Predicting and Preventing Loss to Follow-Up Among Women in HIV Care in Rwanda, 2025: A Machine Learning Approach - Policy brief

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KEY MESSAGES

Rwanda has achieved the global 95–95–95 HIV targets, but sustaining retention in HIV care remains essential for maintaining viral suppression and reducing HIV-related morbidity and mortality.

Women receiving antiretroviral therapy (ART), especially younger women and those experiencing treatment or demographic instability, remain at increased risk of loss to follow-up (LTFU).

Machine learning models using routine national HIV case-based surveillance (CBS) data can accurately identify women at high risk of disengagement before prolonged interruption of care occurs.

Random Forest models demonstrated strong predictive performance for identifying women at risk of LTFU, with recall performance of 73.9% and an AUC of 78%.

Integrating predictive analytics into Rwanda's national HIV program could strengthen differentiated service delivery, improve targeted retention interventions, and reduce avoidable treatment interruption among women living with HIV.

PROBLEM STATEMENT

Rwanda has made substantial progress in HIV prevention, treatment, and care over the past decade. The country has achieved the UNAIDS 95–95–95 targets, with most people living with HIV aware of their status, receiving antiretroviral therapy (ART), and achieving viral suppression [1]. Despite these achievements, maintaining long-term retention in HIV care remains a major public health priority.

Retention in HIV care is essential for sustained viral suppression, prevention of HIV transmission, reduction of opportunistic infections, and improved survival outcomes [2,3]. However, some women receiving ART continue to experience interruptions in care due to social, clinical, behavioral, and structural factors. Pregnancy, postpartum transitions, regimen modifications, delayed ART pickups, and geographic mobility can all disrupt continuity of treatment and increase the risk of disengagement from care.

Loss to follow-up (LTFU) among women living with HIV has serious implications for both individuals and the national HIV program. Women who disengage from care are at increased risk of viral rebound, treatment failure, drug resistance, preventable hospitalizations, and HIV-related mortality [2,3]. At program level, LTFU reduces efficiency, increases the burden on healthcare systems, and threatens national HIV epidemic control goals.

Current retention approaches within routine HIV programs are largely reactive. Women

are often identified only after repeated missed visits or prolonged absence from care. This limits opportunities for early intervention and increases the likelihood of treatment interruption. Routine monitoring systems frequently fail to identify subtle warning signs of instability before disengagement occurs [2,6].

Rwanda's national HIV case-based surveillance (CBS) platform offers an important opportunity to strengthen retention strategies through predictive analytics. By using routine clinical and programmatic data, machine learning models can identify women at highest risk of LTFU before interruption becomes prolonged. Similar approaches using machine learning in HIV care have demonstrated promising results in improving early identification of patients at risk of disengagement and poor treatment outcomes in other settings [6,7].

EVIDENCE AND FINDINGS

This policy brief is based on analysis of anonymized national CBS data from 33,191 women receiving ART in Rwanda between 2020 and 2025. The study used longitudinal routine program data reflecting real-world HIV service delivery conditions across the country.

Loss to follow-up was defined as absence of clinic or pharmacy contact for 90 days or more after the expected visit date. Multiple demographic, clinical, behavioral, and facility-level variables were extracted and analyzed. Four machine learning algorithms were developed and compared, including Random Forest, XGBoost, LightGBM, and CatBoost. To improve model performance for imbalanced health data, under-sampling and Synthetic Minority Oversampling Technique (SMOTE) approaches were applied.

Overall, 1.4% of women in the analytic sample were classified as LTFU. Among the tested models, Random Forest with under-sampling performed best overall, with an accuracy of 71.8%, recall of 73.9%, and area under the curve of 78%. Model performance comparison is presented in Table 1.

The analysis identified several major predictors associated with increased risk of LTFU among women receiving ART, including frequent art regimen changes, longer intervals since last art pickup, delayed viral load suppression, recent demographic changes or instability, younger age groups, and geographic mobility. On the other hand, protective factors associated with improved retention included clinical stability, older age, completion of tuberculosis preventive therapy (TPT), fewer opportunistic infections, and residence in northern, western, and southern provinces compared with eastern province.

The findings demonstrate that LTFU among women in HIV care is not random. Instead, it clusters around identifiable clinical and programmatic indicators already available within routine national data systems. This suggests that predictive analytics can feasibly be integrated into Rwanda's HIV program to support earlier intervention and strengthen differentiated service delivery.

POLICY OPTIONS

To reduce LTFU among women receiving HIV care in Rwanda, it is essential to strengthen early identification of women at risk of disengagement and improve targeted retention interventions. Current retention systems are effective but remain largely reactive, often identifying women only after prolonged interruption of care has already occurred [1-3]. To address this challenge, two policy options have been proposed and compared with the status quo below.

Policy Option 1: *Status Quo*

What: Continue existing HIV retention strategies based on routine appointment tracking, adherence counseling, community health worker follow-up, differentiated service delivery, and tracing of women after missed visits.

Table 1: *Model performance comparison*

Model	Accuracy	Recall	Area Under the Curve (AUC)
Random Forest	0.718	0.739	0.780
XGBoost	0.585	0.782	0.744
LightGBM	0.692	0.753	0.776
CatBoost	0.723	0.662	0.762

Challenge: Although Rwanda has achieved strong HIV treatment outcomes [2], routine retention systems often identify women only after missed visits or prolonged absence from care. This limits opportunities for early intervention and increases the risk of viral rebound, treatment failure, and permanent disengagement from care. Current approaches also make it difficult to prioritize women at highest risk of LTFU using available routine data.

Policy Option 2: *Integrating Machine Learning Risk Prediction into the National HIV Case-Based Surveillance (CBS) Platform*

What: Integrate machine learning–based predictive analytics into the national HIV CBS platform to identify women at high risk of LTFU before prolonged disengagement occurs.
Why: Analysis of national HIV routine data demonstrated that machine learning models can accurately identify women at increased risk of disengagement from HIV care. The Random Forest model achieved strong predictive performance with a recall score of 73.9% and an AUC of 0.780. Key predictors of LTFU included frequent ART regimen changes, delayed ART pickup, delayed viral load suppression, younger age, and demographic instability.
Using predictive analytics would allow healthcare providers, data managers, and community health workers to intervene earlier among women at highest risk. This would strengthen differentiated service delivery, improve continuity of treatment, and reduce preventable treatment interruption.
How: Risk prediction algorithms would be integrated into the national CBS platform to generate automated risk scores for women receiving ART. Women identified as high risk would receive targeted retention interventions such as enhanced adherence counseling, active tracing, peer support, closer follow-up during pregnancy and postpartum periods, and fast-track refill or multi-month dispensing services.
Implementation should begin through phased pilot testing in high-volume facilities and high-mobility districts before national scale-up. Standard operating procedures should guide ethical use of predictive analytics, data governance, confidentiality, and clinical action thresholds.

Feasibility: *High.* Rwanda already has a strong national HIV case-based surveillance infrastructure and well-established differentiated service delivery models. The predictive model uses routinely collected national HIV data, making implementation operationally feasible within the existing HIV program structure.

Policy Option 3: *Strengthening Targeted Retention Support for High-Risk Women*

What: Strengthen targeted retention interventions for younger women and women identified with clinical or social instability associated with increased risk of LTFU.
Why: Women aged 18–24 years, women with delayed ART pickups, regimen changes, demographic instability, and delayed viral suppression were more likely to disengage from care. Targeted support for these groups can improve adherence, reduce missed visits, and strengthen long-term retention in HIV care.
How: Healthcare providers and community health workers would provide intensified adherence counseling, active follow-up, peer support, appointment reminders, and closer clinical monitoring for women identified as high risk. The national HIV program would also expand multi-month dispensing, community ART delivery, and fast-track refill systems to reduce structural barriers to care.
Feasibility: *High.* Rwanda already implements differentiated HIV service delivery models and community-based follow-up mechanisms. These systems can be adapted to prioritize women identified as high risk for LTFU.

RECOMMENDATIONS AND NEXT STEPS

The Rwanda Biomedical Centre should integrate machine learning–based risk prediction into the national HIV case-based surveillance platform to support earlier identification of women at high risk of loss to follow-up. Implementation should begin through phased pilot testing in high-volume facilities and high-mobility districts before national scale-up.
Younger women, especially those aged 18–24 years, and women experiencing recent regimen changes, delayed ART pickups, or demographic instability should receive intensified retention support. Enhanced adherence counseling, active follow-up, peer support, and closer monitoring during pregnancy and postpartum periods should be prioritized for these vulnerable groups.

The national HIV program should strengthen differentiated service delivery models by expanding multi-month dispensing, community ART delivery, and fast-track refill systems. These approaches can reduce structural barriers to care and improve continuity of treatment among women receiving ART.

Health facilities should improve routine documentation of clinical stability, opportunistic infections, tuberculosis preventive therapy uptake, and patient engagement indicators. Better data quality will improve both patient management and the performance of predictive models.

The Rwanda Biomedical Centre should also establish standard operating procedures for ethical and equitable use of predictive analytics in HIV care. These procedures should define how risk scores are generated, interpreted, and used while ensuring patient confidentiality, minimizing stigma, and promoting fair use of data-driven interventions.

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