Understanding Enablers and Barriers for Deploying AI/ML in Humanitarian Organizations: the case of DRC's Foresight

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Abstract

Artificial Intelligence (AI) and Machine Learning (ML) capabilities have the potential for large-scale impact to tackle some of the world's most pressing humanitarian challenges and help alleviate the suffering of millions of people. Although AI and ML systems have been leveraged and deployed by many humanitarian organizations, it remains unclear which factors contributed to their successful implementation and adoption. In this study, we aim to understand what it takes to deploy AI and ML capabilities successfully within the humanitarian ecosystem and identify challenges to be overcome. This preliminary research examines the deployment and application of an ML model developed by the Danish Refugee Council (DRC) for predicting forced displacement. We use qualitative methods to identify key barriers and enablers from a variety of sources describing the deployment of their Foresight model, a machine learning-based predictive tool. These results can help the humanitarian community to better understand enablers and barriers for deploying and scaling up AI and ML solutions. We hope this paper can spark discussions about the successful deployments of AI and ML capabilities and encourage sharing of best practices by the humanitarian community.

***Keywords*— Artificial Intelligence, Machine Learning, Humanitarian Aid.**

1 Introduction

Global trends, such as climate change, may result in a rising number and greater severity of natural disasters in the coming years. Simultaneously, the rise of worldwide geopolitical and economic tensions may prompt an increase in man-made disasters. Meanwhile, the humanitarian community is striving to respond to the increasing needs by stretching its resources to reach as many people around the world as possible. As the scale and cost of responding to humanitarian needs is growing, new ways to improve efficiency and responsiveness need to be explored.

During the World Humanitarian Summit, there were many calls to promote and adopt innovative solutions to improve the efficiency and effectiveness of humanitarian aid delivery [1]. Artificial Intelligence (AI) and Machine Learning (ML) stand out as potentially transformational innovations, with ability to solve complex problems and change the future of businesses in this digital age [2]. Studies emphasize the potential for the anticipatory capabilities of AI and ML to be harnessed by the humanitarian community [3, 4, 5]. While the adoption of AI and ML solutions is now happening at a faster rate, there is still, in practice, a need for more systematic knowledge and understanding about the enablers and barriers. Practitioners need to cope with a variety of decisions and hurdles in order to avoid missing out on current and future AI and ML opportunities [6]. Despite the need for guidance and hands-on knowledge, academic literature on the subject is limited.

This study is a preliminary attempt to address this gap by analyzing a single case study to identify enablers, barriers, and influential factors that contributed to the successful development of an AI and ML anticipatory tool (Foresight) developed by the Danish Refugee Council (DRC). This study seeks to provide preliminary evidence and facilitate understanding of this emerging topic.

2 Literature Review

AI and ML solutions are being employed as anticipatory tools for making data-driven forecasting in various contexts and sectors because of their ability to use intelligent algorithms for facilitating knowledge discovery and formulating key insights [7]. Unlike traditional models, such as statistical and operations research techniques, AI and ML have the ability to learn from vast data and imitate human behavior [8]. Research and case studies from commercial and humanitarian sectors show many potential advantages of using AI and ML to analyze data and support human decisions [9].

Humanitarian actors are under increasing pressure to improve efficiency and effectiveness, and AI and ML capabilities may be able to support this goal. They can process massive and complex data to derive insights and predictions that can support decision makers [10]: a task that might take a human hours or days to do can be handled in mere seconds by algorithms. Many similarly novel technologies, such as the Internet of Things (IoTs), big data analytics, and blockchains, along with AI and ML, have been seen as potential solutions for improving the operational performance of humanitarian action; they may represent building blocks of transformational digitization for improving humanitarian response [3]. A study of over a hundred social impact use cases shows that while AI and ML technologies are not cure-all solutions, they can contribute to the mix of solutions that aim to tackle challenges and issues faced by humanitarian actors aiming to achieve efficiency [6].

Many humanitarian organizations have started to realize the potential benefits of deploying AI / ML solutions. The COVID-19 response contributed to the recent wider and accelerated adoption of AI / ML, which was hailed as a game changer for anticipatory forecasts [11]. The United Nations agencies are demonstrating a great interest for exploiting the power of AI and ML technologies to achieve the Sustainable Development Goals and improve operations [12]. The increasing attention that is given to the use of AI and ML for humanitarian actions shows promise for wider adoption; however, it is essential to note that using these technologies also comes with significant challenges and risks.

One study discussed the minimum requirements for developing humanitarian-focused AI and ML systems and highlighted potential opportunities and risks of scaling up these systems in the humanitarian context [5]. Additionally, the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) study on emerging technologies showcases both the promise of AI and ML capabilities and the need for further understanding about the requirements and pitfalls associated with the deployment and adoption of these solutions [13]. Despite the piloting and adoption of AI and ML solutions by humanitarian organizations, there is still, in practice, a lack of understanding about the enablers and barriers and a need to cultivate knowledge about factors that can lead to a successful or unsuccessful deployment of AI and ML capabilities in the humanitarian context [13, 5, 6]. Further research is crucial to inform and guide humanitarian actors developing and integrating AI and ML capabilities into their larger system [13].

As knowledge about AI and ML solutions in humanitarian context is still nascent, this study is an attempt to broaden our empirical knowledge base by conducting a case study to identify enablers, barriers, and influential factors for the successful development and deployment of AI and ML systems in the humanitarian context. We seek to facilitate the understanding of this emerging topic by examining one successful case in detail.

3 Background: The Foresight Tool

This paper analyzes the experience of developing and deploying a tool for predicting forced displacement. Increasing war, conflict, violence, and food insecurity have led to increasing forced displacement in many parts of the world [14]. Forced displacement refers to both internal displacement (people who leave their homes but remain in their own countries) and refugees, who cross borders and flee outside their countries. For example, the recent war in Ukraine resulted in a major displacement, and the humanitarian community mobilized their resources to provide aid and shelter to the vulnerable people. Forced displacement drives an urgent need to respond with humanitarian aid, as people who have fled their homes may be very vulnerable, with few resources, and require aid to survive and thrive. A timely and appropriate response requires anticipating needs; this drove the international community to explore new ways (shifting from reactive to anticipatory mode) for predicting the number of people who are likely to be displaced.

The DRC is one of the leading international NGOs that plays a major role in assisting people affected by forced displacement. The organization is part of humanitarian efforts in both responding to protracted displacement situations and designing and implementing interventions that could reduce displacements and their impacts. As part of the efforts to use anticipatory tools for planning, DRC partnered with IBM to develop a model that can predict forced displacement. The machine learning model, Foresight, utilizes data from multiple sources to predict how many people will be displaced and from where. In addition, the model has several features including causal network and scenario analyses. The model is intended to be used for developing plans, informing decision makers, and supporting policy formulation. Currently, the model has been used to predict displacement from 26 countries, which accounts for approximately 87 per cent of all the global displacement.

4 Methodology

The study's methodology comprises qualitative archival research based on publicly available data sources detailing the implementation of an ML technology in a humanitarian organization. Qualitative case study research is chosen because of the need for greater insight into the factors affecting the adoption of AI and ML solutions in the humanitarian context. It is a first step intended to gain deeper understanding about one case as a basis for future study of AI and ML projects in the humanitarian context. The DRC Foresight project was chosen for this study because it is one of the most prominent successes with the most information sources available to understand its implementation.

Various sources of information were collected, including official reports and videos by the organization describing the development and usage of the tool, scholarly published articles, and other documents published by reputable organizations, such as UN-OCHA and IBM, about the project. However, there were only a small number of published resources about the project, so the findings from this preliminary study are limited to the perspective of public-facing documents from the authoring organizations. Future research should examine a wider array of sources, but here we also include other sources of information as available, such as news outlets, for triangulation and validation purposes.

The analysis of data was an iterative process aiming to find patterns in the data that represent the enablers and barriers for deploying AI and ML solutions. The documents and other information sources (e.g. videos) were coded (open coding; [15]) to identify factors that impacted the tool's development and adoption. Three main themes emerged: data, development, and applications. In the next iterations, the codes and coded data were re-examined and the codes refined, aiming to combine similar emerging themes. Through this process, a set of themes emerged that described the factors that influenced development and adoption of the Foresight tool, from the perspective of the data sources. To summarize these themes, a table that contains category, code, definitions, and a summary of the evidence was developed. The table summarizes the findings from the data analysis process.

5 Results

The findings of the study shed light on the factors that impact the deployment and development of AI and ML systems by humanitarian actors. The enablers, barriers, and influential factors are summarized in Tables 1-3, categorized into three main thematic areas, namely, data, development, and applications. The table lists factors and their definitions along with evidence that supports the findings. Enablers are defined as the factors that contributed to the successful development of AI / ML tools and/or facilitate adoption, while barriers are obstacles that prevented wider adoption and/or exploitation of the tool capabilities. We also highlight some influential factors, which did not directly impact the development and adoption of the tool; however, they are worth considering during various stages of the development. Note, however, that a factor that functioned as an enabler in this context, such as data availability, may function as a barrier in another context, for example if data availability were limited. In this paper, we describe which factors were enablers and barriers for the case studied here. Second, note that the limited information about the Foresight model did not always provide strong evidence about whether a factor actually influenced the adoption of a tool, only that the factor was considered important by the authors of the data sources. Therefore, the discussion of enablers and barriers should be considered preliminary as a basis for future work.

It was surprising to find out that data availability was one of the enablers for the Foresight project (this fact is supported by most of the information sources that are studied), since data is typically seen as scarce in humanitarian aid. Its availability for this application is an indicator of the progress made in collecting and cultivating humanitarian data during the last few decades. AI and ML systems are data-hungry technologies that are trained on a vast amount of data to produce accurate results [5]. Based on the collected evidence, there appears to be an adequate amount of data for the development of some AI and ML systems, without the need to invest in additional data collection efforts. There was even sufficient data available for the Foresight model to utilize a comprehensive set of indicators (148 indicators) that cover 8 dimensions. Having such data, from reputable sources, gives flexibility to expand the number of indicators and build a holistic model. On the other hand, uneven data quality hindered the tool's development, and ethical considerations prevented the use of some kinds of data such as social media.

Table 1: Summary of findings: data

Data		
Factors	Definitions	Evidence from case
Data availability	A key enabler is the availability of a wide range of open-source data from reputable sources to train the model	The Foresight model data was all derived from open and reputable sources, such as the World Bank, UN agencies, NGOs and academic institutes
Data quality	Uneven coverage, outdated, and/or delayed data are potential barriers and limitations of short-term and timely forecasting	Foresight experienced various issues with data, including uneven data availability across different indicators and geographical regions, with some indicators having better data availability than others. Additionally, delayed data was also a concern. Therefore, the model was not designed to provide timely and subnational level short-term forecasts, but rather to provide strategic forecasts at the national level
Updating data and handling missing values	Handling outdated or missing values are critical enablers, e.g. through automatic updating or techniques for dealing with missing data	Whenever possible, regression and heuristic approaches were used to treat data gaps. Additionally, techniques for updating data automatically, when a new set is available, were used
Extent and breadth of indicators and data	Large sets of indicators and data from relevant contexts is a potential enabler	An extensive list of over 148 indicators from 18 sources was used for training the Foresight model, along with techniques for leveraging data from relevant countries

Regarding the model development process, one of the more interesting findings is how the partnership between DRC and IBM resulted in incorporating both operational context and technical expertise. The process of developing the model was guided by the outcome of a survey of over 15,000 forcibly displaced people (the aim of the survey was to identify indicators to use for building the model) and dozens of interviews conducted by IBM developers with field offices and people familiar with the context. Building a context-centered anticipatory model, while ensuring the users and affected population are involved, bridges the gap between understanding the context and designing a relevant tool. The other major influences in model development involved the validation and evaluation of the model; extensive and ongoing evaluations were critical to building trust in the model outcomes.

The most challenging domain was neither the data nor the model development but rather the application or use of the tool. A critical enabler was Foresight's clear positioning as a supplemental source of information for decision-makers rather than as a replacement to existing decision approaches. Nevertheless, its limitations, such as its inability to predict unprecedented events, was a major concern and a barrier for wider adoption. Another critical challenge was information sensitivity. The humanitarian community recognizes the importance of developing tools and technologies that are centered around ethics and have harmless impact on the vulnerable people, which reflects a commitment to responsible and ethical use of AI and ML. However, this fact could limit the exploitation or wider application of AI and ML capabilities. In general, these barriers are one of the main hindrances for adopting ML learning models and may undermine trust [16], particularly in the humanitarian field [17].

6 Conclusion

This study is an attempt to understand enablers and barriers that impact the development and deployment of AI and ML technologies for humanitarian aid. We complement existing studies that focus on identifying opportunities, challenges, and risks of AI and ML systems in the humanitarian context by examining one successful tool's development and deployment. The case study format enables us to delve deeper to understand how a combination of factors contributed to success in one case.

Since these findings are based on a preliminary analysis of a single case, further research is needed to refine this set of influential factors and understand how they function in different contexts – e.g., for different types of models, different organizations, and with different data and expertise availability. Also, the case considered for the study generated a successful tool. For the future, including cases where an organization failed to deploy AI/ML could provide broader perspectives, especially on the barriers to deployment. Finally, the limited availability of information sources means that the findings are based primarily on the perspective of published information sources generated mainly by the organizations

Table 2: Summary of findings: development

Development		
Factors	Definitions	Evidence from case
Technical expertise through partnership	Partnering with technical experts for developing the model can be an essential enabler	DRC partnered for three years with IBM to support the initial development phase of the Foresight model, while it will be maintained by DRC
Incorporation of operational context	Incorporating operational considerations and knowledge from stakeholders and data sources is important	DRC leveraged expertise from stakeholders such as field offices and feedback from other organizations, such as the Health Sector in Syria. Additionally, both IBM and DRC employed other qualitative and quantitative methods for guiding the development of the Foresight model. For example, a survey of over 15,000 people involved in the forced displacement helped to identify relevant indicators
Model evaluation and revision	Conducting revisions and evaluation, both internal and external, are critical to success	In additional to the internal evaluation by DRC and IBM teams, the model was evaluated by external organizations (UNHCR - through UNOCHA evaluation matrix and model card)

involved in the project. A better understanding of enablers, barriers, and, critically, their link to the tool's reception and use in the humanitarian community, would require deeper insight from those within and outside of the project.

References

[1] Filippo Grandi. World Humanitarian Summit: Addressing Forced Displacement. *UN Chronicle*, 53(1):16–18, June 2016.

[2] Bernard Marr. *Artificial intelligence in practice: how 50 successful companies used artificial intelligence to solve problems*. Wiley, Hoboken, first edition edition, 2019.

[3] Oscar Rodríguez-Espíndola, Soumyadeb Chowdhury, Ahmad Beltagui, and Pavel Albores. The potential of emergent disruptive technologies for humanitarian supply chains: the integration of blockchain, Artificial Intelligence and 3D printing. *International Journal of Production Research*, 58(15):4610–4630, August 2020.

[4] Liye Ma and Baohong Sun. Machine learning and AI in marketing – Connecting computing power to human insights. *International Journal of Research in Marketing*, 37(3):481–504, September 2020.

[5] Sarah W Spencer. Humanitarian AI: the hype, the hope and the future. *Humanitarian Practice Network - Humanitarian Policy Group*, (1), November 2021.

[6] Michael Chui. Notes from the ai frontier: Applying ai for social good. *McKinsey Global Institute*, 1(1):5–8, 2018.

[7] Daniel E. O'Leary. Artificial Intelligence and Big Data. *IEEE Intelligent Systems*, 28(2):96–99, March 2013.

[8] Andreas Kaplan and Michael Haenlein. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1):15–25, January 2019.

[9] Wenjuan Sun, Paolo Bocchini, and Brian D. Davison. Applications of artificial intelligence for disaster management. *Natural Hazards*, 103(3):2631–2689, September 2020.

[10] Ana Beduschi. Harnessing the potential of artificial intelligence for humanitarian action: Opportunities and risks. *International Review of the Red Cross*, 104(919):1149–1169, April 2022.

[11] Francesco Piccialli, Vincenzo Schiano di Cola, Fabio Giampaolo, and Salvatore Cuomo. The Role of Artificial Intelligence in Fighting the COVID-19 Pandemic. *Information Systems Frontiers*, 23(6):1467–1497, December 2021.

[12] Eleonore Fournier-Tombs. Towards a United Nations Internal Regulation for Artificial Intelligence. *Big Data & Society*, 8(2):205395172110394, July 2021.

[13] Leonie Arendt-Cassetta. From digital promise to frontline practice: new and emerging technologies in humanitarian action. *Policy Briefs Studies - UN OCHA*, 1(1):1, 2021.

Table 3: Summary of findings: applications

Applications		
Factors	Definitions	Evidences
Relationship to human decision-makers	Positioning the model's relationship to human decision-makers is critical: e.g., to provide an additional source of information rather than to replace human judgment or qualitative analysis	The Foresight model was intended to support decision makers by serving as an additional source of information and was not intended to replace a human decision-maker or dictate action in isolation.
Use cases and general applicability	Use cases may be broad or narrow, such as providing one or several types of analyses and insights, with capability to include more contexts	Foresight has additional uses beyond forecasting forced displacement, such as causal analysis, scenario and network analysis, and visualization with links for relevant articles and reports. The list of the included countries is expanding to include more countries with time
Acknowledgment and understanding of limitations	It is critical to acknowledge and understand a model's limitations and assumptions that are based on historical patterns. These limitations may be an enabler or a barrier or neither	The Foresight model was not able to predict and capture unprecedented and sudden-onset crises, such as the Rohingya crisis in 2017. The model is trained on historical data and on the assumption that historical relationships are valid for the future
Information sensitivity	The ethical implications limit how model results can be shared or even which model capabilities are explored and used	Some Foresight predictions, such as the possible destination(s) of the forced displacement, were excluded to eliminate exploitation that can harm vulnerable people
Performance relative to current techniques	Even where model accuracy may not be perfect, it may still be better than the current qualitative forecasting and planning techniques used by humanitarian organizations. Developing such comparisons may facilitate model acceptance	The accuracy of the Foresight model was compared with Humanitarian Response Plans (HRPs), and the model shows lower margin error and better forecasting in 13 out of 17 of the cases, which suggests that its performance is superior to the currently employed techniques

[14] Ryan Wallace. New Reasons for Forced Displacement: A Multimodal Discourse Analysis of the Construction of Refugee Identity. *Journalism Practice*, 16(2-3):244–261, March 2022.

[15] Juliet M. Corbin and Anselm L. Strauss. *Basics of qualitative research: techniques and procedures for developing grounded theory*. SAGE, Los Angeles, fourth edition edition, 2015.

[16] Jeremy Petch, Shuang Di, and Walter Nelson. Opening the Black Box: The Promise and Limitations of Explainable Machine Learning in Cardiology. *Canadian Journal of Cardiology*, 38(2):204–213, February 2022.

[17] Giulio Coppi, Rebeca Moreno Jimenez, and Sofia Kyriazi. Explicability of humanitarian AI: a matter of principles. *Journal of International Humanitarian Action*, 6(1):19, December 2021.