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Mitigation of HIV Treatment Interruption Using Machine Learning, Kenya

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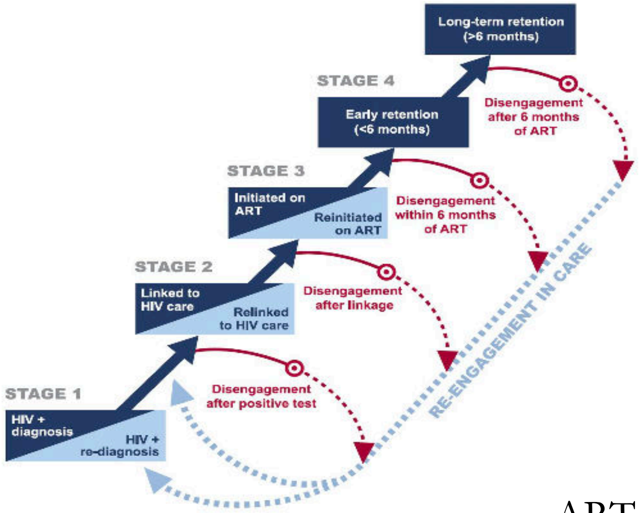
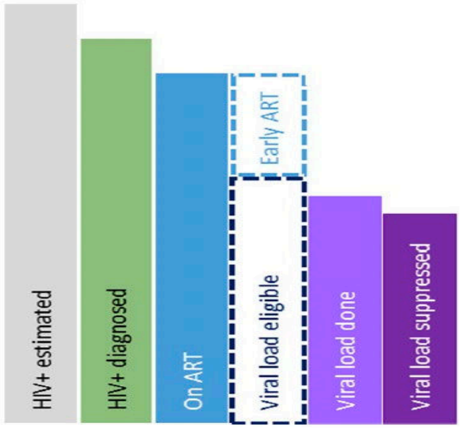
CQUIN 9th Annual Meeting | Delivering Differently: Prioritize. Adapt. Sustain

Treatment Interruption a Barrier to HIV Epidemic Control

- Kenya's performance against 95-95-95 targets is at **95-97-94***
- Life-long ART is essential for sustained virologic suppression, reduced HIV morbidity and reduced risk of onward transmission
- Treatment interruption slows down the progress towards HIV epidemic control
- Traditional linear cascade useful, but does not account for nuances in the ingress and egress from care
- Cyclical cascade with potential to provide deeper insights for targeted interventions
- Utility of de-duplicated, longitudinal dataset of HIV population for analysis of cyclical cascade remains uncertain



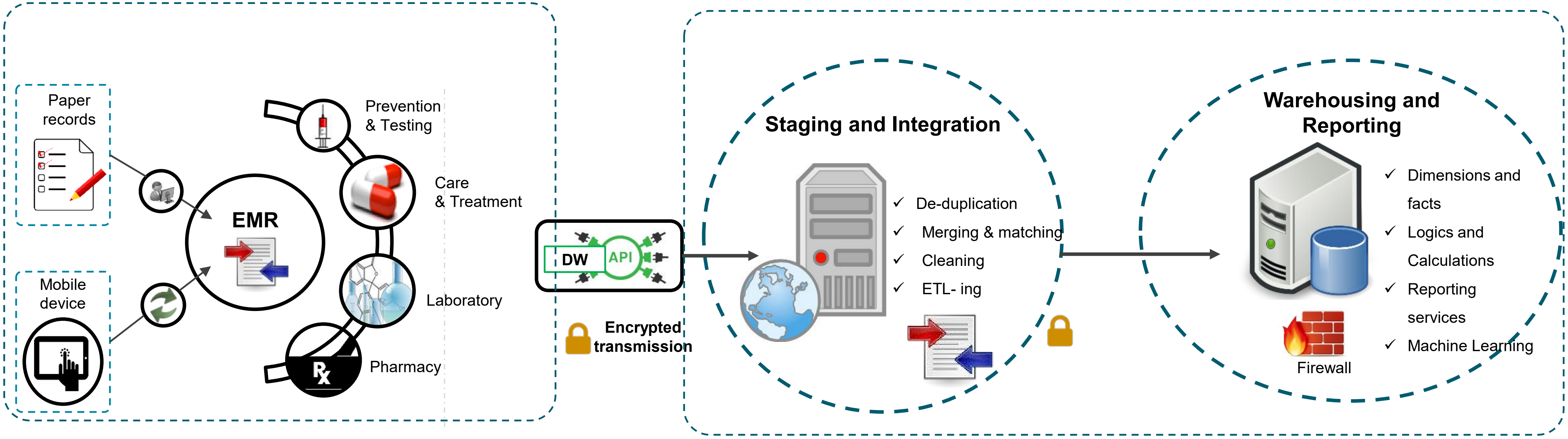
ART Cyclical cascade*



ART Linear cascade*

**(“Source for the 97-97-93 estimate”; PROGRESS-REPORT-2024.pdf. Available from: https://analytics.nsdcc.go.ke/estimates/PROGRESS-REPORT-2024.pdf)*

Data Transmission, De-duplication, and Data Warehousing



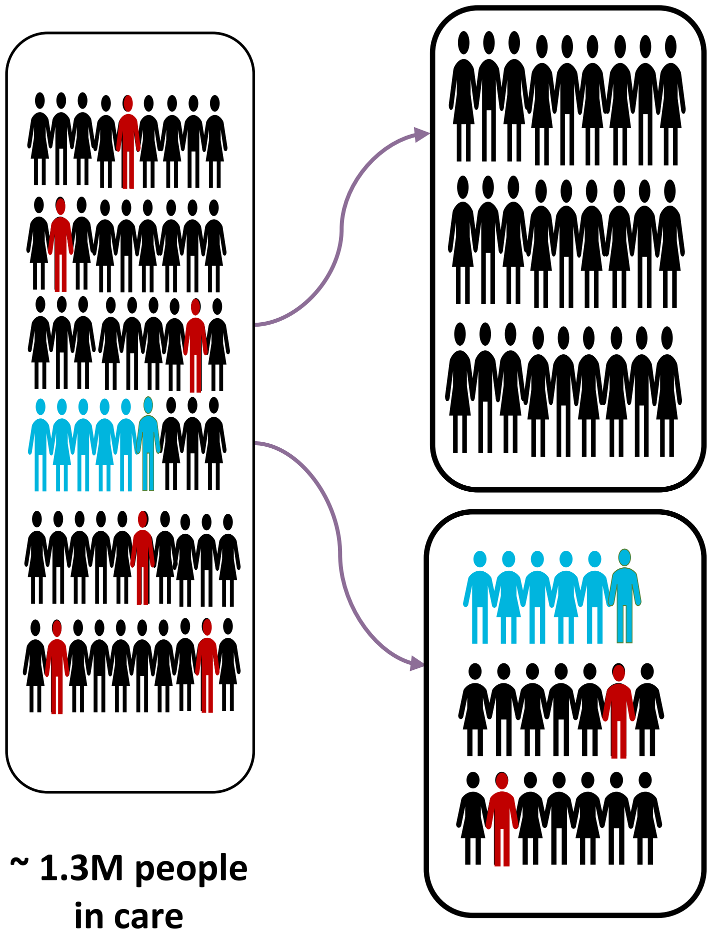
- Demographic, clinical care data is recorded in Electronic Medical Record (**EMR**) system during routine clinical visits.
- National ID number is used to derive a National Unique Patient Identifier (**NUPI**)

- NUPI is applied for records matching and deduplication
- Data is cleaned and **ETL**'d (Extract, Transform and Load) for various use cases

- Longitudinally linked dataset of unique patients living with HIV (**PLHIV**) is availed in an easy to consume approach

**sourced from (Ndisha M et al, BMC Med Inform Decis Mak 2023) and updated for context*

The IIT ML Solution in Kenya



~ 1.3M people in care

Greater than **70%** are Honoring their Appointment

~ **300K** are missing appointments

This population experiences different treatment interruption factors

Common Problem in HIV Care

- The standardized approach to HIV treatment delays timely responses to interruptions and relies on manual tracing of clients with interruptions in treatment (IIT), leading to inefficient use of resources.

IIT ML

- This is a ML powered alert system embedded in KenyaEMR that identifies and flags clients at risk of interrupting HIV treatment, enabling proactive and targeted interventions before interruptions occur.

Harnessing ML at the Frontline for Treatment Continuity

Inputs

Data Inputs

- Program data
- Survey data

Data Science expertise

- ML modeling techniques
- Experts

Program Interventions

- Program experts
- Program guidelines

Strategies

ML integration in EMR

- Build an ML model
- Integrate Model in EMR
- Early Warning predictive Alerts/Flags in EMRs

Clinical Interventions

- Pre-emptive package of Services
- Case Managers & clinician orientation

Technology based interventions

- Targeted SMS to at risk

Output

ML assisted Targeting

- Early action on IIT risk clients
- Accurate and timely alerts on at risk clients

Early, risk based targeted action

- Uptake of preemptive clinical interventions
- Targeted preventive action to avert IIT

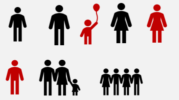
Outcome

- Reduced IIT incidence
- Growth of TX Cohort

Approach for Implementing IIT ML Model

Clients/ Persons'

Clients with different risk profiles visit facilities



Problem Statement:

Current Clinical Practice

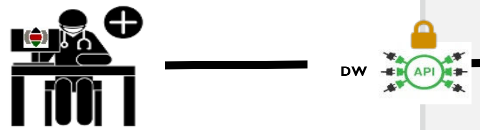
- Non-standard processes
- Provider discretion
- Missed opportunity

Current Public Health Practice

- Manual data analysis
- Delayed intervention

Facility Level

- Standard of care is similar for all clients
- Delayed Response (after IIT)
- Manual Tracing of IIT clients



Intelligent clinical decision support

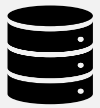
- **Clinical alert system** for Frontline Workers

Features

- Intelligent IIT risk alerts and flags
- Line-list of High IIT-risk clients
- Targeted care plans to avert IIT

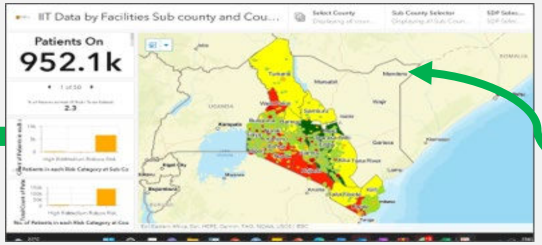
Above Site

- De-identified data is transmitted and hosted in the NDW
- Manual Data Analysis to identify Risk factors for IIT



Intelligent public health decision support

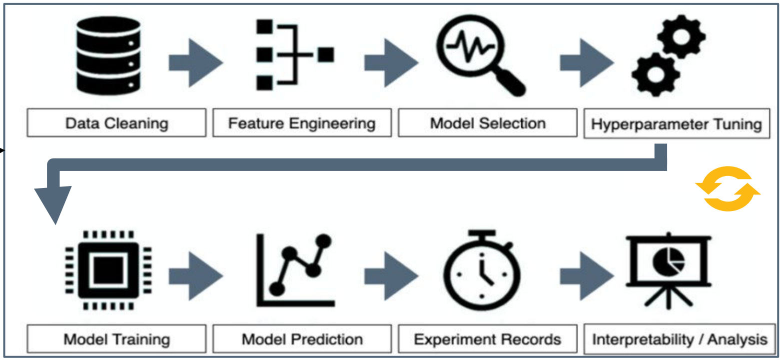
- Public Health **Early Warning System for IIT**



Features

- Risk Mapping of IIT hotspots
- Pre-emptive action to avert IIT
- Reduce missed opportunities for interventions

ML Model Development



Prediction models

Predictive IIT model

Continuous feedback

***

Model updates with new data

***

Model integration in HIS

ML for IIT Prevention

Intelligent decision support for predicting clients at High IIT risk for action

What is it?

- An intelligent alert system that relies on a machine learning model to identify and flag persons at risk of Interrupting in Treatment (IIT)

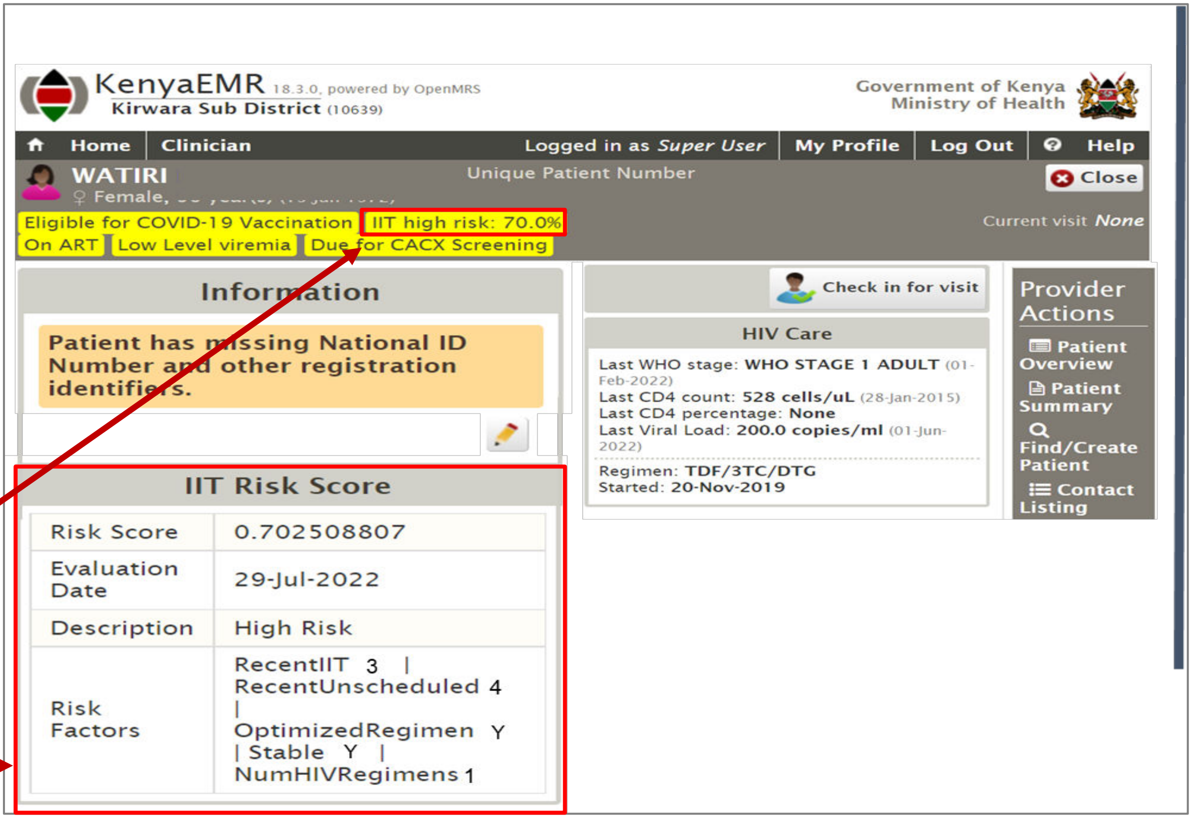
How does it work?

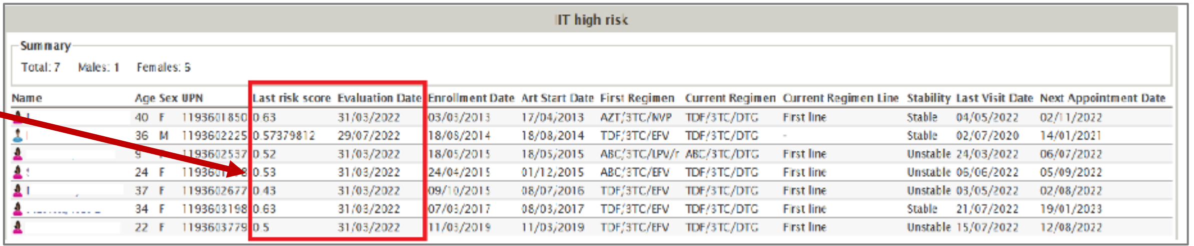
1. Clinical providers receive alerts regarding persons risks status and scores
2. Providers can customize interventions accordingly with guidance on risk factors to avert the risk
3. Availability of reports to guide programming & monitoring

- Provide targeted appointment SMS to clients at risk of treatment interruption

Clinical decision support:

Intelligent Alerts and high IIT risk line-lists





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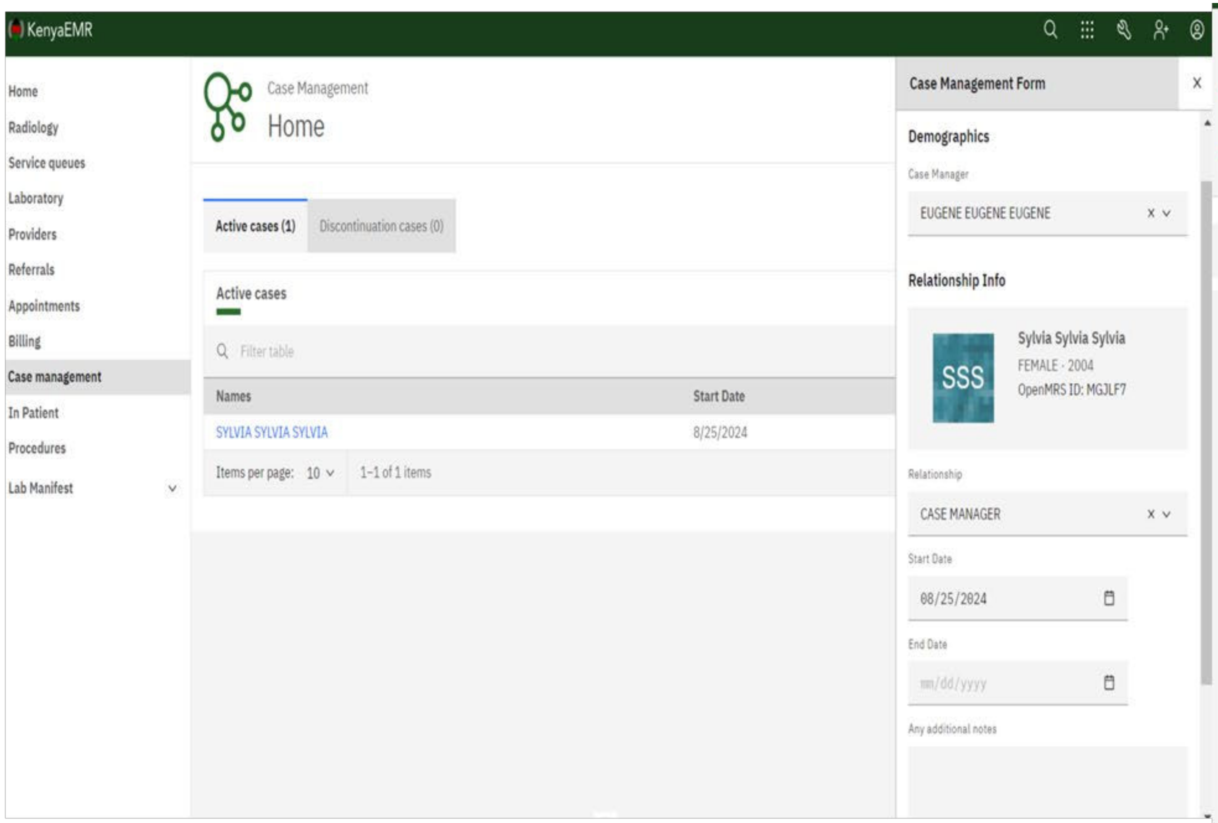
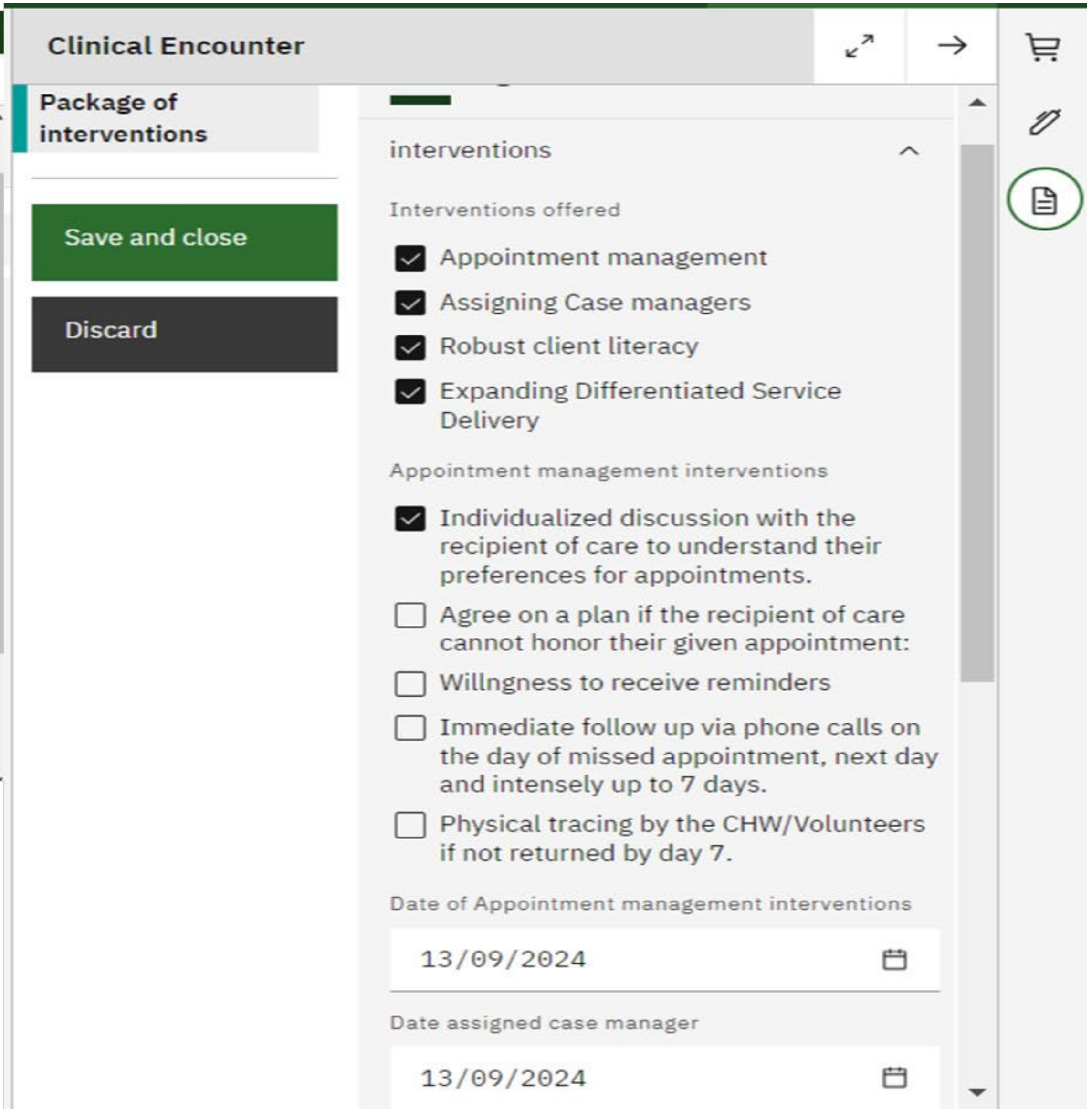
Package of Care to Avert IIT Based on Risk Profiles

Risk Level	Pre-emptive Interventions With Personalized Care
High Risk	**Appointment management:** Individualized discussion on appointment preference; ○ Give options for early drug pick up, ○ ARV pick-up or by treatment buddy/supporter/from nearby facility, ○ Enrollment into SMS/phone reminder program, ○ Overnight medication pick-up reminders on clinic eve, ○ Missed appointment follow-up **Assign Case Managers** ○ Targeted follow-up **Robust client literacy** ○ Minimum 3 sessions of treatment education/support **Differentiated Service delivery** ○ Community drug delivery ○ Community pharmacy (new)
Medium Risk	**Appointment Management** ○ Appointment management (reminders etc.) **Case managers** ○ For targeted follow-up & support **Treatment literacy** ○ Minimum 1 session of ongoing patient education **DSD**
Low Risk	Per standard of care

How Clinicians Interact With the IIT Model





Able to assign a case to a case manager in the EMR and offer interventions to avert the risk of a client being IIT.

Results: IIT Model Predictions vs. Actual Outcome

These results are based on data from 1st July 2024 through 30th September 2024.

IIT Prevalence by ML Risk Category

	Total Appointments	High Risk	Medium Risk	Low Risk
Total	1,120,784	280,196	280,196	560,392
%	100%	25%	25%	50%
IIT	35,374	22,511	7,246	5,617
% IIT	3.16%	8.03%	2.59%	1.00%

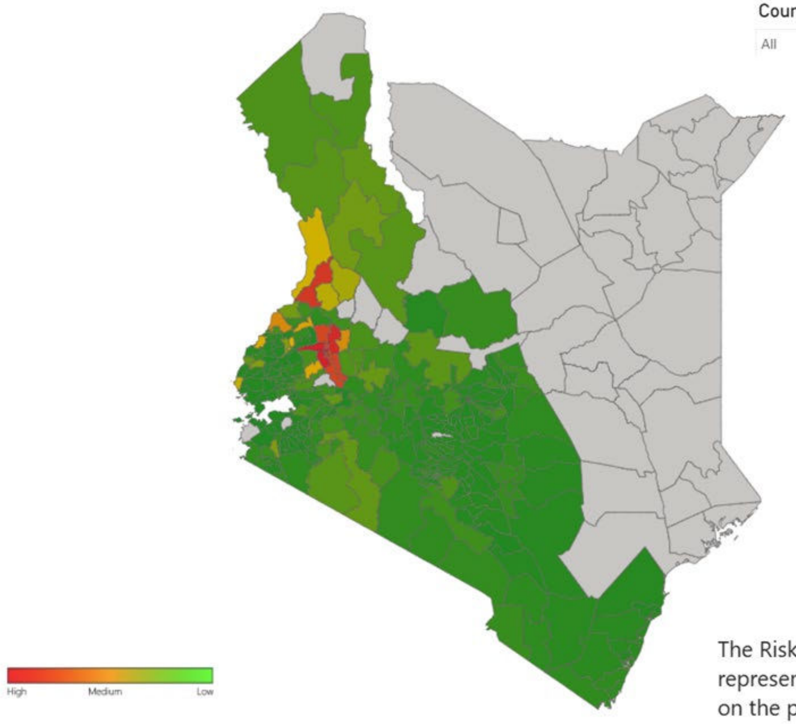
Among the 50% of clients considered high or medium risk, the rate of IIT was 5.3%, representing 84% of all instances of IIT.

Leveraging on the IIT Model for Public Health Action

Risk Heatmap: Mapping High-Risk Regions for Treatment Interruption

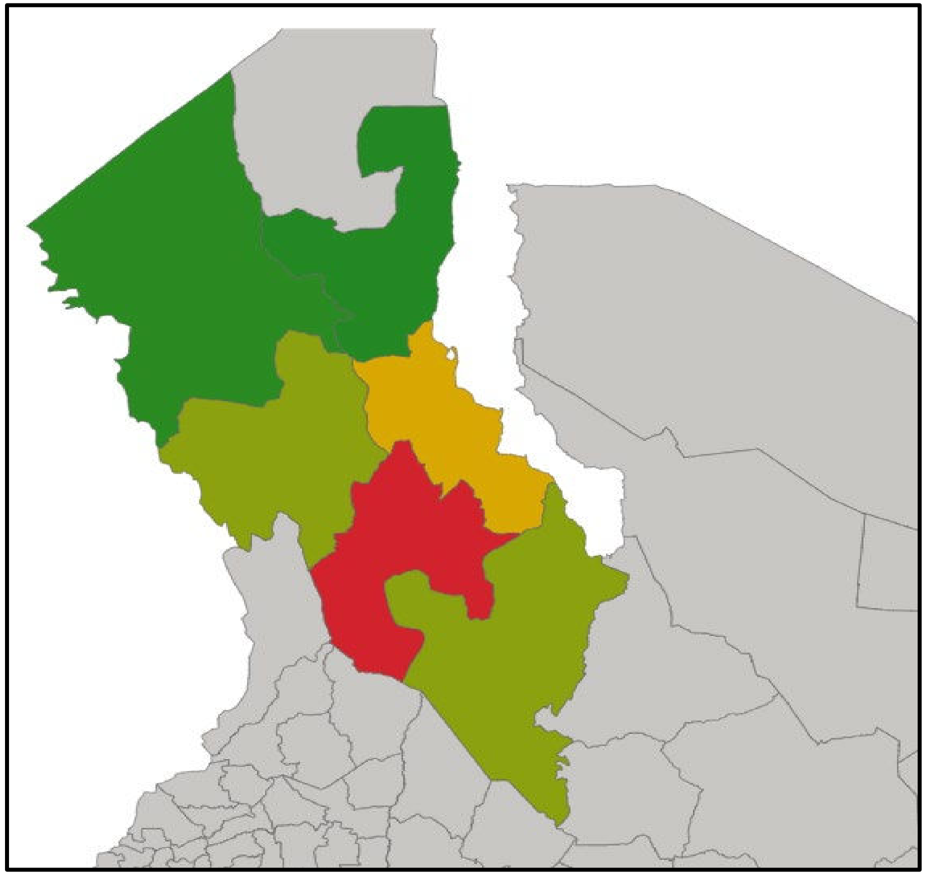
County
All

SubCounty
All



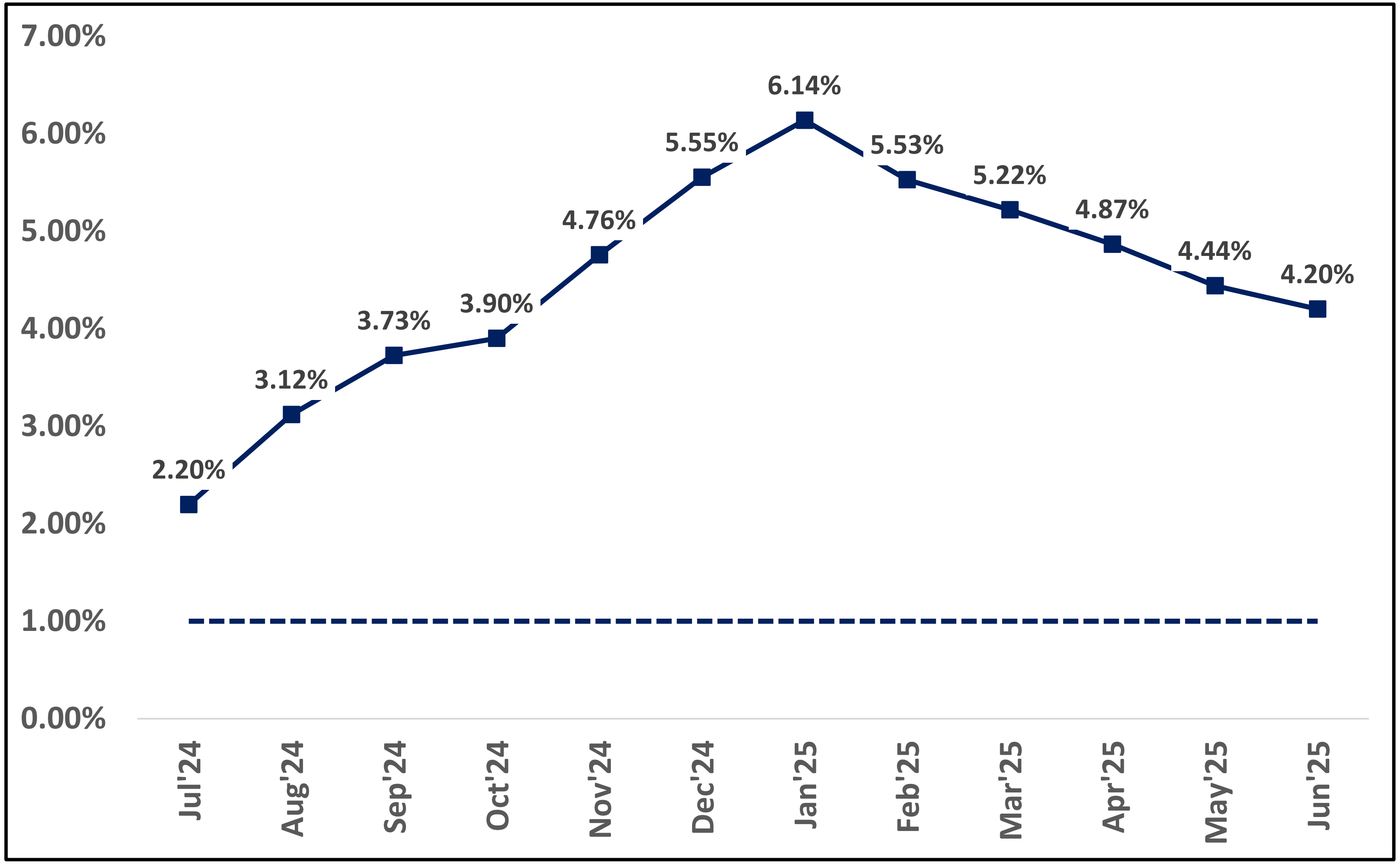
The Risk Heatmap dashboard displays a visual representation of sub counties color-coded based on the percentage of high-risk clients for treatment interruption to guide public health action. Powered by machine learning, this dashboard provides a quick and insightful overview of areas that need targeted interventions and resources to improve retention and treatment outcomes.

Grey regions represent underserved counties based on Low HIV prevalence and digital systems penetration within the ASAL counties. **GoK is working on expanding digitization as part of UHC initiatives**



Sub-County	% of Clients With IIT High Risk
Turkana South	0.21
Turkana Central	0.16
Turkana East	0.14
Loima	0.14
Turkana West	0.11
Turkana North	0.11

IIT Patterns and Progression: A Longitudinal View from Project HIFADHI



From February to June 2025, IIT rates showed a steady decline, indicating potential recovery or improved follow-up mechanisms. Predictive targeting of high-risk clients may be contributing to improved retention outcomes.

Navigating Challenges, Seizing Opportunities

Challenge	Solution
🖧 Variable Data Connectivity	"Offline-First" EMR integration for reliable use in low-bandwidth settings
🤝 Workflow Integration	Co-creation with clinicians to design usable alerts and action plans.
📈 From Data to Action	Automated bulletins & TWG forums to ensure predictions trigger a consistent public health response.

🚀 Future Opportunities

- Smarter AI: Evolve from predicting "who is at risk?" to prescribing "which intervention works best?".
- Continuous Learning: Use intervention outcomes to continuously re-train and improve model accuracy.
- System-Wide Scale: Leverage the proven blueprint and data infrastructure to expand into TB, Maternal Health, and beyond

Conclusion & The Path Forward

- Kenya has successfully deployed a scalable AI model to proactively reduce treatment interruption, demonstrating the power of combining strong data infrastructure (EMR, NUPI) with cross-functional collaboration for tangible public health impact.

Together, we are turning predictive insights into preventative action.

🔭 Scaling the Impact: Our Strategic Priorities

Priority	Key Actions
📈 Expand Predictive Analytics	Apply the model to HTS, PrEP adherence, and TB prevention.
📱 Enhance Client Engagement	Integrate risk insights into client-facing apps & SMS for self-management
🏛️ Strengthen Governance	Develop policy frameworks for sustainable and ethical digital health
🤝 Foster Regional Collaboration	Share the blueprint to support replication & cross-country learning

Thank You!

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