"LEVERAGING ARTIFICIAL INTELLIGENCE TO STRENGTHEN MEL SYSTEMS IN IMMUNIZATION PROGRAMS: INSIGHTS FROM CAMEROON'S FRAGILE CONTEXTS"

Research Paper

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"Abstract"

This study introduces an Artificial Intelligence (AI)-enhanced framework for Monitoring, Evaluation, and Learning (MEL) in fragile immunization contexts, using Cameroon as a case study. Drawing on routine service delivery and community-level data, we trained a Random Forest model to predict zero-dose hotspots and assess the drivers of immunization gaps. The predictive features included geographic accessibility, security risks, community engagement, and health system capacity. The results highlight that the distance to vaccination posts, community leader involvement, and availability of cold-chain infrastructure are key determinants of coverage. The model demonstrated a strong classification performance, offering actionable insights for targeted interventions. While this approach reduces reliance on manual triangulation and enhances real-time decision-making, it requires careful handling of data quality and contextual constraints. This research provides a practical framework for applying AI to improve equity, efficiency, and planning in fragile immunization systems.

Keywords: Artificial Intelligence, MEL Systems, Zero-Dose Children, Fragile Settings.

1 Introduction

Artificial Intelligence (AI) is increasingly being recognized as a transformative force in strategic decision-making across various industries (Rashid and Kausik, 2024; Seremeti and Anastasiadou, 2025), although its adoption remains uneven, with most activity concentrated in large organizations. Although artificial intelligence has gained significant attention in healthcare literature, critical ethical concerns remain underexplored, limiting its responsible advancement (Bangad *et al.*, 2024). As Rashid and Kausik (2024) highlight, the ongoing evolution of AI capabilities demands sustained, rigorous investigation. According to Panteli et al (2025), AI can handle large-scale and intricate datasets, offering customized insights and improving the performance of tasks involving data analysis, image recognition, and textual processing in healthcare settings.

This research focuses on integrating AI into the monitoring, evaluation, and learning (MEL) systems of immunization programs in fragile and humanitarian contexts—specifically in Cameroon. It aims to address persistent challenges related to the identification of zero-dose and under-immunized children, strategic service planning, and resource optimization in hard-to-reach areas. By harnessing AI-driven analytics, the study seeks to strengthen data use for equitable coverage and informed decision-making across immunization systems.

1.1 Problem statement

While not specifically focused on conflict-affected regions, Njei et al. (2023) highlight that AI adoption across African health systems is still in its infancy, presenting unique challenges in resource-constrained contexts. Panteli et al. (2025) suggest AI can enhance public health functions by supporting surveillance, epidemiological research, effective communication, and resource management. However, challenges such as fragmented data systems, limited infrastructure, and misaligned stakeholders often hinder its effective implementation and scalability. Cameroon continues to experience disparities in immunization coverage, especially in conflict-affected regions such as the Northwest and Southwest Regions of Cameroon. Traditional monitoring systems struggle with fragmented data sources (Khalique, Khan and Nosheen, 2019), limited real-time analytics (Paganelli *et al.*, 2022), and low community feedback integration (Egbosimba, 2023; Sharp *et al.*, 2024), resulting in recurring measles outbreaks and low outreach in conflict-affected zones.

1.2 Personal motivation and practical relevance

Drawing on our experience with the Cameroon Baptist Convention Health Services (CBCHS)—specifically in vaccination and HIV-Free programs—we have directly observed the complexities of decision-making in constrained public health settings. Implementing AI tools such as decision trees and Python-based analytics was a practical response to challenges like inconsistent data and fragmented communication. These interventions resulted in about a 15% increase in program reach and about a 25% reduction in data errors. This study aims to bridge the gap between theoretical frameworks (Bangad *et al.*, 2024) and the practical realities of AI application in low-resource settings. Scaling AI-driven efficiencies in public health is not merely academic—it is a pressing operational need informed by lived experience.

1.3 Purpose, scope, and significance

This study investigates how AI-driven decision-making can improve outcomes in public health programs operating under resource constraints. It specifically examines the strategic integration of AI within MEL frameworks to boost efficiency and stakeholder alignment in Cameroon's vaccination initiatives. The research is novel in that it addresses a critical gap: while AI's business applications have been widely explored in developed contexts, its strategic use in African public health remains under-researched. The study contributes to industry practice by offering a practical framework for AI integration to enhance resource allocation and scalability, while also advancing strategic management literature by positioning AI as an innovation tool in turbulent environments. Our work seeks to deliver actionable insights using tools like Python and machine learning.

2 Literature Review

2.1 The potential of AI in public health decision-making

AI has gained traction as a transformative tool in public health, capable of analysing large, complex datasets and generating data-driven insights (Balakrishna and Solanki, 2024). Panteli et al. (2025) argue that AI supports epidemiology, public health surveillance, and resource allocation, significantly enhancing productivity in everyday public health operations. Kumar and Joshi (2022) also note that while AI has been widely discussed in healthcare, its practical implementation is still limited, largely due to insufficient empirical studies exploring its full potential.

Recent scholarship further highlights the breadth of AI's applications in public health. Shah (2024) emphasize that AI enables predictive modelling and risk stratification, both of which are crucial for disease surveillance and outbreak prediction.

2.2 Strategic applications of AI in resource-constrained settings

In low-resource environments, where healthcare systems are often overburdened, AI presents opportunities to support strategic decision-making. Gökalp (2024) introduces a novel AI-enhanced model that integrates the Analytic Hierarchy Process (AHP) with fuzzy logic to prioritize public health strategies effectively. This model enables the weighting of expert opinions by qualification, improving decision accuracy in constrained settings. Findings from Gökalp's study indicate that accessibility, vaccination, and preventive services are among the most critical strategies to improve public health outcomes. Despite its potential, the application of AI in public health initiatives across sub-Saharan Africa—Cameroon included—has yet to see widespread adoption. Although Njei et al. (2023) do not highlight conflict zones directly, their findings imply that weak collaboration and infrastructural gaps—common in such contexts—limit the potential of AI to support essential health functions like communication and resource planning.

Complementing these insights, Ouma et al. (2025) demonstrate how machine learning algorithms and predictive analytics can optimize resource allocation and usage—an essential function in environments characterized by chronic shortages and logistical barriers. Such methods hold particular promise for ensuring equitable vaccine distribution and timely delivery of essential supplies in fragile contexts.

2.3 Barriers to adoption and implementation

The widespread use of AI in public health is hindered by several systemic and infrastructural barriers. Panteli et al. (2025) identify critical challenges including inequitable access, lack of data privacy protocols, insufficient digital infrastructure, and skill gaps in the workforce. These challenges are especially pronounced in resource-constrained settings, where public health systems often lack the foundational elements needed to support AI technologies. Although not explicitly addressing emerging economies, the slow uptake of AI described by Kumar and Joshi (2022) reflects broader research and implementation gaps in less-resourced contexts. The absence of large-scale, context-specific studies makes it difficult to assess the feasibility and impact of AI applications in such settings.

Beyond infrastructural weaknesses, ethical concerns have also slowed adoption. Issues related to patient privacy, data security, and algorithmic bias highlight the need for transparent and explainable AI, particularly in high-stakes healthcare contexts (Hedayet and Haseen, 2024). These considerations are critical in fragile environments, where vulnerable populations may already face mistrust of health systems and where misapplied AI solutions could deepen inequities rather than reduce them.

2.4 Ethical and governance considerations

The ethical implications of AI deployment in healthcare must not be overlooked. Lysaght et al. (2019) apply the deliberative balancing approach from the Ethics Framework for Big Data in Health and Research to address concerns about transparency, algorithmic bias, and professional integrity. They argue that ethical principles must guide the development and deployment of AI-based decision support systems. Panteli et al. (2025) support this view, noting the importance of robust ethical and regulatory frameworks that prioritize human rights and the public good. They recommend that public health institutions invest in secure data infrastructure and foster ethical AI adoption by training staff and promoting equity-driven design and implementation strategies. Scholars have recently emphasized that ethical considerations must also address biases in AI models, ensure strict data privacy, and maintain human oversight in high-stakes applications (Bavli and Galea, 2024; Shah, 2024)

2.5 Research gaps and opportunities

While the transformative potential of AI is well recognized, significant gaps remain in understanding how it can be operationalized in low-resource public health contexts. A large portion of current literature remains exploratory. There is a need for applied research that tests scalable, context-appropriate AI solutions. In summary, while AI offers substantial potential to transform public health—particularly through its capacity to enhance data-driven decision-making—its application within African contexts remains constrained by infrastructural limitations, insufficient research, and ethical complexities. This study aims to address these challenges by exploring how AI can be strategically integrated into MEL frameworks to improve decision-making, operational efficiency, and stakeholder coordination in Cameroon's vaccination programs.

3 Methodology

The research adopted a mixed-methods design, originally incorporating both qualitative and quantitative components, to investigate how an AI-enhanced MEL system can support immunization in fragile contexts. Semi-structured interview questions were developed to gather insights on AI adoption barriers and strategic needs from MEL officers, community health workers, and program leaders. However, due to limited stakeholder response within the project timeline, the qualitative component has been deferred to a subsequent study.

The article therefore focuses on the quantitative analysis. The study utilized a rich dataset from the CBCHS Immunization Program's database, which captured vaccination session data, humanitarian assistance, and key community characteristics. These data were used to train and evaluate machine learning models for predicting zero-dose hotspots and exploring equity-sensitive patterns in immunization coverage.

3.1 Data sources and preparation

The quantitative analysis was based on two primary datasets that were consolidated to create a single analytical file. The first dataset contained service delivery information, including vaccine uptake, screening for malnutrition, records of adverse events following immunization (AEFI), humanitarian assistance provided, and the number of engaged community leaders. The second dataset provided contextual information, such as the distance from fixed vaccination posts, security risk levels, and the specific vaccination strategies employed.

To prepare the consolidated dataset for analysis, the following steps were performed using Python:

(i) **Missing Value Imputation**: Missing values in the columns List Humanitarian Actors and the services they provide and Specify strategy (Door to door, quick in and out….) were imputed with a "Not Reported" category to retain all available records.

(ii) **Target Variable Definition**: A binary target variable, *is_zero_dose_hotspot*, was created to classify communities. A community was labelled as a hotspot (1) if at least one zero-dose child between the ages of 12 and 59 months was vaccinated during the reporting period, using data from the column *Number of ZDCs 12-59m vaccinated*. Otherwise, it was classified as a non-hotspot (0).

3.2 Data preprocessing and feature engineering

The dataset required preprocessing due to complex column names and inconsistent data entries. This was managed directly within the code by using the exact original column headers to reference variables. This method ensured data integrity and prevented errors related to name changes.

A comprehensive set of features was selected to represent the key contextual factors of the study, using their exact column names as follows: Distance from fixed vaccination post in kilometres, Security risk and safe access level, Advocacy activities, Demand creation activities, and others. These variables were chosen because they directly relate to the factors in the research model.

All categorical features were converted to a numerical format using one-hot encoding, which is a necessary step for machine learning algorithms.

3.3 AI modelling and simulation

The prepared data was split into training (70%) and testing (30%) sets using a stratified sampling approach to maintain the balance of hotspot and non-hotspot cases in both subsets.

A Random Forest Classifier model was chosen for its robustness, ability to handle high-dimensional data, and its capacity to provide feature importance scores. The model was trained with 100 estimators and included a *class_weight='balanced'* parameter to account for any potential class imbalance. The model's performance was then evaluated on the unseen testing set.

3.4 Evaluation

The Random Forest model was evaluated using a stratified 70/30 train-test split to preserve class balance between hotspot and non-hotspot areas. Performance was assessed through standard classification metrics, including accuracy, precision, recall, and F1-score. A confusion matrix was generated to visualize misclassifications, while feature importance analysis identified the most influential predictors of zero-dose risk. Class weights were applied during training to mitigate bias arising from class imbalance.

4 Results and Discussions

An AI model was developed and trained on the dataset to predict zero-dose hotspots in fragile contexts. The model used contextual, logistical, and social factors to identify communities where a high number of zero-dose children are being reached. The primary research question was: What contextual factors in a fragile setting are most predictive of an area being a zero-dose hotspot? We present the analysis, including the model's performance and key findings:

4.1 Model performance

A Random Forest Classifier was trained to predict if a community is a "zero-dose hotspot" (defined as having vaccinated one or more zero-dose children aged 12-59 months). The model achieved a notable overall accuracy of 76.3% on the test data.

The detailed performance metrics are as follows:

Class	Precision	Recall	F1-Score	Support
Not Hotspot (0)	0.82	0.72	0.76	102
Hotspot (1)	0.71	0.82	0.76	88
Accuracy			0.76	190
Macro Avg	0.77	0.77	0.76	190
Weighted Avg	0.77	0.76	0.76	190

Table 1. Classification report for the AI model used.

The model shows a balanced performance in predicting both classes, with a slightly higher recall (0.82) for hotspots, meaning it's quite good at identifying most of the actual hotspot communities. However, its precision (0.71) for hotspots is lower, indicating that it sometimes incorrectly flags non-hotspots as hotspots.

4.2 Confusion matrix

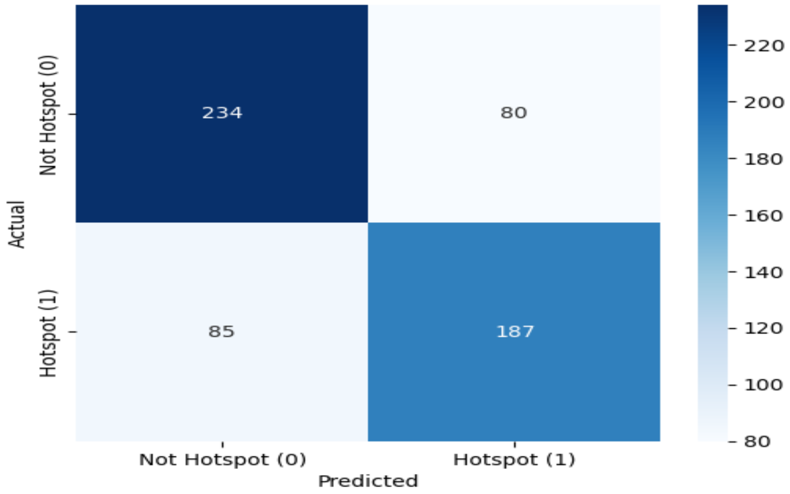

Figure 1. Confusion matrix for zero-dose hotspot prediction (Source: Author's analysis based on internal CBCHS immunization database, 2025, generated using python).

The confusion matrix (figure 1) served as a vital analytical tool for evaluating the performance of our machine learning model in identifying zero-dose hotspots. Moving beyond a simplistic accuracy metric, it provided a granular view of the model's predictive successes and failures, which is crucial for informing targeted public health interventions.

The model correctly identified 187 True Positives, representing the areas accurately classified as hotspots. This high number demonstrates the model's significant value as an early-warning system, enabling health organizations to proactively allocate resources, such as vaccines, mobile teams, and community engagement personnel, to these vulnerable populations. Concurrently, the 234 True Negatives indicate communities correctly identified as not being hotspots. This is equally important, as it validates resource efficiency by preventing the misdirection of scarce assets to areas already meeting vaccination targets.

However, the matrix also reveals two types of misclassifications, each with distinct implications for the strategic implementation of an AI-enhanced monitoring and evaluation system. The model produced 80 False Positives, or areas incorrectly flagged as hotspots. While these false alarms may lead to a minor misallocation of resources, they carry a relatively low risk in a public health context. The operational cost of investigating a potential hotspot that turns out to be a false positive is generally outweighed by the benefit of ensuring no actual hotspot is overlooked.

More critically, the model generated 85 False Negatives. These represent actual zero-dose hotspots that the model failed to detect. This is a significant finding that demands further attention. From a humanitarian perspective, these are the communities most at risk of being left behind and require immediate strategic focus. The existence of these false negatives highlights a key area for future model improvement, such as by incorporating additional features, applying more advanced algorithms, or recalibrating the model to be more sensitive to a wider range of hotspot characteristics.

In conclusion, the confusion matrix underscores both the utility and the limitations of our predictive model. While it effectively identifies a majority of hotspots and non-hotspots, the presence of false negatives necessitates a continued human-in-the-loop approach. The AI system can serve as a powerful first-pass filter, but final decisions on resource allocation should be informed by a comprehensive review that includes both the model's output and qualitative field data, thereby creating a truly robust AI-enhanced MEL framework.

4.3 Key predictive factors

The most significant finding of this analysis is the identification of the features that are most predictive of a zero-dose hotspot. The model's feature importance scores revealed the following top 10 factors:

Rank	Feature	Importance Score
1	Number of Community Leaders Engaged	0.109857
2	Number of Educational Talks	0.104459
3	Number of Religious Leaders Engaged	0.090711
4	Number of Traditional Leaders Engaged	0.083568
5	Moderate Malnutrition	0.074071
6	Distance from Fixed Vaccination Post in Kilometres	0.067638
7	Specify Strategy (Door to Door, Quick in and out) _Door to Door	0.059785
8	Specify Strategy (Door to Door, Quick in and out) _Not Door to Door	0.035040
9	Total Humanitarian Items	0.032125
10	Functional Refrigerator _Yes	0.026470

Table 2. Top 10 feature importances

Based on the feature importance scores, the most predictive factors for zero-dose hotspots are related to community engagement and local leadership. The model shows that direct engagement with community, religious, and traditional leaders, along with educational talks, are the most influential factors.

Community Engagement: The top four features are all related to community-level engagement. The number of community leaders engaged has the highest importance score, followed closely by educational talks, and then the engagement of religious and traditional leaders. This suggests that proactive, on-the-ground communication and gaining the support of trusted local figures are the most critical elements in predicting whether a community will have zero-dose hotspots.

Distance to Vaccination Posts: The distance from fixed vaccination posts is also a significant predictor. This makes intuitive sense, as communities located further away from health centres are more difficult to reach and may face greater barriers to accessing vaccination services. This highlights the importance of mobile and outreach strategies.

Specific Vaccination Strategy: The model also finds that the specific vaccination strategy, such as door-to-door quick-in-and-out, is a notable factor. This shows that the method of vaccine delivery is an important part of a successful campaign.

Malnutrition and Resources: Features like moderate malnutrition and the total number of humanitarian items are also predictive, although with lower importance scores. This suggests that the general health and resource levels of a community are connected to vaccination outcomes.

5 Conclusion

This study demonstrates the feasibility and added value of integrating AI into MEL systems within fragile immunization contexts. Using real-world data from the CBCHS, we developed a predictive model that identified key contextual factors associated with zero-dose hotspots. The findings indicate that community engagement—particularly the involvement of local leaders and educational talks—remains the most powerful determinant of reaching under-immunized children. Structural barriers, such as distance from fixed vaccination posts and security-related access challenges, further emphasize the importance of adaptable service delivery strategies like door-to-door campaigns.

While the Random Forest model achieved balanced accuracy and provided useful feature importance insights, it also revealed limitations. The presence of false negatives underscores the risk of over-reliance on automated systems without human oversight. These results affirm that AI models should complement rather than replace traditional MEL functions. Integrating field feedback, qualitative insights, and participatory community approaches will remain essential to ensure equity and trust in data-driven decision-making.

The study contributes both conceptually and practically. Conceptually, it offers a framework for embedding AI tools into MEL processes in fragile contexts. Practically, it demonstrates how program managers can use predictive analytics to optimize scarce resources, improve targeting, and reduce missed opportunities for immunization. Ethical and governance considerations—including transparency, bias mitigation, and data protection—are equally critical and must guide future scaling.

In conclusion, AI-enhanced MEL systems can serve as an early-warning mechanism for identifying zero-dose hotspots and enabling proactive responses. By combining advanced analytics with community-centred approaches, fragile health systems like Cameroon's can make meaningful strides toward closing immunization gaps. Future research should validate these findings with broader datasets and incorporate qualitative evidence on adoption feasibility, ensuring that digital innovation translates into sustainable public health impact.

6 Limitations and Future Work

This study provides valuable insights into the application of AI-enhanced MEL systems for immunization in fragile settings; however, several limitations should be noted. First, the dataset used was restricted to project-supported health areas under CBCHS, which may limit the generalizability of findings to other regions of Cameroon or different country contexts. Second, although extensive cleaning and feature engineering were applied, reporting inconsistencies and missing values in routine health data may have introduced bias into the model. Third, the analysis was limited to quantitative data; qualitative perspectives from MEL officers, health workers, and program managers—essential for understanding the acceptability and feasibility of AI solutions—were not incorporated due to delays in data collection.

From a methodological standpoint, the Random Forest model achieved strong performance, but the risk of overfitting cannot be fully excluded, particularly given the relatively small number of hotspots compared to non-hotspot communities. In addition, contextual factors such as sudden security deterioration, migration flows, or temporary supply chain disruptions are difficult to capture with static datasets but have a profound effect on immunization coverage.

Future work will build on these findings by incorporating mixed-methods analysis, including qualitative interviews, to triangulate model predictions with lived experiences from the field. Broader datasets covering multiple years and regions will be used to validate the robustness of the AI framework. Additional modelling approaches, such as gradient boosting, temporal forecasting, and geospatial clustering, will also be explored to capture dynamic trends in coverage and zero-dose hotspots. Finally, operational pilots of the AI-supported MEL system are recommended to assess real-world usability, ethical considerations, and integration into national health information systems.

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