CREATING HOPE IN CONFLICT: A HUMANITARIAN GRAND CHALLENGE

LEARNING FROM INNOVATIONS USING ARTIFICIAL INTELLIGENCE

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THE RESEARCH PEOPLE

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Glossary

Artificial Intelligence (AI): Computer systems that can perform tasks that typically require human intelligence, such as visual perception, speech recognition, decision-making, and language understanding.

Classical AI: Early approaches to AI, characterized by rule-based systems to mimic human decision-making.

Deep Learning: Uses human-brain-inspired structures (neural networks) to process and analyze complex data, enabling them to make more sophisticated decisions and predictions without explicit programming for every task.

Generative AI: A type of AI that can create new, original content like text, images, or music, based on patterns it has learned from existing data.

Image processing: The ability of a computer system to interpret and understand visual information from the world, such as images or videos.

Machine Learning (ML): A subset of AI where computers are trained to learn from data, identify patterns, and make decisions or predictions.

Natural Language Processing (NLP): A branch of AI that focuses on enabling machines to understand, interpret, and generate human language in a way that is meaningful.

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The front cover image was created using Midjourney, a generative AI program.

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INTRODUCTION

The introduction of Chat GPT[1] in November 2022 ushered in a wave of new technologies. People sought to understand the intricacies of these large language models (LLMs) like ChatGPT and this led to an increased interest in and scrutiny of the broader field of artificial intelligence (AI).

Amongst humanitarians, enthusiasm for AI's potential contrasts with caution about unknown risks.[2] Automated data analysis may enable rapid needs assessment and targeted resource allocation. Natural Language Processing can facilitate multilingual communication. However, algorithmic bias potentially exacerbates inequalities, and data privacy and security concerns loom large. Moreover, over-reliance on AI may diminish human decision-making. Navigating these opportunities and risks necessitates ethical, transparent, and context-sensitive implementation.

CHIC has already funded 18 projects that aspired to use AI in their proposals. It commissioned a review to see what could be learned from these projects and the implications for future funding of AI projects in humanitarian contexts.

The learning review addresses three questions:

What are the opportunities and risks of using AI in humanitarian response?

What types of AI initiatives has CHIC invested in?

What have CHIC-funded innovators learned about implementing AI initiatives in humanitarian settings?

The findings are drawn from an analysis of the CHIC-funded projects conducted from August to September 2023 alongside a review of key literature.

AI in funding rounds 1, 2 & 3

CHIC identified an initial sample of 18 innovation projects thought to incorporate AI. The projects were delivered over a 12-24 month period through the Covid-19 pandemic between March 2019 and March 2023. They represent $8.2M of grants, around 28% of all CHIC funding.

12 of the projects received seed funding of approximately $250,000 each, while a further six received 'transition to scale' (TTS) funding of up to $1.7M. Four of the projects had leveraged additional funds of between $600,000 and $19M. Unlike other innovations funded by CHIC, the AI-enabled projects were all delivered by organizations headquartered in the USA (ten projects), Canada (three projects) or Europe (five projects).

There were projects across the three traditional AI domains of image processing, natural language processing (NLP), and forecasting. There was a roughly even split in the number of projects attempting technology in each domain.

In terms of the technologies used, around half attempted machine learning (see Figure 2). One project set out to develop a deep learning approach in-house. Two natural language processing (NLP) projects adapted off-the-shelf deep learning technology. The remainder employed classical AI methods such as mathematical models or did not specify their methods.

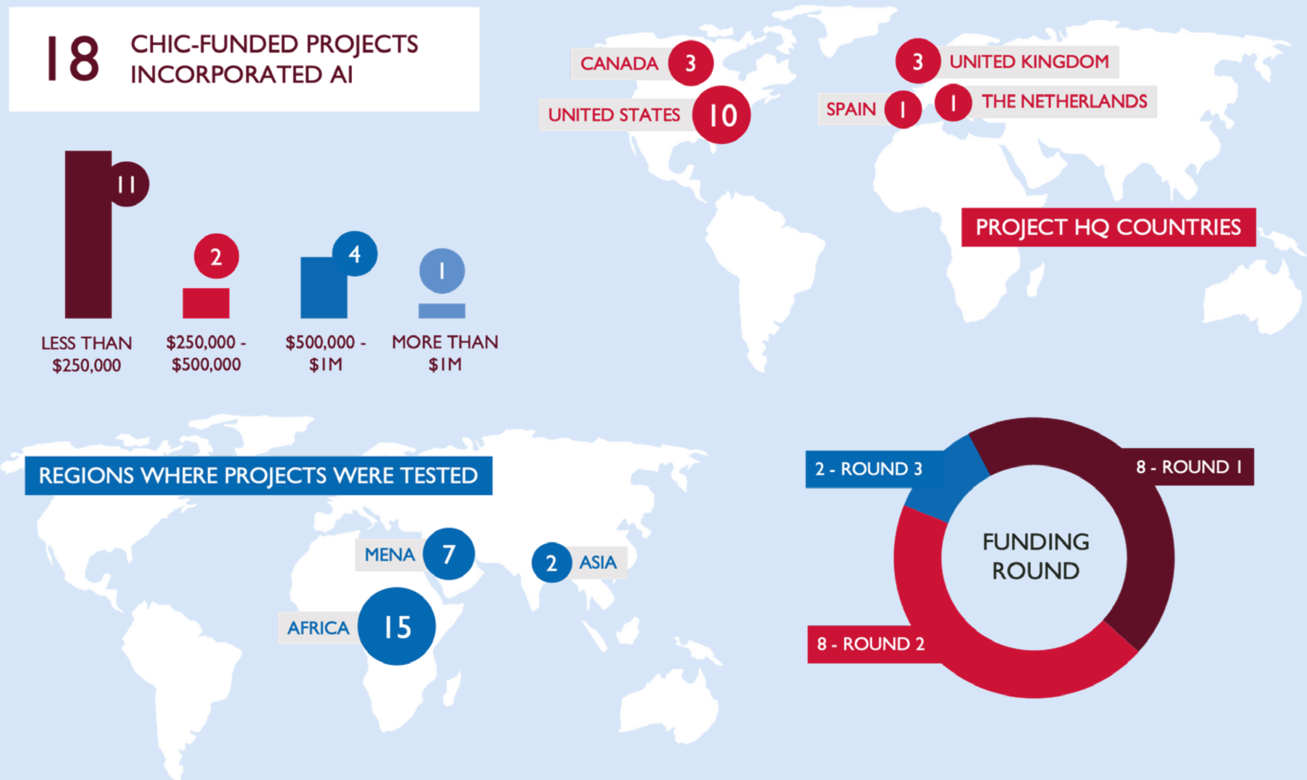


Figure 1. CHIC-funded projects that incorporated an element of AI in their proposals

The projects took place before modern foundation or generative models came to market, such as large language models (LLMs) like ChatGPT or Google's Bard. So there were no examples employing these technologies.

As we'd expect, the projects were not primarily AI projects, but humanitarian projects with an ambition to use AI. Against the AI component of their original proposals, two of the projects achieved a very high degree of success, and seven a high degree of success. Based on project reports, we found that around half did not achieve their AI objectives, or had a low degree of progress on AI objectives, or their AI progress was unclear. This is not a comment on the overall success of the project, just on the aspiration to exploit AI in their original proposals. In practice, AI tended to be a stretch objective for many teams, which was only attempted after the core requirements of the project were met.

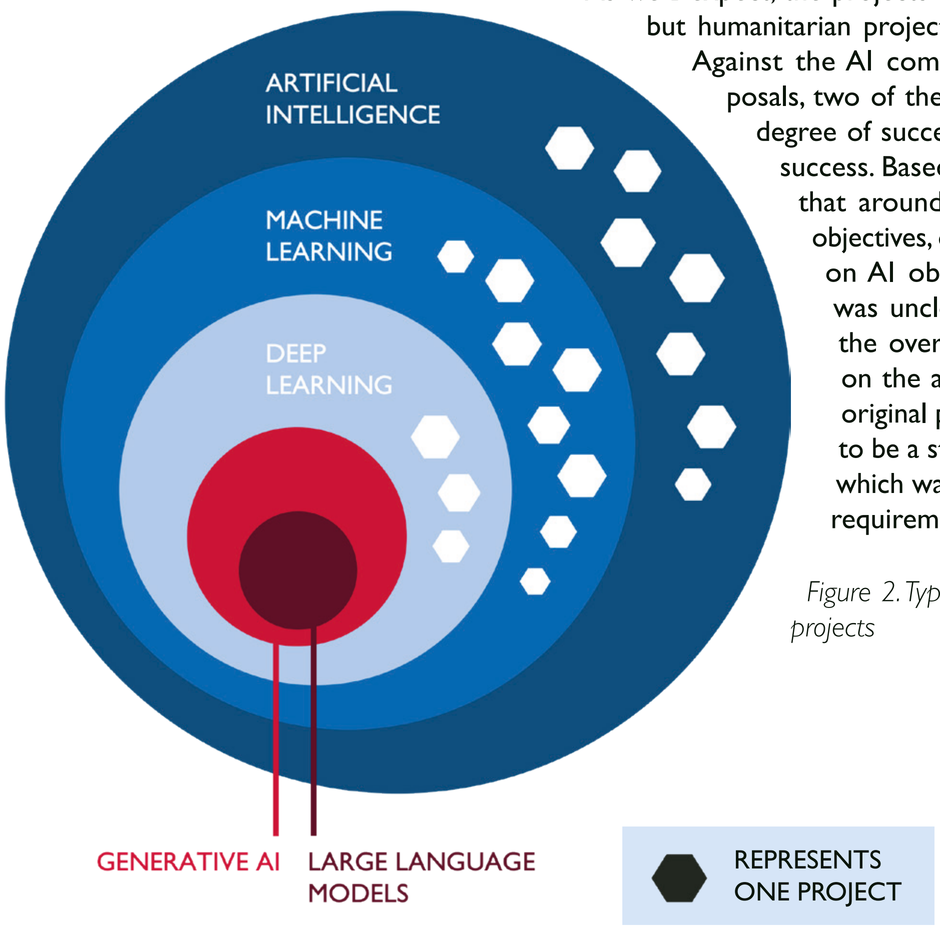


Figure 2. Types of AI used in the CHIC-funded projects

LEARNING & IMPLICATIONS

The review identified four common lessons across the portfolio of projects.

1. Have a data strategy and devote a significant proportion of available resources to it

Data is widely recognized as central to the success of AI projects, both in the sector and more widely. AI systems learn and make predictions based on patterns and information within data. The quality and quantity of data directly impact the accuracy and effectiveness of AI models.

Access to data

Access to sufficient high-quality data was the single most common issue preventing success. More than half of the projects encountered data as an issue and it was the primary issue for almost half of the projects (see Table 1). Access to data was often constrained or managed by on-the-ground third-party organizations, a very common situation in humanitarian settings.

Table 1. Data problems experienced by different organisations

Organisation	Data problem
Automatic assessment of child malnutrition from scans	Projects struggled to accurately assess child malnutrition from images to differing degrees.[3] A lack of sufficient contextualized data may have impaired performance; for example, some projects used images from Spain and the US to help them source sufficient training data.
Automatic translation of marginalised languages	A project was unable to collect sufficient conversations in the Kanuri language to train an automated translation tool. In the Hausa language, the team were able to use spoken recordings of the Bible to produce a high-quality dataset which, though not large, was sufficient for a text-to-speech application.
Enterprise Resource Planning for the humanitarian context	One team wanted to build an AI-enabled database for managing humanitarian data. They needed sufficient data to build a prototype application that would provide helpful insights. They were unable to provide enough immediate value to users to drive engagement.
Demand forecasting for refugee camps	A tool for predictive analytics of refugee camp supply chains was hampered at the camp level by a lack of data quality/standardization (data stored in differ-ent formats and structures making comparison hard - a problem that future AIs will be able to help address). The tool was more useful at a regional level where data standards were better.
Monitoring safe water / medicine cold-supply chains	Three projects faced issues of securing sufficient data to fully validate their approaches as they originally planned.[4] Relationships with implementing partners were critical for the data collection processes.

Data strategy

AI's reliance on high-quality data means that it can no longer be seen as an add-on. Indeed, in some cases it may be better to prioritise investment in usable data collection and coordination tools, linking with as many agencies as possible, to serve as "fuel" for future applications.[5] This may mean prioritizing investment in data collection before AI development, as the Humanitarian OpenStreetMap team[6] did. This approach would mirror industry, where there has been a consolidation of methods and increased focus on data.[7]

A data strategy is an important part of many technology companies' business plans and should form part of any AI project plan. These offer a systematic way to plan for and avoid the pitfalls associated with data-dependent projects and could form a part of the standard application materials for projects. Many successful private-sector AI and tech companies arguably owe their success to an effective data strategy. Grammarly, Kabbage and Casetext (forecasting tools in writing, loans and legal research respectively) depend on a continuous data feedback loop to constantly improve their performance. These data-first companies are good examples of data strategy driving product development. Another example relevant to the humanitarian sector is Zipline, which uses real time weather data to make decisions over drone delivery of healthcare supplies.

Data standards

Sykes also makes the suggestion that AI projects should consider using already curated data. This would require open standards for data management so that data could be useful across multiple projects.[8] Where CHIC has projects clustered around a specific theme there may be benefits of collaborating on data standards to allow each of the innovation teams to have access to all the data. This could have been helpful for the three projects looking at automated approaches to assessing childhood malnutrition, which all struggled to source sufficiently large high-quality datasets.[9]

Acceptance and explainability

Similarly important is planning how to collaborate with gatekeepers to data - often on the ground organizations - at all stages of the AI development cycle.[10] This was a particular challenge for all three organizations that relied on sampled/sensor data.[11] Better collaboration will likely require projects to spend more time on the transparency and explainability of their AI systems to promote understanding and acceptance of the technology among a wider group of partners (often called explainable AI or XAI).[12]

PHOTO SOURCE:
SMART PLUS APPLICATION

2. Include appropriate AI and data-science skilled professionals in project teams

Developing new AI technology is a significant challenge and the projects illustrate the need to invest in experienced talent.

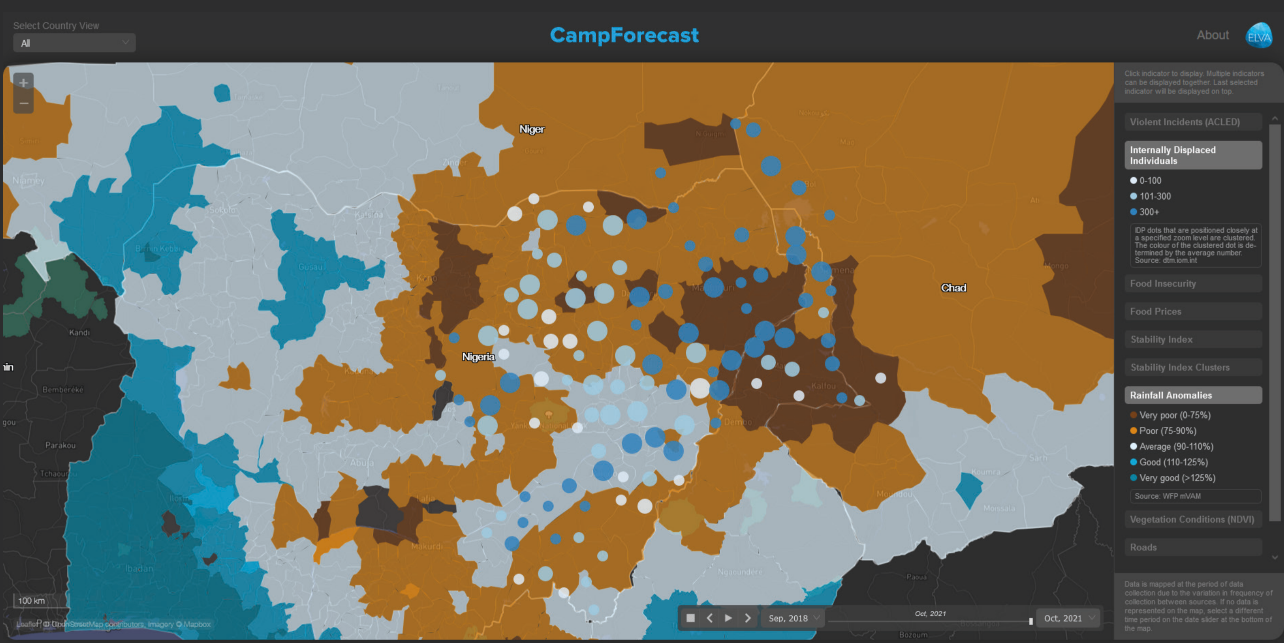
One of the most successful novel projects in the portfolio was a system for assessing water quality. The York University project team included an AI PhD researcher alongside an experienced research team. With this expertise, they were able to develop a novel neural network-based method of forecasting the decay of chlorine in water. The work was peer-reviewed and published.[13]

Even with a skilled team in place, AI projects can be challenging. Kobo Inc. had an experienced technical team and developed an NLP application for their existing analysis platform. The goal was to automate the transcription and translation of humanitarian needs assessments. The team was sensible in buying off the shelf NLP technology, and then focusing on building a product. Despite having a highly experienced software development team, the technical challenge of developing a high-quality product led to them prioritizing a smaller number of features within the project period.

Mentoring and support

In general, there remains a lack of AI knowledge and expertise in the humanitarian sector. Humanitarian organizations should build up their skill base over time, 'either in-house if AI is to become a core part of [their] value proposition, or through a strategic partnership, if not'.[14] Given how hard it is to find appropriate talent, CHIC should consider how to offer projects technical expertise in AI technologies, and mentors experienced in scaling such technologies.

The UN is trying to do this through its AI for Good Innovation Factory[15] which will provide startups with matchmaking and mentoring. Similarly, the UK's BridgeAI programme aims to help innovators assess and implement trusted off-the-shelf AI solutions.[16]



SCREENSHOT OF STITCHING ELVA PLATFORM

3. Be responsible data custodians for humanitarian settings

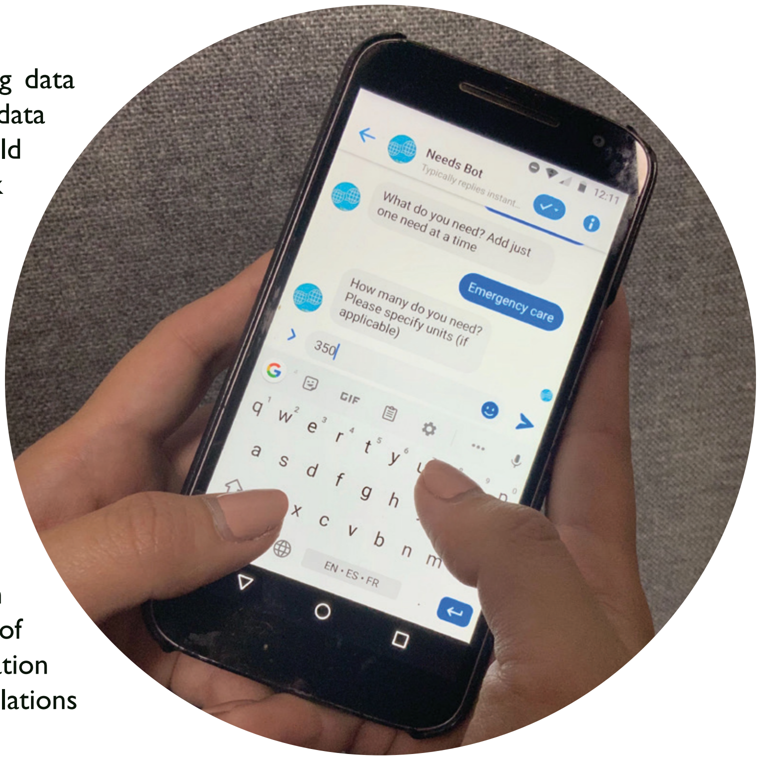
In humanitarian contexts, the level of risk from data breaches, hacks and exposures can be significant. Where there are active conflicts, personal data can be used to facilitate targeting. Data can be the means of discrimination. In aggregate, data can provide a military advantage. In short, the price of breaches may be paid in lives.

The digital risks vary between projects. Hala Systems, for example, aimed to develop an early warning system to detect incoming airstrikes and send advanced warnings to civilians in Syria and Yemen (Hala also delivered a second distinct cold-chain project mentioned earlier). Data was stored in a central database. Hala appeared to have carefully considered the data they stored and data security throughout product development. Nonetheless, in the wrong hands, this data could be used by unintended or hostile actors with serious consequences.

Other projects introduced risk by capturing personal information such as demographic details, images, and potentially sensitive health and well-being information divulged to chatbots. The projects appeared to have taken safety, security, and data privacy seriously. They often mentioned GDPR compliance and additional measures given their contexts. However, more focus must be given to responsible data use as the amount of humanitarian data increases and as AI algorithms become more powerful.[17]

Data protection impact assessments

CHIC has already taken steps toward addressing data risks, including expanding its roster of advisors on data protection and security in conflict settings. It could also adopt measures from the ICRC's Handbook on Data Protection in Humanitarian Action,[18] a compendium of minimum standards for data protection in humanitarian contexts based on GDPR. The ICRC is regarded as a leader in data protection and aims to extend the humanitarian principle of 'do no harm' to data protection.



This includes the standard use of data protection impact assessments (DPIAs) to manage threats from data breaches.[19] The ICRC argues for including measures to prevent re-identification. They note that "In the humanitarian context, anonymization may not be enough to prevent the re-identification of vulnerable populations, and failure to retain information in a cyber-secure manner risks exposing such populations to persecution and harm."[20]

Consent

Consent to process personal data can be especially challenging in AI projects in humanitarian contexts. Consent should be fully informed, specific, unambiguous, and freely given.[21] This requires particular consideration where there are language barriers, low literacy levels or people may be confused or afraid. Often, the specific uses of data may not be known at the time of data collection - for example, if it may be used as training data for multiple systems. ICRC recommends maintaining contact with data subjects. This helps account for changes in data use and provides a means of redress in the event of data breaches.

PHOTO SOURCE: NEEDSLIST

PHOTO SOURCE:
HALA SYSTEMS

4. Design around the humanitarian context throughout the development cycle

CHIC is likely to continue funding frontier AI projects that are being developed in America, Europe and China. Humanitarian settings often have specific practical, infrastructure and language requirements and people may have limited access to devices. Apps created using training data from outside humanitarian contexts can also lead to challenges with performance, accuracy, and bias.

The Global Strategy Network recognized context issues from the outset. Their Snap Truth to Power app assured photographs against manipulation. The team designed the app to work offline without being able to rely on cloud services, in contrast to equivalent commercial technologies designed for use in mass market settings.

The contextual requirements for the project were not always known at the proposal stage. Needslist, for example, aimed to produce an NLP-based chatbot to simplify how NGOs requested supplies in humanitarian settings. During piloting, they found their users lacked internet connectivity where they needed to work. As a result, they redesigned the technology and developed an offline alternative system, which uploaded requests when data became available.

Design for the context

Projects should be designed for the planned context throughout the development cycle. This is especially important when using off-the-shelf tools that may perform unexpectedly in humanitarian contexts. The ICRC also note examples from both Ebola and COVID-19 where forecasting tools failed to support medical decision-making as effectively as traditional methods. In these cases, past data did not account for changes in human behavior and the environment.

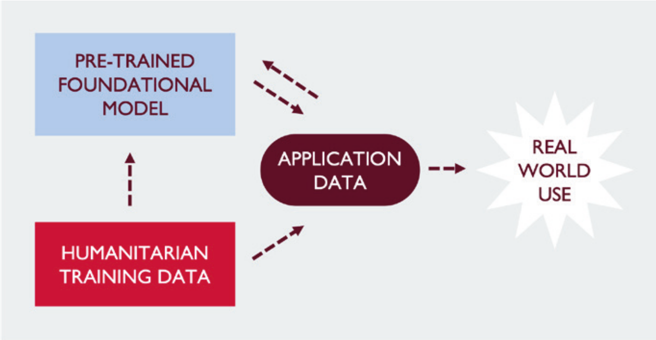
Biases

None of the CHIC-funded projects reported issues with bias. However, we would expect to see biases arising, especially in classification and generative AI applications. Off-the-shelf tools are often trained from publicly available data. Google's early face recognition tools famously performed less well on darker skin tones and women.[22] Bias is a factor of training data and explicitly accounting for likely sources of bias before the data collection phase will be vital.

The future

The CHIC-funded projects started before the widely-recognized recent advances in AI. These advances are a result of progress in developing foundational models, which has made exploiting AI easier, cheaper, and more effective. There have been breakthroughs in many technologies and applications from natural language processing to weather prediction. Generative AI has gone from being an academic interest to taking center stage, with an explosion in use cases.

Figure 3. Foundational models



Just as humanitarian organizations now buy cloud services, future organizations will build applications based on foundational models (see Figure 3). CHIC's future grantees are likely to use more powerful AI models for more demanding use cases. For example, we would expect future grantees' chatbots to use large language models not only for understanding inputs but also for analysis and generating outputs. These applications are likely to be fully automated and not include any of the manual processes that were needed for some of the current chatbot applications. As CHIC and other humanitarian organizations integrate AI into their funds, proactive measures are essential to ensure the ethical, effective, and responsible use of this technology.

Key considerations for shaping a future robust AI strategy include:

GOVERNANCE: While there is increased activity around AI safety and governance, there are notable divisions within the AI community and a lack of concrete progress towards establishing governance frameworks. Clear governance frameworks are important for managing the humanitarian sector's distinct risks. CHIC should engage with other actors in defining policies, procedures, and decision-making structures that govern AI deployment.

CONSIDERATION OF OPEN SOURCE VERSUS COMMERCIAL MODELS: Open-source models may have benefits for humanitarian contexts, as a result of their transparency, cost-effectiveness, and adaptability. However, they can also vary widely in terms of quality, accuracy, and reliability. Because open-source models are accessible to anyone, they can also be scrutinized by both well-intentioned researchers and potentially malicious actors. CHIC and the innovators it funds will need to give careful consideration to the appropriate models.

STANDARDS FOR DATA PROTECTION AND SHARING TRAINING DATA: The single most important factor in the success of CHIC's AI-related projects was the availability of large-scale, high-quality training data. This will be even more important for future AI technology,[23] requiring a step-change in the availability of data and methods to collect and manage it. Robust protocols for data sharing will be needed to create large datasets, as well as skills in assessing quality and bias in the training data.

ENVIRONMENTAL IMPACTS: Finally, some researchers have argued that AI has "a terrible carbon footprint".[24] It requires significant computational resources to perform complex calculations. At the same time, rapid technological advancements will lead to the premature obsolescence of computing hardware, contributing to electronic waste. Managing the environmental impacts of AI will be crucial to its ethical use.

So far CHIC has supported a portfolio of 18 AI-related projects, which have generated valuable lessons about curating data, building skills, data protection, and designing for the context, which align with trends in the larger economy. These challenges will become even more significant in future deep learning technologies. This document provides a roadmap to help CHIC make sound investments for the next generation of AI.

ENDNOTES

1. *https://openai.com/blog/chatgpt*
2. Margffoy, M. (2023). AI for humanitarians: A conversation on the hype, the hope, the future. The New Humanitarian.
3. Even the tool reporting the best performance, the SAM Photo application noted 'a lack of data-images to be analysed in order to refine its quality indicators'.
4. Hala Systems developed coin-sized bluetooth vaccine shipment temperature sensors. OmniVis produced a device for detecting cholera in water. York University developed a method to produce personalized instructions on the treatment necessary to make water safe to drink in humanitarian settings. The York University project was peer-reviewed and published but was not validated for real-world use within the project period.
5. P. Sykes (2023). AI and humanitarianism: Keeping the human in humanitarianism.
6. Humanitarian OpenStreetMap obtained satellite data from DRC, Uganda and Tanzania and worked with multiple teams of volunteers to trace the maps and then to add place name labels. Completed maps provide the data for future innovation.
7. See for example former Director of AI at Tesla Andrew Karpathi discussing the consolidation of AI methods. *https://twitter.com/karpathy/status/1468370605229547522*.
8. A specific example of this is proposed for Disaster Risk Reduction (DRR) in Kuglitsch, Monique, Arif Albayrak, Raúl Aquino, Allison Craddock, Jaselle Edward-Gill, Rinku Kanwar, Anirudh Koul et al. (2022). Artificial intelligence for disaster risk reduction: Opportunities, challenges, and prospects. Bulletin n° 71, no. 1.
9. Data standards must be developed before any data is collected. For example, the three projects focussed on detecting malnutrition all had different approaches to ensuring the anonymity of the saved data, with one saving all data as silhouettes. Because the raw data has been discarded the teams can not use each other's data. A data standard could, for example, allow images to be shared between the teams with blurred faces. This would allow teams to use their data on future unforeseen technology so that the data isn't wasted even when the applications fail.
10. Ryan-Mosley, T. (2023). How AI can actually be helpful in disaster response. MIT Tech Review.
11. The three projects were implemented by Hala Systems (cold chain), OmniVis and York University.
12. Kuglitsch, Monique, Arif Albayrak, Raúl Aquino, Allison Craddock, Jaselle Edward-Gill, Rinku Kanwar, Anirudh Koul et al. (2022). Artificial Intelligence for disaster risk reduction: Opportunities, challenges, and prospects. Bulletin n° 71, no. 1.
13. De Santi, M., Khan, U.T., Arnold, M. et al. Forecasting point-of-consumption chlorine residual in refugee settlements using ensembles of artificial neural networks. npj Clean Water 4, 35 (2021). *https://doi.org/10.1038/s41545-021-00125-2*.
14. P. Sykes (2023). AI and humanitarianism: Keeping the human in humanitarianism.
15. *https://aiforgood.itu.int/about-ai-for-good/innovation-factory/#*
16. *https://iuk.ktn-uk.org/programme/bridgeai/*
17. For example, researchers were recently able to reverse engineer information that had been input to ChatGPT.
18. Kuner, C., Marelli, M., Barboza, J. Z., & Jasmontaite, L. (2020). Handbook on data protection in humanitarian action. International Committee of the Red Cross.
19. Gazi, T. (2020) Data to the rescue: how humanitarian aid NGOs should collect information based on the GDPR. Int J Humanitarian Action 5, 9.
20. Beduschi, A. (2022). Harnessing the potential of artificial intelligence for humanitarian action: Opportunities and risks. International Review of the Red Cross, 104(919), 1149-1169.
21. GDPR Article 4(11).
22. Christian, B. (2020). The alignment problem: Machine learning and human values. WW Norton & Company.
23. Foundational models are built using deep learning technology, where their capabilities are 'emergent' from their training data. They require vast quantities of data to achieve sophisticated capabilities; ChatGPT was famously trained on 300 billion words. They can often be adapted to new contexts with additional training data.
24. Hao, K. (2019). Training a single AI model can emit as much carbon as five cars in their lifetimes (2019). *https://www.technologyreview.com/2019/06/06/239031*.
25. This categorization of type of technology is based on the author's assessment of project proposals and not on a review of the technology itself.

ANNEX 1. BIBLIOGRAPHY

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Ryan-Mosley, T. (2023). How AI can actually be helpful in disaster response. MIT Tech Review.

Sykes, P. (2023). AI and humanitarianism: Keeping the human in humanitarianism.

ANNEX 2. CHIC-FUNDED PROJECTS INCORPORATING AI

Project title	Organisation	Description	Country	Tech type[25]
SMARTplus: digital system for fast, reliable malnutrition data tackling the health-crisis in Somalia	Action Against Hunger ACF (Canada)	SMARTplus uses 3D scans to streamline nutrition and mortality data collection. It analyzes and verifies data, aggregating it for visualization on a public dashboard. This prevents delays and reliance on potentially false information.	South Sudan	Image processing
HOPE and HELP: Modeling for complex humanitarian engagement	Humanity Data Systems	HOPE and HELP, created by Lensinsight and AllSource Analytics, use advanced technology like Machine Learning and Complex Event Processing to simplify gathering community feedback in humanitarian efforts. They also aid in project and stakeholder management.	None	Forecasting
Language technology to improve data quality and engagement	Translators without Borders US Inc.	TWB aims to create advanced language technology in marginalized languages for efficient information gathering. This pioneering effort could revolutionize understanding of humanitarian needs and priorities in remote regions.	Nigeria	Natural language processing
Real-time last mile vaccine cold chain monitoring to increase quality vaccines in remote communities	Hala Systems Inc.	Hala is developing an affordable solution for cold chain monitoring, replacing manual methods with a small wireless sensor and mobile apps. This ensures prompt alerts about spoiled shipments and gives an overview of cold chain health. The technology aims to be cost-effective and efficient, potentially reducing costs by up to 50%.	Syria	Data collection for future forecasting

Project title	Organisation	Description	Country	Tech type[25]
Camp forecast: AI-driven supply chain forecasting to reach 7% more refugees without spending more.	Stichting Elva	The "Camp Forecast" (CF) tool employs AI for camp managers to make precise demand forecasts, potentially saving 7% of operational costs. It predicts resident numbers and required supplies in humanitarian camps, pioneering AI-driven forecasting in this context.		Forecasting
Humanitarian language toolkit: AI-enabled qualitative engagement with conflict populations	Kobo, Inc.	This project aims to create a toolkit using NLP to record, transcribe, and translate qualitative interviews in humanitarian settings. Field workers can use standard data collection platforms for automatic recording and correction of transcriptions and translations.	None	Natural language processing
Smart and effective communication in nutrition; "Chatbot photo diagnosis platform"	Fundación Acción Contra el Hambre (Spain)	This project establishes a smart communication channel for effective malnutrition diagnosis and monitoring, a joint effort between the World Food Programme (WFP) and Action Against Hunger (ACF).	Senegal	Image processing
PathVis: A water monitoring device for Vibrio cholerae detection	OmniVis Inc	A groundbreaking smartphone diagnostic tool for rapid V. cholerae detection, providing results in under 30 minutes. Data is instantly sent to a cloud-based server for automated logging. In remote areas, a wifi hotspot enables data upload. This is the first water-based V. cholerae detection device, offering automated, time-stamped, and location-specific data logging.	Bangladesh	Data collection for future forecasting
NeedsBot - Aggregating real-time needs from anywhere via chatbot	Needslist	NeedsBot enables vetted frontline responders to text urgent information, supply, and resource needs into the NeedsList platform. This data is then securely aggregated and accessible to multiple stakeholders, facilitating real-time response from individuals, corporations, and governments in the humanitarian aid sector.	Uganda	Natural language processing
Using technology to combat violence against female refugees	ActionAid in London (UK)	A low-cost mobile platform for at-risk women and girls to offer essential information on rights, services, safe spaces, and GBV referrals. It enables incident reporting and risk mapping in urban areas. Pilot 1 will launch in collaboration with a Mobile Network Operator and Women's Protection Action Groups.	Jordan	Natural language processing
AutoAnthro: 3D scanning for improved malnutrition assessment in conflict areas	Body Surface Translations, Inc.	Body Surface Translations' AutoAnthro is a cutting-edge 3D scanning system revolutionizing child anthropometry. It swiftly captures precise digital measurements, enhancing outcomes for malnutrition at both individual and population levels. AutoAnthro extracts crucial data, measuring length/height, mid-upper arm circumference (MUAC), and head circumference for children aged 0-5 years.	South Sudan	Image processing
Machine learning enabled safe water optimization tool for humanitarian response	York University	This project aims to create a cloud-based tool using AI to optimize safe water practices. By analyzing existing water quality data, it generates customized chlorination instructions for specific field sites worldwide, ensuring safe drinking water based on evidence and site conditions.	Nigeria	Forecasting (using neural networks)

Project title	Organisation	Description	Country	Tech type[25]
Combatting disinformation in conflict zones	The SecDev Foundation	SecDev Foundation collaborates with local partners in Yemen to empower conflict-affected communities in combating harmful health misinformation. They provide guidance through trusted local networks via various channels like emergency alerts, online campaigns, and radio bulletins to ensure accurate information reaches those in need.	Yemen, Rep.	Natural language processing
"We would've died without this warning": How technology-driven early warning for airstrikes can save lives and reduce trauma for millions	Hala Systems Inc.	Hala will utilize a network of air-raid sirens administered by civil society, combined with predictive algorithms, training and community engagement efforts to monitor other forms of violence (e.g. artillery, mortars), It will employ blockchain to generate immutable evidence of war crimes.	Yemen, Rep., Syria	Forecasting
Missing maps project	Humanitarian OpenStreetMap Team United States	Missing Maps, a global collaboration, mobilizes volunteers to map uncharted areas through user-friendly tools and open-source apps. Remote volunteers use satellite imagery to create base maps, then local volunteers and agencies refine and verify the details. This hyper-local data supports life-saving crisis response programs.	Congo, Dem. Rep., Uganda	Data collection for future AI models
Fighting COVID-19 misinformation with language technology	Translators without Borders US Inc.	The chatbot engages people in their native language, providing accurate pandemic information and informing targeted responses to misinformation. Currently in the Democratic Republic of the Congo, TWB plans to expand to more languages and countries. This innovative solution, accessible via platforms like WhatsApp and Messenger, ensures reliable COVID-19 information reaches vulnerable communities in a language they comprehend.	Congo, Dem. Rep., Nigeria	Natural language processing
Snap truth to power	Sealr	Sealr, a mobile app, combines AI and blockchain to authenticate imagery from conflict zones. This empowers vulnerable populations to report needs securely. As the first verified image-capture app for humanitarian crises, Sealr has the potential to revolutionize a sector often hindered by inefficient feedback systems.	Syria	Image processing
Countering COVID-19 misinformation in areas affected by conflict	Murmurate	Murmurate tracks how misinformation spreads in communities via social media. Using Computer Vision and Natural Language Processing, Murmurate maps COVID-19 conversations online, identifying misinformation that delivers false and damaging public health statements. These insights drive the production and distribution of COVID-19-related counter-messaging.	Nigeria, Syria	Natural language processing