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Artificial Intelligence for Conflict Early Warning: A Comparative Analysis of AI-Enabled Forecasting Systems and Implications for Peacebuilding Policy

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ABSTRACT

Artificial Intelligence (AI) is transforming how governments, international organizations, and peacebuilding actors anticipate violent conflict. Conflict early-warning systems now integrate machine learning, natural-language processing, and geospatial analysis to forecast political violence with increasing sophistication. Yet the proliferation of such systems raises a policy-relevant question that has received insufficient systematic attention: how do existing AI-enabled early-warning systems actually compare in scope, method, transparency, and demonstrated accuracy, and what do these differences imply for how policymakers should use their outputs? This article addresses that gap through a systematic comparative analysis of five prominent AI-enabled conflict early-warning systems - the Violence & Impacts Early-Warning System (ViEWS), the Global Conflict Risk Index (GCRI), the Early Warning Project (EWP), PREVIEW, and Conflict Forecast - evaluated across geographic scope, forecasting method, update frequency, transparency, and reported predictive performance. Drawing on this comparison and on the broader literature on conflict forecasting and preventive peacebuilding, the article develops a Human-Centred AI Peacebuilding Framework that positions AI as a decision-support mechanism rather than an autonomous predictor of, or solution to, violent conflict. The analysis finds substantial variation across systems in transparency and accessibility, meaningful overlap in the countries they flag as high-risk, and a persistent gap between predictive sophistication and institutional capacity to act on warnings. The article concludes with policy recommendations for governments and peacebuilding institutions - including those in South Asia, a region that recurs among the highest-risk countries in several of the reviewed systems - on the responsible integration of AI-enabled early warning into conflict-prevention practice.

Keywords: *Artificial Intelligence; Peacebuilding; Conflict Prevention; Early Warning Systems; Conflict Forecasting; ViEWS; Comparative Policy Analysis; South Asia*

INTRODUCTION

International peace and human security is still beset with one of the greatest challenges: violent conflict. Traditional approaches to conflict prevention have been through diplomacy, monitoring missions and institutional early-warning processes bolstered by experienced area experts. In the last ten years, the availability of massive amounts of machine learning, AI-enabled early-warning systems, and machine-readable conflict-event databases has led to the development of parallel infrastructure of AI-driven quantitative, data-driven forecasts of political violence, which are often produced monthly and for the entire world.

This has been fueled largely by academic and multilateral institutions and not by any single dominant platform. The Violence & Impacts Early-Warning System (ViEWS) at Uppsala University and Peace Research Institute Oslo (PRIO) makes ensemble-based forecasts of organized violence every month for all countries worldwide and at higher resolution for Africa and the Middle East. The European Commission's Global Conflict Risk Index (GCRI) assists the European Union's conflict prevention system. The Early Warning Project of the United States Holocaust Memorial Museum and Dartmouth College ranks countries every year by their statistical risk of mass killing. The German Federal Foreign Office is running PREVIEW with quantitative modelling and regional qualitative expertise. In addition to competing and complimentary forecasts from academic groups, a Cambridge-based effort that is creating the Conflict Forecast model, contributes more forecasts.

Living alongside these two systems creates a question of direct policy importance: can these tools be interchanged or do their differences in scope, method, and transparency have ramifications for the policy use of these tools, and for how carefully? To date, scholarship has focused on the technical effectiveness of one system, or the general ethical dimensions of the prevention of conflict through AI, rather than a systematic comparison of the major operational systems and their differences and implications for institutional users, including governments in conflict affected and conflict adjacent regions, such as South Asia.

This article will fill that void. It compares and contrasts five key AI-powered conflict early-warning systems, detailing their geographical coverage, forecasting targets, timelines and methods, frequency of updates, transparency, and accuracy. It contextualizes these empirical facts in a wider conceptual argument that builds on the peacebuilding and forecasting literature that states that predictive capacity does not necessarily lead to preventative action. The key point in the article is the requirement of institutions for there to be a capacity to build transparency, verification and response capabilities that can turn any of these systems' warnings into a legitimate and timely preventive response.

Research Questions

- To what extent do current AI tools for conflict early-warning systems vary in geographic scope, prediction methodology, transparency, and in terms of their predictions' accuracy?
- What are the trajectories of convergence and divergence of the outputs and design decisions of these systems when compared systematically?
- What are some of the political, ethical and institutional risks to the use of these systems in conflict prevention and peacebuilding?
- Under which conditions can early warnings produced by these AI systems help to take meaningful preventive action, and what are the implications for policies, including in South Asia?

LITERATURE REVIEW

Conflict Early Warning and Conflict Forecasting

The goal of the early-warning systems for conflict is to identify signals that signal an increased risk of violent conflict. Traditional systems were based on political, economic, demographic and security markers that used to be determined, in major part, by qualitative area expertise, like the International Crisis Group. Alongside structured data on conflict events, quantitative methods also came and became more sophisticated in the last decade, with the advent of machine-learning techniques.

ViEWS is the most comprehensively documented development in this area. It was introduced by Hegre and colleagues to be maximally transparent, publicly available, and to be updated frequently to give uniform coverage worldwide, as contrasted with some other competitive systems. The system has since been adapted numerous times and now is backed by an open, versioned machine-learning pipeline, referred to as the "views-platform," and routinely tested in public prediction competitions in which outside researchers are given the opportunity to compare systems using different machine-learning methods with the ViEWS ensemble.

Despite substantial overlap in the highest-risk countries identified, there was significant variation between systems across all three dimensions - transparency and accessibility, key design parameters, and outputs of the forecasts - and a persistent lack of transparency and accessibility of underlying data and code for several systems in operation. While this article is the first to employ the comparative approach, the closest precedent is the above-mentioned review, which did not go into any policy recommendations for specific regions or institutional contexts, however.

AI and Preventive Peacebuilding

The biggest impact AI can have on peacebuilding could be its ability to change the approach from a reactive to a more proactive conflict management strategy. AI-powered systems, in theory, can help peacebuilding actors detect rising threat earlier, by analyzing and integrating information from all sources of conflict events, social-media discourse, economic and financial trends and patterns of displacement, satellite photography, and demographics. The Secretary-General of the United Nations has noted that in the future this potential will be used to detect patterns of unrest ahead of time, but has warned that effective human oversight and governance mechanisms could be undermined by a lack of such governance.

AI and Mediation

AI's impact on peacebuilding goes beyond prediction to assisting mediation and dialogue - summarising negotiation histories, mapping stakeholder positions, and processing large volumes of documents. Recent scholarship has conceived of this as a hybrid intelligence, where the human mediator still decides, but AI can decrease the informational load on the mediator.

Research Gap

While there has been an increasing body of scholarship on the topic of AI and conflict, three gaps remain applicable to this study. Second, much of the existing comparative literature, most recently that of Rod, Gasste and Hegre's review, is now outdated given the rate of change in this field and not focused on the extraction of policy implications for specific institutional or regional groups. Second, much of the wider literature assumes a linkage between prediction and prevention that has not been fully theorized, between the prediction and the decision to take preventive action—and no institutional process is specified to stand between them. Third, the countries that are most often identified as high-risk by these systems, and that consistently appear in publicly available indices, such as Afghanistan, Pakistan, Yemen, Myanmar, Ethiopia, and South Sudan are not the ones that are typically the intended recipients of such literature; these systems are overwhelmingly designed, governed, and interpreted by institutions in North America and Europe. The article aims to fill these gaps by updating and expanding the comparative analysis of early-warning systems powered by artificial intelligence and explicitly connects the findings with policy implications for regions like South Asia, where there is a high risk of significant data needs.

METHODOLOGY

The study presents a qualitative and comparative approach using a systematic comparative analysis of operational early-warning systems and an integrative review of the policy and academic literature. It does not rely on original survey, interview, or experimental data nor does it reproduce or rerun any system's forecasting model; instead, it systematically compiles and compares documented characteristics and reported performance of the major systems in operation, and this systematic task is similar to that employed in previous comparative reviews of this type.

System Selection

Five of these systems were chosen because they are in operation; they are not discontinued or purely experimental models so that their status is not unclear; and enough information is available in the public domain to allow comparison of the methodology, coverage and performance of the systems. The systems chosen for this study are: ViEWS, the Global Conflict Risk Index (GCRI), the Early Warning Project (EWP), PREVIEW, and Conflict Forecast. This selection builds on and updates the list of systems identified as being central to this field by Rod, Gasste and Hegre in the comparative review, and excludes purely commercial or access restricted systems (like the proprietary index of the PRS Group) which lack adequate public documentation.

Comparative Dimensions

The seven dimensions assessed for each system were adapted from the transparency-accessibility-forecasts framework used in previous comparative studies: (1) the institution in charge of the system; (2) the geographic scope and resolution of the system; (3) the target and time horizon of the forecasts; (4) the method underlying the system; (5) the frequency of updates; (6) transparency and public accessibility of data, code, and forecasts; and (7) the predictive accuracy of the system as reported by the institution and/or independently assessed. For each dimension, the data were drawn from the methodological documentation of the systems, from peer-reviewed articles describing each system and from independent comparative or evaluative studies, if available.

Analytical Strategy

The analysis is divided into three steps. First, the study provides documentation of each system on the seven comparative dimensions (Section 5). Second, it compares the systems to each other and looks for convergence and divergence on both the trade-off between transparency and operational restriction (Section 6), and the trade-off between geographic granularity and forecast horizon (Section 6). Third, it incorporates these empirical insights into the conceptual Human-Centred AI Peacebuilding Framework, and draws policy recommendations (Sections 7-9).

COMPARATIVE ANALYSIS OF AI-ENABLED EARLY-WARNING SYSTEMS

Table 1 summarises the five systems across institution, geographic scope, forecasting target and horizon, method, update frequency, transparency, and reported accuracy.

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System	Institution	Geographic Scope	Forecast Target & Horizon	Method	Update Frequency	Transparency / Open Data	Reported Accuracy
ViEWS (Violence & Impacts Early-Warning System)	Uppsala University / PRIO	Global (country-level); 55x55 km subnational grid for Africa & Middle East	State-based, non-state and one-sided violence; monthly forecasts 1-36 months ahead	Ensemble of statistical and machine-learning models (logistic regression, random forests, Bayesian model averaging, neural nets)	Monthly	Fully open data, code and methodology; public dashboard	~95% of country-months in conflict correctly classified, ~35% false-positive rate (self-reported)
Global Conflict Risk Index (GCRI)	European Commission Joint Research Centre (EU)	Global, with a Dynamic Conflict Risk Model (DCRM) for sub-national tracking	Civil war onset/intensity (1-4 years); DCRM sub-national risk (1-6 months)	Regression model; DCRM adds an LSTM recurrent neural network on event data (GDELT/ICEWS)	Periodic (DCRM more frequent, sub-annual)	Open-source input data; model internals partly restricted (feeds EU policy process)	Reported to outperform six other published systems on 10 of 12 evaluation metrics
Early Warning Project (EWP)	US Holocaust Memorial Museum / Dartmouth College	Global (~160 countries)	Onset of state- or non-state-led intrastate mass killing, 2-year horizon	Logistic regression with elastic-net regularization on ~30 risk factors	Annual	Fully open, publicly documented methodology and data	About two-thirds of countries that later experienced a mass-killing onset ranked in the top 30 the prior year

PREVIEW	German Federal Foreign Office	Near-global, with regional prioritisation (e.g. Sahel)	Political violence, blending quantitative modelling with qualitative regional assessment	Quantitative model plus expert/qualitative regional input	Regular, policy-cycle driven	Limited public access; built for internal government use	Not independently verifiable in open literature
Conflict Forecast (CF, incl. Mueller-Rauh Dynamic Early Warning and Action Model)	University of Cambridge / academic consortium	Global, country-level	Probability of conflict onset/continuation, near-term horizon	Machine-learning classifiers on newspaper text and structural indicators	Monthly/near-real-time	Downloadable forecast data; partial code availability	Competitive performance in independent comparative reviews

Table 1. Comparative summary of five AI-enabled conflict early-warning systems.

ViEWS

ViEWS is the most documented and, in terms of transparency, the most transparent system of the systems reviewed. It produces forecasts of state-based, non-state and one-sided violence each month on a country level and at approximately 55x55 km sub-national resolution in Africa and the Middle East with a lead time of up to 36 months. Its own reporting suggests that it accurately classifies about 95 percent of pre-existing country-months in conflict, and a false-positive rate of about 35 percent, which corroborates the broader result from the forecasting literature that predicting conflict onset is much more difficult than predicting conflict continuation. The methodology, code and historical forecasts are fully open, and the system has become something of a benchmark with many independent research groups now reporting their own model's performance against the ViEWS ensemble, that has provided an unusually rich source of independent validation.

Global Conflict Risk Index (GCRI)

GCRI is developed by the European Commission's Joint Research Centre, and directly contributes to the European Union's conflict-prevention policy process. Its main regression model predicts both the likelihood and magnitude of civil war over a period of 1–4 years; a newer model called Dynamic Conflict Risk Model (DCRM), which employs a recurrent neural network (LSTM) developed from the event-coded data (GDELT, ICEWS) provides sub-national risk scores for 1–6 months. It is noteworthy, however, that not only is the GCRI's method of regression relatively simple, but also, according to the GCRI's own validation studies, its forecasts were superior to those of six other published, quantitative early-warning systems on 10 of 12 evaluation parameters. Notably, the GCRI's regression method is not the most complex and sophisticated method available, and it was also found to outperform six other published quantitative early-warning systems on 10 of 12 evaluation parameters according to the GCRI's own validation studies. It is not as open as ViEWS, as GCRI is only a partial input to an internal EU policy process.

Early Warning Project (EWP)

Although the Early Warning Project is a collaboration between the US Holocaust Memorial Museum's Simon-Skjodt Center and Dartmouth College, it is more limited in analytical scope than the other systems: ViEWS or GCRI. Early Warning Project predicts only the onset of intrastate mass killing (the deliberate killing of 1,000 or more civilians) but not organized political violence of the other two categories. It has a statistical model which is trained once a year, not month to month, on about 30 risk factors over some 160 countries, and predicts risk over a two-year period. Historically, around two-thirds of the countries that saw a new mass killing onset were among the project's top 30 highest-risk countries the year prior, the project reports - a performance the project itself admits is "a beginning rather than a conclusion to the study. As in previous assessment cycles, Afghanistan, Pakistan and Yemen have been among the countries with the highest risk levels in the world in its latest assessments.

Preview

In structure, PREVIEW is also different from the other systems reviewed here in that it makes a point of including both quantitative modelling and qualitative regional assessments prepared by the country and regional assessments experts of the Foreign Office, but also in that it highlights certain regions, e.g. the "Sahel", based on German foreign-policy interests instead of a uniform global coverage. It is mainly used for internal government use, so there is much less methodological detail (not at all independent downloadable forecast data) available to the public, thereby restricting the extent to which its accuracy can be tested externally.

Conflict Forecast

Conflict Forecast and related academic research, such as the Dynamic Early Warning and Action Model at Cambridge, utilize machine-learning classifiers on newspaper articles along with structural factors to produce near-term, near real-time probability forecasts regarding conflict initiation or escalation at the country level. These systems are not as transparent as the Early Warning Project or ViEWS, but they provide downloadable forecast data and partial access to their code, and have been competitive in independent comparative evaluations, although with a shorter history of external verification than the other systems.

CROSS-SYSTEM PATTERNS

Table 2 scores the five systems on six dimensions most relevant to a prospective institutional user deciding how much weight to place on a given system's output.

Dimension	ViEWS	GCRI	EWP	PREVIEW	Conflict Forecast
Transparency (data + code)	High	Moderate	High	Low	Moderate-High
Geographic granularity	Sub-national (Africa/ME)	National + sub-national (DCRM)	National only	National + regional priority zones	National

Dimension	ViEWS	GCRI	EWP	PREVIEW	Conflict Forecast
	+ global country level				
Forecast horizon	1-36 months	1-6 months (DCRM) to 1-4 years	24 months	Varies (policy cycle)	Near-term (weeks-months)
Update frequency	Monthly	Sub-annual / periodic	Annual	Regular, non-public schedule	Monthly/near real-time
Public accessibility of forecasts	Full (dashboard + downloads)	Partial	Full	Restricted (government use)	Partial (downloadable subsets)
Independent validation in literature	Extensive (competitions, benchmark studies)	Moderate	Documented self-validation	Limited (not independently reviewed)	Emerging

Table 2. Relative comparison of AI-enabled early-warning systems on transparency, granularity, and validation.

A Transparency-Access Trade-off

The comparison shows a steady trend: the first group of systems that were designed mostly to be open research platforms (ViEWS, the Early Warning Project) are rated as being more externally verifiable and transparent, while the last group of systems designed mostly to be internal government policy processes (GCRI, PREVIEW) are rated as less externally verifiable and transparent, with GCRI in particular claiming good comparative accuracy. This does not mean that this is a problem with any one system, it is a tension between the institutional function and openness to external examination of a system. That's a challenge for a policymaker: the system that is easiest to audit is not necessarily the one that's designed to inform the decisions of that policymaker's government.

Convergence on High-Risk Countries

Although the methodologies, the variables measured, and the institutional sources vary, the systems reviewed here, and other ones that are the subject of a comparison of ten systems by Rod, Gasste and Hegre, have a significant degree of overlap in terms of the countries they identify as being at high risk. The top five countries on the most recent published rankings of the systems are Afghanistan, Pakistan, Yemen, Myanmar, Ethiopia, and South Sudan. This convergence is analytically noteworthy in two ways. On the other hand, it gives credence to the risk signal itself, as independently developed models using different datasets are pointing to the same set of countries. However, the systems are also to some extent learning from each other's historical conflict data and the same structural indicators (governance, demographic and economic variables) and this should not necessarily be interpreted as full independence.

Granularity Versus Horizon

Another pattern is a compromise between granularity and horizon. Systems with the highest sub-national levels of resolution (ViEWS's grid-cell forecasts, the GCRI's DCRM) typically have a shorter (or less consistent) forecast horizon at that resolution, while those systems that have a multi-year forecast (GCRI's civil-war model at the national level, the Early Warning Project) are generally national level systems. This lack of both fine sub-national resolution and long-term time horizons means that neither system can be used to inform both short-horizon operational planning and longer-horizon strategic prioritisation. This means that directly, neither system can be used to inform both short-horizon operational planning and longer-horizon strategic prioritisation.

The South Asia Signal

As, the recurrence of Pakistan and Afghanistan among the highest risk countries in the independent assessments of the Early Warning Project, in the GCRI linked assessments, and also in the country level forecast by ViEWS is a signal which needs to be given direct attention as a policy audience is located between the borders of Pakistan and Afghanistan, and not a modelling artefact of any particular system. Given that these rankings are based on variables that are structural and historical in nature and change over time only gradually, a continually high ranking should be interpreted as an indication of underlying structural risk factors that need ongoing focus, rather than as a prediction of imminent, specific events.

RISKS AND CHALLENGES

Algorithmic Bias and Data Inequality

AI systems can learn from data, and if the data used is politically, geographically, or socioeconomically skewed, then so can the predictions of the AI. This risk is exacerbated by an institutional imbalance apparent in the comparison above: all of the systems reviewed here are created, financed and managed from Europe or North America, whereas those most often cited as high-risk are located primarily in the Global South, in South Asia. This does not negate the forecasts, but it does mean that the interpretations and governance structures around these tools have not been continually developed with state and community involvement in the assessment of their risk.

False Positives and False Negatives

There is no system in the comparison that is entirely free of forecasting errors, and ViEWS' reported false-positive rate of about 35 percent is an example of the proportion of its predictions of conflict that are never realised. The costs and consequences of false positives (unnecessary securitization, stigmatization) and false negatives (false sense of security, delayed preventive action) are real and should not be underestimated. Policymakers should not consider the information they receive from a single system as a certain indicator of future events.

Surveillance and Privacy

Many of the data sources that are input to these systems, including those using event-coded data from news and social media, come with privacy and surveillance issues in some political settings. In theory, information gathered or repurposed for prediction may be used for other purposes, such as political surveillance, keeping an eye on activists, or targeting of opposition parties, especially in fragile or authoritarian contexts. It is therefore essential that there be explicit privacy and human-rights protections for these systems if they are to be used for peacebuilding purposes.

Technological Determinism and the Marginalisation of Local Knowledge

Peace is not an "information problem". Political exclusion, inequality, historical grievance, and lack of robust institutions are the roots of the conflict that a forecasting model can characterize, but not solve. There may be community dynamics that are not captured in any of the data sets examined here. AI generated warnings should never replace local knowledge; rather, the output of AI, local knowledge, and expert judgment should all inform the action taken to prevent the event.

THE HUMAN-CENTRED AI PEACEBUILDING FRAMEWORK

On the basis of the comparative results presented above, this article suggests a five-stage set of pathways that connect the use of AI for forecasting with peacebuilding outcomes.

Stage 1: Data

Data from the conflict events, structural and economic indicators, satellite images and (in some systems) text-based media data are all used in the forecasting process, all of which may not be used in every system, as detailed in Section 5.

Stage 2: AI Analysis

There are a variety of statistical and machine-learning models ranging from ViEWS's ensembles, to GCRI's LSTM-based DCRM, to the Early Warning Project's regularized logistic regression, and each have strengths and documented limitations across granularity, horizon, and interpretability.

Stage 3: Human Verification

The fact that these AI tools all seem to be generating similar warnings, but with variations in transparency and false positive rates as discussed in Sections 5 and 6, makes it crucial that the tools be reviewed by conflict experts, local actors, and peacebuilding practitioners before the warnings are used to inform decisions – even more so as the convergence and divergence among the tools becomes apparent.

Stage 4: Preventive Action

The relevant institutions are left to decide upon an appropriate reaction in response to the prediction of the system, ranging from mediation, dialogue and diplomatic engagement to humanitarian preparation or targeted preventive diplomacy (see Section 6.3), depending on the system's forecast horizon.

Stage 5: Peacebuilding Outcome

The goal is less violence, more robust institutions, social cohesion and peace that is sustainable, assessed not just by the accuracy of a system's prediction, but by its role in stimulating appropriate, legitimate preventive measures.

This framework rests on a principle central to the article's argument: AI should inform peacebuilding decisions, not make them. The comparative evidence in Sections 5 and 6 - variation in transparency, a persistent false-positive rate even in the best-validated system, and a documented institutional gap between prediction and response - reinforces rather than undermines this conclusion.

DISCUSSION: FROM PREDICTION TO PREVENTION

The key theme of this article is that prediction is not prevention. An AI system could accurately determine that the chances of political violence have risen in a specific country, as some of the systems compared here seem to do, albeit with less than perfect accuracy, but such information does not automatically lead to a suitable political response. Even if the prediction is statistically reliable, if governments do not pay attention to the warning, if the international organisations have not got the resources, and if there is no political will on the part of institutions, it cannot have a preventive impact.

This can be referred to as an Early-Warning Paradox because the more capable the AI systems are at detecting conflict risks, the more critical the human and institutional capacity is in determining what to do about them. The above comparisons empirically highlight this point. The Early Warning Project explicitly states that their results are a means to a discussion rather than a conclusion; the false positive rate in systems like ViEWS is already large, even under the best configuration; and the fact that it is possible to improve the performance of the relatively simple model used by GCRI in comparison to the more complex models suggests that improvements in raw accuracy of prediction may be limited when compared to improvements that can be gained by how well the institutions translate existing forecasts into action.

It's more helpful to think about the effectiveness of peacebuilding in this terms: Peacebuilding Effectiveness = Predictive Capacity x Institutional Responsiveness x Human Judgment x Local Legitimacy. The overall effectiveness of AI-driven early warning is significantly reduced if any of the five systems analysed in this article approaches zero.

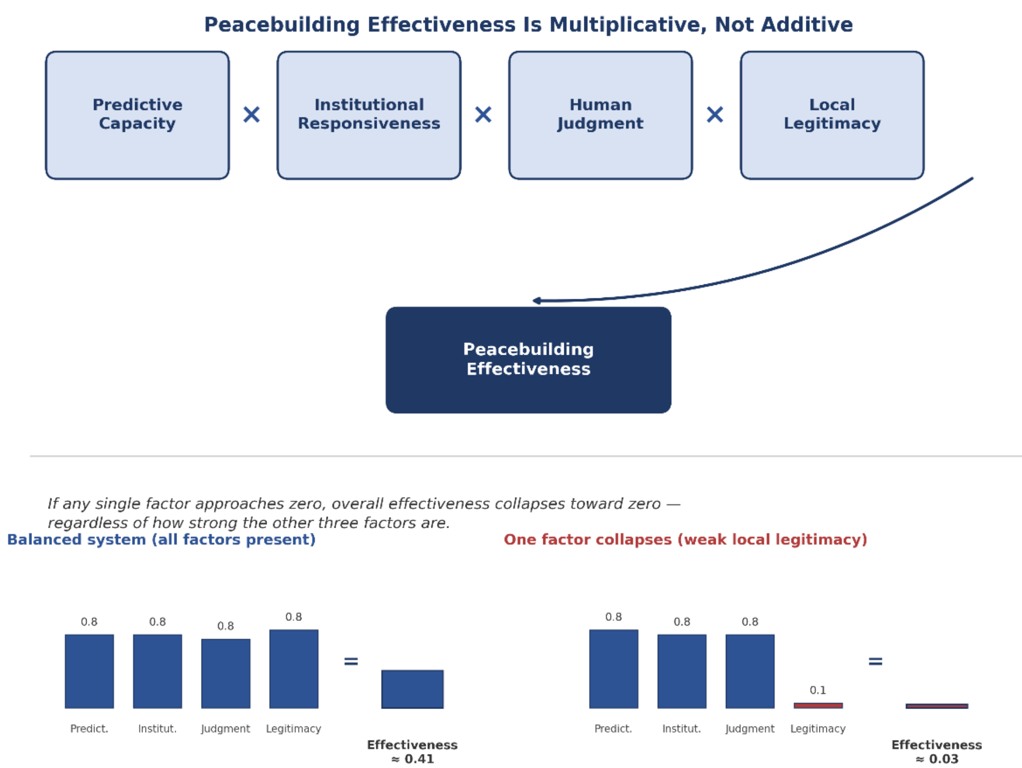

Figure 1: Pictorial representation (All values shown are illustrative and not derived from comparative systems analyzed above)

POLICY RECOMMENDATIONS

The following recommendations are aimed at governments, regional organisations and peacebuilding institutions and are particularly relevant for policy makers in Pakistan and South Asia, based on the comparative analysis, where Pakistan consistently features in the highest-risk list of these systems.

- Use convergent signals, not single-system rankings to prompt attention. When more than one independently developed system (such as ViEWS, GCRI and the Early Warning Project) converge on an increased risk, as discussed in Section 6.2, this consistency is a more robust foundation than any single system's endorsement for policy action.

- Match the system to the decision. Apply outputs of a short horizon and high granularity (ViEWS, GCRI's DCRM) for operational planning, and longer horizon, national-level outputs (Early Warning Project, GCRI's civil-war model) for strategic prioritisation and allocation of resources, as the granularity-horizon trade-off identified in Section 6.3 has been followed.

- Create a standing institutional arrangement – within a foreign ministry, the national security apparatus, or a separate research institute – to examine early-warning outputs of open systems like ViEWS and the Early Warning Project and to distill them into policy briefings, instead of leaving these open systems open to unchecked government.

- Increase investment in local and regional forecasting capacity, to complement institutions designed and controlled in Europe and North America, so that the assessment of domestic risk is not solely reliant on such systems, as highlighted in Section 7.1 for data-governance asymmetry.

- Ensure that before any artificial intelligence warning tells a security/political response, it must be verified by human experts and integrated with local knowledge, in line with Stage 3 of the framework in Section 8.

- Ensure that transparency is emphasized in any system developed or adopted domestically, favouring open data and methodology, such as how the ViEWS/Early Warning Project works, over closed, unauditable systems, to allow independent checks on the accuracy claims.

- Examine these systems, and any future domestic system, based on downstream outcomes, such as if warnings resulted in timely and legitimate preventive action, instead of only on reported predictive accuracy.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

There are a number of limitations to this article. Second, the comparative analysis is based on information about each system that is available in the public domain, rather than on independent replication of each system's underlying models or information, and, in the cases where access to information is limited (GCRI's operational internals, PREVIEW), the comparative analysis was limited to information available in the public domain. Second, these are systems that are constantly changing: In the case of ViEWS, the comparison of the parameters presented here is a snapshot of a platform revision that was reported as late as the end of 2024. Third, this article does not independently assess the accuracy each system reports on itself, except in the instances where they report on their own accuracy, which are explicitly mentioned in Table 1.

There are three directions in particular that future research should go. First, an empirical assessment of these systems' past predictions, followed by a comparison with the outcomes that actually occurred with regards to subsequent conflict in South Asia would lend weight to or qualify the frequent alert that was mentioned in Section 6.4. Second, interviews with the policymakers in high-risk countries regarding their current use (or lack thereof) of outputs of such systems would provide an evaluation of the institutional-responsiveness aspect of the framework outlined in Section 8. Third, additional comparative studies of newer entrants and platform revisions should examine the transparency-accuracy relationship found in Section “A Transparency-Access Trade-off”.

CONCLUSION

Artificial Intelligence has become a substantial and increasingly institutionalised feature of contemporary conflict early warning. The comparative analysis in this article shows that the five leading operational systems - ViEWS, GCRI, the Early Warning Project, PREVIEW, and Conflict Forecast - differ meaningfully in geographic scope, method, update frequency, transparency, and validated accuracy, even as they converge substantially on which countries they flag as highest-risk, including Pakistan and Afghanistan in recent assessment cycles.

The central contribution of this article is the argument, grounded in that comparison, that the value of AI in peacebuilding depends not simply on which system produces the most accurate forecast, but on whether human institutions can translate any of these systems' outputs into legitimate, timely, context-sensitive, and locally informed preventive action. AI can identify patterns, but humans must interpret them. AI can generate warnings, but institutions must respond. The future of AI-enabled peacebuilding should therefore be built not on replacing human decision-makers with the best-performing algorithm, but on developing human-centred, transparent, and locally grounded institutional processes in which AI - whichever system, or combination of systems, an institution chooses to rely on - strengthens rather than substitutes for human judgment in conflict prevention.

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