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Harnessing Predictive Modeling to Advance HIV Self-Testing in Sub-Saharan Africa: A Viewpoint on Equity-Driven Implementation

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ABSTRACT

Predictive modeling presents a transformative opportunity to enhance HIV self-testing (HIVST) uptake across Sub-Saharan Africa (SSA). While machine learning techniques such as Random Forest (RF) and Classification and Regression Trees (CART) offer powerful tools for identifying high-risk populations and optimizing HIVST distribution, their adoption in public health remains limited. This Viewpoint examines how stigma, economic constraints, and urban-centric data biases hinder the integration of predictive analytics into HIVST and argues for equity-driven implementation strategies. The authors argue that leveraging predictive modeling requires an ethical, community-driven approach that prioritizes fairness, transparency, and real-world applicability. Without inclusive implementation strategies, predictive analytics risks reinforcing disparities rather than reducing them.This article presents a strategic framework for integrating machine learning into HIVST policy and practice while addressing concerns around data bias, public trust, and stakeholder engagement. By bridging the gap between artificial intelligence (AI) and global health equity, predictive modeling can serve as a catalyst for achieving UNAIDS' 2030 goals for broad, equitable HIV testing access.

Keywords: Predictive modeling, HIV self-testing (HIVST), Public health intervention, Sub-Saharan Africa, Machine learning, Equity in healthcare.

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INTRODUCTION

Sub-Saharan Africa (SSA) remains central to the global HIV epidemic, carrying a disproportionate share of cases worldwide [1]. The persistent challenge of ensuring broad and equitable access to HIV testing demands a radical shift from traditional strategies. HIV self-testing (HIVST) offers a powerful tool to decentralize testing, increase uptake, and reduce stigma—especially among populations disproportionately affected by HIV, such as men who have sex with men (MSM), female sex workers (FSWs), adolescents, and those facing economic hardship [2, 3]. Yet, despite its transformative potential, HIVST adoption remains uneven, hindered by systemic barriers that continue to marginalize the most vulnerable. Current public health strategies often fail to proactively address the socio-cultural and economic dynamics that shape HIVST uptake. Stigma remains a formidable deterrent, preventing individuals from testing despite the confidentiality HIVST provides [4]. Economic constraints—exemplified by affordability challenges in Botswana [5], and the urgent need for culturally tailored strategies in Nigeria [6] - further highlight the inadequacy of one-size-fits-all approaches. The time for reactive, broad-spectrum interventions is over. This Viewpoint argues that predictive modeling must be at the core of a new, data-driven HIVST strategy that prioritizes equity, precision, and community trust over generic, blanket approaches. By analyzing socio-cultural and economic patterns, predictive models can identify blind spots in current outreach efforts, mitigate stigma-driven disparities, and optimize resource allocation [7]. However, technology alone is not a silver bullet. Machine learning techniques, particularly Classification and Regression Trees (CART) and Random Forest (RF) offer advanced capabilities for understanding HIVST behaviors [8]. Yet, their success hinges on how they are designed, whom they serve, and whether they reflect real-world inequities. Too often, predictive models are built on urban-centric, health facility-driven datasets that exclude rural and marginalized populations, thereby reinforcing disparities instead of resolving them [9, 10]. If predictive modeling is to revolutionize HIVST implementation, its deployment must be intentional, ethical, and people-centered. We must move beyond theoretical efficiency and focus on practical, equity-driven solutions that ensure every individual—regardless of geography, income, or identity—has access to HIV testing. This article makes the case for integrating machine learning into HIVST policy and practice in a way that not only enhances efficiency but actively dismantles exclusionary barriers.

Ensuring Equity and Accuracy in HIVST Predictive Modeling

While machine learning techniques offer powerful insights for optimizing HIVST, their effectiveness is contingent on the quality and inclusivity of training datasets. Nisa et al. [11] demonstrated that RF-based models could accurately predict high-risk HIV populations, yet Van Der Ploeg et al. [12] cautioned that machine-learning approaches can be data-intensive and may underperform when datasets are limited. Norori et al. [13] further highlighted the risks of bias in training datasets, emphasizing that urban-centric data could lead to the underrepresentation of rural populations, thereby diminishing the effectiveness of predictive modeling in HIVST outreach. To mitigate these challenges, CART and RF stand out as the most viable options for HIVST predictive modeling [14]. These models excel at processing large, heterogeneous datasets while maintaining interpretability and earning stakeholder trust, both of which are critical aspects of public health decision-making [15, 16]. Their ability to capture intricate socio-demographic patterns makes them the optimal choice for ensuring targeted HIVST interventions that are scientifically robust and socially inclusive. While logistic regression is widely used for its simplicity and interpretability, it often fails to capture non-linear and interactive effects, limitations that machine learning models such as Random Forests can address [17]. Similarly, Naïve Bayes, though efficient in high-dimensional spaces, relies on independence assumptions that do not always hold in real-world settings [18]. k-Nearest Neighbors (KNN), while effective in clustered datasets, struggles with large-scale, noisy data, limiting its application in diverse SSA populations [19]. The superior performance of RF in HIV-related studies is well-documented, with models achieving high precision (96.15%), recall (100%), and AU-ROC values (0.989), making RF the most reliable tool for balancing accuracy, precision, and interpretability [20]. These findings reinforce the importance of prioritizing CART and RF, ensuring that predictive modeling for HIVST is not only effective but also aligned with the realities of implementation across SSA. **Leveraging Predictive Modeling to Enhance HIVST Outreach:**Predictive modeling offers a transformative approach to HIVST by enabling targeted, data-driven interventions that improve efficiency and accessibility. Models such as CART and RF excel in revealing intricate data patterns, particularly in diverse and complex environments like SSA [9, 12]. For instance, RF models can pinpoint high-risk subpopulations with low HIVST uptake, ensuring that testing resources are allocated where they are needed most [11]. The potential impact extends beyond static predictions. These models can inform dynamic and adaptive distribution strategies, identifying informal settlements where traditional health interventions are limited. A study demonstrated how RF successfully identified such settlements using high-resolution imagery and spatial indicators with 91% accuracy—a methodology that could be replicated for targeted HIVST outreach [21]. Moreover, predictive modeling fosters real-time adaptability in HIVST distribution. In SSA's resource-limited settings, models can anticipate fluctuations in demand and adjust supply chains proactively [22]. By integrating demographic and behavioral data, predictive analytics can help public health programs establish responsive, demand-driven HIVST distribution networks, reducing logistical inefficiencies and ensuring continuous availability of self-test kits in high-risk areas. While these capabilities present a compelling case for leveraging machine learning in HIVST, equitable implementation remains critical. Predictive analytics must not become another top-down, exclusionary approach—its success depends on contextual alignment with local health systems and community engagement. This calls for a hybrid approach that combines technological innovation with human-centered public health strategies, ensuring that predictive modeling enhances—not replaces—existing HIV response efforts.

Ethical Imperatives for Equitable HIVST Predictive Modeling

Predictive modeling has the potential to redefine HIVST outreach, yet its implementation must be guided by ethical principles that ensure fairness, inclusivity, and social responsibility. One of the primary concerns is data bias, as models such as CART and RF heavily depend on training datasets that may not adequately represent the populations they aim to serve. If these models are predominantly trained on urban-centric data, they risk excluding rural and underserved communities, reinforcing preexisting inequities instead of addressing them [13, 23].To prevent predictive modeling from becoming a barrier rather than a bridge, an equity-driven approach must be integrated into the design, validation, and deployment of these models. This requires:

Inclusive Data Collection – Ensuring representation from rural, marginalized, and low-income populations by integrating data from community health networks, informal healthcare providers, and grassroots organizations. This broader data scope enhances accuracy and fairness in predicting HIVST uptake [24]. Studies show that predictive models trained on heterogeneous datasets perform significantly better at identifying high-risk subpopulations, reducing disparities in HIVST uptake [25, 26].

Participatory Model Development – Engaging local communities in model refinement through focus groups, stakeholder workshops, and user feedback mechanisms ensures that predictive models reflect the lived realities of those they are designed to serve [27]. Research has demonstrated that community participation in AI-driven health interventions leads to higher adoption rates, as it fosters trust, cultural relevance, and usability [28]. In HIV prevention programs, participatory approaches have been linked to greater intervention uptake and sustainability [29].

Transparent and Explainable AI – CART and RF offer interpretability advantages over black-box algorithms, making them ideal for transparent decision-making in public health [30]. When AI-generated insights are communicated clearly to health professionals, policymakers, and community leaders, it enhances trust in HIVST interventions. A study on AI ethics in healthcare found that explainability fosters accountability, reduces resistance to new technologies, and improves implementation success [31].

Ethical Validation Practices – Rigorous testing must be conducted to identify and mitigate biases before model deployment. This includes cross-demographic testing to ensure that no subgroup is systematically excluded from accurate predictions. Ueda et al. emphasize the importance of testing machine learning models across diverse demographic groups to avoid bias and promote equitable performance in real-world healthcare settings [32]. Without such measures, machine learning models risk entrenching the very disparities they seek to address.

Fostering Community Participation in Predictive Modeling for HIVST

Ensuring fairness, inclusivity, and contextual relevance in predictive modeling requires active community engagement throughout the model development process. Predictive tools should not operate in isolation—stakeholder collaboration is essential to build trust, refine model parameters, and ensure practical applicability. Participatory approaches, such as focus group discussions, key informant interviews, and community workshops, are crucial in integrating qualitative insights into data-driven decision-making.For instance, involving end-users—including clinicians, public health officials, and community stakeholders—in model development has been shown to enhance usability and foster trust in predictive analytics [33]. Without these interactions, predictive models risk being perceived as detached, reducing real-world impact and adoption rates. Similarly, structured feedback loops have been instrumental in identifying gaps in training data, addressing biases, and improving overall model accuracy. A study on machine learning applications in healthcare found that continuous user feedback enables the refinement of feature sets, ensuring models remain adaptable to diverse settings [34]. In socio-culturally diverse settings like SSA, community engagement is a necessity, not an option. Predictive models that do not account for localized cultural dynamics risk misrepresenting high-risk populations and reinforcing exclusion rather than mitigating it. User-centered design and stakeholder engagement can help surface equity concerns in predictive modeling, including risks to marginalized populations, and inform how models are communicated and used in care settings [35]. Furthermore, multi-stakeholder engagement is key to ensuring equity in predictive modeling. A position paper on machine learning ethics highlights that inclusive model development not only improves agility and accuracy but also aligns interventions with the real needs of diverse healthcare users [36]. This holistic, participatory framework ensures that predictive modeling transitions from being purely algorithm-driven to community-centered, resulting in better health outcomes, stronger trust, and more sustainable HIVST adoption.

Harnessing Predictive Modeling for Public Health Impact

The successful integration of predictive models in SSA underscores their transformative potential in strengthening HIV prevention and self-testing strategies. In Nigeria, Bayesian predictive modeling has been employed to estimate HIV prevalence and optimize testing approaches [31]. Similarly, in South Africa, machine learning has helped improve treatment retention by identifying dropout predictors in HIV care [37]. In Kenya, predictive modeling combined with SMS-based reminders has enhanced PrEP adherence among youth, a key demographic in HIV prevention [38]. The practical application of CART and RF models in HIV response has been explored beyond SSA. In Pakistan, RF was used to predict future HIV acquisition risks among high-risk populations, analyzing socio-demographic, behavioral, and biological factors. The model achieved 82% accuracy, outperforming traditional classifiers and demonstrating its ability to guide targeted testing, counseling, and treatment interventions [11]. While these models have demonstrated significant value in optimizing HIV responses, challenges such as data quality, equitable inclusion of marginalized populations, and technological constraints necessitate ongoing refinement. Table 1 summarizes the specific applications of predictive modeling techniques in HIVST interventions, showcasing their role in enhancing targeted outreach and optimizing resource allocation across SSA [11, 30, 39].

Table 1. Predictive Modeling Applications for HIVST in Sub-Saharan Africa

Application Area	Predictive Model Used	Description	Public Health Implications
Targeted Kit Distribution	RF	The model identifies regions with low HIVST uptake and high HIV prevalence, guiding where kits should be allocated for maximum impact.	This approach helps efficiently allocate resources to high-need areas [39]
Real-Time Demand Prediction	CART	The model predicts areas with fluctuating HIVST demand to support better stock management and timely replenishment.	It helps reduce stock outs and optimize supply chains [30]
Demographic Risk Profiling	CART and RF	Socio-demographic data are analyzed to categorize individuals by their likelihood of using HIVST, enabling more personalized outreach.	This supports tailored educational interventions and outreach efforts [11].
Outreach Optimization	Mixed Methods Approach	Predictive modeling is combined with qualitative feedback to identify stigma-related barriers and customize outreach strategies.	This integration improves trust, engagement, and the accuracy of public messaging [40]

Legend: CART - Classification and Regression Tree; RF - Random Forest

The insights generated from predictive models shift HIVST strategies from broad, generalized approaches to precise, evidence-based interventions (as illustrated in Table 1). In SSA, where resources are limited, predictive analytics can pinpoint high-burden areas with low HIVST uptake, enabling targeted deployment of mobile health units, local pharmacy distribution, or digital self-testing campaigns.

Early trials in Nigeria and South Africa support this potential, showing that data-driven outreach significantly improves HIVST engagement among underserved populations [31, 37]. Recent findings from Kenya further demonstrate how integrating predictive modeling with SMS-based interventions has led to increased engagement among youth, a critical demographic in HIV prevention [38]. These successes highlight the need for continued investment in AI-driven public health solutions, ensuring that predictive modeling is ethically implemented, community-driven, and inclusive of marginalized populations.

Moving forward, public health leaders must:

- Establish ethical AI guidelines that prioritize equity and inclusivity.
- Develop collaborative frameworks between data scientists, public health experts, and

community representatives to refine predictive models.
- Invest in public awareness initiatives to ensure that AI-driven HIVST interventions are understood and trusted by the populations they aim to serve.

Evaluation Metrics for Predictive Modeling

While predictive modeling enhances HIVST outreach, rigorous evaluation is essential to ensure models are reliable, actionable, and equitable. RF and CART models must be assessed using standard performance metrics that validate their ability to accurately identify high-risk populations and optimize intervention strategies. Key evaluation criteria include accuracy (correct classifications), AU-ROC (risk group distinction), precision (true positive identification), recall (sensitivity to high-risk cases), and F1-score (balance between precision and recall) [9, 12, 13].Among these, the F1-score is particularly crucial, as it balances false positives and false negatives, ensuring that predictive models neither overlook high-risk individuals nor misallocate resources. In HIVST outreach, an RF model achieving an AU-ROC above 0.95 and a high F1-score signals strong predictive capability, effectively guiding targeted testing and resource allocation [9].

Beyond numerical validation, transparency and interpretability are non-negotiable. CART models, known for their decision-tree structure, must be assessed for their ability to clearly justify predictions and inform real-world interventions. Reporting these metrics strengthens confidence in predictive models, promotes their continuous refinement, and safeguards ethical AI adoption in public health. Future research must prioritize evaluation metrics not only to enhance scientific rigor but also to ensure predictive modeling translates into measurable health impact. Without this accountability, machine learning in HIVST risks becoming a theoretical exercise rather than a transformative tool for equitable healthcare. **Transforming Predictive Modeling into Actionable Strategies:** Figure 1 illustrates how predictive modeling is integrated into the implementation of HIVST programs across SSA. The diagram highlights key stages, including data collection, predictive modeling processes, and actionable insights for program design. This visualization complements the narrative by providing a clear framework for understanding the workflow and its impact on targeted HIVST distribution and outreach optimization.

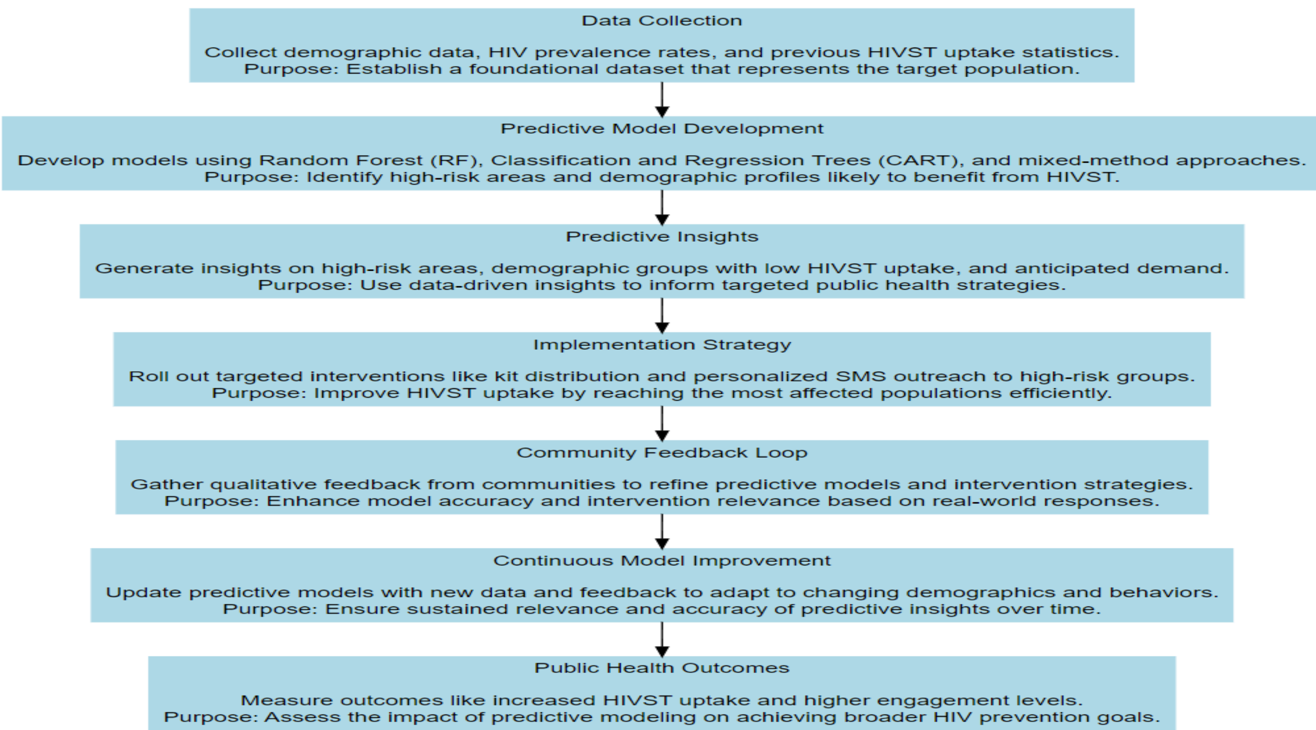

Figure 1: Integrating Predictive Modeling with HIVST Implementation in Sub-Saharan Africa

Bridging the Gap between Predictive Analytics and Policy

For predictive modeling to be effective in HIVST, it must be embedded within national HIV strategies and community health frameworks. Governments and health organizations should prioritize regulatory frameworks that ensure transparency and accountability in AI-driven health interventions. Moreover, predictive insights should not exist in isolation. They must be accompanied by on-the-ground community engagement to address socio-cultural determinants of HIV testing behavior. For instance, a model may predict low HIVST uptake in a certain region, but without qualitative community insights, the underlying cause—whether stigma, misinformation, or economic barriers—remains unaddressed. A blended approach, integrating predictive analytics with ethnographic research and participatory health planning, is essential to making these models actionable.

Conclusion

HIV self-testing in SSA is at a pivotal moment. Predictive modeling offers a powerful tool for improving HIVST outreach, but its impact depends on ethical implementation, equitable data strategies, and strong community engagement. Without these safeguards, predictive modeling risks perpetuating rather than reducing health disparities. This Viewpoint advocates for a human-centric, culturally responsive, and ethically grounded approach to AI in public health. Integrating predictive analytics with community-led interventions and policy frameworks can drive more equitable and effective HIVST adoption. Future research should explore comparative assessments of alternative modeling techniques, such as logistic regression, SVM, and hybrid machine learning, to determine their effectiveness across diverse epidemiological settings. Addressing biases in training data and involving local communities in model validation will be essential for ensuring fair and impactful predictive modeling in HIV prevention. By advancing methodological rigor and interdisciplinary collaboration, predictive analytics can be a cornerstone in achieving UNAIDS' 2030 goal of universal HIV testing access while upholding data fairness and public health inclusivity [41]. The time to act is now!

Declarations

Authors' Contributions

FEA, MNS, and OO conceptualized the manuscript. FEA drafted the original version of the manuscript, and OO and MNS critically contributed and reviewed it. All authors approved the final version for submission. FEA's doctoral is being supervised by MNS and OO.

List of Abbrevations

Abbreviation	Full Form
AI	Artificial Intelligence
CART	Classification and Regression Trees
FSW	Female Sex Workers
HIV	Human Immunodeficiency Virus
HIVST	HIV Self-Testing
KNN	*k*-Nearest Neighbors
MSM	Men Who Have Sex with Men
RF	Random Forest
SSA	Sub-Saharan Africa

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