

Using Machine Learning to build and *use* Relative Risk profiles for ART

in South Africa and Nigeria

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Palindrome Data, Cape Town, South Africa

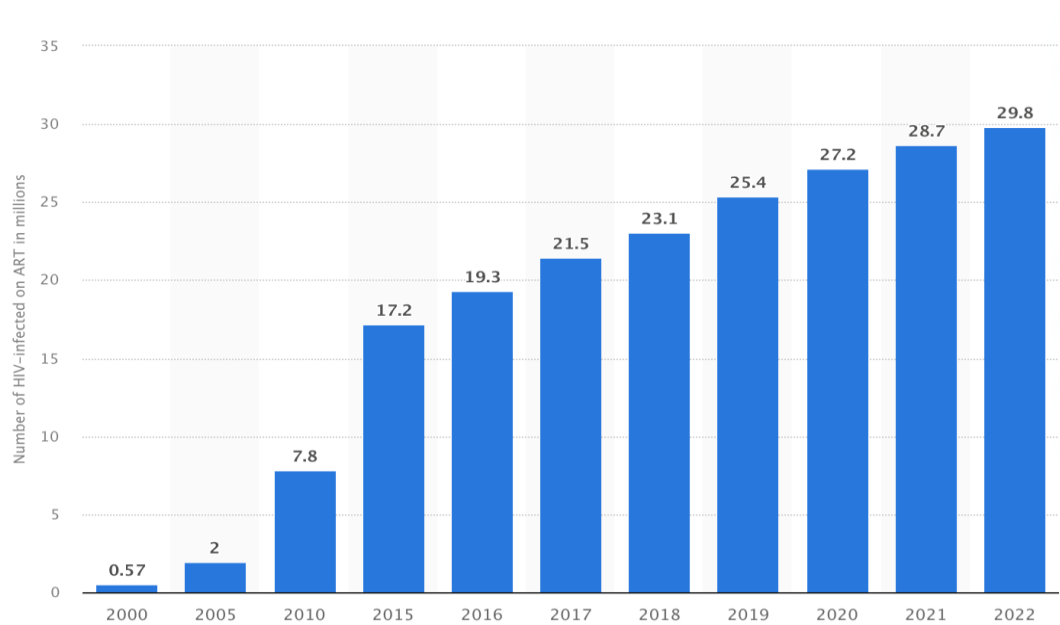
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WORLD CONGRESS OF EPIDEMIOLOGY 2024



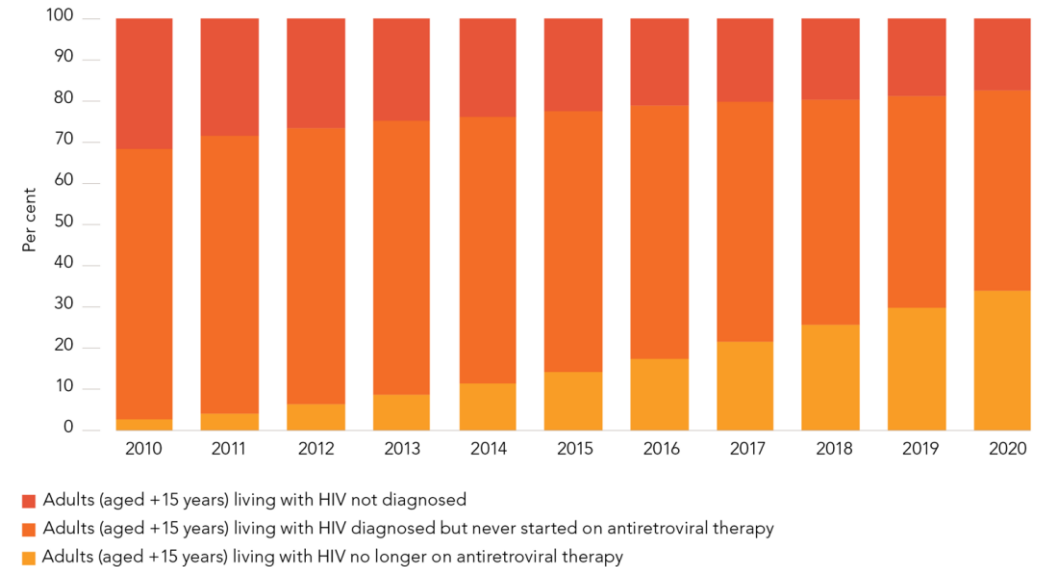
HIV is *trying* to Personalise Care at Scale

Access to ART worldwide has increased



Disengagement from care has also increased

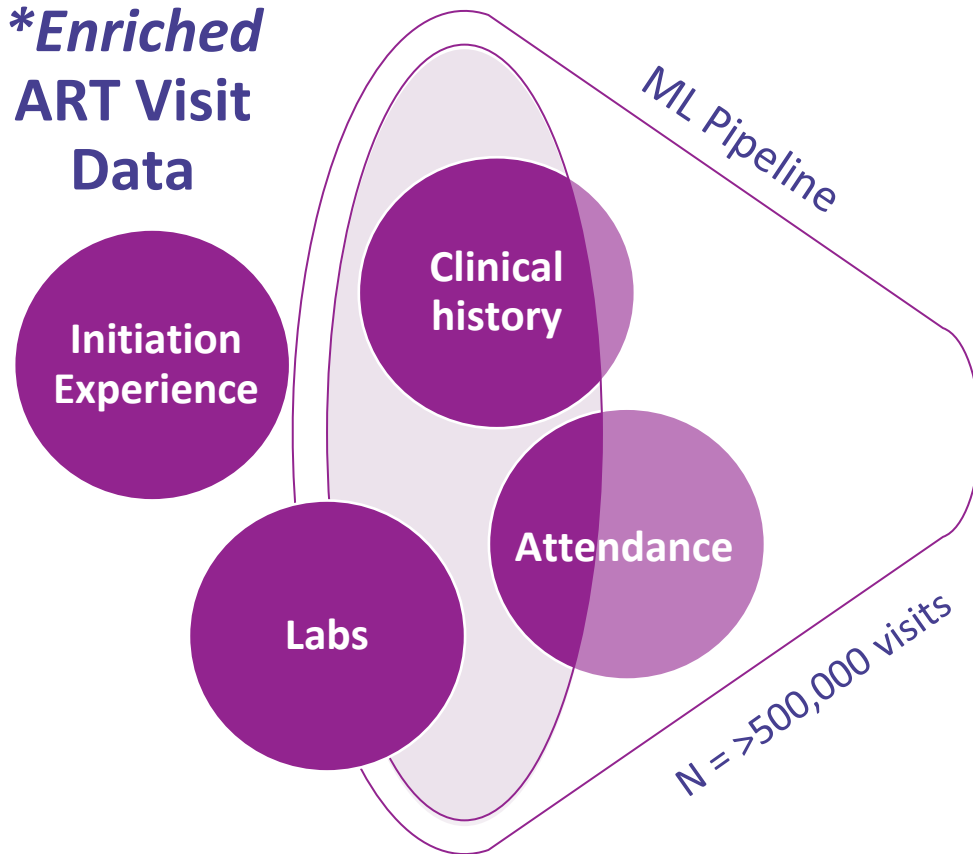
People living with HIV not on antiretroviral therapy, adults (aged 15+ years), South Africa, 2010–2020



Method:

Predict Interruption using EMR visit data & ML classifier

***Enriched
ART Visit
Data**



**Interruption-in-Treatment
Predictions**

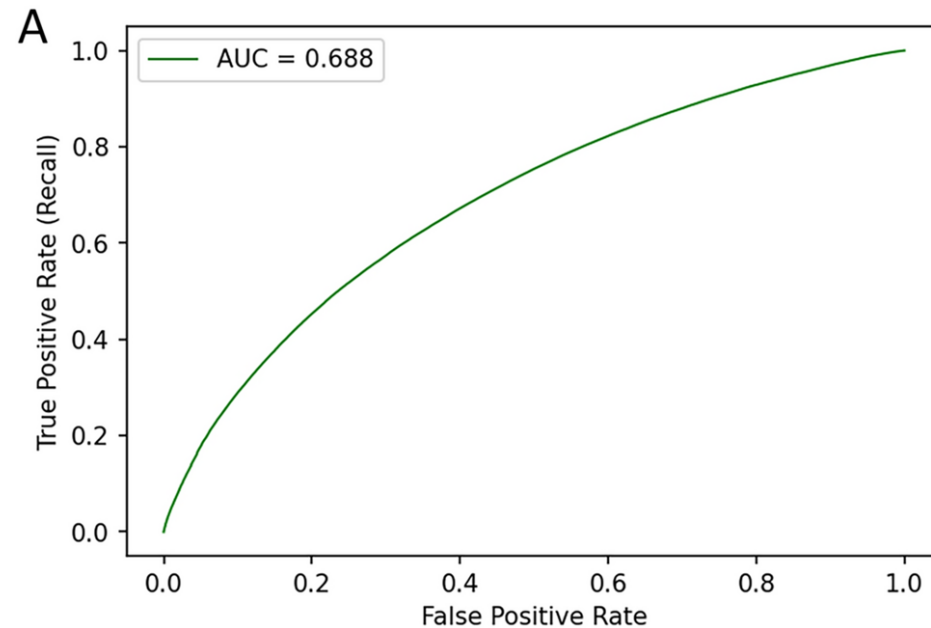


Screening Tool

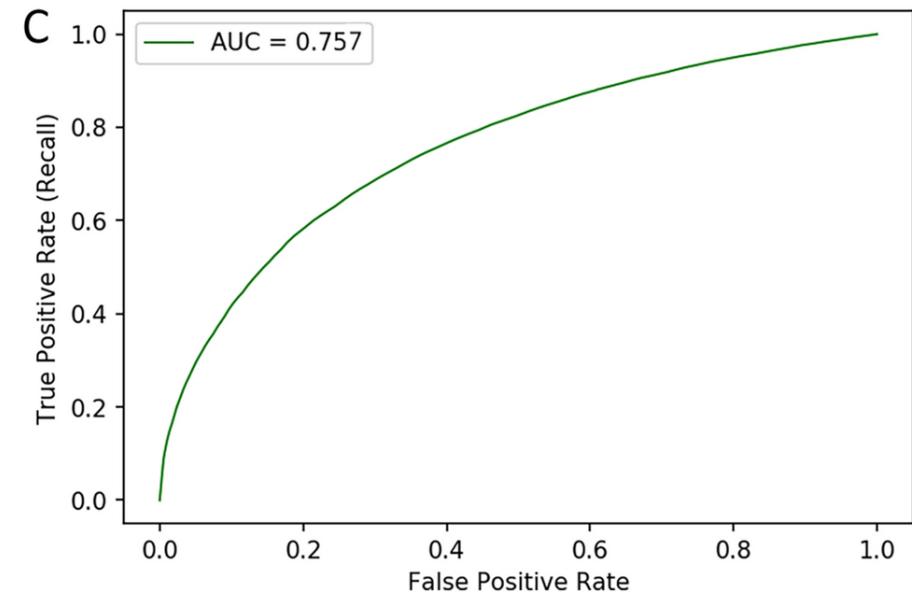


Results: The results indicated that prior patient behaviour and treatment history were extremely important in predicting both visit attendance and viral load results in these datasets and that traditional demographic predictor variables were less useful than behavioural indicators

Interruptions in Treatment Classifier

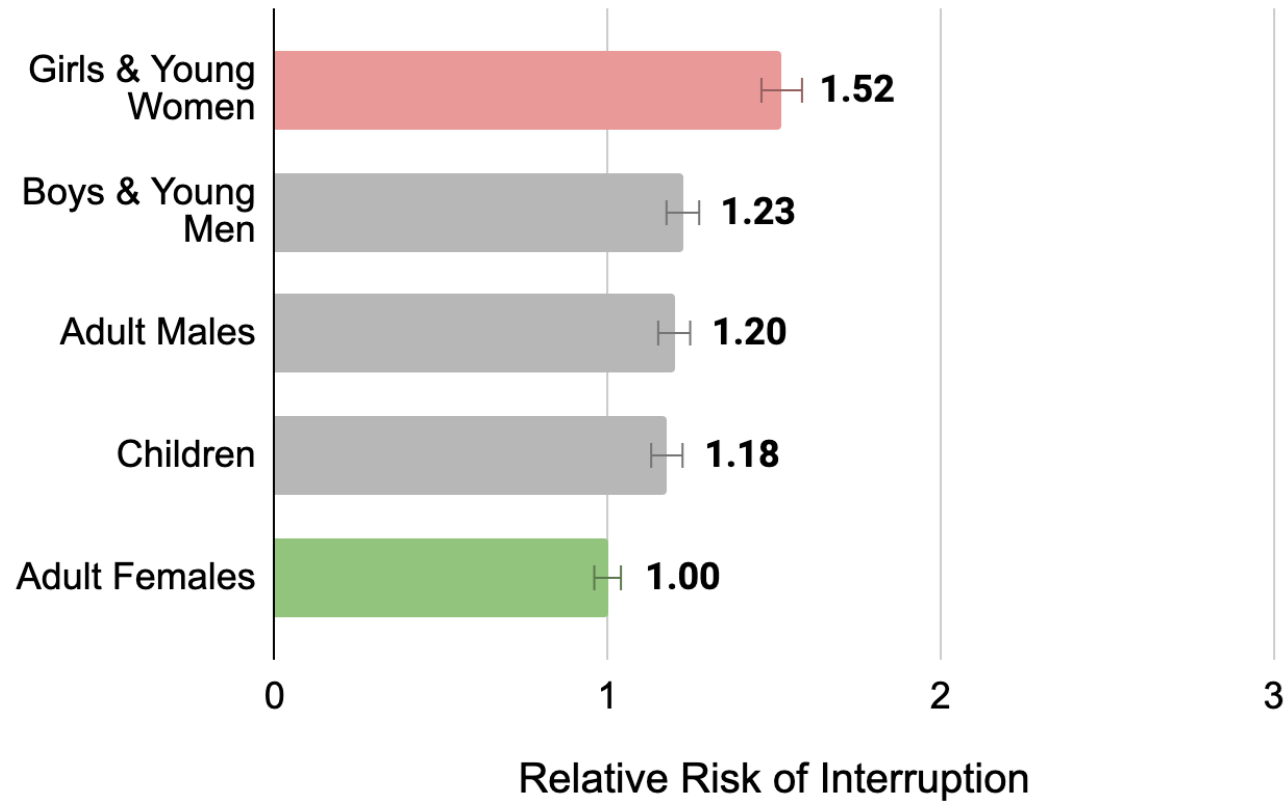


High Viral Load Classifier



Results: Traditional Demographics

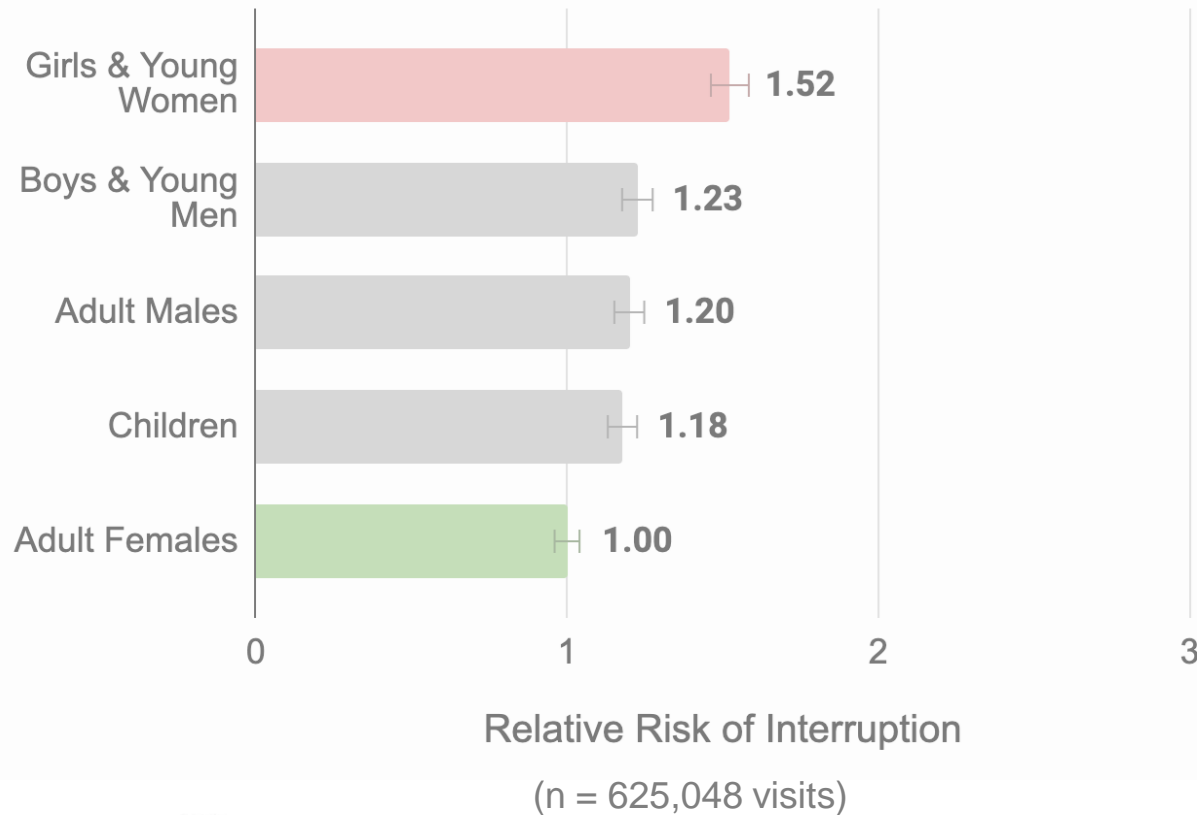
Risk of ART Interruption at Next Visit by Demographic Profile



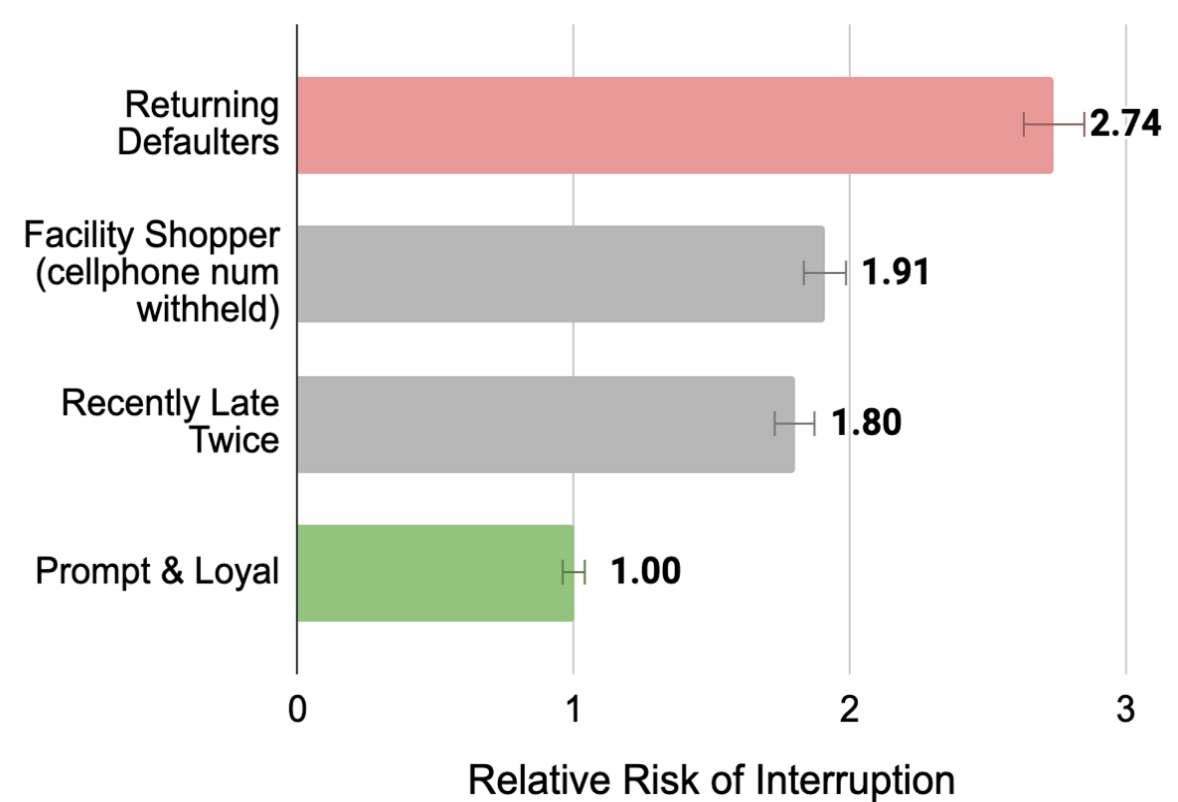
(n = 625,048 visits)

Results: ML identified behaviours

Risk of ART Interruption at Next Visit by Demographic Profile

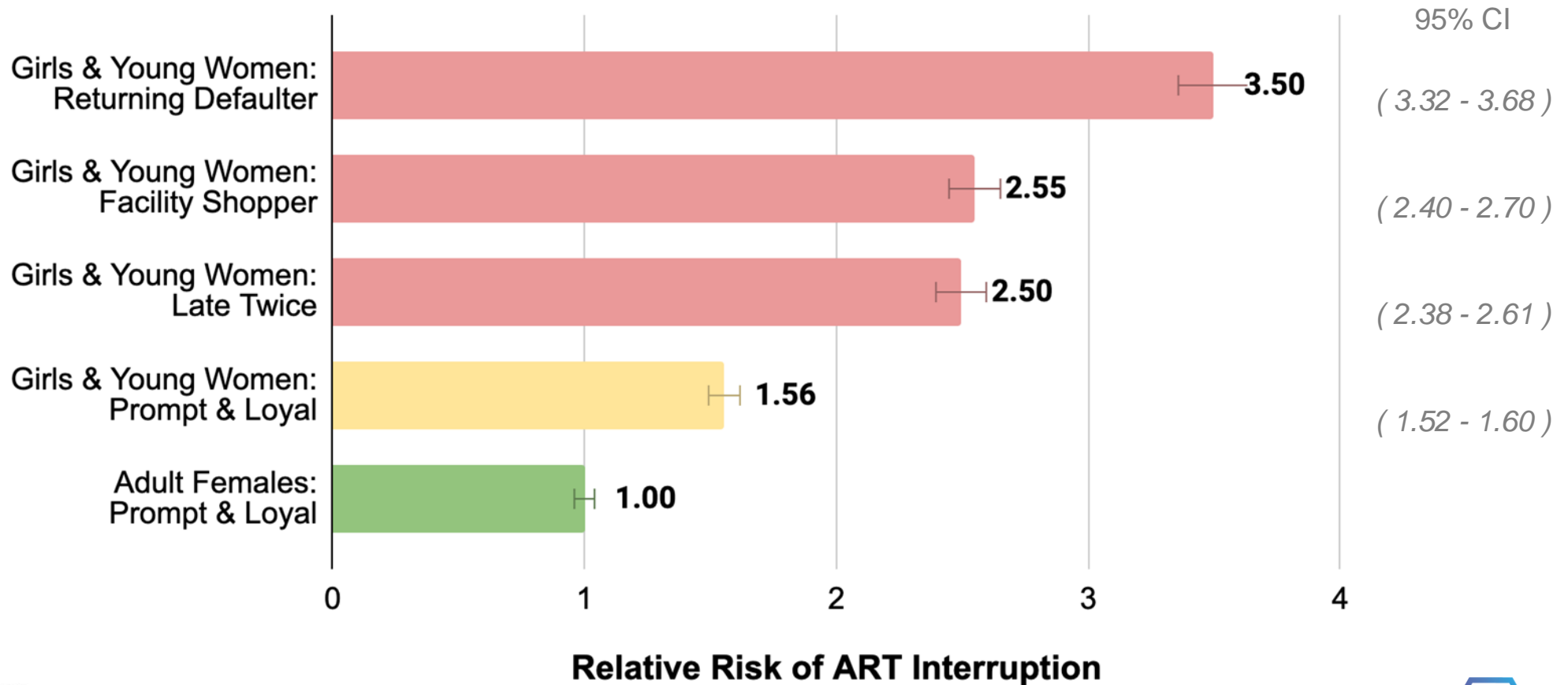


Risk of ART Interruption at Next Visit by Behavioural Profile



Results: ML identified behaviours

Risk of ART Interruption at Next Visit for AGYW by Behaviour Profile



(n = 625,048 visits)

Heterogeneity

**“all happy families are alike,
while each unhappy family is unhappy
in their own way”**

- from *Anna Karenina*

Results: Replicated in South Africa & Nigeria



Method works on different EMRs

- 2 Provinces in South Africa

Results replicate

Very similar signal across

- Geography
- Time (covid)



- 4 States in Nigeria

- more variance between states and localized predictors
- Behaviour always a important factor >> demographics

Methods & Results

Applying machine learning and predictive modeling to retention and viral suppression in South African HIV treatment cohorts, Nature Scientific Reports, 2022

[<https://doi.org/10.1038/s41598-022-16062-0>]

Validation and improvement of a machine learning model to predict interruptions in antiretroviral treatment in South Africa, JAIDS,

[<https://doi.org/10.1097/qai.00000000000003108>]

Historical visit attendance as predictor of treatment interruption in South African HIV patients: Relating linear risk factors to a validated machine learning model, PLOS,

IMPLEMENTATION SCIENCE

Predictive Analytics Using Machine Learning to Identify ART Clients at Health System Level at Greatest Risk of Treatment Interruption in Mozambique and Nigeria

Stockman, Jeni MA^a; Friedman, Jonathan MA^b; Sundberg, Johnna BA^a; Harris, Emily MA^c; Bailey, Lauren ScM^c

[Author Information](#) ✓

JAIDS Journal of Acquired Immune Deficiency Syndromes
10.1097/QAI.00000000000002947 ©

Predicting Treatment Interruption Among People Living With HIV in Nigeria: Machine Learning Approach

Ogbechie M, Fischer Walker C, Lee M et al.

JMIR AI 2023, URL: <https://ai.jmir.org/2023/1/e44432>, DOI: 10.2196/44432

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j; jhpiego
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Application: Feasible point of care risk tool

Adherence Scorecard

Scoring Instructions

- For each question, circle one answer and add the points in the "score" column. Sum all scores into "Total"
- Match this score to the "Total Adherence Score", and consider what guidance your client might need

Adherence Scorecard		0	1	2	Score
1. What is the client's age group?	Young adult (18-35)	Adult (36-55)	Senior (60+)	Child (0-17)	
2. For today's visit, is the client:	Late	First visit	On Time	Early	
3. For their last visit, was the client:	Unknown	First or second visit	On Time	Early	
4. Has the client ever been over a month late?	More than once	Once	Never		
5. When was the client's last visit?	5 or more months ago	3-4 months ago	0-2 months ago		
6. How many times has the client ever visited this facility?	0 - 4 visits	5 - 10 visits	11 or more visits		
7. Have you disclosed your HIV status to your friends or family?	None	Partial	Full disclosure		
8. How much time did it take you to get here?	More than 30 mins	30 mins or less			
9. How many people do you live with?	Other number	2 - 6 other people			
10. Are you employed or studying?	No	Yes			
Total					

Total Adherence Score

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
low-score										mid-score						high-score						

Do you agree with the score for this client? Yes No

What group should this client be in? low-score mid-score high-score

Comments: Score-Study-ID#

Health Worker Initials: _____

Paper Scorecard



2:26 PM

Risk Score Card

Martha Sibongile (Active)
0004

This client will likely remain in care

You did not agree that this client is Medium Risk.

Score card details
Risk score details

2023-08-16

Client's Age: 33

Late last visit?: Early

Number of visits to facility: 5

Time on treatment: 75 Months

Prescription duration: 6 Months (MMD6)

Number of viral load tests: 2 tests

Number of interruptions in treatment: 0

Intervention Recommendations

Digital Scorecard



✓ 98% Predictions Agreeable for Healthworkers

✓ Fast – bimodal consultations

✓ Observed training prediction distribution

? *Personalise interventions*

? *Improve Outcomes*

A good time to **Embrace** new methods

- Existing routine data
- Modern data science
- Non-linear Complexity

Thank You!