



Machine Learning for Identification of High Risk Negatives for Prevention Services - Kenya

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Background







- Kenya has made great strides towards achievement of 1st 95
 - Gaps remain among children, AYP and men
- Resources for TB/HIV are steadily decreasing
- Use of HTS screening tools recommended for identification of persons at risk of HIV infection^{1,2}
 - Machine Learning is a key screening tool in HTS for case finding and for identification of high risk HIV negative persons
- eHTS system used in provision of services and data submitted to the national data warehouse (NDWH)
 - Kenya HIV prevention and Treatment guidelines, 2022
 - 2. The Kenya HIV Testing Services Operational Manual, 2022



NDW Data Flow, Use & Coverage





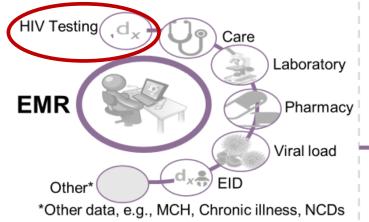
Data sources



Data repository

Implements the concept of collect once use multiple times

Data capture / integration



- mHealth systems
- Patient Surveys
- Referrals
- Non-EMR sites
 - Clinical, Labs, etc
- Aggregate
 Data Sources
- KHIS
- DATIM

National Data Warehouse (NDW)

Encrypted and secure HIV clinical data



Extraction Transformation Loading

 Hosts longitudinal data for 91% (1,228,320) of Active ART patients in Kenya (Jan 2024)



Data use cases and applications

Program monitoring

itoring 1. The



Program monitoring and evaluation (M&E)

- 1. The 95-95-95 cascade
- 2. Monitor program priorities
- 3. Longitudinal tracking
- 4. Self-service



Case Surveillance

- 1. Case-level outputs
- 2. Dynamic dashboards/reports
- 3. Cohort studies



Machine learning (ML)

- 1. Target HIV case identification
- 2. Referral for prevention services
- 3. Predicting interruption in treatment (IIT) risk of PLHIV



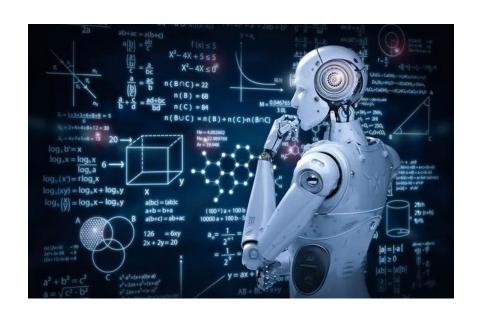
Implementation and Program

- · Abstracts and Manuscripts
- Program reports, bulletins and briefs
- Slide decks and Newsletters



Feedback Loop to facilities

Leveraging on Machine Learning for Risk Assessment



- The risk profiling machine learning (ML) model leverages patterns in existing data to better predict clients likely to be HIV positive
- During eligibility screening, providers generate the risk of positive results (low, medium, high, very high), and recommend testing if risk generated falls within the higher risk categories (medium, high, and very high)
- ML can assist providers to identify and SCREEN IN highrisk patients for HTS who could have been missed by manual screening and recommend HIV prevention services like PrEP for high-risk clients that turn HIV negative

ML in HTS

Optimize HIV case identification

Identify high risk HIV negative for prevention services

Augment provider decision to test

Data driven resource allocation





Outcomes of the ML Model (Apr 2023 - Mar 2024)

	Highest Risk	High Risk	Medium Risk	Low Risk
No. of Tests	103,573	241,879	663,094	904,147
No. of Negatives	94,031	231,881	649,283	896,532
No. Enrolled in Prevention Services				
(PrEP)	6,263	13,115	29,809	26,227
% Enrolled (PrEP)	6.66%	5.66%	4.59%	2.93%

- Data captures linkage to PrEP
- Ongoing efforts to improve linkage as well as documentation of other combination prevention strategies from HTS



Acknowledgement

- Kenya MOH NASCOP
- PEPFAR
- Palladium Kenya
- CQUIN

