SEEING IS PREDICTING

Anticipatory Action in Violent Conflicts

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EXECUTIVE SUMMARY

There has been a rapid acceleration in efforts to use artificial intelligence, machine learning, and big data to advance the United Nations' Sustainable Development Goals and anticipate humanitarian responses to some of the world's most significant challenges. Humanitarian organizations, from the United Nations to the Red Cross, and large technology firms such as Google and Microsoft are at the forefront of efforts to develop models for anticipatory action. These models involve the extraction of data from multiple data types (satellite images, social media, etc.) from numerous providers (satellite company, telecommunication companies, etc.) and the development scenarios of escalating crises that, in turn, help to identify future shocks and interventions before they turn into humanitarian catastrophes. But such efforts are usually siloed, and there is little exchange and common understanding driving efforts and priorities forward.

In response to the lack of evidence and critical assessment of anticipatory action for addressing the impact of violent conflict, the University of Oxford's Programme in Comparative Media Law & Policy at the Centre for Socio-Legal Studies convened a workshop, Seeing is Predicting, in June 2022 in Oxford under the European Research Council's ConflictNET project. The workshop engaged participants from public, private, and academic sectors, specializing in a wide range of expertise on the application of anticipatory action for conflict prevention. Organizations represented included United Nations agencies, government bodies, telecommunications companies, and international non-governmental organizations. As this is very much an emerging field, we sought to map out the range of anticipatory action projects that are currently being carried out, the applications these projects adopt, and the implications for the future of humanitarian action in conflict settings.

There is a significant lack of existing research and evidence on anticipatory action specifically related to conflicts, including conflict prevention. Participants outlined numerous areas for future research and the need to explore the social, political, economic, and legal contexts of anticipatory action. This report captures the insights that emerged from the presentations and discussions during the workshop. While the debate on data-driven anticipatory action focuses on its significance in strengthening humanitarian preparedness for climate hazards, the workshop's contributions pointed out the potential limitations of this approach for conflict prevention. By providing a basis to further our understanding of the scope, scale, and application of forecast data and risk analysis, this report enhances the debate on applying artificial intelligence and machine learning and data-driven humanitarian policies in fragile and conflict-affected areas.

The critical areas of discussion and recommendations included the need to:

Investigate the design-implementation gap

There is a gap between where data is collected and where it is analyzed. The protocols and technology underlying data infrastructure are more often designed and developed far away from intervention contexts. We must query how data is collected and analyzed to ensure the explainability of predictive models.

Investigate the data gaps

There are significant gaps in the data input into AI/ML models. Notably, the availability of datasets is geographically skewed. Qualitative, nuanced, and context-specific perspectives are often not captured.

Inequalities are amplified

Data-driven anticipatory action risks amplifying and perpetuating pre-existing power inequalities between the Global South and Global North, as well as between marginalized groups and decision-makers. Data collection varies because structural violence and inequalities remain invisible, and there is a lack of algorithmic accountability and transparency.

Recentering to institutions and actors in conflict-affected regions

To address the design-implementation gap and structural inequalities, international and global AI/ML models must be based on existing knowledge and systems in the national and subnational level rather than international assumptions.

Algorithmic accountability

Data system developers and analysts must build-in mechanisms to evaluate and validate their models. This includes investigation into the black box problem to ensure that biases are not amplified and place ethical AI/ML at the centre of the debate.

Humanitarian accountability

When developing anticipatory action frameworks, all actors involved must consider accountability structures from the beginning and for the entire program cycle. This includes discussions around the moral of saving lives while upholding the humanitarian principles. Can violent conflict or its impacts be prevented without interfering in the conflict situation itself, or worse, fueling it? We must consider who is responsible for ensuring anticipatory action for conflict prevention is ethical and what protocols we have in place for assessing the ethical use of AI/ML in humanitarian contexts.

Explore the disconnect between anticipatory action and long-term funding

Are anticipatory action and general preparedness funding part of the same organizational and political aims? How can we ensure continuity between anticipatory action and long-term resilience-building actions?

The potential of AI/ML is significant for anticipatory humanitarian action

Despite the many apparent limitations, actors from different fields see the potential of data-driven and risk-informed anticipatory action, particularly for complementing traditional humanitarian responses that come after a climate-related hazard. There are growing expectations that, if properly implemented, anticipatory action could also help mitigate the humanitarian impact by acting prior to climate-related hazards in violent conflict situations or even in advance of the forecasted onset or deterioration of violent conflict situations. As policy makers and implementers call for scaling up this approach, there is an increasing urgency to respond to criticisms and challenges.

INTRODUCTION

There has been a rapid acceleration in efforts to use artificial intelligence (AI), machine learning (ML), and big data to advance the United Nations' (UN) Sustainable Development Goals (SDGs) and anticipate humanitarian responses to some of the world's most significant challenges. Humanitarian organizations, from the UN to the Red Cross, and large technology firms such as Google and Microsoft are at the forefront of efforts to develop models for anticipatory action. These models involve the extraction of data from multiple data types (satellite images, social media, etc.) from numerous providers (satellite company, telecommunication companies, etc.). The models are trained to develop scenarios for escalating crises that help to identify future shocks and interventions before they turn into humanitarian catastrophes.

Planning and justifying humanitarian interventions on the basis of big data and algorithmic models comes with great risks. There are significant challenges posed by collecting and protecting the data of vulnerable communities, as well as inherent problems in attempting to impose technologies, algorithms, and models that have been trained and developed in high income countries in the Global North and in different contexts. As the recent testimony from Facebook whistle-blower Frances Haugen highlighted, even with well-placed intentions, without proper understanding of contexts, oversight, and safeguards, there are real concerns that such technologies may cause more harm than good. This risk is particularly acute for communities in the Global South, where there is less oversight as to how data is collected, protected, and used. As the United States' forces abruptly pulled out of Afghanistan in August 2021 for instance, Human Rights Watch (2022) found that not only did sophisticated military biometric devices fall into the hands of the Taliban, but they gained access to detailed and sensitive government databases containing detailed records of members of the government, police, and army.

The existing research on the potential of applying data-driven anticipatory action to prevent large-scale human rights atrocities and violent conflict (hereafter referred to as anticipatory action for conflict prevention) is scarce. The work of government agencies, technology companies, and non-governmental organizations (NGOs) in this space is at the forefront of shaping the debate on this complex and sensitive application of AI/ML and big data. In response to the lack of evidence and critical assessment of anticipatory action for conflict prevention, the University of Oxford's Programme in Comparative Media Law & Policy at the Centre for Socio-Legal Studies convened a one-day workshop, Seeing is Predicting, in June 2022 in Oxford under the European Research Council's ConflictNET project. The workshop hosted two dozen participants from public, private, and academic sectors, specializing in a wide range of expertise on the application of anticipatory action for conflict prevention. Organizations represented included UN agencies, government bodies, telecommunications companies, and international NGOs. The panels focused on mapping what kinds of anticipatory action projects are being carried out to prevent conflict and the challenges therein.

The Seeing is Predicting workshop came at a unique and critical moment. In early 2021, UN Secretary-General Antonio Guterres argued that “anticipatory action was core to [his] prevention agenda” (para 4), not least because acting earlier is seen as cost-efficient. This shift has been reflected in the UN Food and Agriculture Organization’s (FAO) pledge to dedicate at least 20 percent of its emergency funding to anticipatory action by 2025 (United Nations Office for the Coordination of Humanitarian Affairs, 2021). The push from prevention to anticipating layered over in the Secretary-General’s 2018 Strategy on New Technologies, which supported the use of AI/ML and other data-driven technology to achieve the SGDs (UN Secretary-General António Guterres, 2018). As part of the Strategy, the UN Innovation Network was tasked with working to advance the applications of data-driven technology (Coppi et al., 2021). The emphasis on the potential of data-driven technology for humanitarian applications gained even more focus due to the COVID-19 pandemic (Beduschi, 2022).

Currently, most data-driven anticipatory action interventions focus on responding to humanitarian crises induced by climate hazards (SDG 13). These interventions rely on a broad range of datasets and are viewed as less politically controversial than in the case of conflict prevention. This workshop explored the future of anticipatory action, namely its application to large-scale human rights atrocities and violent conflict, both of which directly intersect with SDG16 (Peace, Justice and Strong Institutions), SDG10 (Reduced Inequalities), and SDG5 (Gender Equality). While humanitarian organizations and technology companies are rapidly trying to diversify anticipatory action beyond climate hazards, there is recognition that early responses to conflicts and atrocities come with greater risks and challenges, particularly when navigating complex political contexts. By critically engaging with the issues that are at the frontier of AI/ML and data-driven anticipatory action and by developing accountability mechanisms for a responsible and transparent application of AI/ML that is specifically suited to communities in the Global South, the workshop aimed to engage and explore the future of the field of humanitarian action.

This report captures the insights that emerged from the presentations and discussions during the workshop to provide an overview of the pressing issues and debates on anticipatory action for conflict prevention, as well as the potential of this type of humanitarian action. By providing a basis to further our understanding of the scope, scale, and application of anticipatory action, this report enhances the debate on applying AI/ML and data-driven humanitarian interventions in fragile and conflict-affected areas. This is crucial in enabling policymakers to identify and develop mitigation strategies for the challenges in applying anticipatory action to conflict prevention.

Funding for anticipatory action in conflict prevention is increasing, and participants outlined that the focus must be on addressing the challenges associated with this application of technology. This report summarizes the workshop, while offering additional context from the academic debates on anticipatory action for conflict prevention.

ANTICIPATORY ACTION AND THE AI/ML INTERFACE

At the outset, it is essential to recognize that anticipatory action is a debated concept in the literature. Sometimes early action, anticipatory action, and forecast-based financing are referred to as separate concepts; other times, they are conceptualized under the same larger umbrella of actions classified as preventative interventions. Pichon (2019, p. 9-10) explains that early action and anticipatory action are most often used as synonyms, whereas forecast-based action is classified as a type of early/anticipatory action. Within the early/anticipatory action framework, there is a further distinction between early warning systems and early responses. Early warning actions are done to mitigate against a crisis, whereas early response involves lifesaving action post-crisis that lessens the scale of the impact of the crisis (Pichon, 2019, p. 9-10). For the purposes of this report, we will use the term anticipatory action to refer to the actions taken before a crisis that are done to prevent either the occurrence or escalation of said crisis (Pichon, 2019).

Anticipatory action is typically triggered when a threshold is reached (e.g. predicted water level, storm strength, or temperature). The data involved in anticipatory action is either automatically labeled or input by humans based on expert opinions and in-field surveys (Hostetter, 2019). Similarly, the decisions arising out of these coding processes can be automated or not (Coppi et al., 2021). AI/ML is used to enhance the decision-making processes involved in anticipatory action models (van den Homberg et al., 2020), particularly for displacement and automated cash transfer applications (Coppi et al., 2021). Data enables humanitarians to better map what is happening and predict what could happen. The UN Refugee Agency's (UNHCR's) Project Jetson is a well-cited example of a predictive analytics project that has been focused on forced displacement (Beduschi, 2022). In his presentation, Marc van den Homberg pointed out that big data and algorithmic models have the potential to improve the speed, quality, and cost-effectiveness of humanitarian aid if the data capacity of the local actors is increased. He also explained that usually a mix of human-out-of-the-loop (using AI and big data) and human-in-the-loop is deployed. For example, in the Philippines, a ML model is used to predict at the municipality level (so a very aggregated level) how many houses will be completely destroyed when a typhoon is about to make landfall and – if a threshold is reached – early actions are triggered. Subsequently, several barangay committees determine which households will benefit from the early actions in their municipality (Bierens et al., 2020).

AI/ML is poised to play a crucial role in shifting humanitarian action from responding to anticipating crises (Beduschi, 2022). AI/ML can strengthen the preparedness of humanitarian agencies by mobilizing financial and logistic resources in advance and enable better coordination of response and recovery action, as seen in the deployment of a rapid emergency response in Mozambique in 2019 (Beduschi, 2022). There are, however, numerous concerns with the anticipatory action and AI/ML interface. Namely, data could be used to target groups or individuals and also that AI/ML is not a replacement for human decision-making processes (Coppi et al., 2021; Beduschi, 2022). Some have gone so far as to call the use of AI/ML in humanitarian crises "surveillance humanitarianism," fearing that the overreliance of local early warning response systems on non-local data infrastructures and opaque predictive models would pave the way to new forms of "techno-colonialism" (Beduschi, 2022, p. 4).

Data-driven anticipatory action applications and methodologies have mainly been tested in contexts vulnerable to, or affected by, climate hazards. There have been significant innovations in using other types of data-driven technology too, including crowdsourcing via social media and mobile apps for flood data or determining the extent of an earthquake, such as the one ravaging Haiti in 2010 (Wang, 2021). In another recent example, there have been efforts to analyze surveillance camera video footage to gather flood data points in flood-fragile areas (ibid.). AI/ML has facilitated the mapping of previously unmapped vulnerable communities (Schneider et al., 2021).

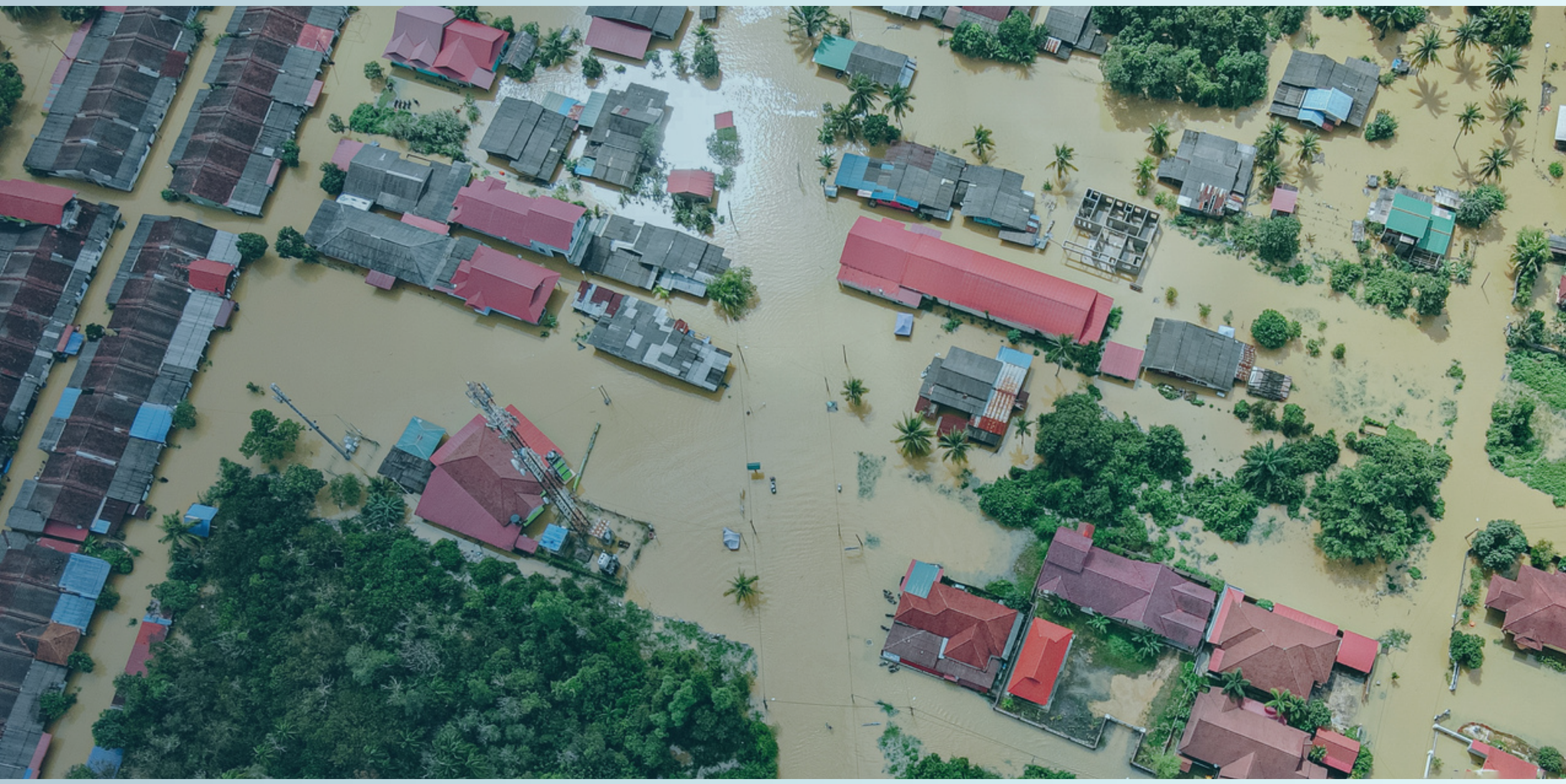
Despite the emergence of hubs to facilitate the exchange of experiences among practitioners and their engagement with policymakers, the anticipatory action landscape remains fragmented. Moreover, most policymakers are cautious about basing decisions on predictive analytics.

In contrast to climate hazards, anticipatory action is less prevalent for conflict forecasting and humanitarian prevention, both in terms of funding for this type of action and commitment from policy and on-the-ground actors. Yet, there is a growing recognition of the importance of this type of data analysis and application. Violent conflict is one of the primary drivers of humanitarian crises and is strongly correlated with other types of insecurity, such as food insecurity and vulnerability to climate shocks and earthquakes.

In one of the few reports explicitly highlighting the potential of anticipatory action for conflict prevention, Wagner and Jamie (2020) acknowledge that the specificities of the drivers of conflict matter. For instance, they observe that politics might weigh on anticipatory action initiatives in conflict-induced humanitarian emergencies more than in climate crises, hindering, as a result, the implementation and effectiveness of such interventions. They thus provide a framework for approaching anticipatory action in conflict, based on the distinction between humanitarian interventions to climate crises in politically fragile or openly conflictive settings and interventions strictly addressing forecasts of conflict. Both types of action would classify as anticipatory action for conflict prevention, but the thresholds and triggers involved are distinct.

In her presentation during the workshop, one of the authors of the study, Marie Wagner from the Global Public Policy Institute (GPPi), focused on addressing how forecasts of climate hazards and conflict situations are linked but also divergent. Wagner reminded us that the building blocks for anticipatory action are the same across climate and conflict applications. She outlined that these blocks are: 1) the collection of data and forecasts and the ability to analyze them; 2) anticipatory action needs to be built into contingency plans through pre-agreed actions; 3) there must be mechanisms to fund anticipatory action; 4) early adaptors must champion anticipatory action and be willing to take decisions; and 5) clear delivery channels must be established. Wagner proposed that all five elements are required before anticipatory action can be adapted to new contexts. After these elements are established, anticipatory action can be, for example, transitioned into new geographic locations and/or new hazards. Wagner suggested that recognizing and establishing these building blocks is an essential first step to transitioning anticipatory action to conflict prevention.

Wagner expanded on her and Jaime's (2020) report on the two broad approaches to transitioning anticipatory action to conflict prevention. For anticipatory action for conflict based on forecasts of climate hazards in violent conflict situations, she explained that the goal is to act early in anticipation of the climate-related hazards in situations of ongoing conflict. In many ways, this type of conflict prevention action is more feasible because it uses the same data as projects already piloted for climate hazards, and the benefit of this type of action is that it can be used as an avenue to dissect conflict. Wagner, however, cautioned that more situation analysis is needed to ensure that anticipatory action for conflict prevention would be able to adapt and take in the specific needs of conflicts beyond climate hazards. The second approach detailed by Wagner and Jaime (2020) is to engage in anticipatory action on forecasts specifically for violent conflict. The goal of this type of action is to act early in anticipation of the humanitarian impacts of violent conflict. Wagner outlined that one of the issues with this approach is that, because of displacement, conflict does not necessarily create humanitarian needs only in the geographic area where it is happening. A few examples of predictions of forced displacement, such as the Jetson Project, which used proxies like changes in food prices to try and predict new conflicts, were highlighted. In another example, Wagner explained how the potential electoral violence in Uganda was modeled based on the historical data of past events to preemptively disperse medical supplies to high-risk areas. Wagner also explained that there are models based on qualitative approaches, like the Start Network, which uses experts on the ground to raise an alert. The session concluded by reflecting on the potential transferability of lessons and best practices from climate hazard anticipatory action to conflict applications, which we explore in the next section.



LESSONS LEARNED FROM CLIMATE FORECASTING

While scholarship on anticipatory action for conflict prevention is still nascent, some lessons of best practices can be pulled out from their application to climate hazards (keeping in mind the caveats previously mentioned by Wagner). Hostetter (2019) found that anticipatory action must prioritize a localized agenda using community-based data sources. Schneider et al. (2021) add that when moving from local to global, anticipatory action needs to be slowly scaled up, ensuring that the technical expertise is acquired by key stakeholders along the way (e.g. through training programs). Local knowledge is essential to ensure ethical data collection and that actions suggested will actually be implemented (Kemmerling et al., 2021). Schneider et al. (2021) also argue that sustainable funding structures must be implemented before any scaling up. In her presentation, Anulekha Nandi from the London School of Economics (LSE) stressed the importance of sustainable funding through outlining the failure of early warning systems in the 2018 Indonesian tsunami. Nandi explored the challenges of anticipatory action for climate hazards and how challenges impact the potential of transitioning anticipatory action to conflict prevention.

In 2018, in Indonesia, an earthquake triggered a massive tsunami that killed more than 1,000 people and foregrounded the breakdown of the country's tsunami early warning system. The early warning system consisted of a seismographic model that involved alerts sent via text; a network buoys (that lacked maintenance so they were not in operation); and tidal gauges to record changes in sea level. The gauges were 200km away from the shore and recorded changes every 15 minutes. Yet, because the tsunami happened within 10 minutes of the earthquake, the gauges only recorded a 2.3-inch change in sea level during the ensuing 15-minute interval. Nandi stressed that, although Indonesia's early warning system was funded by international donors, not enough budget was allocated to maintenance. International aid was curtailed in 2011, coinciding with drastic budget cuts to Indonesian agencies responsible for maintaining the system. The result was a poorly functioning system. Nandi drew on the failures of Indonesia's early warning system to highlight lessons for broader applications of anticipatory action. As anticipatory action is triggered by forecasts that have pre-agreed thresholds, Nandi queried: when do we evaluate the appropriateness of the threshold? This question is paramount in situations of conflict. Where state capacity is diminished because there is a push towards automating these systems, the selection of parameters is critical.

This session also highlighted that there is a need to ensure there is financing in non-disaster times so that the systems of data collection remain functional. She put forth that we need to consider the place of anticipatory action in humanitarian funding, specifically how it intersects with longer-term capacity-building initiatives that enable communities to be more resilient and manage risks more sustainably. The success of anticipatory action relies on the strength of existing systems and local partnerships at different levels.

Forecasts are shaped by different approaches and kick in at different operational levels, which affects how these processes shape government structures. This variability makes it difficult to transfer learning across contexts and makes us question who we are protecting and who needs to be protected. Even the most sophisticated AI/ML system needs local capacity, and this is the most vulnerable aspect of the system.

Concerns were also raised about the contextualization process of AI/ML. Anticipatory action technologies are built using different statistical models. Increasingly, they are developed further away from the field. It is difficult to access appropriate data, particularly in conflict, so de-contextualization is happening, and, highlighting one of the strong themes across sessions, there is a strong need to better capture local realities.

Schneider et al. (2021) support that ethical data collection and sharing practices need to be central to the debate on how best to scale up anticipatory action (Schneider et al., 2021). Marc van den Homberg from 510, a data and digital initiative of the Netherlands Red Cross, discussed how 510 is assessing algorithmic fairness and non-discrimination in their natural hazards forecasting work in his presentation. Part of ensuring the principles of fairness and non-discrimination has led 510 to expand its risk database by making sure that the most vulnerable communities are included. This has been done by engaging in activities such as Missing Maps (Humanitarian Open Street Map), where through mapathons volunteers trace buildings and roads on maps. More and more, however, this can be done AI-assisted or fully AI-based. For each trigger model, 510 is creating a hazard-impact database with the impact of multiple historical events to train ML models. In some cases, they use text mining of local newspapers to enrich the impact data from official sources (van den Homberg et al., 2022). For some cases, 510 develops trigger models using a simple composite index approach and, for others, more advanced statistical ML models. With the composite index approach, the deployment area is determined by overlaying a layer in GIS with the flood forecast with layers and with the vulnerability information (such as poverty) and exposure information (such as houses in flood-prone areas). In the Philippines, 510 did not use the composite model. Instead, they developed a so-called xgboost ML model with around 40 predictors such as physical vulnerability (wall type and roof material), social vulnerability, and hazard (in relation to the typhoon, but also its consecutive events such as floods and landslides). The ML model predicts the damage to houses. This model is trained on over 50 historical typhoon events and is now used by both the UN Office for the Coordination of Humanitarian Affairs and the Philippine Red Cross (OCHA, 2022).

To ensure ethical data collection, Gettliffe (2021) suggests that anticipatory action should first be piloted on a very small scale before it is even moved to the regional level. One way to achieve this is by building-in anticipatory action for conflict prevention into existing processes (Gettliffe, 2021; Kemmerling et al., 2021). Accordingly, Maxwell and Hailey (2020) demonstrate that the focus on anticipatory action should be on addressing the current issues such as biases in algorithms before scaling up. To do so, Maxwell and Hailey (2020) find that collaboration is essential at all levels of anticipatory action, from international organizations to local action recipients. It is also vital to ensure that more research is done on the drivers of conflict to ensure that appropriate correlational factors are included in the algorithmic models, as well as to address the gaps in the data (Kemmerling et al., 2021; Maxwell and Hailey, 2020).

Notably, Maxwell and Hailey (2020) highlight the importance of ensuring anticipatory action decisions are subject to structures of accountability, which includes consideration of the role of politics in responding to conflict and the role of government in doing so.

Another participant, Linda Speight from the School of Geography and Environment at the University of Oxford, expanded in her presentation by exploring what information decision-makers need to take action for floods and how we can assess the sustainability and impact of flood forecasting in the context of GloFAS (Global Flood Awareness System).

Compared to conflict prevention, Speight explained that there are quite well-established protocols for climate hazards. However, climate hazard forecasting is still a work in progress, and there are not any fully developed operational systems. Speight particularly highlighted that impact forecasting is a weak area. She also pointed to the need to integrate warning and decision systems. Speight gave the example of the Scottish Flood Warning system, which does not have established protocols for what to do when a warning is triggered.

The presentations from Wagner, Nandi, Speight, and van den Homberg shared the conclusion that it remains challenging to predict a climate hazard, let alone a conflict. Real-time data are often patchy, hard to access, and not shared with the humanitarian sector. In expanding to conflict applications, Wagner explained that one of the main challenges is trying to determine what we are predicting – What do we mean by conflict? What do we mean by data? Is it the onset of a violent conflict? What is the trajectory of the conflict? Once we determine what we want to predict, Wagner argued that a series of other challenges arise, such as establishing a threshold for triggering action and how to ensure that this action is in line with humanitarian principles.

Speight brought into question how we can evaluate and validate climate forecast models, as this can enable us to better develop conflict forecast models. People who design the systems know that probability systems are not always correct, but this is not necessarily the same for the actors who use them. In this context, the main risks in anticipatory action for climate hazards are that action will happen in vain or action will not happen, but an event will. This requires reflecting on the acceptable false alarm ratio. Referring to the findings from Coughlan de Perez et al. (2016), Speight proposed building in reviews of models after events to reflect on the description of the event, the actionability of the forecast, and the vulnerability to the hazard. She argued that co-design and co-production are very important to ensuring that models have applicability on the ground. Reflecting what van den Homberg et al. (2020) call the evaluation of horizontal and vertical accountability, models must be accountable to those who use them, those they collect data from/about, and the wider global structures in which they operate. Weingärtner and Wilkinson (2019) agreed that more evaluation and validation are needed for anticipatory action forecasts for hazards and food insecurity. They found that assessments must also determine if the financial costs of anticipatory action are worth the benefits. Weingärtner and Wilkinson (2019) also question, however, the utility of cost-benefit analyses when the goal is to save human lives – not all benefits are quantifiable. Of the research that has been done, there is great variance in how costs and benefits are defined and calculated (Weingärtner and Wilkinson, 2019).

More broadly, because there are few impact assessments of anticipatory action for climate hazards, it is difficult to draw definite conclusions (Wagner and Jaime, 2020; Weingärtner and Wilkinson, 2019). This lack of evidence is in part underscored by the range of action that qualifies as anticipatory action and the multiplicity of settings where action is implemented (Weingärtner and Wilkinson, 2019). There are also distinct approaches to qualitative data, where some research evaluations have included this as indicators in anticipatory action models and others focus solely on quantitative measures (Maxwell and Hailey, 2020).

This limited evidence is overlaid by significant geographic data gaps (Schneider et al., 2021). In the context of climate hazards, there is often a dearth of reliable demographic data, or outdated infrastructure mapping to refer to ahead of, in the aftermath of an earthquake or a hydrometeorological disaster (Maxwell and Hailey, 2020; Schneider et al., 2021). Two known unknowns intersect: what is the combined impact of the hazard and the technology on the local population? Inaccurate or biased data can risk the safety of the target population (Beduschi, 2022).

CASE STUDIES OF PREDICTIVE MODELS IN CONFLICT SETTINGS

And while there are few robust evaluations of anticipatory action for climate hazards, there are important lessons to be learned as outlined above. In the next section, we highlight the case studies on anticipatory action for conflict prevention presented during the workshop.

Several instances of best practices for anticipatory action in situations of conflict were highlighted during the workshop. Alexander Kjærum from the Danish Refugee Council (DRC), Diana Suleimanova from Brunel University, Paola Vesco from Uppsala University, and Sofia Kyriazi from the UN Refugee Agency (UNHCR) presented examples of forecasts specifically for conflict-induced displacement. These examples of best practices, however, were not implemented without challenge, and the presenters highlighted numerous areas for consideration in future projects. We explore these case studies in turn before reflecting on the normative considerations of anticipatory action for conflict prevention in the next section.

Foresight, WACAFI, and SODRD models

The DRC partnered with IBM to explore predictive analytics. Through this partnership, DRC developed three models: Foresight, WACAFI, and SODRD. These models operate at different geographic levels. The Foresight model uses open-source data to predict the number of displaced persons (internally displaced persons, refugees, and asylum seekers) from a given country one to three years into the future. It is a random forecast model that uses 120 indicators, including fatalities from conflict and violence against civilians. DRC uses the model to support overall annual strategic planning. The WACAFI model predicts the number of displaced persons in administrative districts three to four months into the future. It is a sub-national random forecast model that uses 25-30 indicators, and it is more scenario-based than the Foresight model, as it includes input from experts in the field. It captures predictions related to conflict, but also food insecurity. DRC use the model to support operational responses. The SODRD model is a household-level dynamic model that focuses on simulating the impact of the drought on future displacement and the possible impact of an intervention. DRC uses the model to support programming and anticipatory action related to drought-induced displacement.

Focusing on the Foresight model, Kjærum argued that it worked quite well in many geographically diverse countries and provided information that was not otherwise available. However, overall, the model performed better the more conflict there had been. There is also an underestimation bias in the model. For example, when tested, the Foresight model only predicted that three million people would be displaced by the 2022 Russian invasion of Ukraine. Generally, the model was less good at predicting a high level of displacement. Greater change in displacement should lead to a higher forecast, but the model had a harder time predicting the more-black swan events like the Ukraine conflict. The model's predictive power is also more accurate in some countries and less in others. There are countries with quite high markings of error within the models.

As such, DRC's key conclusion was that the model could not be used for automated decision-making. The model was triangulated with qualitative analysis and information around these forecasts to develop more scenario-based forecasts. They found that anticipatory action based on displacement forecasting should include several inputs from communities.

Kjærum explained that despite these limitations, the model still holds great value for DRC's annual strategic planning, assessment of the impact of events on displacement, hypothetical displacement scenarios (such as climate change displacement scenarios for Myanmar and Afghanistan and scenario-based forecasts of displacement resulting from ISIS/US withdrawal), and anticipatory action mechanisms. Kjærum concluded that the real challenge is not building the models (although this is a technical challenge), but figuring out how to act on them. Over their three models, Kjærum explained that DRC had learned that displacement is a complex and highly contextual phenomenon requiring many tools.

ITFLOWS FLEE Code

The FLEE code was developed by Brunel University to analyze where people flee once conflict erupts. Brunel started their simulation research on FLEE in 2016. The agent-based FLEE code has three objectives/types of potential impacts: to save lives by helping governments and NGOs to better allocate humanitarian resources to refugee camps; to help complete incomplete data collections on forced displacement; and to investigate the humanitarian consequences of a nation closing its border for refugees and other interventions. The FLEE code is based on ACLED data, geospatial information, UN refugee data, and population data. It also includes data points on conflict zones, route construction, camp location, and the behaviours of refugees in conflict. The code is based on assumptions informed by the literature on how refugees move from conflict zone to refugee camps. Input parameters include movement speed, maximum walking pace, probability of moving (Is the area safe or unsafe? Move to a camp or otherwise?), attractiveness/value of camp locations, and attractiveness/value of conflict locations. FLEE focuses on ensemble models, coupling macro-micro automated sensitive forecast modelling with food and weather data. The FLEE code is a public code on GitHub and is written in Python 3. The agent-based model simulates one day at a time, and each agent represents one displaced person. Each agent decides: Do I stay put or move to a neighbouring location? If I move, which location shall I go to? So far, the main simulations of the FLEE code are Mali, Nigeria, the Central African Republic, South Sudan, Burundi, Ethiopia, and Syria. The FLEE approach was validated against refugee registration data from UNHCR and predicted >75% of the arrivals correctly across conflicts. Suleimanova explained that the main aims for the FLEE team are to improve the accuracy of their forecasting ability up from the current 75% and enable simulation construction and use within one week (currently three to four weeks).

The FLEE code has gone through three versions, with the second version being developed with input from the International Organization for Migration (IOM) and the third in collaboration with Save the Children. These inputs have been valuable in improving the model. For example, with the IOM input, the FLEE team learned that when people flee conflict, they walk first. This led the FLEE team to analyze whether people take the main or side roads. With Save the Children, the FLEE team improved their forecast modelling for the current Ethiopia (Tigray) conflict situation. They are building a more guided randomizer that follows specific scenarios defined in collaboration with Save the Children to forecast increased rates in camp arrivals in Sudan if the conflict were exacerbated.

Participants queried the ethics of the FLEE code, wondering if the simulations could create risks for individuals by knowing their location. For instance, a few participants raised questions about whether the simulations could be used to track the movements of minority racial and ethnic groups. Suleimanova explained that they focus on the distribution number, open research, and open data. The code does not make predictions for people with identifiable traits. She stressed that it is important not to violate ethical considerations when developing models.

S@R and ViEWS

The Societies at Risk (S@R) program at Uppsala University is relatively young but the S@R model builds on the ViEWS model for forecasting violence and the impact of violence. S@R aims to quantify the expected negative consequences of violence (psychosocial well-being, household income loss, access to water, etc.). ViEWS aims to forecast future political violence. The model is based on the assumption that conflict emerges under certain conditions, such as incentives to use political violence to capture rent-generating resources and strong pressure for regime change, as well as when constraints on those in power are weak (e.g. situations of poverty, non- or half-democratic government). ViEWS is also based on the assumption that conflict legacy/proximity is the best predictor of violence in the short term, as conflict tends to re-occur, spread, and/or persist. ViEWS is based on a database built as part of the Uppsala Conflict Data Program (UCDP), which has tracked violent conflicts since the 1970s. ViEWS uses three types of data: state-based conflict, one-sided violence, and non-state conflict. ViEWS produces and releases monthly forecasts of the risk of political violence for one up to 36 months into the future. The forecasts are obtained through ensembles of decision-tree based algorithms, such as random forests and extreme gradient boosting. Each model in the ensemble is based on themes and topics. The importance of each model varies over time. For instance, previous conflict history is important to predict violence one to three months ahead, but political regime matters more to predict the risk of conflict in the longer-term, up to three years into the future. The outcome to be predicted in ViEWS is the risk of occurrence of political violence (all three categories defined by UCDP). According to this definition, an episode of violence is defined as a conflict if it leads to at least 25 fatalities at the country-month (cm) level, or at least one death at the sub-national, dissagregated, PRIO-GRID-month level (ppm)[1], or one fatality per so-called PRIO-GRID cell for predictions up to 36 months in the future. At the cm level, by accepting 40% false alarms, ViEWS can predict 95% of all conflicts. At the ppm level, by accepting 80% false alarms, ViEWS can predict 45% of conflicts in the right location and time. By adopting this holistic approach, Vesco argued that ViEWS can offer insights about the main drivers of conflict.

[1] The PRIO-GRID dataset is a grid structure developed by the Norway-based Peace Research Institute Oslo (PRIO) to facilitate the organization of spatial data for the entire world. Each grid cell includes data ranging from socio-economic conditions to ethnic composition and climate.

Vesco characterized ViEWS as committed to maximal transparency, and the team behind it only uses open access and publicly available data. Currently, the ViEWS team is working on updating their outcome variables. Instead of binary variables, they are moving towards developing a spectrum to predict the likely number of fatalities associated with each conflict. This change comes in response to requests from policymakers, as it could help showcase conflict escalation or de-escalation. Vesco explained that she had been specifically focusing on integrating extreme climate events into the model. However, she found these have a limited impact upon conflicts and, even then, only when they interact with other variables, such as institutional fragility and a previous history of conflict. As a stand-alone variable, Vesco argued that the evidence collected so far suggests that extreme climate events are not key drivers of conflict.

The ethical implications of publishing forecast data openly was discussed at length by the participants. Vesco explained that they are not concerned about making the forecasts public. Instead, she put forth that the greater risk is that some actors or governments can fabricate their forecasts, which may be inaccurate or biased. She found this more concerning than making accurate or transparent forecasts public. For instance, if the military makes a forecast, it can be a self-fulfilling prophecy.

Project Jetson

Data innovation at UNHCR is premised on using data science techniques, including AI/ML, for analyzing non-traditional data sets for advocacy preparedness and operational responses. The priority of these techniques rests on providing solutions that cater to the well-being and dignity of the forcibly displaced. Kyriazi underscored the importance of UNHCR's data innovation because it enables evidence-based decision-making and better coordination between partners to improve the quality of services. She did, however, highlight that accountability and transparency are crucial as stakeholders must be on the same page for understanding the technology – e.g. the user must be able to interpret the technology. Kyriazi explained that UNHCR's innovation process is a response to field challenges that are demand-driven, not supply driven. They search in-house and externally for existing solutions and collaborate to identify the best solution.

In terms of current applications of humanitarian data innovation, Kyriazi outlined several examples of non-predictive projects such as satellite imagery in Syria, call detail records in Turkey, sensors being used in the WASH sector, and agent-based scenario building for COVID-19 measures in Bangladesh. Other areas of data innovation included radio outlets, social media, news outlets, and text-based responses. For predictive models, Kyriazi focused on Project Jetson. Jetson covered 18 regions of Somalia and used deep learning to predict movement (because of the situational memory of the populace from the drought in 2011). Similar conditions (consecutive failed rain seasons) were experienced at the beginning of 2016 and early 2017, which led UNHCR to design and implement Jetson. Jetson enabled UNHCR partners to make semi or fully automated decisions to provide assistance, automatic targeting, and cash assistance provisions. Jetson set a precedent for this type of predictive analytics work in the humanitarian sector. UNHCR has also engaged in predictive modelling in South America focusing on Venezuelan migrants crossing the border into Brazil. Yet, Kyriazi also pointed out that many challenges in developing these models remain including how to account for COVID-related factors.

The session concluded by discussing the great potential for using AI/ML and data science in refugee/humanitarian settings. However, ongoing adaptation, integrating ethical concerns, questioning and reflecting on methods, revising the metric of success, countering opacity, and developing guidelines are crucial to ensure applications that are aligned with humanitarian principles.

NORMATIVE CONSIDERATIONS

Humanitarian interventions are generally understood to have to abide by at least four core ethical principles: humanity, neutrality, impartiality, and independence (Coppi et al., 2021). Ethical AI/ML has its own set of principles including: beneficence, non-maleficence, autonomy, justice, and intelligibility (Coppi et al., 2021). Collectively, these principles raise significant normative considerations in the context of anticipatory action and the AI/ML interface. Ethical anticipatory action for conflict prevention involves questioning not only what such actions are, but also the processes by which those actions were identified in the first place: who does the data represent (or not); what data is being used; when was the data collected; where was the data collected; how is it being used; and why have we decided that data needs to be collected (Coppi et al., 2021)?

The guiding approach to both humanitarian interventions and AI/ML-driven action is the principle of "do no harm" (Beduschi, 2022; Schneider et al., 2021). Conflicts are challenging to anticipate and forecast (Coppi et al., 2021; Duursma and Karlsrud, 2019; Fortnam et al., 2020; Hostetter, 2019; Kemmerling et al., 2021; Pichon, 2019; Wagner and Jaime, 2020). They are also very sensitive to predict. What does it mean to say that an area is pre-determined to have conflict (Hostetter, 2019)? What implications does this have for structures of global governance and the relationship between those who hold geopolitical power and those subject to it?

There can also be gaps between forecasts and action. A lack of political will, for example, can mean a needed intervention is not implemented (Pichon, 2019). What does it mean, in that case, to say a conflict is pre-determined, but not intervened (Hostetter, 2019)? From a resourcing perspective, how can we understand which conflicts are responded to by anticipatory action compared to those that are not? Wherein, the implication is potentially that some conflicts are more worthy of international attention than others. There could be a justified reason – the scale and scope of the conflict – but there is great potential that a hierarchy of conflict interventions is developed along pre-existing delineations of structures of powers.

AI/ML technologies present some well-known risks, which ought to be addressed by humanitarian actors before AI/ML systems are deployed in humanitarian action. For example, humanitarian organizations using data-driven AI/ML systems should identify risks concerning data security breaches that could lead to the disclosure of sensitive information about their staff and their beneficiaries. They should also evaluate whether using AI/ML systems would negatively impact affected populations – for example, by revealing their location while mapping the evolution of a conflict and thereby inadvertently exposing them to persecution (Beduschi, 2022).

The discussion around the potential and risks of anticipatory action for conflict prevention raises many important questions about the norms governing the use of AI/ML and geospatial data. The opacity of AI/ML systems, the so-called black box problem or opacity problem, underpins numerous ethical, legal, and practical considerations (Coppi et al., 2021; van den Homberg et al., 2020). Although agreements between large donors and humanitarian organizations, such as the Grand Bargain, are pushing for streamlining data collection, the workshop participants highlighted that numerous challenges remain, which we explore in turn.

Amplification of Inequalities

Big Tech typically boasts neutrality and efficiency as key virtues of AI/ML, but growing evidence from the fields of critical data studies and data justice have largely debunked this claim, showing how algorithms encapsulate, reproduce, and, often, entrench opaque and ultimately negative and damaging biases. Humanitarian practitioners are reaching similar conclusions (van den Homberg et al., 2020), although careful comparisons should be made between existing decision making processes not using AI/ML and (future) decision making processes including AI/ML.

Notably, the biases of those who design the technology are embedded in the technology they develop, often without them being fully aware of it (Beduschi, 2022). These designers determine which indicators are chosen and how they are entered into the models (Hostetter, 2019). There are numerous examples where AI/ML technology has led to discriminatory gendered and racialized outcomes (Noble, 2020; O'Neill, 2017). Beduschi (2022, p. 12-13) outlines, for example, how facial recognition technology is significantly less accurate in identifying black women and that AI/ML are largely unable to identify people with disabilities. The strongest evidence that demonstrates the gendered and racialized outcomes of AI/ML technology is predictive policing (Coppi et al., 2021). Military and law enforcement have used AI/ML technology to engage in targeted surveillance operations (Coppi et al., 2021). Without structures to assess the accuracy of data, there is also a risk that the data can be mismanaged and “mathematical manipulation” can occur, which can involve altering data so that it looks like a crisis is not specifically impacting one ethnic group over another, for example (Coppi et al., 2021, p. 13; Hostetter, 2019). van den Homberg et al. (2020, p. 459) describe AI/ML technology in humanitarian settings as “blur[ring] care and control.”

In her presentation, Wagner argued that we can always gather more data, but, without a clear understanding of the boundaries to draw around that data and its application first, anticipatory action risks being ineffective at best and dangerous from a human rights perspective at worst. Scientific forecasts for decision-making can create a false sense of security. Forecasts do not capture human values and are not as apolitical or as neutral as humanitarian action should be. Wagner highlighted that we need to assess anticipatory action through the lens of questioning inequity and the structures of power embedded within the data and technology being used. AI/ML can undermine localization and participatory approaches and result in the unequal production of knowledge.

She referred to this as the data production divide – assessing who produces, analyzes, and communicates data and science is even more important in conflict. Wagner urged that we must approach anticipatory action with a heightened awareness of who produces the data and where it is implemented, a concern echoed by most participants. Data analytics risk replicating structures of inequalities. Working with data is also an ever-expanding and increasingly specialized professional expertise, which privileges the same set of people with these skills to begin with and excludes the data subject, despite our attempts not to. In her presentation, Larissa Fast from the Humanitarian and Conflict Response Institute at Manchester University referred to these missing voices as demarcating the invisible barriers to local action. For example, she explained that donors from the Global North are more likely to fund larger, international humanitarian organizations than small local ones, and Global North research institutions are much more likely to get funded than Global South ones. Such practices exacerbate the asymmetry of knowledge between the Global North and the Global South and marginalize local knowledge (van den Homberg et al., 2020).

To ensure that anticipatory action for conflict prevention does not amplify inequality, van den Homberg focused on raising questions about building accountability into the technology itself in his presentation. He specifically queried what the triggers are missing out on and how we reconcile different humanitarian organizations using different triggers. He focused on the notion of algorithmic accountability and how we assess who the actor is and the judges of that actor (van den Homberg et al., 2020). For example, is the actor the organization that initiates the early responses or actions, or is it those involved in algorithmic development? Are the judges the affected people, donors, or the validation committees? Comes et al. (2016) outlined how cognitive and motivational biases influence how results are used for decisions making. Anticipatory action can fluctuate based on motivation biases, desire for a specific decision or event due to political affiliation, pressure to underreport, media coverage, and/or access. Cognitive biases are linked to the simplification of results because of the complexity or data overload, where decision-makers construct simplified mental models when dealing with complex problems such as a disaster, and these simplifications are likely to introduce biases (Comes, 2016).

van den Homberg used the example of 510's practices in auditing predictions to automate damage assessments to highlight the importance of algorithmic accountability. He outlined that emergency responders need to know two key elements: where people are in need (geographic location) and how bad the situation is (scale of damage). Primarily, current processes rely on going to the field and surveying or manual input from experts. 510 uses deep learning to try and map this (Valentijn et al., 2020), which can be done in about 30 minutes after satellite imagery of the impacted area becomes available. To audit this new intelligence workflow, 510 has been looking at the steps in the model. At the data collection and preparation stage, they analyze points of representation bias as it relates to the sampling of the population – e.g. was cloud cover limiting satellite imagery? For model inference and evaluation, is there an evaluation basis? 510 looks at what kind of labelled data they have and how the model has been trained to use that data. Then, they assess the hyper-parameter bias – how fair is the algorithm? – wherein fairness and non-discrimination generally refer to the absence of bias in datasets and algorithms.

Data Protection, Management, and Sharing

Not only is there often a data gap in developing countries, where data does not have the required highly granular data resolution or data is missing on some risk indicators, but also there is a gap in data capacity. Data responsibility is about using what we collect and not overburdening those who collect it/respond to it. For Fast, such considerations of inequality in data capacity are exacerbated by the formal and informal frameworks that govern the collection and sharing of disaggregated humanitarian data with donors. Anticipatory action requires data sharing, but there are issues with the proliferation of data collection in humanitarian settings: receipt, storage, processing, analysis, sharing, use, retention, and description of data and information. There is operational data, monitoring and evaluation data, case management data, etc. There are frequently multiple definitions, characteristics, and regulatory frameworks involved in data collection and sharing. This makes it hard for organizations to figure out what to do aside from do no harm and the protection of personal data. Fast explained that how you share data and why you share it becomes quite challenging to evaluate – How do you aggregate data and get the level of precision you need from those who are collecting data? How do you return it to them in ways that are relevant? How do you collect it in a way that is not burdensome?

Fast illustrated how youth is defined differently across countries, as an example of the challenges in aggregating data. Practically, data is also often shared in PDFs, which means they must be translated into other formats before they can be analyzed. Research and practice are also often at odds. Researchers typically want as much data as possible to make assessments around data quality, but this is very labour intensive for practitioners. Moreover, the more granular the data, the more there is the risk of identifying people.

There are also many questions about consent and using data beyond its application – Does informed consent mean you can share it with donors? Data sharing is usually justified in terms of legitimate humanitarian interest. Still, it can lead to sharing data for purposes other than initially intended, like developing future AI/ML models (Beduschi, 2022). For instance, in one of the recent data sharing failures, the UN shared data on the personal information of ethnic Rohingyas with the Myanmar government (Human Rights Watch, 2021). There are questions about the ethics of sharing data to being with, particularly location-specific content from conflict settings. Fast outlined the example of health actors in Syria who refused to share data on the location of health facilities for fear that the information would be used to target the facilities. At the same time, making this information public meant that military and ISIS forces could not get away with saying they did not know they were targeting a health facility, which has different implications from a geopolitical intervention standpoint.

There are many constraints on sharing data, such as an under-investment in the systems and platforms used to manage data and the translatability of the data. Fast outlined that it is difficult to explain data to colleagues within the same organization, let alone those from outside that do not share a common working language. One of the other primary constraints is who controls the data. Data is a currency of power, influence, and authority. What is shared and how it is shared reinforces power in the humanitarian system. The organization that controls the data controls the narrative and acts as a gatekeeper for who has access to that information. Fast summarized that data mark the territorial boundaries of an organization.

Data collection practices can also intersect with a skepticism of humanitarian organizations. Donors do not always trust the quality of the data provided. Donors ask for more and more data to ensure that money is going where it should and that the data is of sufficient quality. Yet, Fast cautioned this could lead to humanitarians inflating numbers because it brings in more financing. Fast referred to this as the paradox of trust: there is an inverse relationship between trust and data sharing. For example, high-profile scandals and breaches of trust result in more scrutiny and more robust data.

Technology Optimism and the Private Sector

Of normative significance is how we develop questions about anticipatory action when there is so little research on its application to climate – and less still on conflict. Quito Tsui from the Engine Room put forth that the current debate on anticipatory action reflects a desire for preparedness based on technology optimisim in her presentation. Among many humanitarian and development agencies and donors, there is a genuine belief that AI/ML technology can protect and improve livelihoods as can be seen from an increase of organizations providing AI/ML solutions to the humanitarian sector and an increase of funding mechanisms. Using technology to predict crises is a highly economical approach. Tsui argued that this shows in the terminology, where refugees are referred to in detached terms such as data subjects or beneficiaries. Analytics takes human interactions and makes them about numbers on a large scale. In some ways, this makes decision-making easier. Humanitarian decisions are difficult, and technology can create a certainty, alleviating some of the burden.

Tsui outlined that we need to develop a framework for asking questions about the usefulness of technological interventions. First, we need to question if these types of interventions are necessary. We must be careful to consider the proportionality: what is the actual specific need we are seeking to address, not just the need to be prepared for the specific need. There is a real danger of having an overpowered response when less can often work better, which relates to how good the data we can gather even is. For example, manual labour distorts fingerprints, so biometrics are not as effective for people who have worked with their hands. Second, we must question if these interventions are plausible. Tsui explained that often we separate the “can we?” from the "should we?” In predictive analytics, however, the ethical implications are fundamentally entwined with action. It is not just an abstract possibility that data will be used wrong. This also raises the question of certainty: Do we know what we are doing? And can we know what we are doing?

We know data is more arming than disarming, as it is used against people all the time (e.g., predictive policing). Once collected, it is hard to say no to people who want to act on it. It is also particularly hard to imagine how data will be misused in the future. Across her framework of questions, Tsui argued that, even if we do not know the answers, asking the question is the most important step to re-orienting the power dynamics of technology optimism.

Participants discussed the challenge that, once the private sector is involved in the collection of data, the ethical implications become even harder to disentangle. While some were skeptical of the influence of the private sector, Susanna Acland from GSMA spoke about the positive potential for enhancing private sector partnerships for digital humanitarian action in her presentation. She explained that private sector data are crucial to population mapping. Specifically focusing on mobile network operators (MNOs), Acland outlined that MNOs can benefit humanitarian action through their technical expertise/services, brand recognition, physical infrastructure (e.g. last mile services), agent networks (i.e. who you buy credit from), financial agility, data and a consumer insight, and regulatory understanding. Acland highlighted the potential of call data records (CDRs) for preparedness. CDRs are automatically generated by an MNO for billing purposes. Every time you make a text or a call, a CDR is generated. Through CDRs, you can identify the cell tower you used last, which means you can track the movement of SIM cards over time. Notably, Acland stressed that this is a very sensitive piece of data that is challenging to use appropriately. Ensuring the data are anonymous is crucial and that access to the data is very difficult to achieve. Acland did, however, outline what she saw as successful pilots GSMA had worked on that used CDRs, such as Flowminder's partnerships with Vodafone in Ghana and Digicel in Haiti. These partnerships have been used to respond to COVID-19, for example. It is crucial to account for transparency, local context, and the local regulation environment.

CONCLUSION

As anticipation is a UN priority, calls to use AI/ML in interventions and for advancing the SDGs will only increase. The potential of data-driven, forecast based, and risk-informed humanitarian interventions is significant, yet not entirely understood. Not only can it enhance cost-effective and timely interventions, it may also enable reach into areas that are particularly challenging. Anticipatory action for climate hazards has displayed some beneficial outcomes, along with significant limits. Namely, what triggers and thresholds are included in the models, what actions are taken after a threshold is reached, and who can take decisions (and with what level of flexibility) after a threshold is reached and anticipatory actions are triggered. There are also numerous obstacles in responding to technological and data gaps, which require the prioritization of local knowledge and methods like citizen science/crowdsourcing.

The workshop highlighted that expanding anticipatory action from climate-related hazards to situations of violent conflict demands a more nuanced consideration of how data are collected and used. Where responses to hazards in conflict-affected areas are comparatively neutral, conflict forecasting is decidedly politically sensitive. Participants called for reflection on what we are trying to predict and why. AI/ML for conflict prevention can also replicate power structures in humanitarian aid, specifically pertaining to the global North-South divide. Moreover, there are examples of AI/ML technology failing to capture the experiences of women* and racial and ethnic marginalized groups.

In addition to amplifying inequalities, AI/ML technology can also be used as a tool for proliferating violence if data protection and security are not guiding principles of use. There are also pressing concerns about consent to data collection in humanitarian settings, particularly in biometrics.

There remain many questions surrounding the plausibility of using anticipatory action for conflict prevention in ethical ways and, if so, how to do so. The growing interest in AI/ML technology makes answering these questions an urgent priority. Addressing these challenges and critiques requires engagement with local actors and large-scale collaborative efforts at the planning, deployment, implication, and future application stages of AI/ML development.

APPENDIX

The following participants took place in the workshop on anticipatory action for conflict prevention in Oxford on June 13th 2022. The participants are listed in alphabetical order.

SUSANNA ACLAND	GSMA, U.K.
MICHAEL COLLYER	Oxford Internet Institute & PCMLP, Centre for Socio-Legal Studies, University of Oxford, U.K.
LARISSA FAST	Humanitarian and Conflict Response Institute, Manchester University U.K.
GIANLUCA IAZZOLINO	PCMLP, Centre for Socio-Legal Studies, University of Oxford, U.K.
ALEXANDER KJÆRUM	Danish Refugee Council, Denmark
SOFIA KYRIAZI	UN Refugee Agency, Switzerland
CAITLYN MCGEER	PCMLP, Centre for Socio-Legal Studies, University of Oxford, U.K.
ANULEKHA NANDI	Department of Management, London School of Economics, U.K.
NICOLE STREMLAU	Univ. of Johannesburg & PCMLP, Centre for Socio-Legal Studies, University of Oxford, U.K.
LINDA SPEIGHT	School of Geography and Environment, University of Oxford, U.K.
DIANA SULEIMANOVA	Brunel University, U.K.
QUITO TSUI	The Engine Room, U.K.
MARC VAN DEN HOMBERG	510, an initiative of the Netherlands Red Cross
PAOLA VESCO	Uppsala University, Sweden
MARIE WAGNER	Global Public Policy Institute, Germany

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