to prevent and control epidemic outbreaks. The [Cholera Prediction Modelling System](#), which analyses data from NASA alongside other demographic data, was developed to forecast the risk of cholera in Yemen. In 2017, the model [achieved 92% accuracy in predicting the regions where cholera was most likely to occur](#) and spread. This data [helped donors and humanitarian actors focus efforts on prevention](#) several weeks in advance of an outbreak.

Academics and others are developing ML models to anticipate food insecurity, drawing on remote-sensing, market, environmental and demographic data. Like many of the tools detailed above, these models are still under development, but the results of some show promise. **One model** correctly identified the food security status of 83% to 99% of the most food-insecure village clusters in Malawi, offering a more granular, sub-national assessment of food insecurity than existing assessment tools (see section 3.1).

## 2.2 Assessment and monitoring

AI/ML could revolutionise the way aid actors conduct assessments and monitor their programmes. These tools collect and analyse vast quantities of data in less time and with less error than humans. By reviewing millions of images from satellites and other remote-sensing tools and layering this with other datasets – such as infrastructure data, subnational data from the **Multiple Indicator Cluster Surveys (MICS)**, **Demographic and Health Surveys (DHS)** or **Humanitarian Data Exchange (HDX)** or call detail records (CDR) – AI/ML is producing maps at a speed, on a scale and of a quality not seen before in the aid industry.

**WFP** is using AI to combine and analyse satellite images of flooding alongside demographic and infrastructure data. This provides WFP with an early, rapid assessment of damage, estimates on the number of people affected by an event and suggestions on the best routes to access affected populations. **Facebook has used ML techniques**, commercially available satellite imagery and population data from **Columbia University's Center for International Earth Science Information Network (CIESIN)** to map hundreds of millions of structures across vast areas and estimate population density. In just a few days, Facebook's AI examined 11.5 billion individual images across Africa and **identified approximately 110 million buildings**. In 2019, after back-to-back cyclones caused widespread damage and flooding in Mozambique, Facebook's maps were used to **support a targeted cholera vaccination campaign** and estimate the number of vaccines required. **Humanitarian OpenStreetMap**, which develops open-source apps and tools for collaborative mapping and geospatial data collection, **uses AI/ML to generate base map data** that is further built upon through volunteer mapping. UAVs or drones can be used to plug gaps in imagery and deliver more granular geospatial information. Using drones, thermal imaging cameras and AI, **ICRC has developed a prototype** to more accurately and safely detect landmines and other explosive remnants of war.

AI/ML is also providing more granular, subnational estimates of poverty and vulnerability to improve targeting of social protection mechanisms. The **Government of Togo** and **GiveDirectly** used algorithms, powered by data from a 2018 household survey, CDR and satellite imagery, to **estimate poverty levels and help disburse emergency cash transfers** in support of vulnerable families affected by Covid-19.

Agencies are using AI/ML systems to better analyse and assess conflict. The **Carter Center has partnered with Microsoft** to monitor, map and analyse the Syrian conflict, maintaining a near

real-time assessment of conflict in the country and auto-updating a map of areas of control. A deep NLP model cleans data and **improves the classification of armed conflict events**, reducing staff time spent on manual data transformation by 80% and allowing staff to spend more time analysing and identifying patterns and trends in the conflict.

AI/ML systems help agencies interact with more people, often in remote or hard-to-reach areas, at a fraction of the cost, collecting and analysing information in real-time. If taken up more widely, this could deepen community engagement and participation efforts. WFP's **mobile Vulnerability Analysis and Mapping (mVAM) project** uses a chatbot – alongside other mobile technologies – to engage with crisis-affected communities and ask questions about household food security and nutrition and food market-related trends in real time. The chatbot also collects images, voice notes and geolocation information, enriching WFP's overall assessment.

Perhaps most importantly, AI/ML could revolutionise the way aid organisations manage the data and knowledge they already have, transforming it into a powerful asset. A virtual assistant designed to support an aid agency could trawl through vast troves of information, breaking down data silos between country offices and departments, and ultimately strengthening institutional knowledge and memory. Imagine, for example, the following scenario. A crisis occurs in a location where the presence of humanitarian actors is currently low but has been high in years past. An agency deploys emergency response staff to the crisis while also tasking its own, custom-built **Siri or Alexa** to develop a preliminary assessment of the crisis. The virtual assistant draws on internal as well as publicly available information from pre-determined sources. The final report identifies broad needs and highlights critical information gaps, flagging outlier pieces of information that require further investigation. Emergency response staff arrive at the crisis-affected area having done their own preliminary assessments and with an AI-generated report in hand that synthesises existing knowledge on the crisis. In that scenario, **Reliefweb**, which at the time of writing hosts just shy of 900,000 documents, maps and other content, no longer becomes a static repository of analyses and assessments but an invaluable trove of information that can be digested and analysed within hours by a virtual assistant tasked to answer a specific question. While this scenario may feel futuristic and fantastic, experts predict that **the use of virtual assistants will grow dramatically** in the next few years.

## **2.3 Service delivery and support**

AI/ML can also improve the delivery of humanitarian support. In the commercial world, chatbots or conversational AI are used to provide more consistent information to customers, reduce human error and wait times, and improve cost-efficiencies by providing around-the-clock information services. Seeking to replicate these benefits, some aid agencies have used conversational AI to provide basic information to refugees and other populations through phones or messaging applications such as WhatsApp, about available services and how to access them. **Translators Without Borders** has worked with a range of partners to develop multilingual, Covid-19 chatbots in the **Democratic Republic of Congo** and **Northern Nigeria**.

Agencies are also using AI/ML to improve the quality of the services they provide. **MSF's AntibioGo**, a fully-offline, smartphone app, helps clinicians and doctors detect **AMR** and prescribe the best course of treatment. AntibioGo uses computer vision to analyse photos of diagnostic test results and provide recommendations for antibiotics. A human expert validates all recommendations, thus assuring human oversight. As the app is more widely used in lower-resource settings, the MSF Foundation hopes it will **improve the accuracy of antibiotic prescriptions and patient outcomes** and ultimately reduce rates of AMR (see section 3.4).

AI/ML is also being used to match refugees, asylum-seekers and other potential clients with services and support. **HIAS** co-developed **software** powered by ML and historic data from previous refugee placements that recommends locations in the United States that are most likely to improve a client's chances of finding employment. Similarly, the **Immigration Policy Lab at Stanford University** and **ETH Zurich** built an **algorithm to optimise the resettlement of refugees and asylum-seekers** in Switzerland. **One study suggests** that these tools could increase employment outcomes by 20% to 70%. IRC's **Project Match** seeks to increase employment opportunities for Syrian refugees and others in Jordan by 'helping job seekers identify employment opportunities and firms to fill vacancies with the right candidates through networks of entrepreneurial employment service officers and **an algorithm that optimally matches jobs and job seekers**'.

From contact tracing and other forms of pandemic surveillance to clinical and molecular research, AI and other data-driven interventions have proven key to stemming the spread of [Covid-19], advancing urgent medical research and keeping the global public informed (**Michael Pizzi, Mila Romanoff and Tim Engelhardt**).

Tech firms and others have developed additional tools and approaches that could deliver impact in low-resource settings but have yet to be fully explored. **SAS is partnering with police services in Europe** and using predictive analytics to assess risks of lethality in domestic violence cases. Police officers use this individual risk assessment to inform decisions about resource allocation and better protect individuals facing higher levels of threat. This tool could be adapted for use in humanitarian programmes rooted in social work, such as child protection and gender-based violence (GBV) programmes, helping social workers assess individual levels of threat and respond with additional resources to support high-risk cases.

## 2.4 Operational and organisational efficiency

Perhaps less noteworthy but equally relevant are the savings and operational efficiencies AI/ML systems offer the aid industry. Private sector firms seeking to reduce costs and boost profits have used AI/ML to automate processes and make them less susceptible to human error. Experts **predict that supply chain management** – a critical component of humanitarian action – is **one of the fields most likely to benefit from AI** by not only helping to manage procurement and distribution more

efficiently, but also offering more reliable and regular forecasts to inform workforce planning and supplier production. The **Covid-19 pandemic has accelerated** this move towards automation and AI-fuelled efficiency.

AI/ML offers a range of solutions for aid agencies seeking to improve their operational performance and efficiency. One financial institution assesses that AI-powered fraud detection tools **save them hundreds of millions of dollars a year**. While their use in the aid industry is still nascent, these out-of-the-box and increasingly affordable tools could be deployed to analyse the hundreds of thousands of financial transactions made by large humanitarian organisations across the globe to not only **spot anomalous financial transactions but also 'predict'** or signal areas where **incidents of fraud in the humanitarian sector** may be more likely.

AI/ML could equally support the predictive maintenance of equipment regularly used by aid agencies, such as generators and vehicles. Historically, equipment maintenance has been either reactive (after a machine breaks) or preventive (performed at regular intervals to help avoid machines breaking). ML-powered **predictive maintenance** helps companies anticipate when equipment will need upkeep by analysing information from a wide range of data points, including fuel usage, maintenance data and engine diagnostics.

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## Chapter 3 The harm and the hype: the risks of deploying AI/ML for humanitarian action

While a number of agencies have demonstrated that it is *possible* to use AI/ML in humanitarian contexts (see Chapter 2), few have demonstrated that we *should* use these tools above others. As AI/ML systems and their algorithms play an increasingly prominent role in everyday life, the magnitude and depth of the potential harm created by biased algorithms increases. AI/ML systems embedded in digital technologies can accelerate the spread of misinformation and disinformation, amplify echo chambers of public opinion, hijack our attention, and even impair our mental well-being. There is still not enough analysis on the costs and risks of deploying AI/ML to humanitarian contexts as it relates to their impact. Do the benefits of deploying AI/ML systems justify the resources required – not only the financial, technological and human costs, but the ethical and opportunity costs as well? Little to no research has been conducted on this in the humanitarian sector. While this is no reason to completely discount the potential of AI/ML, in and of itself, it is certainly justification to exercise caution, ask the right questions when designing and deploying these systems and find novel and efficient ways to both prove concept and assess impact. This chapter explores the risks and ethical implications related to AI/ML and its use in the humanitarian aid industry.

### 3.1 Effectiveness

One of the most critical questions aid experts ask when assessing the benefits and risks of AI/ML is ‘Does it work?’ The answer, inevitably, is that it depends. For example, AI/ML is extremely effective at quickly developing detailed maps of disaster-affected areas or areas previously unmapped. As discussed above, Facebook AI reportedly created ‘**the world’s most accurate, highest-resolution population density maps**’ by assessing 11.5 billion individual images across Africa and identifying approximately 110 million buildings with 99% accuracy in just a few days. This task alone would have taken a team of 20 humans reviewing images continuously, without any break, several decades to achieve the same scale.<sup>4</sup> MSF’s *Antibiogo* is delivering great value at the individual level, rapidly improving the accuracy of recommendations made by clinicians and health workers to treat microbial infections more effectively and reduce AMR. And AI/ML systems that create efficiencies through automation may help humans reallocate their time to tackle more critical problems (see Chapter 2).

While AI systems can exceed human performance in many ways, they can also fail in ways that a human never would (**The malicious use of artificial intelligence: forecasting, prevention, and mitigation**).

The impact and effectiveness of other AI/ML tools, such as predictive analytics, is less clear. While aid agencies are developing models to predict disasters, displacement and disease, few are

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4 Assuming 2–5 seconds per image.

publishing the success rates of these models. For example, in early 2021 the United Nations Office for the Coordination of Humanitarian Affairs (OCHA) partnered with Johns Hopkins University's [Applied Physics Laboratory](#) to develop the [OCHA-Bucky model](#), a tool that issued forecasts of new Covid-19 cases, hospitalisations and deaths at sub-national and national levels. These forecasts were developed to help inform Covid-19 response strategies in a range of countries. However, the accuracy of these forecasts has not been published, nor has any information on their impact.

Critics of predictive analytics argue that, by using historical data to make predictions about crises, models only project the past into the future. In the worst cases, they amplify decades and centuries of discrimination and bias (see sections 3.2 and 3.6). The mixed results generated by some models may signal poor data quality as well as questionable data collection or recording methods. In fact, predictive models may perform better in cases where human behaviour has less of an immediate effect on data. So, for example, while these tools may yield promising results in predicting hazards, crop yields and the spread of disease, their results are less encouraging when predicting conflict-related population displacement.

The current fixation on predictive analytics in humanitarian settings raises perhaps a more important question about impact and effectiveness: what problem are we trying to solve and is it the right one? Advocates of predictive analytics claim this tool will improve humanitarian action by informing the design and delivery of humanitarian interventions, mobilising more funding in less time, and prepositioning aid by improving supply chain management. But two important fallacies underpin this assumption:

1. Donors and policy-makers fail to respond adequately to crises because they lack accurate and timely information about these crises.
2. Once they have more accurate and real-time information, particularly in advance of a crisis, key actors will respond in a more *benevolent* or effective way.

These fallacies ignore the politics which drive these crises and affect their response. The shortage of funding to address humanitarian need in Venezuela – with just 3% of that country's Humanitarian Response Plan funded as of May 2021 – is driven by political choices, not a lack of data. Aid agencies responding to the crisis in Tigray report that the restrictions imposed by the government of Ethiopia have prevented the effective distribution of aid. Other aid experts warn that, if they aren't used carefully, the outputs of predictive models can actually encourage a harmful response to crises such as sealing borders, blocking displaced populations and migrants' freedom of movement, and diverting aid away from areas of political opposition. One tech firm interviewed for this paper reported that their client, the national public health authority of a country in sub-Saharan Africa, explicitly and intentionally ignored the forecasts produced by their Covid-19 model, which identified specific populations across the country who faced higher threats from Covid-19, allocating limited health resources to other groups instead. When asked to explain this decision, the respondent replied, 'Not all of these decisions are about data'.

Governments aren't the only ones to spurn data and analysis. Humanitarians conduct countless assessments and amass endless amounts of data, but in a study of humanitarian decision-making, the overall conclusion was 'that the rationale for humanitarian action is constructed without significant use of current evidence. When a new disaster occurs, the humanitarian system essentially repeats past operations, with minor adjustments.'<sup>5</sup> In fact, the problem we face is not necessarily the accuracy or granularity of the information available – a problem that AI/ML can help with – but the high-level of 'path dependency' in decision-making compounded by a persistent mistrust and poor cooperation between agencies, fuelled by interagency competition and donor requirements.

Even if AI/ML models reliably and accurately predict the next famine or flood, this information will only be effective if aid agencies or policy-makers act on it. Designing more effective AI/ML in humanitarian settings requires a change in the way we define the problems that need solving, and how we identify AI/ML use cases. While there are exceptions, a majority of those developing AI/ML use cases and shaping the discourse around humanitarian AI are technology experts, few of whom have any deep understanding of humanitarian need or operational experience responding to humanitarian crises. One aid expert interviewed for this paper joked, 'AI sounds great, but can it fix my generator?'. While the answer is a resounding yes,<sup>6</sup> his comment reveals a wider challenge: many AI/ML pilot projects are being designed around a specific capability – for example, predictive analytics – rather than a specific problem. To truly determine whether AI/ML can help humanitarians do more with less, this must change. Aid agencies should be driving the humanitarian AI agenda, collectively identifying critical challenges where new technologies may be able to help (see Chapter 5).

### 3.2 Bias and discrimination

Some advocates claim that AI/ML provides more avenues for making dispassionate and fairer decisions, free from human prejudice and bias. While AI/ML systems may indeed be able to reduce human subjectivity in some very specific cases, claims that algorithms are fundamentally more objective or accurate than humans risks failing to fully recognise the difficulty of removing and accounting for bias in these systems. As Kate Crawford and Trevor Paglen argue, datasets aren't simply raw materials used to power AI/ML, but are political interventions, in and of themselves:

As such, much of the discussion around 'bias' in AI systems misses the mark: there is no 'neutral', 'natural', or 'apolitical' vantage point that training data can be built upon. There is no easy technical 'fix' by shifting demographics, deleting offensive terms, or seeking equal representation

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5 Nissen, L.P. (2016) 'Gandalfs and geeks: strengthening the accountability of humanitarian decision-making', in *On the road to Istanbul: how can the World Humanitarian Summit make humanitarian response more effective?*. Geneva: CHS Alliance.

6 Purchasing and maintaining generators is costly and labour-intensive, but AI tools could improve efficiency and generate savings through predictive maintenance. See section 2.4.

by skin tone. The whole endeavor of collecting images, categorizing them, and labeling them is itself a form of politics, filled with questions about who gets to decide what images mean and what kinds of social and political work those representations perform.

It is difficult to argue that technology is neutral when it extracts and interprets historic data that was and is collected in deeply political ways. For example, if we were to rely on service-generated data collected by humanitarian actors in the 1980s and 1990s, would we expect it to give us a reliable assessment on the experience or needs of women and girls when most aid actors weren't collecting this information to begin with? Because they gain their insights from the existing structures and dynamics of the societies they analyse, data-driven technologies like AI/ML are as capable as humans of **reproducing, reinforcing and amplifying existing bias and discrimination**. Or, as many computer and data scientists say, '**garbage in, garbage out**' (GIGO). Without the right quality and quantity of data, aid agencies might (at best) generate inaccurate results and (at worst) perpetuate patterns of marginalisation, inequality and bias. In her book *Weapons of math destruction: how big data increases inequality and threatens democracy*, Cathy O'Neil argues that AI/ML systems can 'distort higher education, spur mass incarceration, pummel the poor at nearly every juncture, and undermine democracy', all while 'promising efficiency and fairness'.<sup>7</sup>

The risks of bias and discrimination in AI/ML have given rise to a growing field of **algorithmic auditors**. Algorithmic auditors review algorithms to ensure they are transparent, protect privacy and are free from bias and discrimination. But this is hardly a cure-all. The results of audits can be distorted or mischaracterised for PR purposes, and **even auditors themselves** note how difficult it is to address bias. Gemma Galdon Clavell, the director of **algorithmic auditing consultancy Eticas**, claims that many firms deploying algorithms have very little awareness or understanding of how to address the challenges of bias, even if they recognise it as a problem in the first place. Some algorithms and AI/ML systems are so complex that even the people who have developed and designed them cannot fully understand why a system had made a particular recommendation (see section 3.4).

Without intervention and oversight, the natural state of data-driven technologies is to replicate past patterns of structural inequality that are encoded in data, and project them into the future. It is vital that policymakers understand this. To avoid this outcome, those who use algorithms to make decisions which affect people's lives, from educational attainment to hiring to pay and promotions, must take active and deliberate steps to ensure algorithms promote equality rather than entrench inequality (**Institute for the Future of Work, Mind the Gap: The Final Report of the Equality Task Force**).

There is currently no requirement for humanitarian actors to audit their AI/ML systems for bias or discrimination, nor is there any systematic regulation of how humanitarian actors use AI/ML. However, **some experts argue** that governments and donors could require algorithmic reviews in

<sup>7</sup> O'Neil, C. (2016) *Weapons of math destruction: how big data increases inequality and threatens democracy*. New York: Crown Publishers.

the future before they are deployed, in the same way environmental impact reports are required before a construction project begins. Establishing an independent authority to review AI/ML-powered projects for use in the humanitarian aid industry could help to manage the risk of bias and discrimination (see Chapter 5). The [Centre for Humanitarian Data's Peer Review Framework for Predictive Analytics in Humanitarian Response](#) aims to create standards and processes for the use of predictive models across the humanitarian aid industry. By applying the Framework to predictive models in development, humanitarian actors can receive advisory support – technical and ethical – on their model and its use. Whilst limited to predictive analytics, this framework, and the support offered alongside it, could serve as a useful foundation on which to build an industry-wide approach and review board for the design and deployment of AI/ML systems.

### 3.3 Localisation and community participation

Humanitarian action has long been dominated by a handful of donors, international public organisations and non-governmental organisations (NGOs) based in North America and Europe. Despite public commitments to address the inequities in the system, most notably announced at the World Humanitarian Summit in Istanbul in 2016, [limited progress has been made](#). Shifting the balance of power towards the Global South requires a wholesale change in the way lifesaving support is designed, procured, delivered and assessed.

AI/ML offers new opportunities to support wider localisation efforts and community partnership. The number of AI/ML firms is [increasing in LMICs](#), giving humanitarian actors more opportunity to shift supply chains and contract tech services from firms in the Global South. And AI/ML provides new ways to engage with more people in less time, soliciting their views and inputs on crises and ongoing relief efforts (see section 2.2).

Despite these opportunities, AI/ML seems more likely to undermine localisation and participatory approaches than not. For one, aid agencies have (at best) a patchy history of local procurement, though [the procurement of goods and services accounts for 65% of the costs of relief operations and could significantly shift resources and power towards the Global South](#). And meaningful community participation across the aid world has lagged not due to a deficit in tools but because the existing business model – and the power dynamics that stem from that model – values expediency over engagement and technical expertise over the experience of communities (see section 3.1).

Further, the depersonalising and de-socialising effects of increasing automation could dehumanise problems and devalue participatory methods aimed at empowering communities and centring their views and lived experiences in the design of aid programmes. An increased reliance on models that predict population movements or outbreaks of conflict may limit the extent to which agencies seek information from frontline staff and the communities they serve. Equally, while models that predict employment outcomes have been used to inform refugee resettlement decisions in the United States (see section 2.3), the views and preferences of refugees themselves [appear neither to have been](#)

solicited nor accounted for by UNHCR or the US Department of State when determining locations for resettlement. And data-hungry AI/ML systems risk further silencing the voices of those who speak non-dominant and non-digitised languages, populations shamefully marginalised by aid agencies for decades.<sup>8</sup> At a time when the trust communities have in aid agencies is increasingly tenuous, it is critical that aid agencies explore the implications of marginal improvements in accuracy and efficiency if those come at the cost of participation, individual empowerment and agency.

### 3.4 Accountability, transparency and human oversight

In her piece ‘[Big Tech’s guide to talking about AI ethics](#)’, [Karen Hao](#), MIT Technology Review’s senior AI reporter, offers tongue-in-cheek definitions of common terms and phrases used by technology firms ‘when they want to assure the public that they care deeply about developing AI responsibly – but want to make sure they don’t invite too much scrutiny’.

- **accountability** (n) – ‘The act of holding someone else responsible for the consequences when your AI system fails.’
- **transparency** (n) – ‘Revealing your data and code. Bad for proprietary and sensitive information. Thus, really hard; quite frankly, even impossible. Not to be confused with clear communication about how your system actually works.’

When developing AI/ML systems, tech firms often require clients to name a human who can be questioned and held to account if the model fails. In practice, these accountability systems lay blame on staff outside their firms when things go wrong and not on their designers or their tools. [Madeleine Clare Elish](#), a researcher at [Data & Society](#) and a cultural anthropologist by training, has concluded that, even in highly automated systems where humans have limited control, they still bear most of the blame for the failures. She calls this the ‘moral crumple zone’, designed to ‘protect the integrity of the technological system at the expense of the nearest human operator’ and ‘treating humans like a “liability sponge”, absorbing all legal and moral responsibility in algorithmic accidents no matter how little or unintentionally they are involved’.<sup>9</sup> ‘**Black box models**’ make it even more difficult to establish accountability or seek redress when things go wrong. As mentioned, some AI/ML systems are so complex that even their designers are unable to explain them. In these cases, who do we hold to account if it leads to harmful actions or a poor outcome for an individual or community?

In addition, most technologists argue that AI should be designed and deployed to enable and support human decision-making, not make decisions themselves. But human oversight is far from guaranteed. Humans are subject to a range of cognitive biases and prejudices that affect the way they make decisions. Without the right training, and where models are poorly designed, humans could increasingly

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8 While some firms and agencies are using AI/ML to help digitise and protect endangered or extinct languages, only 7% of the world’s languages are reflected online and 98% of all internet content is published in just 12 languages ([BBC Future](#)).

9 Hao, K. (2019) ‘[When algorithms mess up, the nearest human gets the blame](#)’, MIT Technology Review, 28 May.

defer to the recommendations made by AI/ML systems. Nobel Laureate Daniel Kahneman theorised that people often rely too heavily on the first piece of information they learn, which can have a serious impact on the decision they end up making (known as an ‘anchoring bias’ or anchoring effect).<sup>10</sup> Others argue that **that the human mind is a ‘cognitive miser’** and, regardless of intelligence, people usually think and solve problems in simpler ways that require less effort. These cognitive shortcuts have been found to shape value judgments about other people or social situations.<sup>11</sup> In operating environments like humanitarian crises, where the context changes rapidly and quick decisions are required, humanitarian staff could increasingly defer to the outputs of an AI/ML model without properly interrogating them.

These challenges make the case for deploying explainable, interpretable AI/ML across the aid industry. **Explainable AI** draws on specific techniques and methods to ensure that each decision made during the ML process can be traced and explained. AI that is not explainable, on the other hand, often arrives at a result using an algorithm, but the AI architects don’t fully understand how the algorithm reached that result. This makes it hard to check for accuracy and leads to a loss of control and weaker accountability.

And yet these measures fall short of addressing wider concerns around accountability and transparency in humanitarian contexts and fail to live up to the spirit of humanitarian ethics and the values embodied within. Even where accountability mechanisms are clear (who or what gets the blame when a model causes harm), how are these enforced? It’s difficult to see how our industry can get accountability and transparency right on an issue like AI/ML when the **yawning accountability gap** across the whole of the aid sector endures.

### 3.5 Regulation, data protection and privacy

WFP is jumping headlong into something they don’t understand, without thinking through the consequences, and the UN has put no frameworks in place to regulate it (**Aid worker quoted in The New Humanitarian**).

Both the humanitarian and technology industries have a disappointing track record when it comes to regulation. Debates persist about **whether and how best to regulate the technology industry**. And the humanitarian industry is arguably one of the least regulated in the world. As one expert noted, ‘We test everything on communities – from new education curricula to job creation projects – in ways that would never pass muster in the EU’.

There is no single, industry-wide authority that regulates the use and protection of humanitarian data or the use of data-intensive technologies like AI/ML. Yet one of the most significant risks linked to the use of AI/ML for humanitarian action is the fragmented regulation of its use. Legislation such as the European Union’s **General Data Protection Regulation (GDPR)** has improved data protection

10 Kahneman, D. (2011) *Thinking, fast and slow*. New York: Farrar, Straus and Giroux.

11 Fiske, S. and Taylor, S. (1991) *Social cognition* (2nd edn.). New York: McGraw Hill.

and privacy by establishing ownership of that data, including PII, with the individual. As the world's toughest privacy and security law (at the time of writing), GDPR has influenced data protection laws across the world. But it doesn't apply to all humanitarian agencies in all contexts. Some humanitarian agencies are not legally compelled to follow national data protection and privacy legislation as their status affords them specific immunities and privileges. And yet large agencies, like UNHCR and WFP, hold data on tens of millions of people, including PII.

Many humanitarian actors – both international organisations (IOs) and NGOs – have now developed internal data protection guidelines and policies, many of which reportedly follow the spirit of GDPR. The [International Committee of the Red Cross \(ICRC\)'s Handbook on Data Protection in Humanitarian Action](#) and the [Inter-Agency Standing Committee \(IASC\)'s Operational Guidance on Data Responsibility in Humanitarian Action](#) offer suggestions on how humanitarian actors can better protect their data and prioritise privacy across their operations. The ICRC Handbook offers guidance on the use of AI/ML as well as other technologies.

However, the quality, including the depth and breadth, of some agency-specific guidelines and policies is mixed. Some fail to include guidance around when and how to destroy data, including PII. Others contradict each other, claiming to prioritise the rights of individuals as the ultimate data owners while simultaneously committing to share information with relevant authorities as necessary. Compliance with and enforcement of these policies is weak. The consequences for breaching agency-specific data protection policies remain largely unknown, as these events are typically treated as internal matters. However, they are unlikely to resemble the penalties associated with violations of GDPR and other data protection legislation. In July 2021, [Amazon was hit with a £636 million fine for violating GDPR](#). Yet no penalties or punitive actions appear to have been taken for any of the recent [UN data hacks](#) or [breaches](#) or linked to the alleged [unethical sharing of data \(including PII\) by UNHCR](#) (see below).

Additionally, the humanitarian industry still lacks a standardised, industry-wide system, fit for the twenty-first century, that consistently and ethically solicits and acknowledges consent from individuals to collect, store and use their data, and allows individuals to withdraw that consent and destroy their data records without losing access to lifesaving support. Several agencies interviewed for this paper admitted to using case-related data to power AI/ML models without seeking any consent from individuals. Others noted that they had not yet worked out a way to explain to individuals how AI/ML was factoring into an agency's decision-making process. Some agencies have invested in advanced tools and guidance to [obtain meaningful informed consent](#), drawing on practice and principles commonly used in social work and human subject research. But the use of these tools across the industry remains patchy, and the rights of individuals are often trumped by interagency information-sharing agreements and international politics (see below).

Voluntary, self-regulation and the almost total absence of enforcement mechanisms ultimately weakens accountability and privileges the needs of humanitarian agencies above the rights of the individuals we are meant to protect. In this regulatory vacuum, with no consistent data protection

requirements, the race to collect data continues. Agencies are collecting more data than ever before with no clear limits on what should and should not be collected; many are reportedly collecting information even when its use or utility is not clearly demonstrable. Some of this race to amass ever-increasing amounts of data has been unintentionally driven by donors who have increased their requirements related to accountability and transparency without fully appreciating the knock-on effect this could have on information management.

Collecting data from affected populations puts an undeniable onus on humanitarian organizations to ensure that affected people's data is not misused and does not put them in harm's way, contrary to the purpose for which it was collected ([Saman Rejali and Yannick Heiniger](#)).

Many humanitarian agencies fail to fully grasp and assess the risks related to the chain of custody of the data they collect and share, increasing threats to that data and undermining principles of consent. Some, acting as implementing partners for IOs like UN agencies, agree to share a range of programme-related data without fully understanding how the data is used, with whom it is shared and under what circumstances. Yet, UN agencies and other IOs, acting as quasi-public institutions and delivering services on behalf of a state, are often obliged to share information with host governments as a condition of their in-country operations and the agreements they sign. These host governments may then share that information with other actors or nation states. In June 2021, Human Rights Watch reported that UNHCR and the Government of Bangladesh had **improperly collected personal information** from ethnic Rohingya refugees and shared it with the government of Myanmar to verify individuals eligible for possible repatriation. Whilst the alleged absence of informed consent was enough to concern most aid experts interviewed for this paper, some were also surprised to learn that UNHCR shared information at all with host governments.

At the heart of these risks related to regulation, data protection and privacy is the very live, though perhaps not always obvious, debate about who fundamentally owns the data that humanitarians collect: the individual, the agencies collecting the data, or the authorities of the state where the data and information is collected. As the digital and data revolutions continue, and in the absence of any effective regulation of humanitarian data and the use of AI/ML, unethical data handling and data breaches will likely continue.

### 3.6 AI safety and sustainability

Well-meaning efforts to deploy digital solutions to age-old challenges in the humanitarian industry can create significant blowback and unintentionally harm those most in need. The **use of blockchain to reduce incidents of fraud in food distributions led to a heated dispute** over data between WFP and the Houthis in Yemen.

While AI/ML offer a range of new ways to understand the world around us, changing the ways we work, live and connect with others, they can also increase the threat of harm. Designing and deploying safe

and sustainable AI/ML – AI/ML systems that reliably achieve the goals their designers and users intend without causing unintended harm – is both a top priority for humanitarian actors, and an unremitting task. This section discusses two key risks related to AI/ML safety in humanitarian contexts: the risk of amplifying bias, and the risk of unintentionally strengthening digital authoritarianism and surveillance. It does not include any analysis of technical AI safety, such as robustness, assurance and specification, as this is well-covered in other fora by subject matter experts.

Because AI systems operate in a world filled with uncertainty, volatility, and flux, the challenge of building safe and reliable AI can be especially daunting (Dr. David Leslie, The Alan Turing Institute).

AI/ML can perform in unexpected ways that cause unintended harm, for example when robots or driverless cars fail to recognise humans, leading to their death or injury, when a hiring AI develops biases against women, or when conversational AI adopt racist or sexist behaviours. In humanitarian contexts, and particularly in instances where data quality is poor, AI/ML can generate inaccurate results or make poor recommendations. This can inadvertently steer assistance or opportunities away from populations or individuals in most need. For example, in one instance predictions of population displacement generated by one ML model allegedly led to the closure of borders, preventing displaced populations from escaping violence and persecution.

Currently these risks are low, as few if any decisions in the humanitarian industry are automated or made by AI/ML. But these scenarios strengthen the already persuasive case for using interpretable AI/ML and keeping the ‘human in the loop’ (see section 3.4). The design of AI/ML can also reduce the costs of getting it wrong, turning high-stakes scenarios into managed risks, for example by making the actions linked to AI/ML output less punitive and more supportive.

The risk of system failures causing significant harm increases as [AI/ML] become more widely used, especially in areas where safety and security are critical (Tim G.J. Rudner and Helen Toner).

The second significant risk is that humanitarians’ use of AI/ML unintentionally boosts the surveillance capabilities of bad actors<sup>12</sup> or otherwise supports digital authoritarianism. Surveillance capitalism – where companies ‘monitor the behaviour of [their] users in astonishing detail, often without their explicit consent’ – and digital authoritarianism present new threats and opportunities for social engineering by corporations, authoritarian regimes or criminals. AI-enabled surveillance technologies are transforming governments’ ability to monitor and track individuals across boundaries. This is particularly concerning in places where data protection legislation and enforcement is weak or non-existent, digital literacy is low and individual rights and liberties are poorly protected (see Chapter 5).

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12 Bad actors are people, organisations or government actions that are harmful, illegal or morally wrong. This includes extremists, criminals, hackers, and authoritarian regimes.

This compounds the vulnerability of the tens of millions of people who are forcibly displaced or targets of persecution, whose lives are increasingly digitised by even the most well-intentioned aid agencies. Problematic data custody chains and weak regulation of humanitarian data **increase opportunities for bad actors to access this information** (see section 3.5). Even where humanitarian actors successfully anonymise their data, it can often be paired with other datasets, such as CDRs, to reveal potentially sensitive information, such as the geographic location of at-risk populations. While authoritarian regimes and their supporters **already have a range of effective tools to track and target their opposition**, few would turn down the opportunity to access more data, especially if it is easy to secure (see Chapter 5).

These are extant challenges related to AI safety that will exist regardless of how the aid community engages with AI/ML. And there are scores of additional, unintended harms and long-term risks related to humanitarian AI/ML that have yet to be properly identified and dissected. This will require both tech and aid experts to jointly interrogate issues related to AI safety.

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## Chapter 4 The runway to scale: enduring obstacles to deploying AI/ML

Like many industries, the adoption of AI across the aid industry has been broad but not deep. In a survey of 2,600 AI use cases to advance the [Sustainable Development Goals](#) conducted by the World Economic Forum, only 20 to 30 were deemed promising. Most projects were still labours of love, consuming resources while failing to demonstrate impact at scale. But is this a technological problem, a design problem or an ecosystem problem?

Developing and deploying effective and ethical, humanitarian-focused AI/ML requires, at a minimum:

- A clearly defined problem.
- **Data**, including the policies and systems to safely and ethically manage it.
- **Funding** for both the technology elements and the humanitarian services and support linked to the tool.
- **Technological tools and know-how** to design and maintain the tool, including software, hardware and staff.
- Well-trained **staff**, the right organisational structures and committed leadership.
- The right regulatory frameworks and policies in place to manage the data and software.

The first and last points are discussed in Chapter 3; this chapter analyses access to data, access to funding, access to technology and access to staff.

### 4.1 Access to data

AI and ML are data-hungry technologies requiring large amounts of data to make them effective (although [this may change](#)). Accessing the quantities of data required to power AI/ML for humanitarian action, however, is becoming increasingly easy.

Humanitarian organisations collect and share more data than ever before. This trend will continue as more systems, sensors and people come online in crisis settings. How the humanitarian community handles the data revolution to inform decisions and improve lives will be a key determinant of its future effectiveness ([Centre for Humanitarian Data](#)).

Humanitarian agencies generate massive amounts of data and information. Some of this information, such as biometric and other PII, is collected by individual agencies as they deliver services, distribute aid and provide support to individuals in need. Other information is collected through needs assessments, surveys and monitoring and evaluation activities.

Access to humanitarian open-source datasets is improving. Designed to make humanitarian data easy to find and use for analysis, the [HDX](#) is an open platform for sharing data. When HDX was

launched in 2014, it held around 800 datasets. Since 2014, that number has grown to 18,200. Last year, HDX saw a record growth in users, with **more than 1.3 million people using the platform and more than 2.2 million datasets downloaded**.

Some aid agencies purchase data or establish partnerships with other actors, such as NASA, the World Meteorological Organization, the UK Met Office or academic institutions, to access their data. UNHCR established strategic partnerships with 14 organisations to secure seven years' worth of data for the initial design of **Project Jetson**, an algorithm that makes predictions about population movements (see section 2.1). But, as the example suggests, this is usually only an option for large organisations able to leverage their reputation or reach to establish these partnerships. And data gaps persist. The Centre for Humanitarian Data estimates that **just 51%** of relevant, complete crisis data is available across 27 humanitarian operations. And, where national-level data exists for some countries of interest, publicly available, sub-national data is still woefully lacking across the globe (see section 2.2).

The Covid-19 pandemic also brought into stark focus the value of predictive models to inform humanitarian response strategies. Significant challenges exist in relation to data gaps and data quality, limiting the viability and accuracy of model development. Model output is only as good as model input (**Centre for Humanitarian Data**).

The integrity and quality of the data that does exist is mixed. Labelling errors abound, for example in naming cities or administrative areas, driven by differences in spelling, simple typos or basic human error. Many aid agencies are still in the early stages of their respective data revolutions and a large number – including the behemoths of aid who turn over close to \$1 billion a year – continue to collect and store data that is largely unstructured and siloed, both between country programmes and between technical teams. Moreover, tools and platforms to collect and store data are of mixed quality or no longer fit for purpose. One senior executive at a global aid agency admitted that ‘a huge amount of our data is still in excel workbooks and saved on the hard drives of laptops in the field. While it’s digital, we’re nowhere near a state where we’d be able to use it to generate meaningful analysis’.

The Centre for Humanitarian Data has called on national governments, the World Bank, UN agencies and global-level clusters to improve the collection and sharing of specific datasets. But other humanitarian agencies have a role to play as well. They sit on vast troves of information, stretching back decades. With the right investment and commitment from senior leadership, aid agencies could transform the data they hold into high-value assets that ultimately improve the quality of support they provide. If even a fraction of the resources invested in maintaining other humanitarian assets – like Land Cruisers and generators – were used to develop new ways to capture, clean and store the data that agencies collect, the result could be transformational.

This is not a call for agencies to collect even more data, but rather encouragement to be more selective and strategic in what data is collected and how it is managed, and to commit the resources needed to clean it and transform it into a valuable asset. Data is meaningless if it can't or won't be used. Humanitarian actors that fail to develop sound data strategies and data management tools in the midst of the 4IR increasingly face the threat of obsolescence (see Chapter 5).

## 4.2 Access to funding

Resources to design and test AI/ML solutions to humanitarian problems are increasing. The tech-for-good or philanthropic arms of large technology firms such as Microsoft, Google, Facebook and Cisco are supporting humanitarian AI projects (see section 4.3). Governments including Belgium, Canada, Sweden and the **United States** are sponsoring hackathons to develop prototypes and other new solutions to humanitarian problems. In 2019, the two-day **Humanitarian Hackathon** brought together 130 technology and innovation experts to foster innovative ideas and build new prototypes to 'transform aid delivery and help eradicate hunger'. A number of innovation funds now exist to help start-ups develop new technological tools to tackle humanitarian and development challenges. **UNICEF's Innovation Fund**, for example, provides \$100,000 equity-free seed funding to start-ups developing open-source tech solutions. Major philanthropic institutions are dipping a tentative toe in the AI-for-Good waters. In January 2019, The Rockefeller Foundation announced the creation of the **Data Science for Social Impact** collaborative in partnership with the **Mastercard Center for Inclusive Growth**. The collaborative's first decision was to award \$20 million in funding to **DataKind**, a global non-profit that 'connects data science talent with social organisations, harnessing the power of data science and AI in the service of humanity'.

But, by and large, existing funding modalities are not fit for purpose, resources are too small and the conditions on aid too restrictive to enable a proper exploration of AI/ML in the humanitarian sector. Most innovation funds are supporting the development of new small and medium-sized enterprises (SMEs) to develop bespoke AI/ML tools and capabilities, but these capabilities are rarely deployed by operational humanitarian agencies (see section 4.3). Some humanitarian agencies find it difficult to resource *both* the more traditional humanitarian components of AI/ML pilot projects and the technological elements. In 2021, a US-based humanitarian agency successfully secured pro bono AI support and services with a market value of \$1 million from a global technology firm but was unsuccessful in attempts to raise the additional \$300,000 required to deliver the humanitarian elements of the project.

This is partly driven by a difference in risk appetite and the metrics of success used by those who support tech-for-good projects, on the one hand, and more traditional supporters of humanitarian action on the other. Unlike venture capitalists or tech-focused philanthropists, most traditional aid donors expect aid organisations to deliver a set of concrete and measurable results in exchange for funding. Without taking a portfolio-approach to risk, the space for risk and the freedom to fail is incredibly small. Equally, government donors can be more susceptible to short-term thinking,

fuelled by changes in political leadership and priorities. A donor may one year fund predictive analytics, and the next may have moved on to UAVs and drones. This undermines the consistency of support required to develop and fully test AI/ML pilot projects across the humanitarian industry.

One big learning is that the operating structures of the humanitarian sector make innovation challenging. For example, while these tests yield promising solutions, the larger grant funding structure – typically short term and relatively inflexible and risk averse – poses a challenge to building on proven concepts. Because aid funding is often limited and inflexible, the sustainability of innovative programming can be hampered (Alexa Schmidt, Mercy Corps).

Large technology firms are not stumping up the cash to cover the cost of these activities. In a March 2021 call for proposals, Microsoft offered support through their **AI for Humanitarian Action** initiative. This included up to \$300,000 fair market value in Azure and data science services, consisting of a combination of Azure credit, Azure enablement engineering support and up to 300 hours of engagement by Microsoft Data Science and Analytics team members. No funding was earmarked for activities related to humanitarian service delivery that would complement these technological interventions (see section 4.3). Nor are they providing free or at-cost support for data cleaning and labelling. In the **call for proposals**, Microsoft explicitly required applicants to ensure their data was labelled or that they had a plan in place to do this.

With such high price points, limited access to unrestricted funding and few donors willing to invest in higher-risk ventures, many humanitarian agencies will continue to lack the funds necessary to effectively pilot and scale AI/ML projects.

### 4.3 Access to technology

The software, servers, processing power and staff required to support AI/ML for humanitarian action are more widely available than ever before, and large technology firms are increasingly supporting projects which claim to have humanitarian objectives. Since 2018, Microsoft has supported 40 **AI for Humanitarian Action** projects in 13 countries, advancing solutions to address challenges around disaster response, refugees, displaced people, human rights and the needs of women and children through grants, technology donations and data science support. Microsoft reportedly ‘hopes to use AI to change “the way frontline relief organizations anticipate, predict and better target response efforts” in areas including famine, human trafficking and providing refugee aid’.<sup>13</sup> Google’s **AI for Social Good** initiative ‘focuses Google’s AI expertise on solving humanitarian and environmental challenges, [using AI to] meaningfully improve people’s lives’. IBM has supported dozens of humanitarian organisations, including **UNHCR**, **Médecins Sans Frontières** and the **Danish Refugee Council** (see Chapter 2). And **Facebook’s Data for Good** claims to use ‘data to address some of the world’s greatest humanitarian issues’.

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13 Patel, R. ‘Predicting how a crisis unfolds’. Carleton University School of Journalism and Communication (<https://cusjc.ca/mrp/dataandthedisplaced/predicting-how-a-crisis-unfolds/>).

In addition to Big Tech, the number of SMEs and start-ups offering more affordable solutions is increasing, including in the Global South. The global platform **Omdena**, for example, draws on the support of dozens of (largely volunteer) AI engineers and data scientists from more than 90 countries around the world to help organisations build ethical and efficient AI solutions.

The marketplace for tech-for-good services is, however, flawed. Opaque pricing and the selective transparency of the market only increase competition between aid agencies who are already fiercely (and unhelpfully) competitive. Few agencies are publishing details about their AI/ML work, either the successes or the failures, making it difficult to know which tech providers and solutions have worked and which haven't. And, without a one-stop shop and no obvious institutional home for humanitarian AI, many aid agencies find it difficult to explore its potential. As one aid worker put it: 'Even if I wanted to develop an AI project, I have no idea where to begin. Who do I ask? At which company?'

The price point and quality of services also blocks supplier efforts to meet demand. While more affordable, the products provided by smaller firms aren't always fit for purpose, and firms lack the investments necessary to repurpose. Out-of-the-box tools developed by larger firms may offer better solutions but can be costly. Many agencies simply need help cleaning and organising their data before they even begin to explore opportunities in AI/ML (see section 4.1).

Only a few aid agencies have the resources required to **purchase technology support outright**. This compels most to seek in-kind support, accessed either through open competition (the flaws of which are discussed above) or well-established, philanthropic partnerships. But again, only large aid agencies have the networks, reputation, operational reach or human resources to successfully broker symbiotic relationships with corporate entities.

Establishing partnerships with technology firms requires a very thorough understanding of a firm's incentives, corporate ethics, business model and wider aims and aspirations. While it is now well-known that millions of consumers across the world cover the cost of 'free' apps by granting access to their data, far less is understood about the incentives for technology firms delivering tech-for-good projects. Yet this is crucial if humanitarian agencies are to equally and meaningfully co-design AI/ML-powered projects.

The tech-for-good movement is influenced by a collection of incentives, the most obvious of which is reputation management. As Big Tech faces mounting criticism for its **role in political insurrections, undermining democratic elections and fuelling genocide**, 'aid-washing'<sup>14</sup> their brand with tech-for-good projects co-led by global aid agencies with brand recognition may offer some reprieve. As one expert notes, 'Facebook is trying to decide whether it wants to be known as the genocide company [for its role in the Myanmar crisis] or the free speech company'. Research suggests that firms in socially or environmentally damaging industries such as oil, chemical and

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14 Funding projects that advance social progress to give the impression of being socially responsible **while not fundamentally changing harmful business practices**.

tobacco use philanthropic work to ‘produce policy outcomes that work *against* public welfare’<sup>15</sup> by building goodwill with policy-makers and weakening political coalitions [emphasis added]. This may hold true for the tech industry if tech-for-good projects undermine or prevent government efforts to impose new regulations and penalties on Big Tech.

Partnering with aid agencies may also offer tech firms access to markets where testing new products is easier, data protection and privacy legislation and enforcement are extremely low or non-existent (enabling greater data harvesting), or where early market entrants increase their potential future earnings as internet connectivity expands. Mixed or weak incentives for tech firms usually means that the work, in the view of one expert, ‘gets shovelled over to the “for good” department. Facebook gives no money for product development to the crisis management people so the tools they use are disproportionately slow and much less powerful than what Facebook could actually deliver’.

The humanitarian community must exercise as much caution over its relationships with the technology industry as it does over its relationships with other sectors, such as the military and state armed forces. Most humanitarians appear to have given little thought to how Silicon Valley has affected the ways we work and the tools we use. ‘User-centred design’ and ‘human-centred approaches’ seem perfectly apt phrases to use when discussing the design of software, but aren’t humanitarian aid programmes – by their very nature – always human-centred? Not only has Silicon Valley’s lexicon seeped into the day-to-day language of humanitarians, but it has also impacted the design of their systems. Pilot projects are now called ‘proofs of concept’, and innovation teams drawing on design tools and processes – like incubators and accelerators – straight out of Silicon Valley’s playbook are spreading across the aid sector. This culture creep suggests lexiconic laziness, but also a deeper and perhaps more worrying belief that technology firms are benign and neutral actors who value higher purpose aims related to social progress above their own profit and data.

Some aid agencies are beginning to interrogate the tech-for-good offers they receive, and several expressed concern about the impact these corporate partnerships could have on their programmes, as well as their brand and reputation. Few aid experts would question the need to build partnerships with like-minded firms whose values and ethics support or align with humanitarian principles and ethics. But in the absence of an ethical litmus test to assess partnerships or an industry-wide benchmark against which to work, promoting more ethical relationships between tech firms and aid agencies will remain a challenge.

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15 Fooks, G., Gilmore, A., Collin, J. et al. (2013) ‘The limits of corporate social responsibility: techniques of neutralization, stakeholder management and political CSR’ *Journal of Business Ethics* 112(2): 283–299.

## Box 2 Innovation funds and hackathons

Donors and aid agencies are increasingly turning to innovation funds and hackathons to expand the marketplace of socially responsible SMEs with **double bottom lines**, those seeking to achieve both financial gain and positive social impact. But the fundamental design of these funds has prevented start-ups from achieving this higher aim. Although tech-for-good ventures reportedly have few problems accessing seed funding or **Series A funding**, there is very little money to take ventures to scale, and the constraints placed on seed funding are ‘so restricted and cumbersome that it forces us to operate like a non-profit which means we’ll never get off the ground’.

Moreover, donors and innovation funders often require recipients to make their product a public good, whether that’s code developed through a hackathon or a suite of software developed with seed funding. However, in some instances the commissioned client or end user may only partially buy into the process and ultimately opt out of using the developed tool. This leaves the creator with little recourse and cash to repurpose or recoup losses.

To improve buy-in, operational humanitarian agencies and other ‘problem owners’ must identify the most pressing problems where technological tools could deliver greater impact. Donors must expand funding and change the conditions attached to that funding to help start-ups and SMEs effectively scale new capabilities to support humanitarian action.

## 4.4 Access to staff

Harnessing the power of AI/ML requires well-trained staff, the right organisational structures and committed leadership. As the need for agencies to better manage and use their data increases, so too does the demand for trained staff. The number of information managers and data scientists working for humanitarian and development agencies is slowly increasing. These staff can build and manage AI/ML models, interpret the models’ results, and analyse their performance. But these specialists are still few and far between. One international NGO with an annual turnover of more than £380 million and 8,000 staff has just two data scientists. Another agency that runs a specific model to predict displacement and turns over more than \$1 billion a year with 15,000 staff has only one data scientist. Even with a shift in recruitment priorities, agencies may struggle to retain experienced data scientists and other experts as they gravitate towards industries that have embraced AI/ML and committed to higher standards of data management and data-driven decision-making.

Poor digital and data literacy among humanitarian aid workers creates more obstacles in the digital transformation of the aid industry. An innovation expert interviewed for this paper argued that ‘aid

workers tend to throw up red flags around the ethics and governance of new technologies not only because these are valid concerns but because many of them still really fail to grasp the basics of how these technologies work and their benefits and risks’.

Equally, most technology experts fail to understand the complexities of humanitarian action, its purpose, ethics and principles and the challenges aid workers face in seeking to support communities in need. Using AI/ML thus requires meaningful collaboration and communication between technology and humanitarian experts. Yet, a common, non-specialist language that unites technologists and aid workers still evades these industries. And the limited publications on humanitarian AI are either so full of  $\Sigma$  and mathematical equations that it puts off all but the most ardent enthusiasts of AI/ML, or so polished that they lose meaning and read more like a brochure.

The organisational structure of some agencies also inhibits the design and uptake of AI/ML by delegating this work to innovation units, IT departments or senior executives. Staff in these teams are typically more removed from the realities of frontline service delivery than humanitarian technical experts such as education advisors, public health specialists, water and sanitation engineers and social workers. As one technology expert explained: ‘we don’t really care how the organisation is structured, we just want to connect with the “problem owner”. But more often than not, I find that senior executives, CTOs or innovation staff are unhelpful gatekeepers and prevent that from happening’.

The UN’s knowledge of the potential implications of new technologies must be continuously updated and sharpened. Beginning at the top, we must all – from headquarters to the country level – engage proactively with technology pioneers, innovators, policy-makers and users. Each staff member must understand how new technologies are impacting their area of work, and they must be provided with the space to explore and test how technology can be leveraged to better deliver on respective mandates ([UN Secretary-General’s Strategy on New Technologies, September 2018](#)).

This behoves a rethink in the way aid agencies structure themselves. Some have already placed information management specialists and data scientists within their technical units. Externalities linked to the 4IR may force further shifts in organisational architecture across the industry. As cutting-edge **fintech** tools become more widespread, finance teams may be dramatically reduced and replaced with bots able to **generate error-free financial statements**. Data scientists may **replace M&E staff**. Logistics teams may be replaced by algorithms, making maintenance and supply chain management more efficient. Those most likely to lose in this scenario? Staff who are less digitally literate and less able to work with technology alongside the locally recruited staff who often fill a majority of the operational roles in-country. This could compound AI-related labour displacement in fragile economies and LMICs where aid agencies typically operate and hinder localisation efforts (see section 3.3).

Successfully navigating these uncertainties requires an industry-wide commitment to improving the digital and data literacy of staff, including marginalised groups such as women and staff in the Global South. This includes designing and fully funding agency-wide training grounded in proven competency frameworks that help staff use data for analysis and decision-making, use data to improve service delivery and communicate effectively with data and technology specialists on data-driven technologies like AI/ML.

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## Chapter 5 Conclusions: what next for humanitarian AI?

### 5.1 AI/ML will change the landscape in which humanitarian aid is delivered

The speed, scale and complexity of the 4IR is unprecedented. Some experts believe that this change is outpacing the evolution of our culture, our institutions and the way we interact as humans. Technology is becoming more affordable and accessible, and the lives of more and more people across the globe are becoming digital. Increased digital connectivity is driving an exponential rise in the amount of data available. Experts estimate that, by 2025, the amount of **data generated across the globe each day will reach 463 exabytes**<sup>16</sup> – roughly the equivalent of 144 trillion pictures or 231.5 billion hours’ worth of movies. ‘**Big data fundamentalism**’ – the belief that large datasets will always yield reliable and objective truths if only we extract them using AI/ML – is fuelling a race for data across countless industries. As part of their wider data and digital revolutions, humanitarian actors are contributing to this trend, digitising the lives of those who may or may not be aware of this parallel, cyberreality. Those with lower digital literacy and/or less understanding of digital threats and opportunities will become increasingly vulnerable to social engineering, micro-targeting and other forms of manipulation.

Data-hungry AI/ML will have a significant impact on the global and national economies, the labour market, conflict and security, international relations and the way in which societies organise themselves. This will necessarily change the nature of the conflicts to which humanitarians respond – including conflict drivers and accelerants, who is impacted and the viable pathways to peace – as well as the ways in which humanitarian actors operate in hostile environments, connect with communities and remain neutral in increasingly complex conflicts that are both on- and offline.

As technologies improve, parties to conflict and their supporters have better and cheaper access to tools which can control populations both inside and well beyond their borders (see section 3.6). Bots and AI systems have industrialised the production and spread of synthetic media, false news, misinformation and disinformation. An **MIT study** found that it takes six times longer for true news stories to reach people than false ones. And AI/ML systems can now produce synthetic images that are nearly indistinguishable from photographs. Google’s own leaders fear that deep fakes ‘**could lead to real chasms in society and misinformation**’. Disinformation campaigns can shift public perceptions of conflicts and humanitarian need, undermine claims of war crimes and IHL violations, or further fuel violence and conflict, as we have already seen in **Syria** and **Myanmar**. They can also convincingly distort information about the rights and services available to populations in need, limiting freedom of movement, contributing to ill-informed decisions about migration or return and degrading the credibility of humanitarian actors. In the near future, aid agencies may find themselves working to counter **troll factories** supported by state and non-state actors, but lacking the tools and capabilities to do so.

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16 An exabyte is equivalent to 1 billion gigabytes.

## 5.2 But AI/ML, on its own, is unlikely to disrupt the humanitarian industry

There is little doubt that tech-focused, social enterprises have emerged as more regular players in the delivery of aid, particularly in less hostile environments or areas where digital infrastructure is more advanced or regulation more permissive. Many of these new entrants to the humanitarian market use data-driven tools to provide aid directly to recipients, mirroring models established by enterprises like [GiveDirectly](#) and [AirBNB.org](#), reducing the middle-men and meeting demand more efficiently. This new approach appeals to some donors – particularly those seeking greater accountability and transparency on the impact of their investments – and differs enough from the existing humanitarian business model so as to slightly stiffen competition over finite resources.

Humanitarian agencies are finally (though slowly) developing the strategies and plans necessary to help them transform their data and information into valuable assets. And large aid agencies are starting to develop and adopt AI/ML solutions, often leveraging their brand, reputation and operational reach to negotiate favourable relationships with big technology firms. While uptake across the industry will continue to be slow, hindered by poor-quality data, erratic investments and contradictory thought leadership, this limited use of AI/ML may be enough to preserve the status quo. Humanitarian agencies, particularly those without access to affordable technologies or robust datasets, may find it increasingly difficult to compete. This could undermine the localisation movement and prevent efforts to shift power towards humanitarian actors in the Global South.

## 5.3 Humanitarian actors should carefully explore ways to use AI/ML

While some applications of AI/ML may not live up to their hype (see section 3.1), other use cases show promise. MSF's [innovative use of computer vision](#) demonstrates how AI/ML can be used to solve a specific problem identified by aid experts and deliver high impact in low-resource settings. Models that offer granular, subnational forecasts about humanitarian crises and epidemics have also helped agencies deploy targeted, preventative interventions, like handwashing stations and public information campaigns, ultimately reducing the potential impact of a crisis. Some AI/ML, such as conversational AI and virtual assistants, can be scaled quite easily, with the overall costs diminishing as use increases. In these cases, the longer-term benefits appear to outweigh any up-front costs, while freeing up time for humans to focus on more complex issues and decisions (see section 2.3).

However, AI/ML tools deployed in humanitarian contexts also offer great potential for harm. Aid actors should thus explore these tools, their opportunities and their threats, with caution. Designing 'mission possible' pilot projects can help minimise the risk to crisis-affected communities while testing the utility of AI/ML in humanitarian settings. Given the high-stakes decisions involved in humanitarian action, these projects should [avoid using black box AI/ML models](#) and employ explainable AI as a way to strengthen accountability and transparency. Furthermore, they should regularly assess how humans use the outputs of AI/ML models to make decisions, with the ultimate aim of assuring human oversight and sound judgment (e.g. a [human-in-the-loop](#) approach).

Aid agencies must think carefully about the consequences of AI/ML adoption on the humanitarian ‘data race’ and the collective impact on the vulnerability and agency of the individuals we serve. Aid actors should operate under the assumption that no data is safe, and thus exercise the highest level of caution when collecting, storing and destroying it. This is particularly true for PII and biometric data. Tech-for-good offers should be expanded to not only include in-kind services, software and staff support, but also assistance with data cleaning and data management. Threat assessment tools, like [Data Protection Impact Assessments](#), and threat-modelling methods may help to identify potential risks, including cybersecurity threats and data breaches as well as unintended consequences, related to the collection and management of humanitarian data. Technologists and aid experts should co-design and develop industry-wide tools that transfer power and control over their data back to individual service-users and allow individuals to both grant and withdraw their consent.

#### **5.4 Well-resourced, cross-industry partnerships led by aid experts may help identify high-impact use cases**

Leaders across the tech and aid industries will have to find ways to work collectively if the benefits of AI/ML are to be realised and the risks successfully managed. This will be difficult, not least as it requires trust and transparency *within* the humanitarian aid industry and *with* the technology industry, both of which are deeply competitive and opaque. The selective transparency of the tech-for-good market ultimately constrains its potential impact. Aid agencies must commit to improved transparency in the use of AI/ML tools for humanitarian action, declaring what they develop and using agency-specific communications tools as well as inter-agency platforms like [NetHope](#) and the [Centre for Humanitarian Data](#) to regularly share information about the tools developed, how they work, where they are deployed and lessons learned. This includes establishing safe and ethical means to share the successes and shortcomings of these projects across the industry, in support of transparency, accountability and wider industry learning. Contact information for humanitarian and tech actors working on these projects should also be shared to enable better collaboration and future partnerships between technology and humanitarian experts.

The development of humanitarian AI/ML tools should be led by aid practitioners and experts who fully grasp the complexity of the operational and political challenges faced when supporting communities in crisis. Aid professionals have the ability – and the responsibility – to [meaningfully influence how these technologies impact people](#) and how technologists design and deploy these tools in humanitarian contexts. Operational humanitarian agencies and their technical experts, such as water and sanitation, logistics, health, education specialists, should identify specific problems where AI/ML tools could deliver greater impact, using interagency platforms and other collaborative fora to draft a plan or roadmap that collectively defines and prioritises these problems. This could help solutions remain problem-centred (not technology-centred) and benefit all humanitarian agencies, not just those with enough cash and cachet to cultivate promising relationships with technology firms.

To fully realise the potential of AI/ML in humanitarian contexts, donors and philanthropists will have to expand existing funding modalities as well as the size of funding envelopes for humanitarian actors seeking to test ways to safely and ethically use these tools. This includes funding both the technology and innovation components of programmes *as well as* more traditional activities related to humanitarian action. Development agencies and other donors with lower risk appetites will need to develop risk management strategies that support collective ownership of both the successes and failures of AI/ML pilot projects. To help start-ups and SMEs scale AI/ML that supports humanitarian action and ultimately widen the marketplace of firms providing high-quality and affordable services, donors will need to increase support beyond **Series A/seed funding** and change the conditions attached to that funding. This is particularly critical for firms in the Global South. And technology firms will need to move beyond gifting services, software and staff time, offering cash grants to cover all project costs, not just the technology components.

Human, as well as financial, resources will have to be expanded. This may include developing organisation-wide **competency frameworks** and learning objectives for staff on data and digital literacy and conducting **regular knowledge assessments** to guide the type and frequency of training offered. Aid actors should promote new models of digital education and broaden and deepen the types of training available to help staff improve their data and digital literacy, including their understanding of data, data ethics and relevant risks and requirements of data management and protection. In support of wider efforts to tackle the global digital divide, training for staff from the Global South and women should be prioritised.

## **5.5 Efforts to regulate the use of humanitarian data and AI/ML must be accelerated**

Proper regulatory bodies and tools are critical to the safe and ethical deployment of AI/ML in humanitarian contexts. Humanitarian actors and their donors should work collectively to develop industry-wide standards and tools to regulate the use of AI/ML and data, building on systems like the **Centre for Humanitarian Data's Peer Review Framework** and the **Data Science & Ethics Group's ethical framework** for data science, as well as **other best practice** developed by humanitarian actors. In addition, the aid industry could consider developing **Sphere Standards** for data management and protection in humanitarian settings, drawing on **existing guidelines** and **policies**. These standards could require aid agencies to establish and maintain information asset registries, set standards for when and how information assets can be used, sold, shared and destroyed, and offer strategies to promote compliance with these standards.

Donors and aid agencies alike must adopt and adhere to agency-specific **data strategies** and policies that promote data availability and integrity by breaking down data silos, making data easily accessible and actionable, and ensuring data is accurate and trustworthy. Strategies should embody best practice and internationally recognised ethical principles while articulating specific data requirements. These should include specifications around the limits of data collection, how data is managed, how consent is solicited for the collection and use of individuals' data, when and how

data is destroyed, and clear actions to be taken when data is breached. Data strategies must be well-resourced and reflect the current and future operational realities, as well as the highest standards in data protection and privacy and humanitarian and AI ethics. Individual consent and data protection should be at the heart of all humanitarian data management systems. Donor requirements to trace and account for cash transfers and other spending must always be balanced against the absolute requirement to protect individual privacy and safety.

Aid actors could operationalise humanitarian and AI ethical frameworks by establishing and funding an independent, interagency ethics review board staffed with world-leading experts in humanitarian aid, AI/ML and ethics. This Review Board could assess the risks and benefits of humanitarian AI projects and the extent to which they comply with best practice and ethics. Donors could require implementing partners to have AI/ML projects assessed by the Review Board to give assurance that key ethical issues and recommended changes have been identified. The Review Board could also develop auditing tools or partner with AI auditing firms to help improve adherence to AI ethics.

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## Appendix Glossary of key terms

<b>AI ethics</b>	AI ethics is a set of values, principles, and techniques that employ widely accepted standards to guide moral conduct in the development and use of AI systems. (Source: <a href="#">UK government</a> )
<b>Algorithm</b>	An algorithm is a set of rules – a recipe – for a computer to follow. An ML algorithm is only as good as its data because it uses data to establish the rules for how the algorithm functions, rather than a programmer establishing what the rules are. (Source: <a href="#">Oxford Sparks</a> )
<b>Artificial intelligence (AI)</b>	There is no one, universally accepted definition of artificial intelligence or AI. Broadly speaking, AI is the science and technology of creating intelligent systems. AI is often used to describe when a machine or system performs tasks that would ordinarily require human (or other biological) brainpower to accomplish, such as making sense of spoken language, learning behaviours or solving problems. There are a wide range of such systems, but generally they rely on computers running algorithms, often drawing on data. In popular culture, AI is often viewed as sentient machines, thinking and behaving like a human. In reality, much AI is computers which are trained to perform tasks independently, and which are already present in many areas of our lives. There has been much publicity about the use of AI in decision-making, for example in the security and justice sectors. These AI are driven by ML tools, which have taught a computer to make decisions based on the data presented to it. AI systems are often enabled by ML and apply data-derived predictions to automate decisions. (Sources: <a href="#">The Alan Turing Institute</a> and <a href="#">USAID</a> )
<b>Artificial neural networks</b>	Mathematical computing systems, loosely inspired by the brain's neurons and synapses, that are at the core of today's AI. (Source: <a href="#">MIT Technology Review</a> )
<b>Big data</b>	Big data are high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing to enable enhanced insight, decision-making and process automation. (Source: <a href="#">Centre for Humanitarian Data</a> )

**Call detail records (CDR)**

A CDR provides metadata – data about data – on how a specific phone number and/or user is utilising the phone system. This metadata typically includes: when the call took place (date and time); how long the call lasted (in minutes); who called whom (source and destination phone numbers); what kind of call was made (inbound, outbound, toll-free); and how much the call cost (based on a per minute rate). CDRs can also include SMS messaging metadata and any other official communications transmissions. However, the contents of the messages/calls are not revealed through the CDR. The CDR simply shows that the calls or messages took place, and measures basic call properties. (Source: [OnSIP](#))

**Chatbot**

At the most basic level, a chatbot is a computer programme that simulates and processes human conversation (either written or spoken), allowing humans to interact with digital devices as if they were communicating with a real person. Chatbots can be as simple as rudimentary programmes that answer a simple query with a single-line response, or as sophisticated as digital assistants that learn and evolve to deliver increasing levels of personalisation as they gather and process information. Driven by AI, automated rules, NLP and ML, chatbots process data to deliver responses to requests of all kinds. (Source: [Oracle](#))

**Cloud computing**

Often referred to as ‘the cloud’, cloud computing is the delivery of on-demand computing resources – including applications, computer processing power and data storage – via the internet or a private network. (Sources: [Amazon Web Services](#) and [IBM](#))

**Computer vision**

Computer vision is a field of AI that uses image processing algorithms to train computers to interpret and understand the visual world. Using deep learning models to analyse digital images and videos collected by cameras, satellites and UAVs or drones, machines can accurately identify and classify objects and react to what they ‘see’. (Source: [SAS](#))

**Conversational AI**

Conversational AI refers to technologies, like chatbots or voice assistants, which users can talk to. They use large volumes of data, ML and NLP to imitate human interactions, recognising speech and text inputs and translating their meanings across various languages. Humans typically interact with conversational AI through telephone calls, SMS or messaging platforms like WhatsApp or Facebook Messenger. Apple’s Siri and Amazon’s Alexa as well as a range of customer relations management (CRM) tools are popular forms of conversational AI. (Source: [IBM](#))

<b>Data cleaning</b>	Data cleaning is the process of correcting and/or standardising data from a record set, table or database. (Source: <a href="#">Centre for Humanitarian Data</a> )
<b>Data literacy</b>	Data literacy refers to the ability of non-specialists to read, write and comprehend data, just as literacy is the ability to read, write and comprehend one's native language. (Source: <a href="#">Statistics Canada</a> )
<b>Data science</b>	Billions of gigabytes of data are generated globally every day. Data science is the drive to turn this data into useful information, and to understand its impact on science, society, the economy and our way of life. The study of data science brings together researchers in computer science, mathematics, statistics, ML, engineering and the social sciences. (Source: <a href="#">The Alan Turing Institute</a> )
<b>Data silos</b>	A data silo is a situation wherein only one group in an organisation can access a set or source of data. Data silos can result from several factors, including: cultural – competition or animosity between departments can cause employees to keep data from each other, rather than working together; structural – especially in large organisations, data silos can stem from a hierarchy separated by many layers of management and highly specialised staff; technological – applications might not be used or even designed to cross-reference or add to each other, or one department may simply not have access to a valuable app from another department because it was not purchased for their specific day-to-day tasks. (Source: <a href="#">Plixer</a> )
<b>Deep learning</b>	Deep learning platforms are a subset of ML developed to deliver solutions to complex problems. The 'deep' aspect refers to the structure of the system, which has multiple layers of ML processing called neural networks. There is an input layer, multiple 'hidden' layers and an output layer. The greater interconnection and sophistication of deep learning systems compared to simpler ML systems means that deep learning is particularly good at dealing with unlabelled and unstructured data, such as data coming in from multiple real-world sources like sensor systems or internet traffic. Deep learning enables applications in complex environments, including autonomous movement, translation of spoken language, price forecasting and medical diagnosis from images. (Source: <a href="#">GSMA</a> )
<b>Digital authoritarianism</b>	Digital authoritarianism refers to the use of digital information technology by authoritarian regimes to surveil, repress and manipulate domestic and foreign populations. (Source: <a href="#">The Brookings Institution</a> )

<b>Explainable AI</b>	Explainable AI draws on specific techniques and methods to ensure that each decision made by an AI or ML model can be traced and explained. AI that is not explainable, on the other hand, often arrives at a result using a series of algorithms, but the architects of AI systems do not fully understand how the algorithm reached that result. This makes it hard to check for accuracy and leads to loss of control, accountability and auditability. (Source: <a href="#">IBM</a> )
<b>Facial recognition</b>	Facial recognition is a software that maps, analyses and then confirms the identity of a face in a photograph or video. (Source: <a href="#">The New York Times</a> )
<b>Forecast</b>	A prediction or estimate of future events and their expected impacts and consequences. It is the output of a predictive model. (Source: <a href="#">Centre for Humanitarian Data</a> )
<b>Forecast-based financing (FbF)</b>	Sometimes referred to as anticipatory humanitarian action, FbF is used by humanitarian actors to release funding for pre-agreed early actions, based on forecast information and risk analysis, to prevent or mitigate the impact of extreme events. Funds are allocated automatically when a specific threshold (trigger) is reached. (Source: <a href="#">Red Cross and Red Crescent Movement</a> )
<b>Fourth Industrial Revolution (4IR)</b>	The Fourth Industrial Revolution (4IR) is a term coined in 2016 by Klaus Schwab, founder and executive chairman of the World Economic Forum. It is characterised by the convergence and complementarity of emerging technology domains, including nanotechnology, biotechnology, new materials and advanced digital production technologies. The latter includes 3D printing, human-machine interfaces and AI, and is already transforming the global industrial landscape. The 4IR is more than a technological leap forward. What sets 4IR technologies apart from others is the novel way in which hardware, software and connectivity are being reconfigured and integrated to achieve ever-more ambitious goals, the collection and analysis of vast amounts of data, the seamless interaction between smart machines, and the blurring of the physical and virtual dimensions of production. (Source: <a href="#">UNIDO</a> )
<b>Garbage in, garbage out (GIGO)</b>	GIGO expresses the idea that, in computing and other spheres, incorrect or poor-quality inputs will always produce faulty output. (Source: <a href="#">Oxford Reference</a> )

<b>General Data Protection Regulation (GDPR)</b>	The General Data Protection Regulation (GDPR) is the toughest privacy and security law in the world. Although it was drafted and passed by the European Union (EU), it imposes obligations on organisations anywhere if they target or collect data related to people in the EU. The regulation was put into effect on 25 May 2018. The GDPR levies large fines against those who violate its privacy and security standards, with penalties reaching into the tens of millions of euros. (Source: <a href="https://gdpr.eu">GDPR.eu</a> )
<b>Humanitarian action/aid</b>	Humanitarian action is intended to save lives, alleviate suffering and maintain human dignity during and in the aftermath of man-made crises and disasters, as well as to prevent and strengthen preparedness for such situations. (Source: <a href="#">Good Humanitarian Donorship</a> )
<b>Humanitarian principles</b>	Humanitarian actors are generally guided by four humanitarian principles: humanity, neutrality, impartiality and independence. These principles provide the foundations for humanitarian action. They are central to establishing and maintaining access to affected communities, whether in a disaster, an emergency or a situation of chronic conflict or instability. (Source: <a href="#">UN Office for the Coordination of Humanitarian Affairs</a> )
<b>Machine learning (ML)</b>	Machine learning (ML) brings together the fields of statistics and computer science to enable computers to learn how to do a given task, without being programmed to do so. ML uses a range of methods to train computers to learn from existing data, where ‘learning’ amounts to making generalisations about existing data, detecting patterns or structures, and making predictions for new data. This differs from how statistical analysis has traditionally been done, where a model is developed based on mathematical rules and then applied to data. ML approaches flip this process by finding patterns in data and returning a model that can make predictions for new data. (Source: <a href="#">Oxford Sparks</a> and <a href="#">USAID</a> )
<b>Natural language processing (NLP)</b>	Natural language processing (NLP) enables computers to read a text, hear and interpret speech, gauge sentiment and prioritise and connect to appropriate subjects and resources. The most familiar application is an automated call centre that sorts calls by category and directs the caller to recorded responses. NLP has become more widespread with voice assistants like Siri and Alexa. NLP uses ML to improve these voice assistants and deliver personalisation at scale. (Source: <a href="#">GSMA</a> )

<b>Natural language understanding (NLU)</b>	Natural language understanding (NLU) is a subset of NLP which uses syntactic and semantic analysis of text and speech to determine the meaning of a sentence. Syntax refers to the grammatical structure of a sentence, while semantics alludes to its intended meaning. NLU also establishes a relevant ontology: a data structure which specifies the relationships between words and phrases. While humans naturally do this in conversation, the combination of these analyses is required for a machine to understand the intended meaning of different texts. (Source: <a href="#">IBM</a> )
<b>Official Development Assistance (ODA)</b>	Official Development Assistance (ODA) is defined by the OECD Development Assistance Committee (DAC) as government aid that promotes and specifically targets the economic development and welfare of developing countries. ODA is provided to countries and territories on the DAC List of ODA Recipients and to multilateral development institutions. Notably, ODA is provided by official agencies, including state and local governments, or by their executive agencies. It is also concessional (i.e. grants and soft loans), and administered with the promotion of the economic development and welfare of developing countries as the main objective. The DAC adopted ODA as the ‘gold standard’ of foreign aid in 1969 and it remains the main source of financing for development aid. (Source: <a href="#">OECD</a> )
<b>Predictive analytics</b>	Predictive analytics involves the use of advanced analytic techniques, statistics and ML to analyse current and historical data in order to uncover real-time insights or anticipate an event or some characteristic of an event. Predictive analytics can support decision-making by examining data or content to answer the question ‘What should be done?’ or ‘What can we do to make X happen?’. It is characterised by techniques such as graph analysis, simulation, complex event processing, neural networks, recommendation engines, heuristics and ML. Aid actors are using predictive analytics to identify trends or characteristics of future crises and events, including their probability, severity, magnitude and duration. Models have been developed to anticipate disease outbreaks and epidemics such as cholera, the movement of populations, changes to food security or extreme climatic events and disasters, such as floods. (Sources: <a href="#">The Centre for Humanitarian Data</a> and <a href="#">IBM</a> )
<b>Remote-sensing</b>	Remote-sensing is the acquisition of information from a distance. (Source: <a href="#">NASA</a> )

<b>Supervised learning</b>	Supervised learning, also known as supervised machine learning, is a subcategory of AI/ML. It is defined by its use of labelled datasets to train algorithms that classify data or predict outcomes accurately. Supervised learning helps organisations solve for a variety of real-world problems at scale, such as classifying spam in a separate folder from your inbox. (See also: Unsupervised learning.) (Source: <a href="#">IBM</a> )
<b>Synthetic media</b>	Synthetic media is an all-encompassing term for the artificial creation or modification of media by ‘machines’ or programmes, particularly programmes that rely on AI/ML. (Source: <a href="#">UneeQ</a> )
<b>Text analytics or text mining</b>	Text analytics – also known as text mining – refers to a discipline of computer science that combines ML and NLP to draw meaning from unstructured text documents. Text mining uncovers insights such as sentiment analysis, entities, relations and key phrases in unstructured text. Text mining is how a business analyst turns 50,000 hotel guest reviews into actionable recommendations and how healthcare providers interpret a broad range of patient experiences. (Sources: <a href="#">Microsoft</a> and <a href="#">Lexalytics</a> )
<b>Training data</b>	Training data is an extremely large dataset that is used to teach an ML model. For supervised ML models, the training data is labelled. The data used to train unsupervised ML models is not labelled. (Source: <a href="#">Techopedia</a> )
<b>Unmanned aerial vehicle (UAV)</b>	UAVs, also referred to as unmanned aircraft or drones, come in a variety of shapes and sizes, ranging from small hand-launched types to aircraft as large as an airliner. Just like ‘traditionally’ manned aircraft, they may be of a fixed wing design, rotary winged or a combination of both. Regardless of the name used, they all share the common characteristic that the person responsible for piloting the aircraft is not on board. (Source: <a href="#">UK Civil Aviation Authority</a> )
<b>Unsupervised learning</b>	Unsupervised learning, also known as unsupervised machine learning, uses ML algorithms to analyse and cluster unlabelled datasets. These algorithms discover hidden patterns or data groupings without the need for human intervention. Unsupervised learning’s ability to reveal similarities and differences in information make it the ideal solution for exploratory data analysis, cross-selling strategies, customer segmentation and image recognition. (See also: Supervised learning.) (Source: <a href="#">IBM</a> )

## Virtual assistant

Data-driven and predictive (conversational) chatbots are often referred to as virtual or digital assistants. They are much more sophisticated, interactive and personalised than task-oriented chatbots. These chatbots are contextually aware and leverage NLU, NLP and ML to learn as they go. They apply predictive intelligence and analytics to enable personalisation based on user profiles and past user behaviour. Digital assistants can learn a user's preferences over time, provide recommendations and even anticipate needs. In addition to monitoring data and intent, they can initiate conversations. Siri and Alexa are examples of consumer-oriented, data-driven, predictive virtual assistants. (Source: [Oracle](#))

# HPN

Humanitarian  
Practice Network

Managed by

Humanitarian Policy Group



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Humanitarian Practice Network (HPN)

ODI

203 Blackfriars Road

London SE1 8NJ

United Kingdom

Tel: +44 (0)20 7922 0300

Fax: +44 (0)20 7922 0399

HPN e-mail: [hpn@odi.org.uk](mailto:hpn@odi.org.uk)

HPN website: [www.odihpn.org](http://www.odihpn.org)

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