Palindrome Data

Capability Statement

Jan 2025

PALINDROME DATA

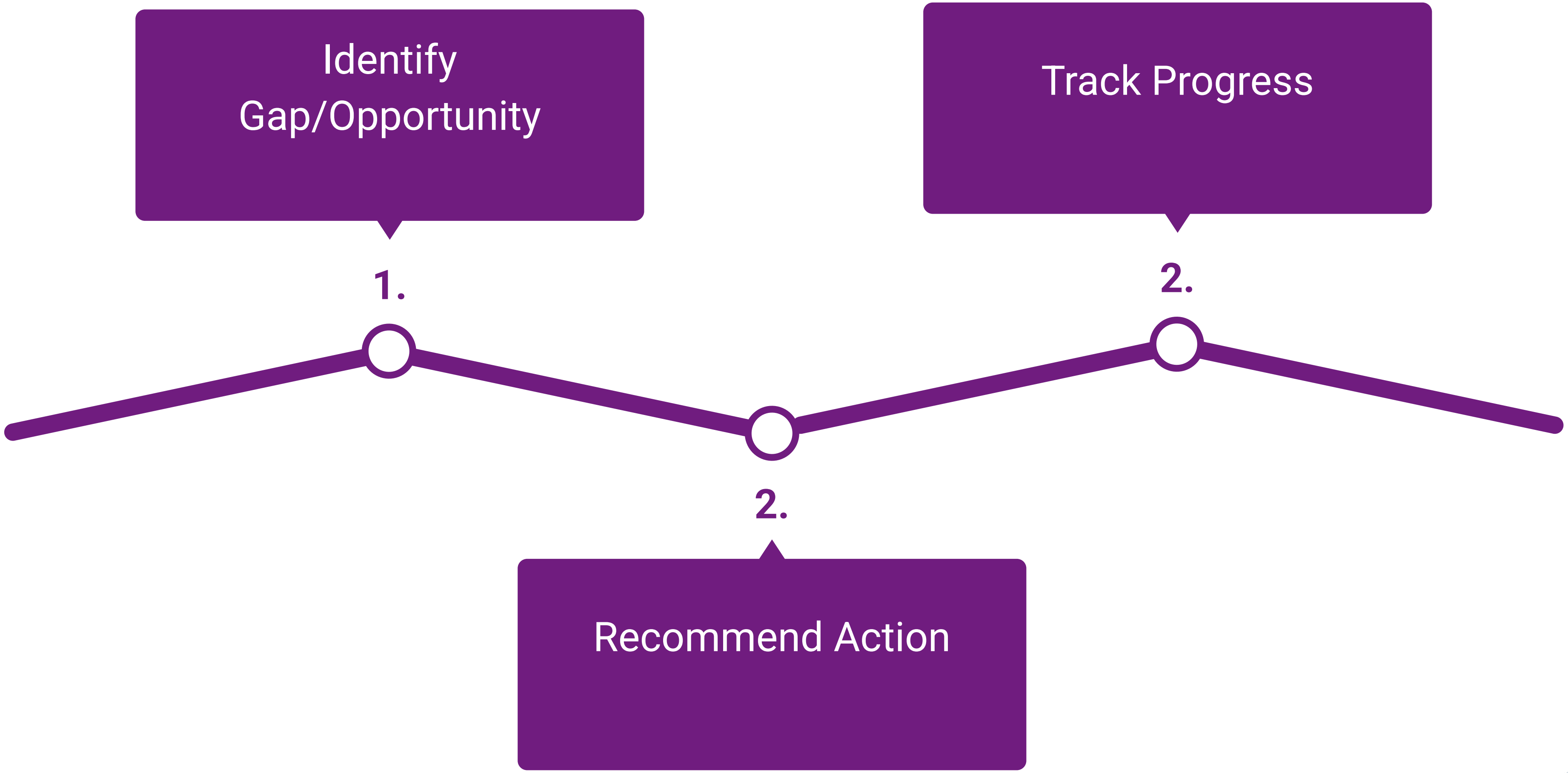
Agenda

1. Introduction
2. Case Study: Nigeria
3. Techniques and Tools

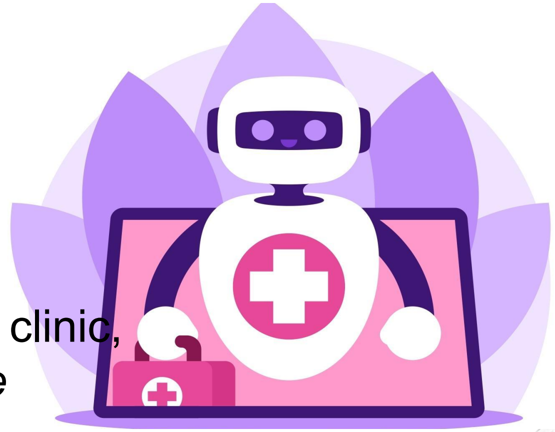
Palindrome Data is an African HealthTech Implementor delivering AI Solutions to Our Communities.

Mission: Deliver Differentiated Care and Personalised Healthcare Experiences to Improve Health Outcomes.

Lesedi AI


Identify Gap/Opportunity
1.
Track Progress
2.
2.
Recommend Action

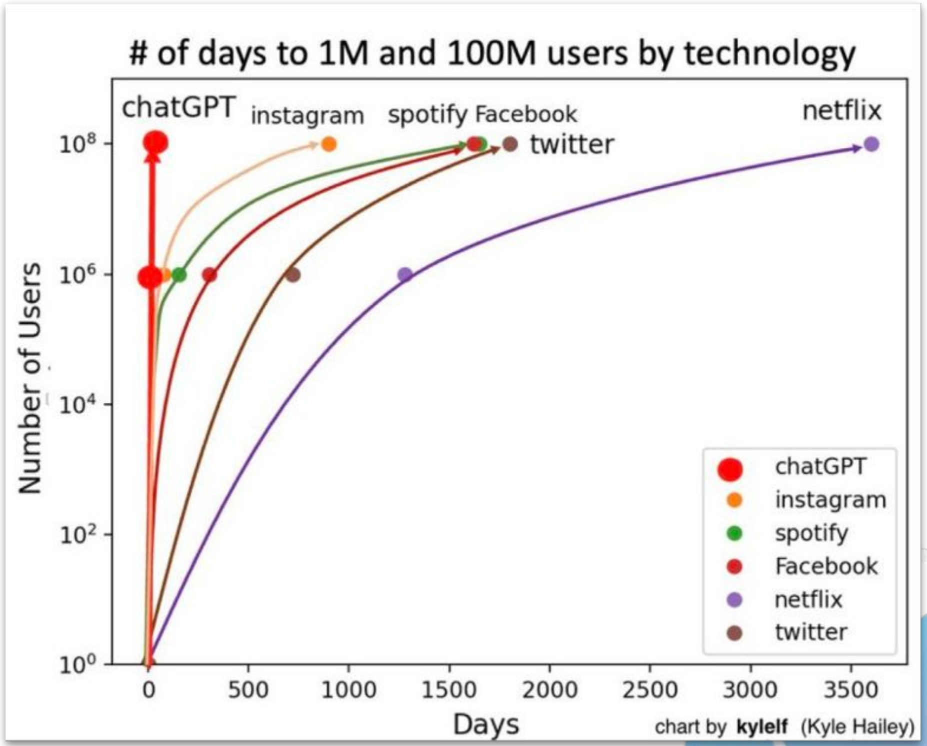
Lesedi AI: The Magic in the Middle



1. Identify gaps and opportunities by feeding client, clinic, and community data to *Recommendation Engine*
2. Engineer super-queries for those less experienced with Data Analytics, AI, and LLMs.
3. Prime LLM with additional context such as program SOPs, Policies, and Guidelines

AI as a Utility

- Programs need to be 10x more effective over the next 3 years
  - Existing approaches have plateaued
  - (We're at 4x using AI 😃)
- AI will get better gradually, and then suddenly
  - To be ready for the future, clinics need to be leveraging existing AI capabilities to keep up
  - Users need time to figure out new technology and to develop their own solutions



⚠️ Closing the Implementation Gap

Knowledge (Ability) and Motivation (Willingness)

- Programs are struggling to systematically roll out policies, guidelines and SOPs at scale in the real world
- Healthcare workers are overwhelmed and uncertain about all the decisions they're having to make
    - clients ✖ touchpoints ✖ interventions
- Burn out results in a vicious cycle of low morale, complacency, and atrophy

Lesedi AI uses Machine Learning & Profiling

Turn *Policy* into *Implementation*

Automates data analytics, M&E, and program intelligence, co-piloting with healthcare workers

Empowers healthcare workers with relevant, actionable recommendations and quality improvement plans (QIPs)

Lesedi AI: Example Connecting the Cs

Community

Lesedi AI identifies the Athlone subdistrict as having lower testing rates and higher positivity rates than the provincial average.

Lesedi AI Action:

Allocates QIP task to the district manager to transfer 5,000 test kits from Lansdown (adjacent subdistrict) to Hanover Park.

Clinic

Lesedi AI flags that Hanover Park Day Hospital and CHC are only testing 20% of pregnant women, well below the neighbouring clinics

Lesedi AI Action:

Generate a personalised WhatsApp messages for the Hanover Park ANC nurses and midwives to inform them that additional test kits will be arriving and that staff need to be trained how to use them.

Client

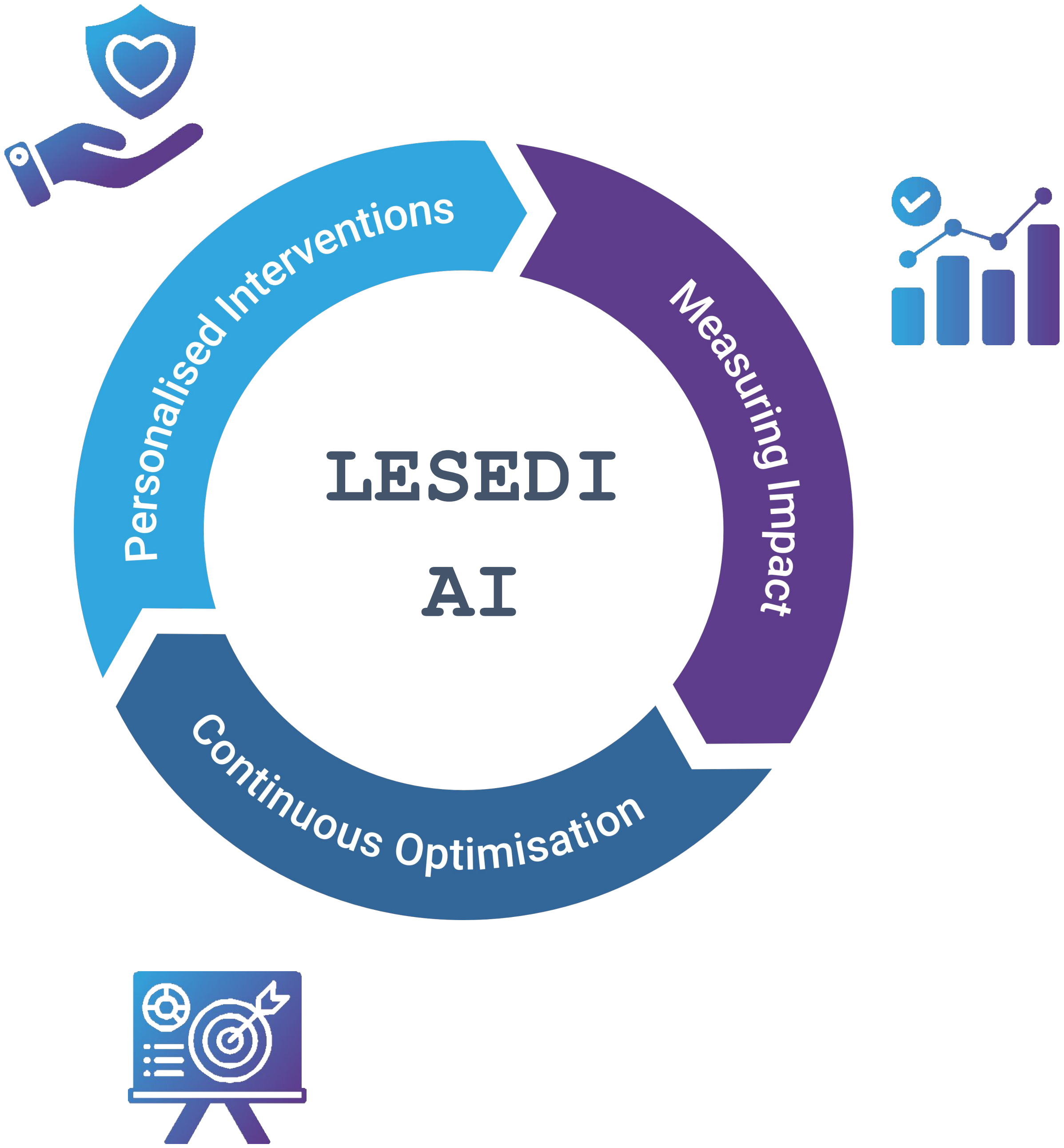
Lesedi AI recognises that Lethabo is attending an ANC visit at Hanover Park CHC and has not previously been tested for HIV.

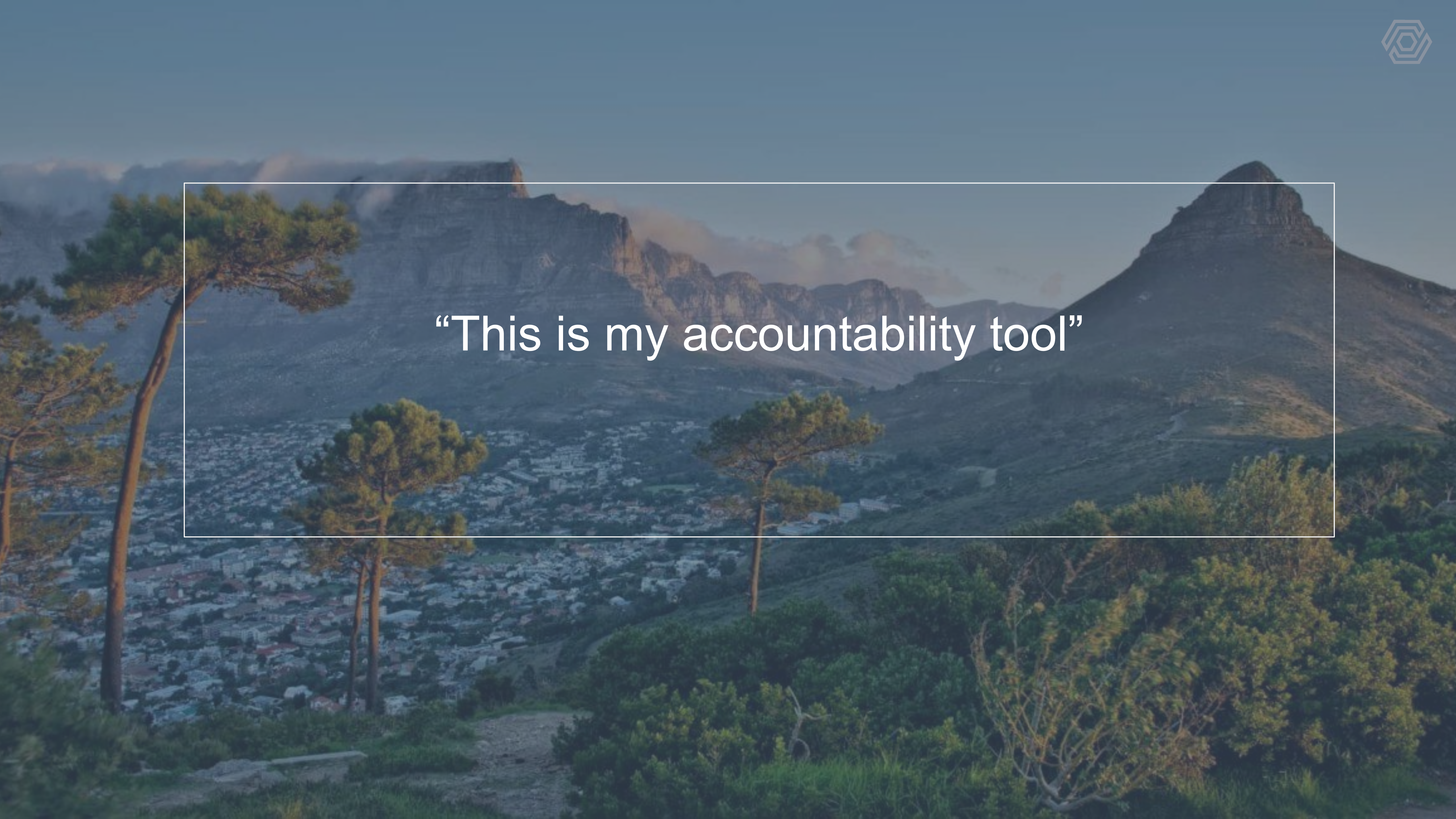
Lesedi AI Action:

Sends the receptionist, clinician, and case manager on the day to encourage/ensure Lethabo gets offered an HIV test during her appointment

IMPACT OUTCOMES THROUGH *CONTINUOUS IMPROVEMENT*.

The Lesedi AI ensures that every step in the journey reinforces the next, driving better outcomes for every individual.




“This is my accountability tool”

The Problem

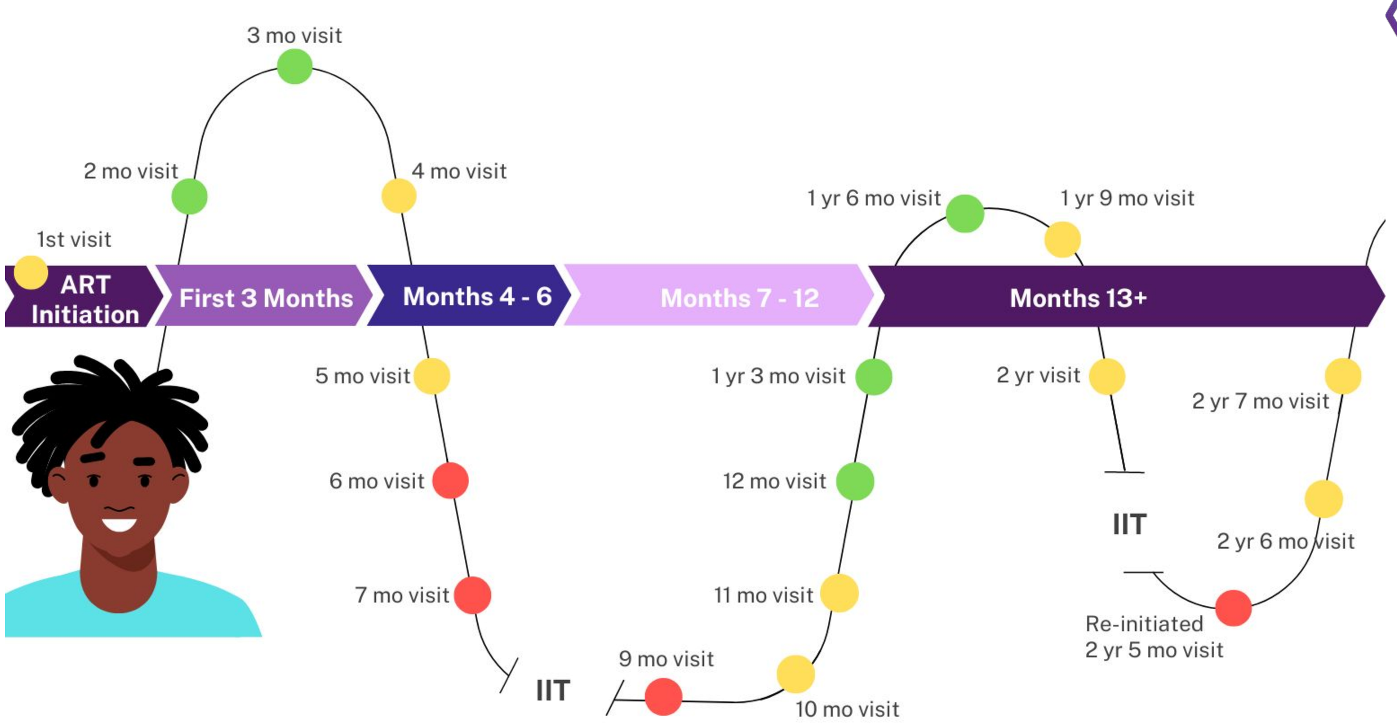
We're over-servicing most patients.
We're under-servicing 20%-30%.

Providers can't easily anticipate which group patients fall into and patients migrate between risk groups over time.

Providers haven't figured out how to systematically differentiate care

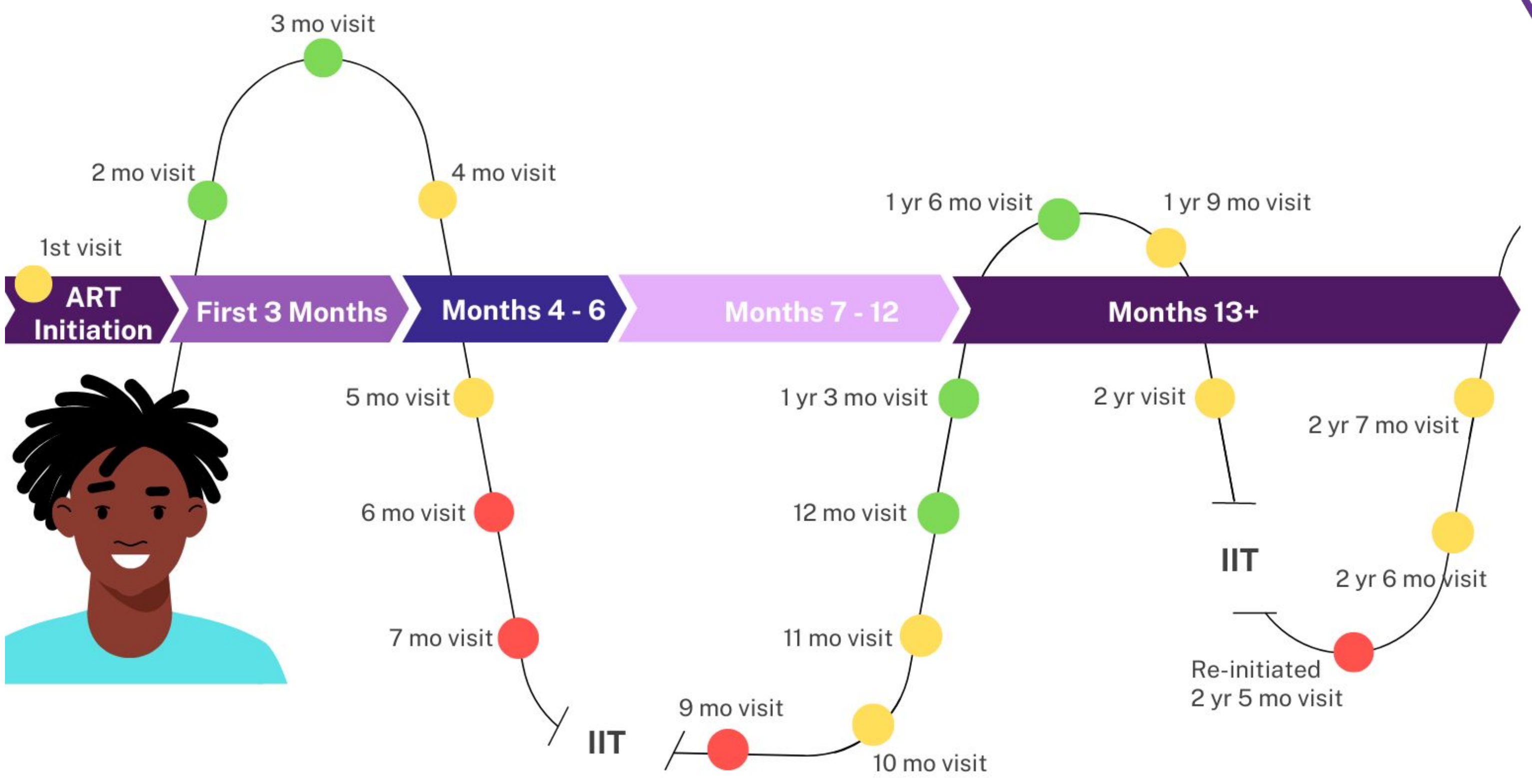
People have different challenges over time

25% of clients change risk group from one visit to the next which can double/half their risk of ITT



- Historic risk triaging over-leveraged static features like age, gender, key pops, etc.
- Our recommendations were **personalised**, **actionable**, and **easy to follow** for **inexperienced**, **novice** counselors
- Clear systematic recommendations reduced how overwhelmed case managers felt about
  - **who** of their 300-500 clients
  - **what** interventions to prescribe (~25 possibilities)
  - **when** they needed to make changes!

People have different challenges over time



IIT Risk typically halves/doubles as patients migrates between groups

IIT Rates by Risk Group		
Low	**Medium**	**High**
7.5%	18.0%	34.4%

Our **Risk Scoring** and **Patient Profiling** guide *how* to best deliver ***timely personalised experiences***

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Case Study: Nigeria

Executive Summary

Our Study In Nigeria Across 49 Facilities Consisted Of Three Groups

1. *Control*: SoC Case Management App with no patient risk scores
2. *Intervention*: Case Management App with patient risk scores; later versions had suggested interventions based on risk scores
3. *Enrolled*: the case manager has viewed the patient risk page OR agreed/disagreed with the risk score OR assigned an intervention from the recommendations presented

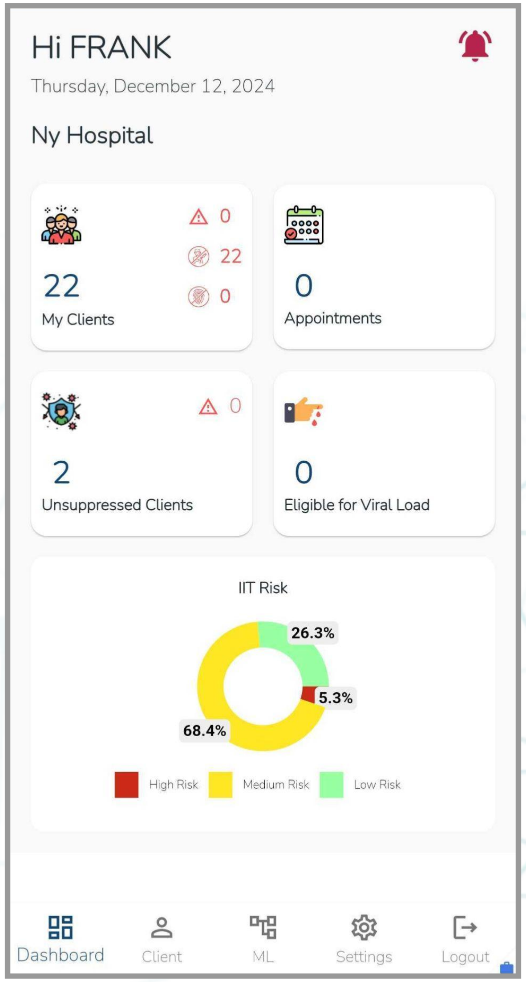
Reduction in ITT (Pre vs. During Study):

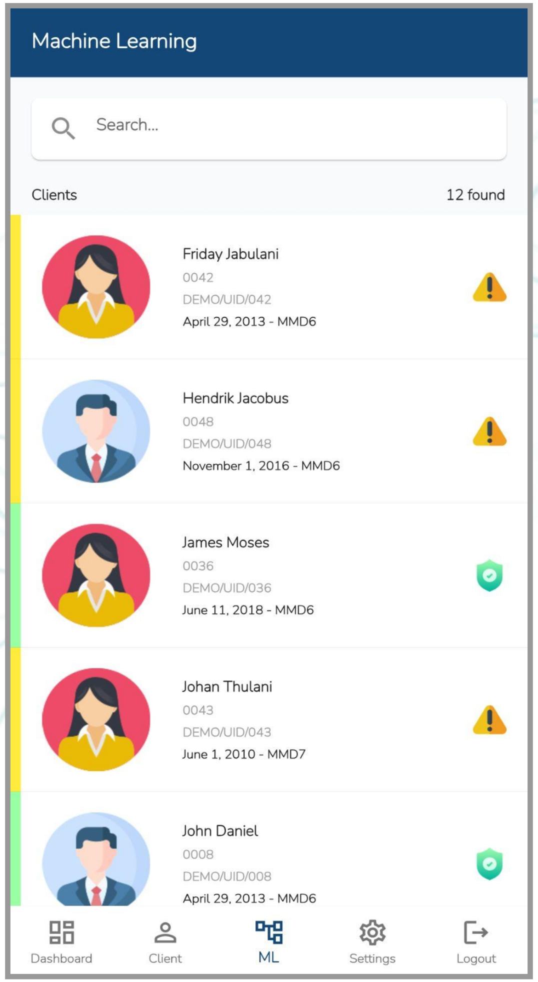
1. Control: 1.26%
2. Intervention: 2.72% (~2x better than control)
3. Enrolled: 5.05% (~4x better than control)

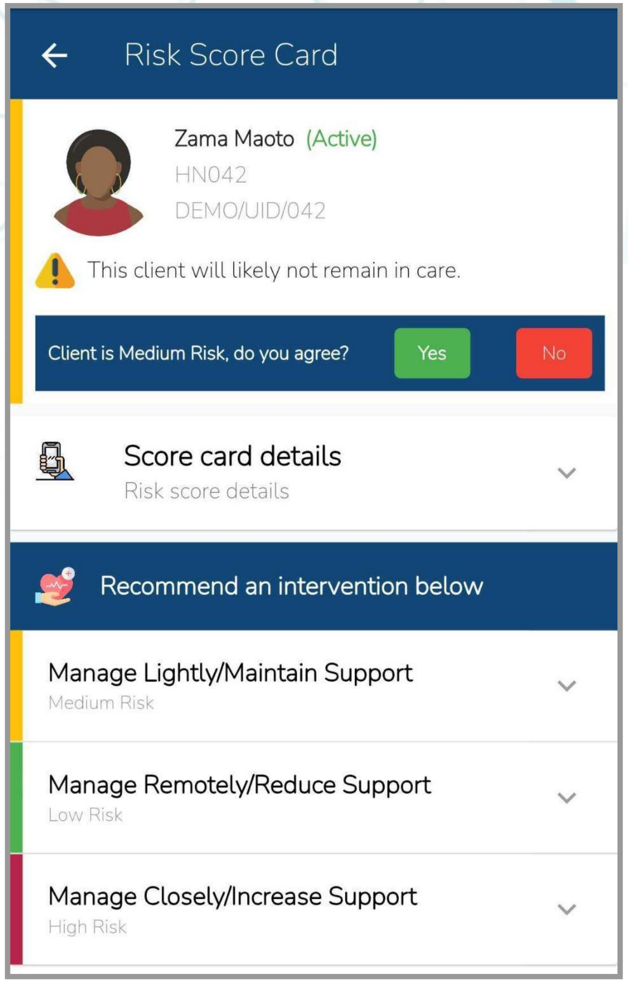
Why Our Approach Works: Dynamic Risk Scoring, Effective Change Management, and Behavioral Nudges

- Traditional demographics (age, gender, key pops, etc.) are static and do not consider the patients' behaviour and time-sensitive realities. Our risk scoring is dynamic and primarily leverages behaviour patterns and a wider range of factors.
- We offered guided nudges on which interventions specific patients should receive, which helped case managers differentiate their care and intervention assignments.
- Systematically scoring all patients allowed us to measure and visualise whether interventions were going to the right patients at the right time. By tracking and re-educating facility staff, we increased our influence and improved the quality of care.

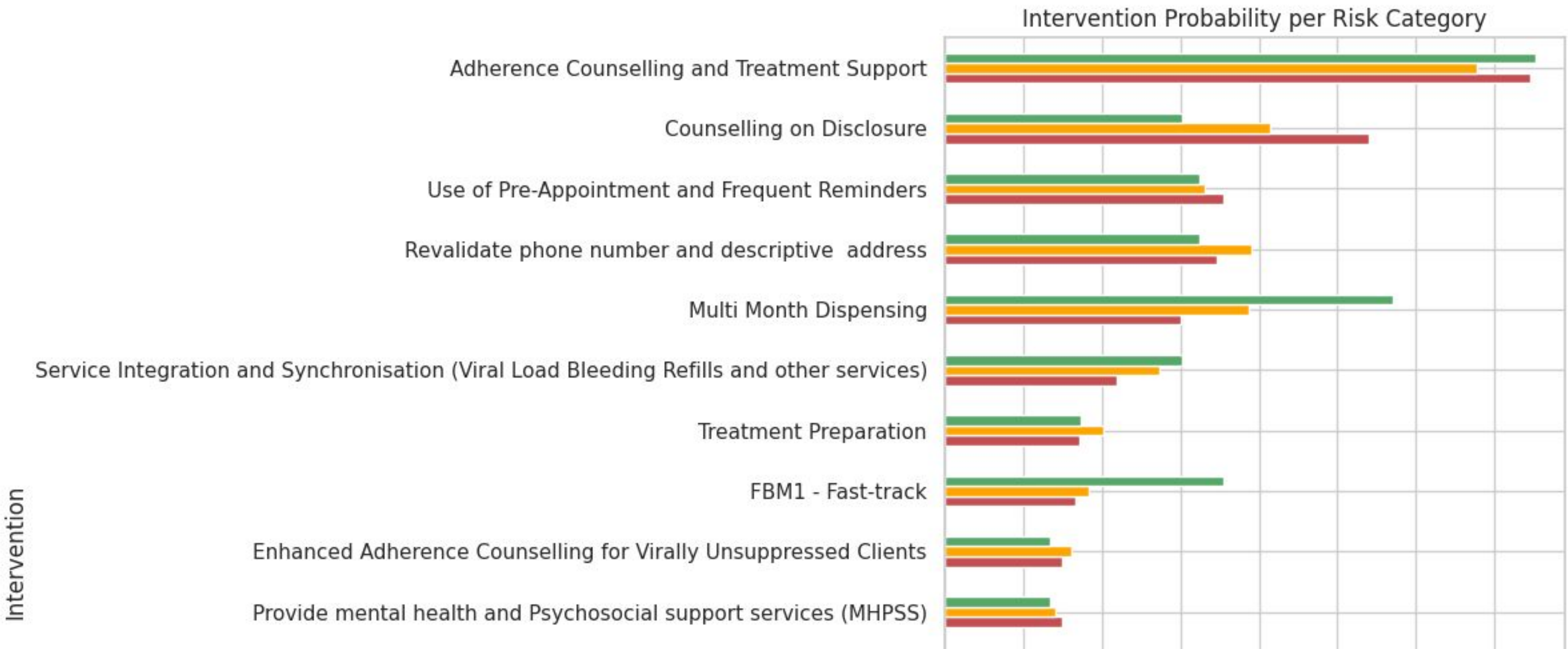
Equipping Case Managers with Patient Risk Information Improves Consultations and Lives





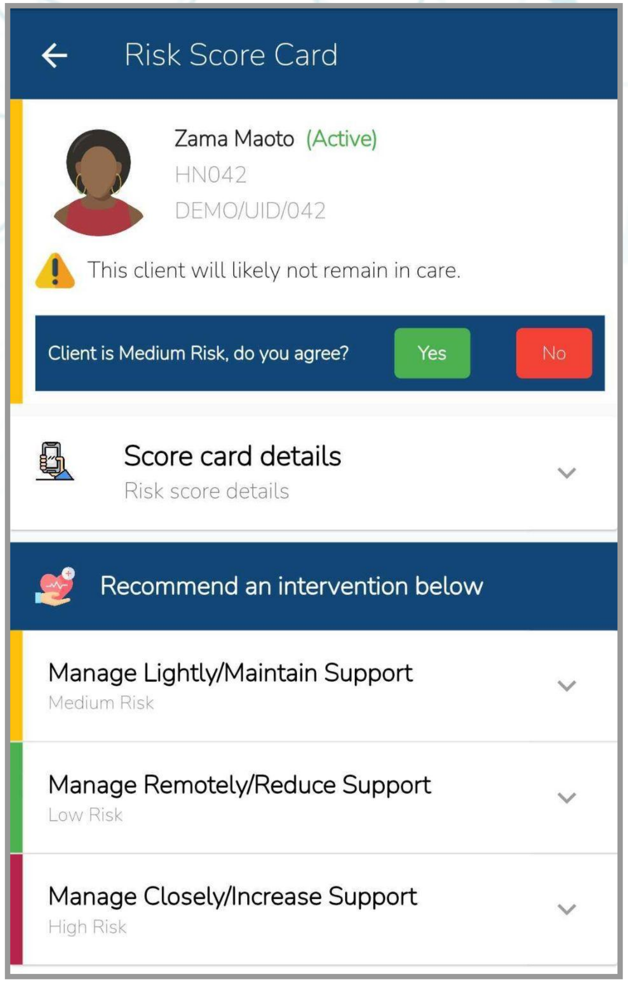


Originally, Most Interventions were Weakly Differentiated



Guided Nudges Helped Case Managers Differentiate their Care and Intervention Assignments

By offering **stronger guidance** and **suggested interventions** we saw a significant increase in **differentiated care!**

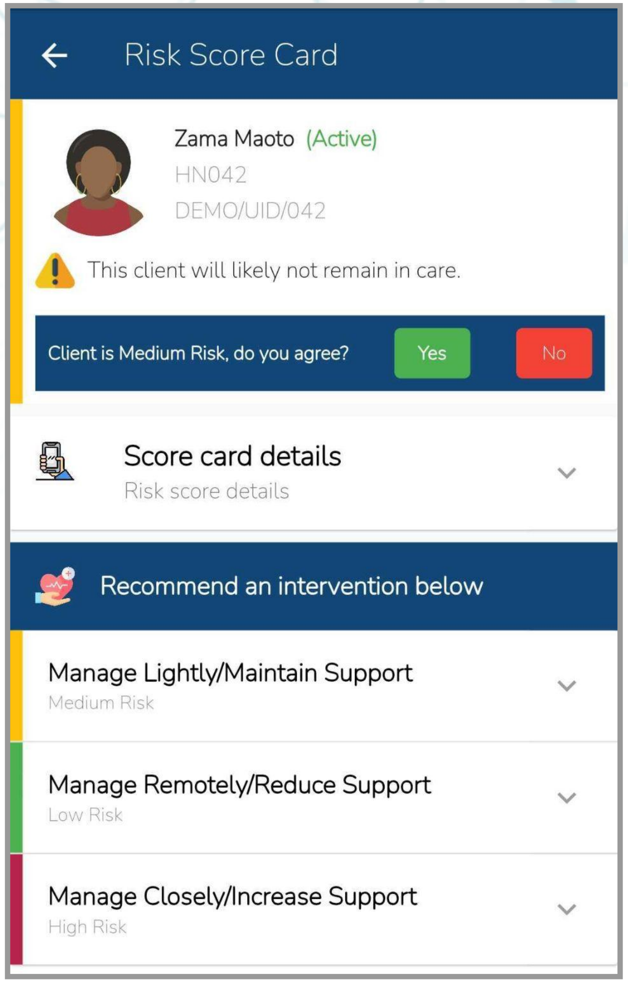


Nudges Helped Case Managers Differentiate their Care and Intervention Assignments

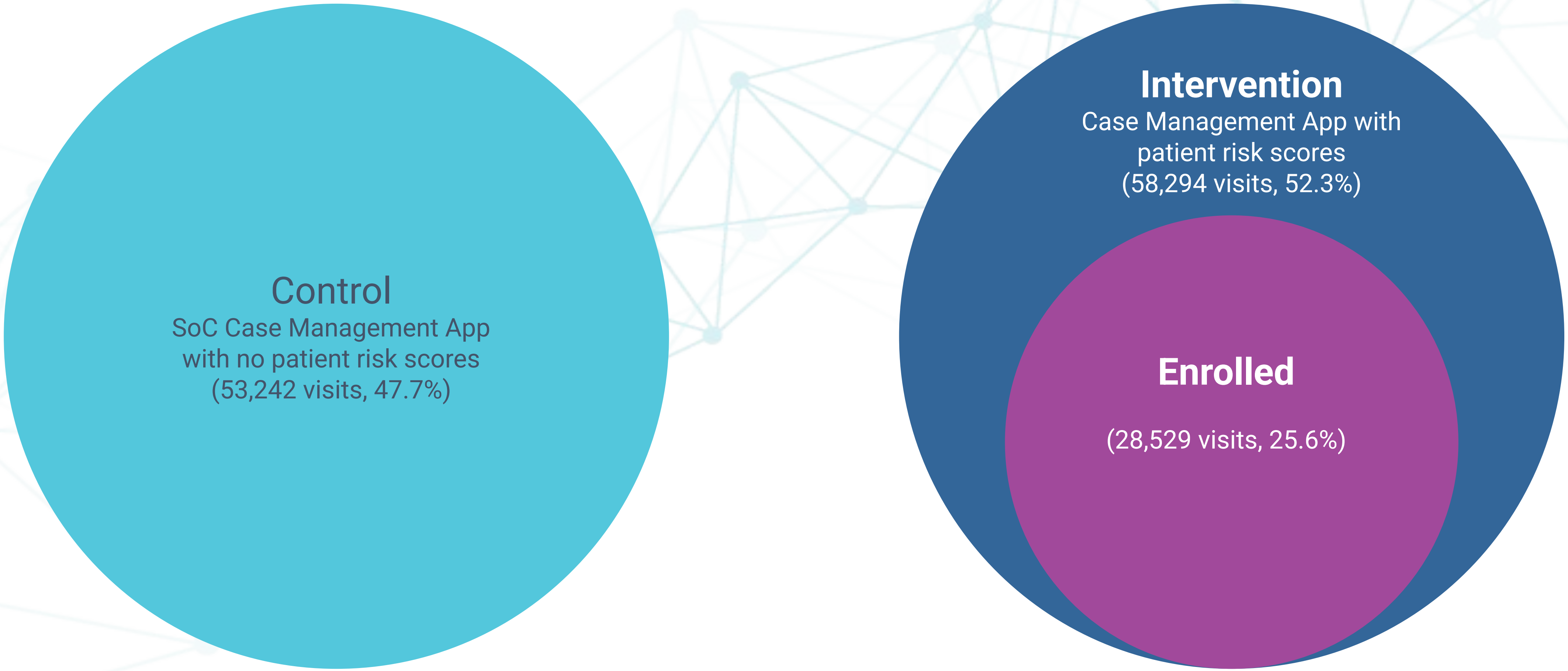
By offering stronger guidance and suggested interventions we saw an increase in differentiated care!

Behavioral Change Result

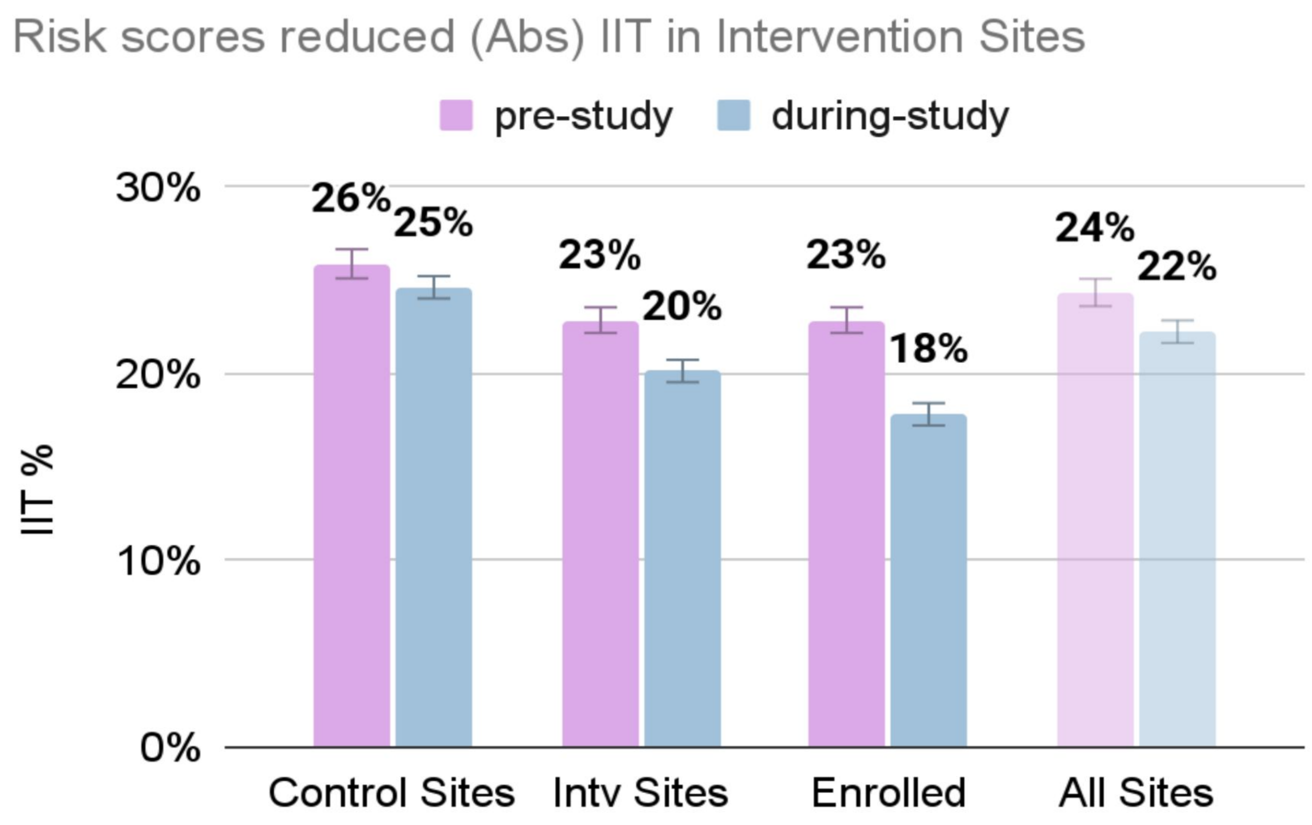
Case managers spent 76% more time on the list of high-risk patients on average than on the list of low-risk patients.



The Study had 19 Control Sites and 30 Intervention Sites with 104,065 visits



Risk Scoring Reduced IIT Fourfold for Enrolled Patients*



Note: Enrolled patient data represents (a) pre-study: all visits at intervention sites and (b) during study: only visits at intervention sites where the risk score was engaged with.

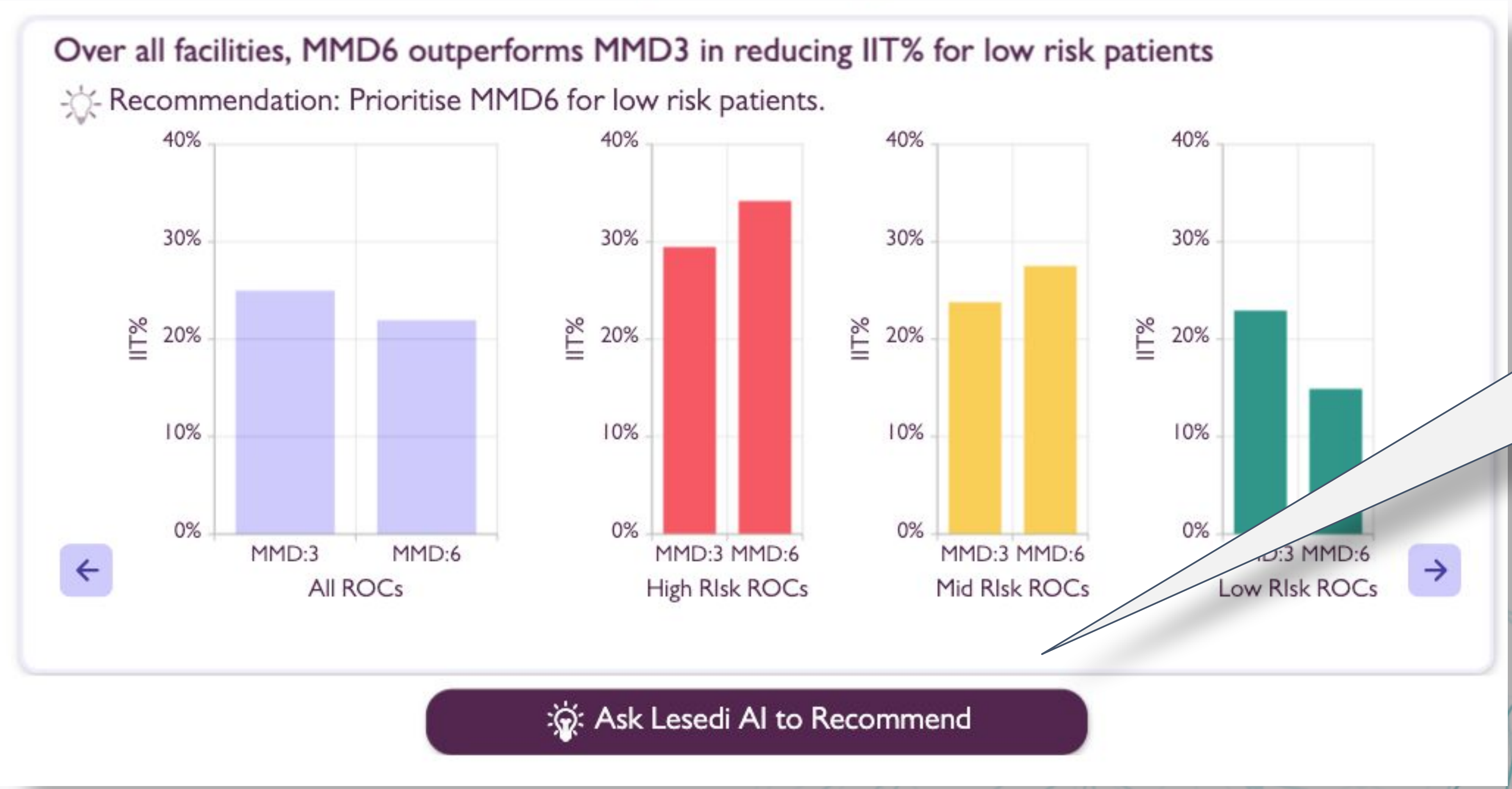
IIT Reduction by Client Group

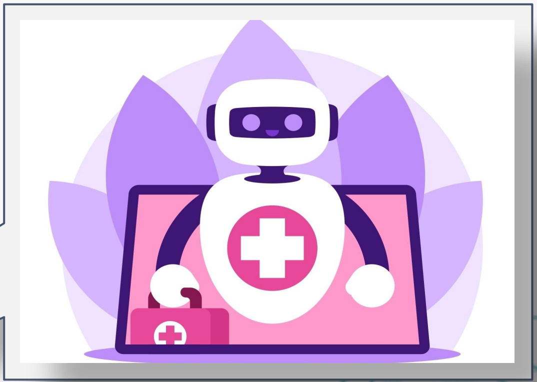
- Control: 1.26%
- Intervention: 2.72%
  - ~2x better than control
- Enrolled: 5.05%
  - ~4x better than control

*CM has ever

- viewed client risk page
- provided feedback on patient’s risk score
- recorded an intervention in the app for that patient

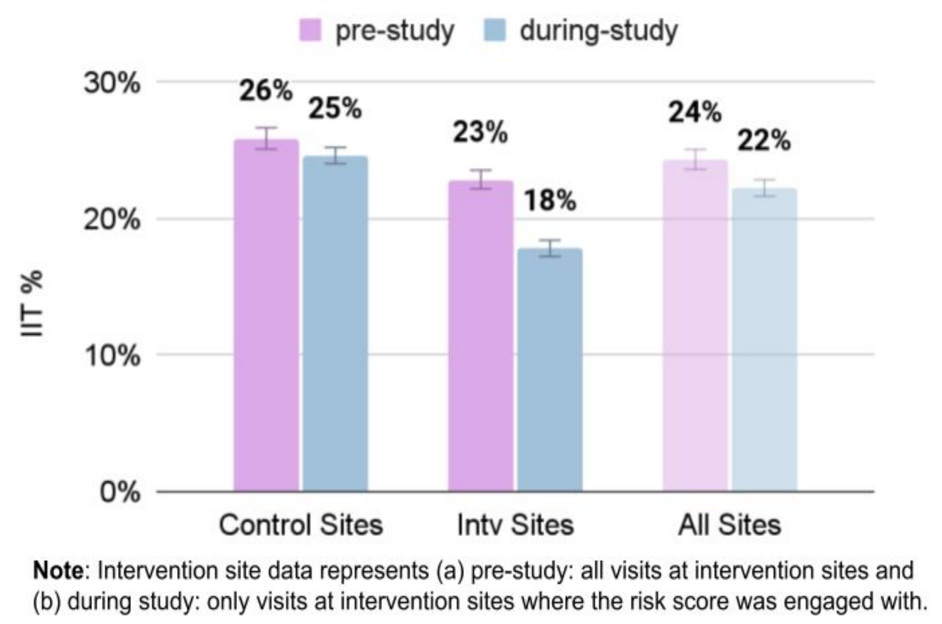
Lesedi AI Automating Insights and Program Recommendations





2. Impact of EMR Risk Model to improve Retention

The implementation of the EMR risk model has significantly enhanced patient care by identifying high-risk individuals and facilitating timely interventions, leading to improved health outcomes across targeted areas.



5%

Reduction in treatment interruptions

70%

More HCW time on High-risk cases

96%

AI Predictions win healthworker approval

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We use machine learning and predictive modeling to analyze HIV treatment, retention, and viral suppression patterns across Sub-Saharan Africa

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Article | Open access | Published: 26 July 2022

Applying machine learning and predictive modeling to retention and viral suppression in South African HIV treatment cohorts

Mhairi Maskew, Kieran Sharpey-Schafer, Lucien De Voux, Thomas Crompton, Jacob Bor, Marcus Rennick, Admire Chirowodza, Jacqui Miot, Seithati Molefi, Chuka Onaga, Pappie Majuba, Ian Sanne & Pedro Pisa

Scientific Reports 12, Article number: 12715 (2022) | Cite this article

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RESEARCH ARTICLE

Historical visit attendance as predictor of treatment interruption in South African HIV patients: Extension of a validated machine learning model

Rachel T. Esra, Jacques Carstens, Janne Estill, Ricky Stoch, Sue Le Roux, Tonderai Mabuto, Michael Eisenstein, Olivia Keiser, Mhari Maskew, Matthew P. Fox, Lucien De Voux, Kieran Sharpey-Schafer

Published: July 19, 2023 • https://doi.org/10.1371/journal.pgph.0002105

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Validation and Improvement of a Machine Learning Model to Predict Interruptions in Antiretroviral Treatment in South Africa

Esra, Rachel MPH, MSc[a,b]; Carstens, Jacques BSc[c]; Le Roux, Sue MA[d]; Mabuto, Tonderai PhD[d]; Eisenstein, Michael BSc[d]; Keiser, Olivia PhD[a]; Orel, Erol MSc[a]; Merzouki, Aziza PhD[a]; De Voux, Lucien MBA[c]; Maskew, Mhari PhD[e]; Sharpey-Schafer, Kieran MSc[c]

Author Information

JAIDS Journal of Acquired Immune Deficiency Syndromes 92(1):p 42-49, January 1, 2023. | DOI: 10.1097/QAI.0000000000003108

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Machine learning to predict retention and viral suppression in South African HIV treatment cohorts

M Maskew, K Sharpey-Schafer, L De Voux, J Bor, M Rennick, T Crompton, P Majuba, I Sanne, PT Pisa, J Miot

doi: https://doi.org/10.1101/2021.02.03.21251100

Now published in *Scientific Reports* doi: 10.1038/s41598-022-16062-0

Abstract | Full Text | Info/History | Metrics | Preview PDF

Our collaborators include Jhpiego, The Aurum Institute, Right to Care, ANOVA Health Institute, the Health Economics and Epidemiology Research Office (HE2RO), Wits University

How to deliver *personalised experiences*?

Systematically serve patients with
the **right interventions** at the **right time**

Impact Calculator

Mild Performing Facilities

Cost	Phase	Cost (USD)	Facilities	Patient Decisions	Outcomes Improved	Cost per Decision	Cost per Outcome Improved
Fixed	**Set Up**	$350,000	50	62,500	523	$5.60	$670
Variable	**Ongoing Maintenance cost per year**	$120,000	550	687,500	5,748	$0.17	$21

Poor Performing Facilities

Cost	Phase	Cost (USD)	Facilities	Patient Decisions	Outcomes Improved	Cost per Decision	Cost per Outcome Improved
Fixed	**Set Up**	$350,000	50	62,500	950	$5.60	$368
Variable	**Ongoing Maintenance cost per year**	$120,000	550	687,500	10,450	$0.17	$11

Impact Calculator

Mild Adherence

Cost	Phase	Cost (USD)	Facilities	Patient Decisions	Outcomes Improved	Cost per Decision	Cost per Outcome Improved
Fixed	Set Up & Scale	$350,000	500	1,250,000	10,450	$0.28	$33
Variable	Ongoing Maintenance cost per year	$120,000	500	6,250,000	52,250	$0.02	$2

Poor Adherence

Cost	Phase	Cost (USD)	Facilities	Patient Decisions	Outcomes Improved	Cost per Decision	Cost per Outcome Improved
Fixed	Set Up	$350,000	500	1,250,000	19,000	$0.28	$18
Variable	Ongoing Maintenance cost per year	$120,000	500	6,250,000	95,000	$0.02	$1

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Techniques and Tools

1. Bringing Data together

Community Data

Helps us understand the local context and major gaps (e.g., Census, DHS, PEPFAR)

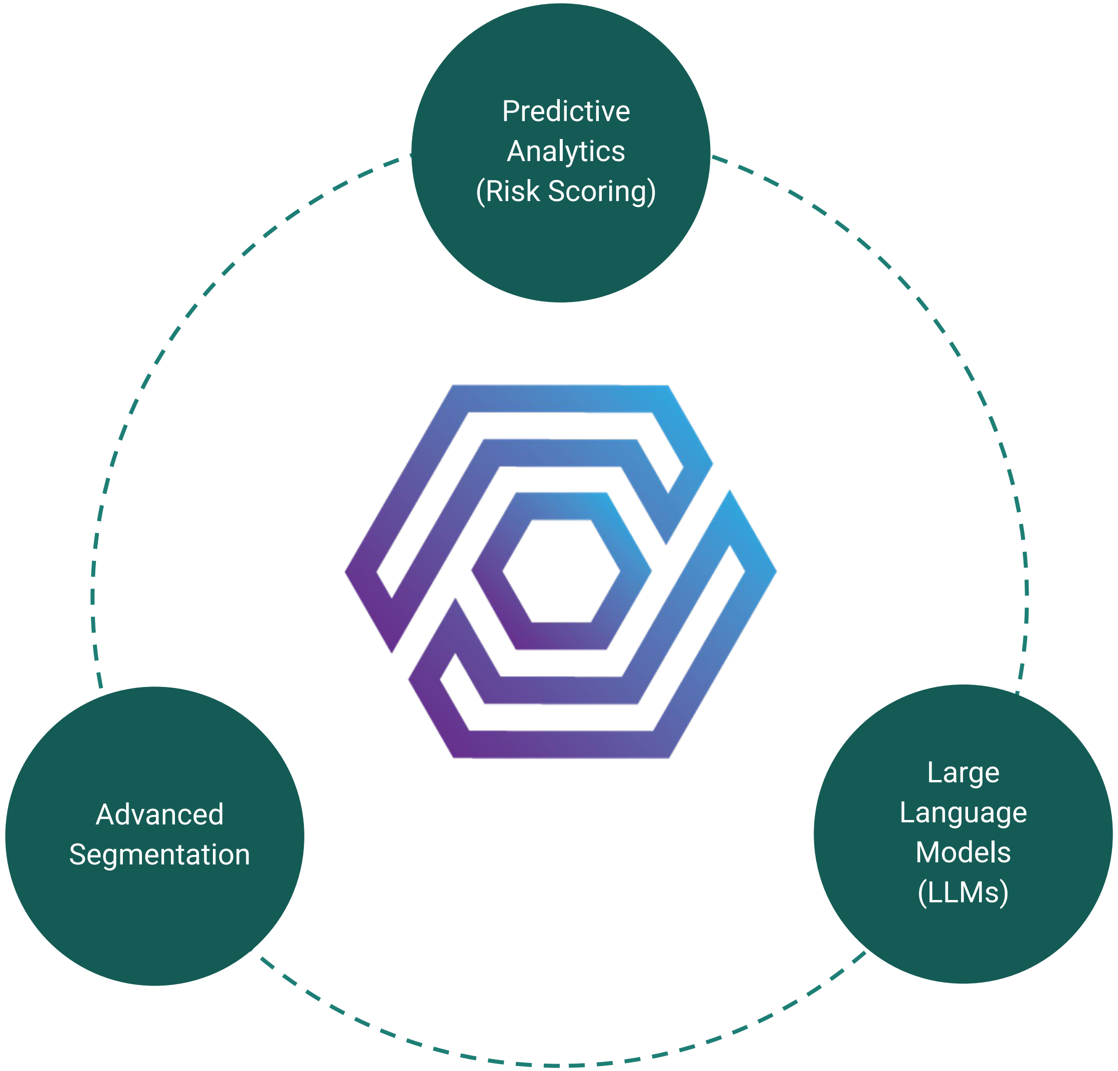
Aggregate Health Indicators

Health facility indicators help understand the throughput from the supply / demand locally. (e.g., DHIS2, Ideal Clinic)

Anonymised EMR Data: Tx, Rx and lab

Treatment-level data can show precise local challenges as well as behavioural patterns affecting outcomes. (e.g., Tier, CCMDD)

Primary Techniques
What we do and how we do it

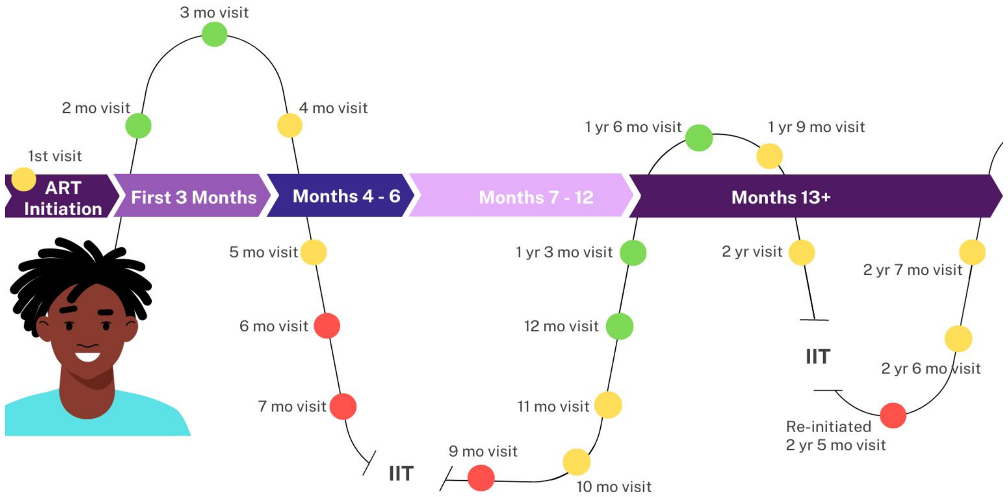


Primary Techniques
What we do and how we do it

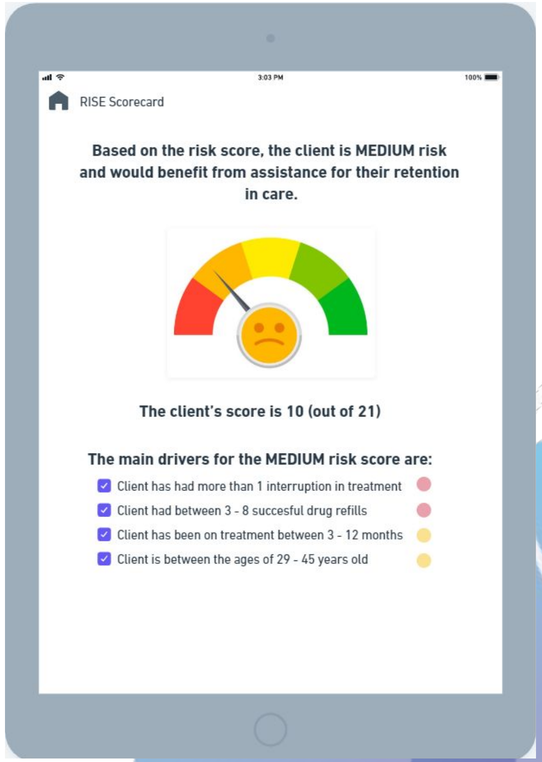
1. **Predictive Analytics (Risk Scoring)**

   Used to **anticipate behavior** and **adverse events** such as payment defaulting, illness, treatment disengagement or, death.

A change in state G → Y → R doubles risk!



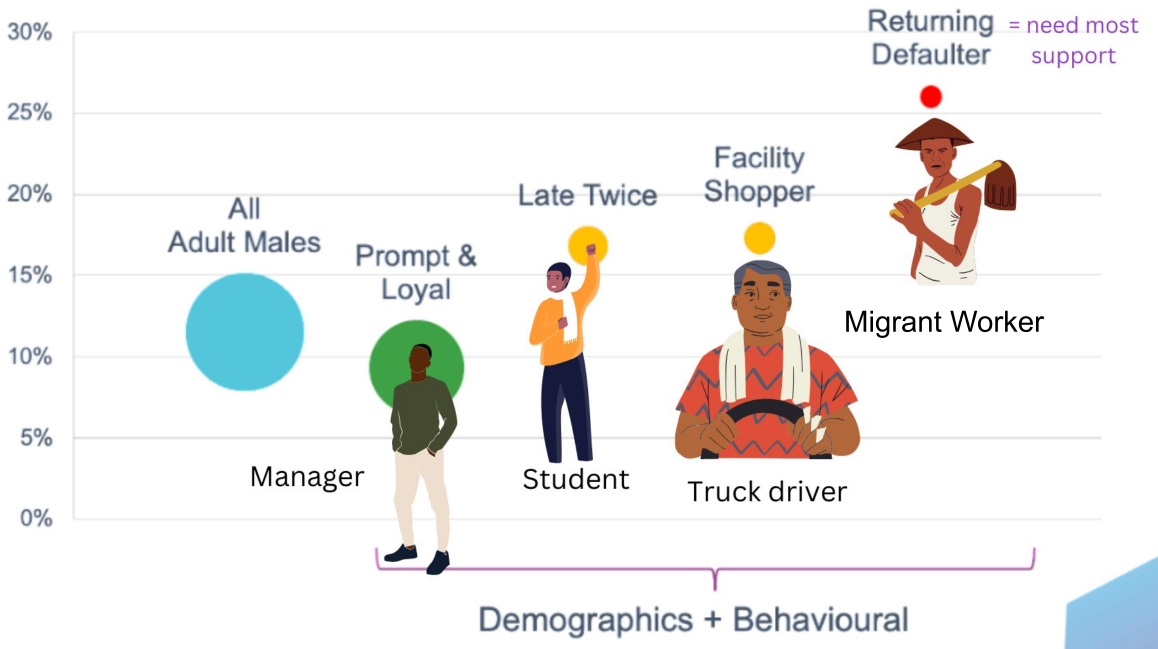
Current Risk Group		
G	Y	R
6.5%	18.0%	34.4%



Primary Techniques
What we do and how we do it

2. Advanced Segmentation

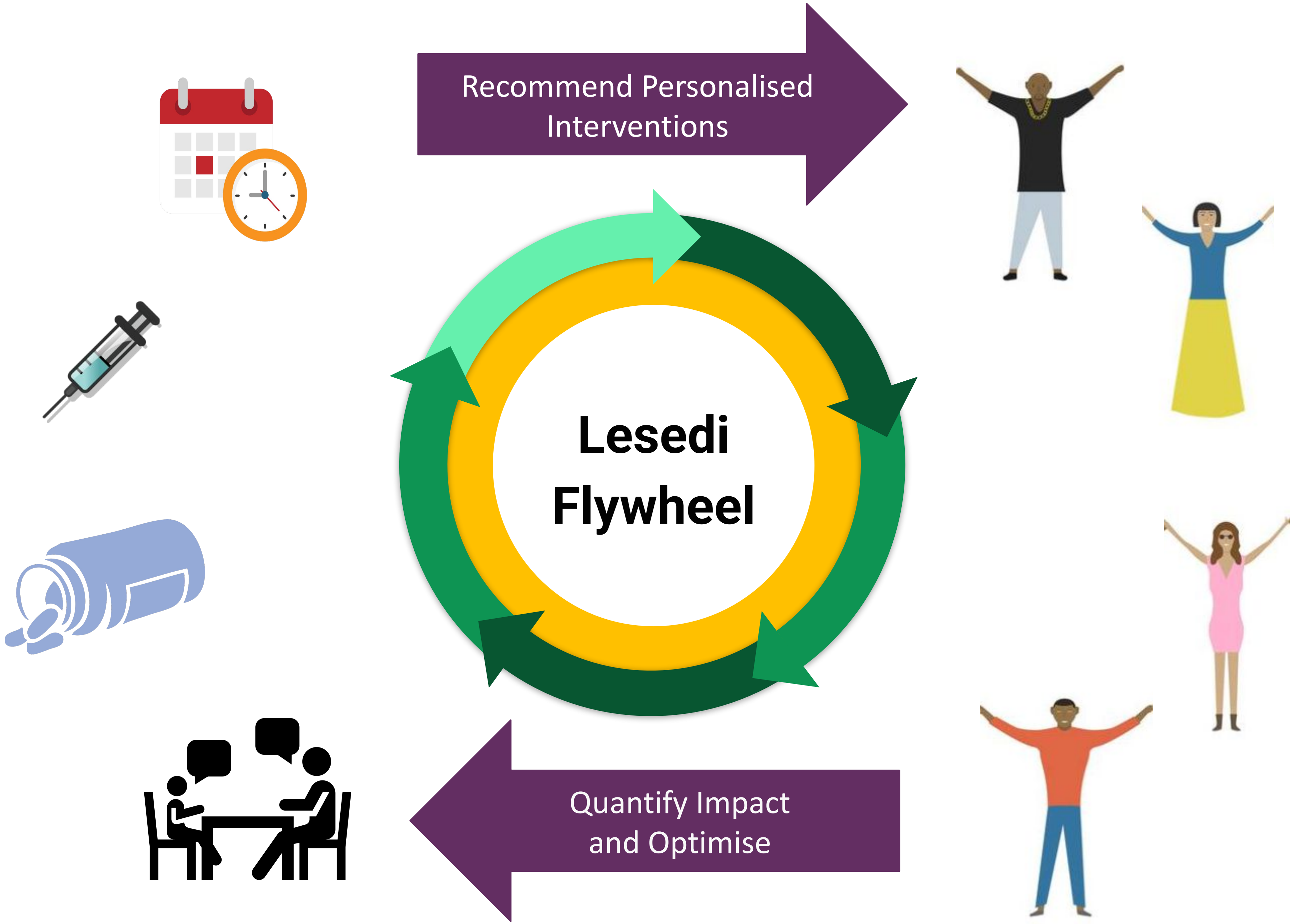
Used to conduct **look-alike-modelling** and **micro-profiling** to **influence outcome** or assign optimal **interventions for behavioral change**



Primary Techniques
What we do and How we do it

3. **Large Language Models (LLMs)**

   Custom built and **fine-tuned LLMs** for specific domains/use cases to deliver **actionable,context specific, humanized messaging** and query responses


Recommend Personalised Interventions
Lesedi Flywheel
Quantify Impact and Optimise

Measuring click-through rates for Targeted Online Ads

Maternity Pants
During Pregnancy

Maternity Pants
After Pregnancy

Measuring click-through rates for Targeted Online Ads

Maternity Pants
During Pregnancy

Diapers
After Pregnancy

The Three Challenges we are Addressing

1. Consultations are, reactive, untailored and inefficient.

2. The backoffice is… backed up and unorganized.

3. Resources and interventions are mobilized reactively, and are not systematically measured, and actioned.

Delivering at Three Levels

Facility Backoffice

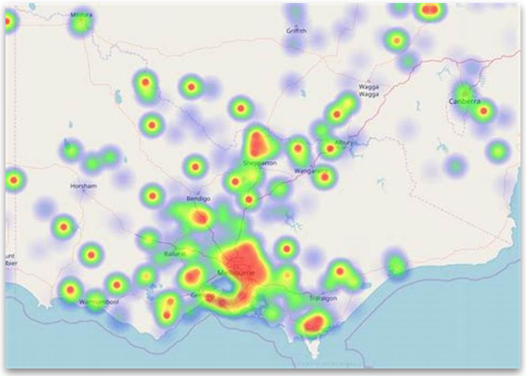
1

2

3

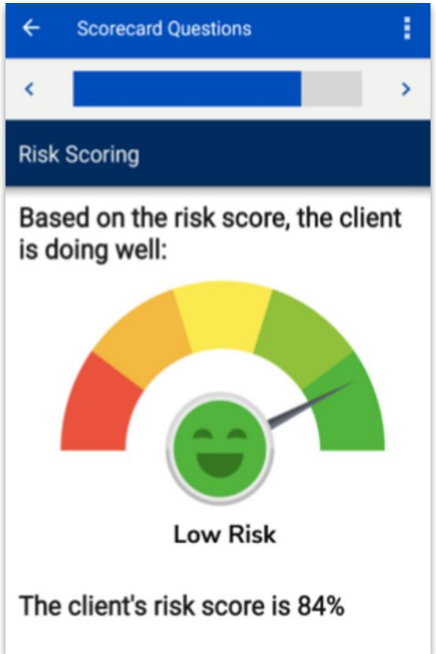
Point of Care

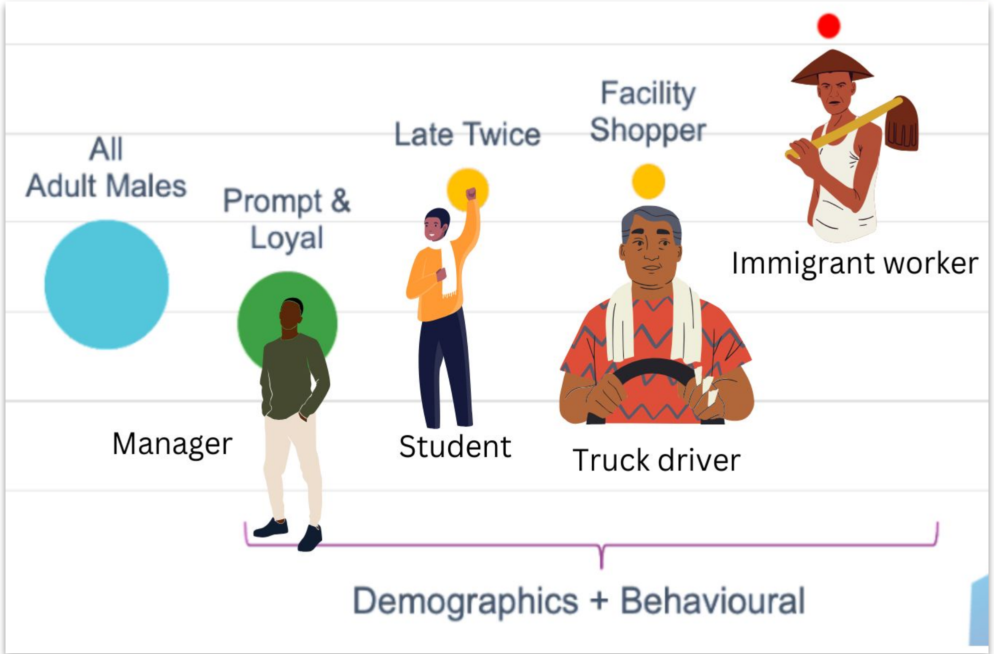
Program Management (Lesedi)



1. Consultations are untailored and are unnecessarily tedious for counsellors & the majority of patients

We embed risk scores, risk drivers and profiles into point-of-care tools*





*powered by machine learning trained on millions of EMR records to assess the stability of the patient

2. The backoffice is… backed up and unorganized

We enrich the backoffice data with actionable information

Patient appointment list (HIV)

Selected level: Athlone CHC
Date generated: 2023/07/27
Period: 2023/07/31 - 2023/08/04
Number of records: 98

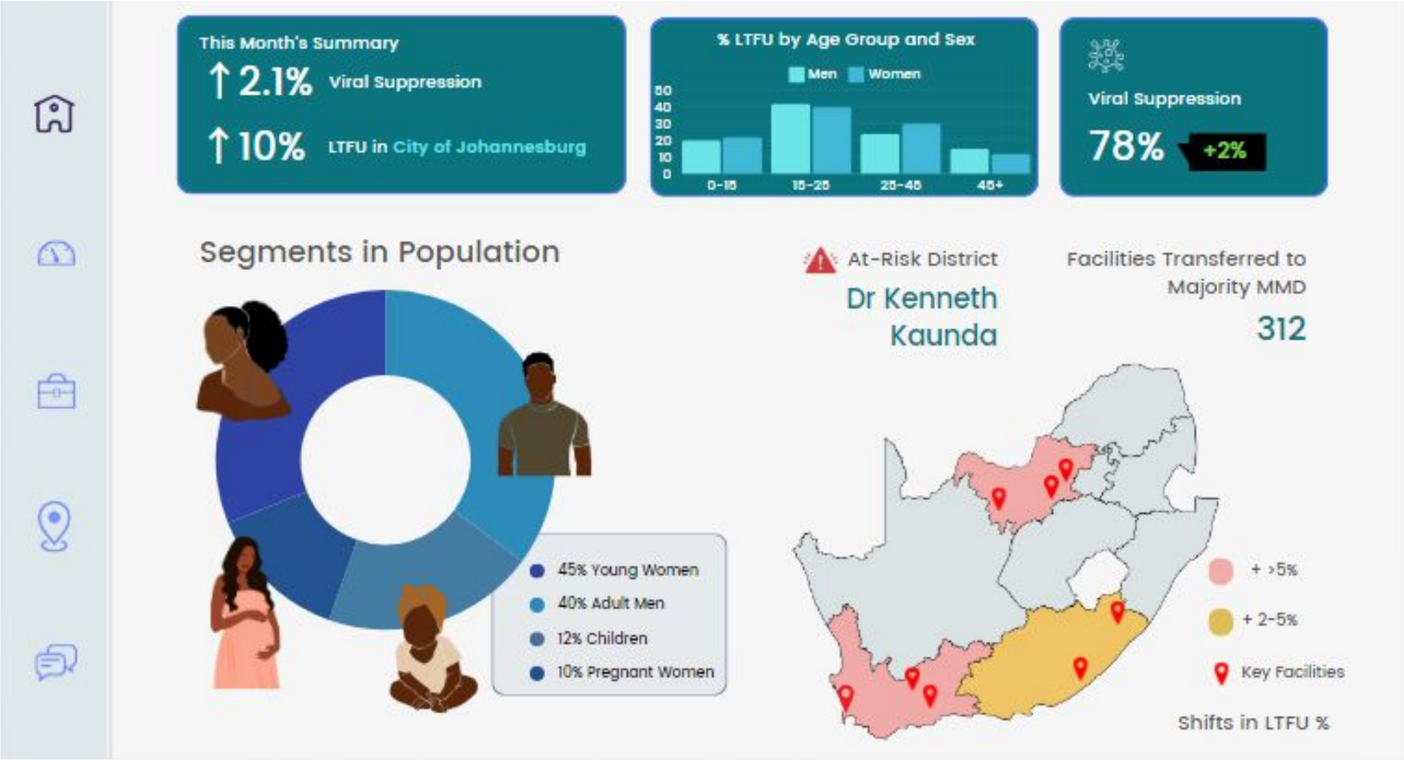
Appointment date	Last visit date	Duration on ART (months)	Last viral load count	Duration on TB	Test due
2023/07/31	2023/07/03	38,2	225	5	28/03/2024
2023/07/31	2023/06/05	58,3	72198	12	28/03/2025
2023/07/31	2023/05/09	129,1	49	10	28/03/2026
2023/07/31	2023/06/05	141,6	12182	20	28/03/2027
2023/07/31	2023/06/05	101,9	23	9	28/03/2028
2023/07/31	2023/07/18	12,6	19	22	28/03/2029
2023/07/31	2023/07/10	6,4	454	9	28/03/2030
2023/07/31	2023/05/15	74,3	19	16	28/03/2031
2023/08/01	2023/06/06	11,0	24	20	28/03/2032
2023/08/01	2023/06/06	186,3	19	14	28/03/2033
2023/08/01	2023/05/08	83,9	393	10	28/03/2034

Signed off by: ______________________
Designation: ______________________

Risk Score Category	Treatment success drivers
High	Appointment Date: Day of the month (31.00), Duration on ART (Months) (38.20), Last VL count (225.00)
High	Last VL count (72198.00), DMOC (nan), Appointment Date: Day of the week (0)
High	Appointment Date: Day of the week (0), DMOC (nan), Test due (nan)
High	Appointment Date: Day of the week (0), DMOC (nan), Test due (nan)
High	Appointment Date: Day of the week (0), DMOC (nan), Test due (nan)
Low	Duration on ART (Months) (12.60), Days since last visit (13.00), Appointment Date: Day of the month (31.00)
High	Appointment Date: Day of the month (31.00), Last VL count (454.00), Days since last visit (21.00)
High	Days since last visit (77.00), Appointment Date: Day of the week (0), DMOC (nan)
Low	Appointment Date: Day of the month (1.00), Test due (nan), Appointment Date: Day of the week (1)
Mid	Appointment Date: Day of the month (1.00), DMOC (nan), Test due (nan)
High	Appointment Date: Day of the month (1.00), DMOC (nan), Test due (Viral Load)

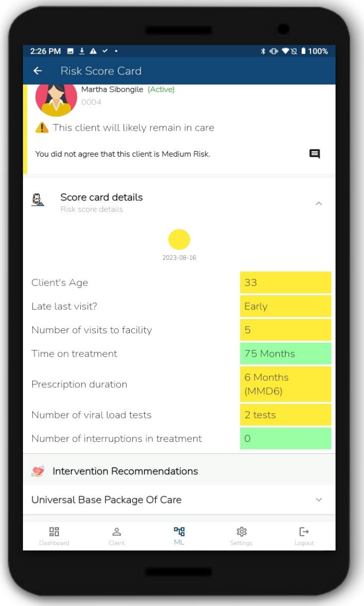
3. Resources and interventions are assigned reactively, and are not systematically tracked, optimised, and actioned

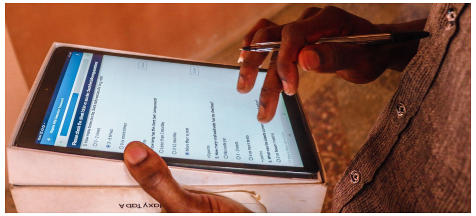
A *recommendation engine* that continually improves and realises the gains of interventions, data collection, and program design through AI



1. Clinic EMR Integration

30 facilities serving **52,000 patients** over two states to grow adoption and compare R-Y-G profiles across sites and interventions.





2. Backoffice Prioritization

15 high volume sites, serving **26,000 patients,** to adapt the technology South Africa's complex clinical settings.

Patient appointment list (HIV)

Selected level: [redacted]
Signed off by:
Date generated: 2023/07/27
Designation:
Period: 2023/07/31 - 2023/08/04
Number of records: 98

Folder number	Alternate number	Surname, Name	DMOC	Service point	Appointment date	Last visit date	Duration on ART	Last viral	Duration on TB	Test due	Risk Score Category	Treatment success drivers
999	999	John Doe			2023/07/31	2023/07/03	38,2	225			High	Appointment Date: Day of the month (31.00), Duration on ART (Months) (38.20), Last VL count (225.00)
999	1000	John Doe			2023/07/31	2023/06/05	58,3	72198			Low	Last VL count (72198.00), DMOC (nan), Appointment Date: Day of the week (0)
999	1001	John Doe			2023/07/31	2023/05/09	129,1	49			Low	Appointment Date: Day of the week (0), DMOC (nan), Test due (nan)
999	1002	John Doe			2023/07/31	2023/06/05	141,6	12182			Low	Appointment Date: Day of the week (0), DMOC (nan), Test due (nan)
999	1003	John Doe			2023/07/31	2023/06/05	101,9	23			High	Appointment Date: Day of the week (0), DMOC (nan), Test due (nan)
999	1004	John Doe			2023/07/31	2023/07/18	12,6	19			Low	Duration on ART (Months) (12.60), Days since last visit (13.00), Appointment Date: Day of the month (31.00)
999	1005	John Doe			2023/07/31	2023/07/10	6,4	454			High	Appointment Date: Day of the month (31.00), Last VL count (454.00), Days since last visit (21.00)
999	1006	John Doe			2023/07/31	2023/05/15	74,3	19			High	Days since last visit (77.00), Appointment Date: Day of the week (0), DMOC (nan)
999	1007	John Doe			2023/08/01	2023/06/06	11,0	24			Low	Appointment Date: Day of the month (1.00), Test due (nan), Appointment Date: Day of the week (1)
999	1008	John Doe			2023/08/01	2023/06/06	186,3	19			Mid	Appointment Date: Day of the month (1.00), DMOC (nan), Test due (nan)

Facility Level Automation:

Patients can be prioritised for intervention, ***before*** they arrive

Patient appointment list (HIV, TB)

Selected level: Mathibestad Clinic

Date generated: 15/05/2022

Period: 02/04/2022 - 09/042022

Number of records: 13

Signed off by: ____________________

Designation: ____________________

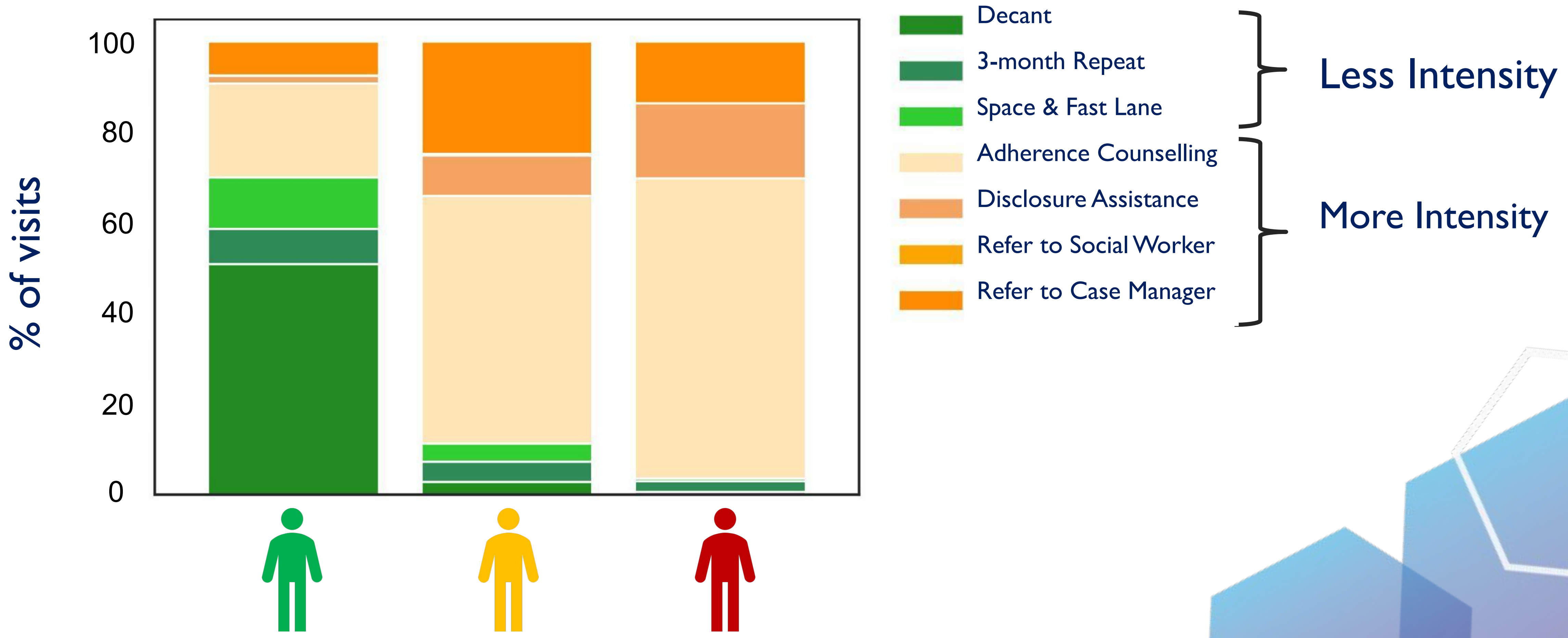
Top 10%

Folder number	Surname, Name	Gender	Age	DMOC	Appointment date	Last visit date	Duration on ART (months)	Last Viral load count	Test due	Risk Group	Risk Driver
File number	Wolf, Mira	Female	17	DMOC	02/04/2022	05/05/2022	Duration on ART	Last VL	Yes	High Risk	Young, missed appointments, first 3 months in care
File number	Wiley, Desirae	Female	24	DMOC	04/04/2022	07/05/2022	Duration on ART	Last VL	Yes	High Risk	Young, missed appointments, returning interrupter
File number	Dikeng, Mpho	Male	22	DMOC	03/04/2022	06/05/2022	Duration on ART	Last VL	No	Mid Risk	Young, first 3 months in care
File number	Hodge, Illiana	Female	14	DMOC	02/04/2022	05/05/2022	Duration on ART	Last VL	Yes	Mid Risk	Young, 1 missed appointment
File number	Ortega, Chase	Male	35	DMOC	04/04/2022	07/05/2022	Duration on ART	Last VL	No	Mid Risk	Missed appointments
File number	Mcdaniel, Tara	Female	42	DMOC	02/04/2022	05/05/2022	Duration on ART	Last VL	Yes	Mid Risk	Missed appointments
File number	Nhlapho, Sizwe	Male	28	DMOC	04/04/2022	07/05/2022	Duration on ART	Last VL	No	Mid Risk	Mid-range VL, first 3 months in care
File number	Jarvis, Leandra	Female	33	DMOC	03/04/2022	06/05/2022	Duration on ART	Last VL	No	Low Risk	Mid-age, prompt & loyal
File number	Monrie, Nyssa	Female	22	DMOC	02/04/2022	04/05/2022	Duration on ART	Last VL	No	Low Risk	Undetectable VL, 6+ months in care
File number	Lott, Clarke	Male	55	DMOC	03/04/2022	06/05/2022	Duration on ART	Last VL	No	Low Risk	Older, 6+ months in care
File number	Andrews, Jeremy	Male	37	DMOC	02/04/2022	05/05/2022	Duration on ART	Last VL	Yes	Low Risk	Mid-age, prompt & loyal
File number	Moss, Johan	Male	40	DMOC	02/04/2022	04/05/2022	Duration on ART	Last VL	No	Low Risk	Mid-age, undetectable VL
File number	Ndlovu, Thandi	Female	31	DMOC	04/04/2022	07/05/2022	Duration on ART	Last VL	No	Low Risk	Mid-age, prompt & loyal

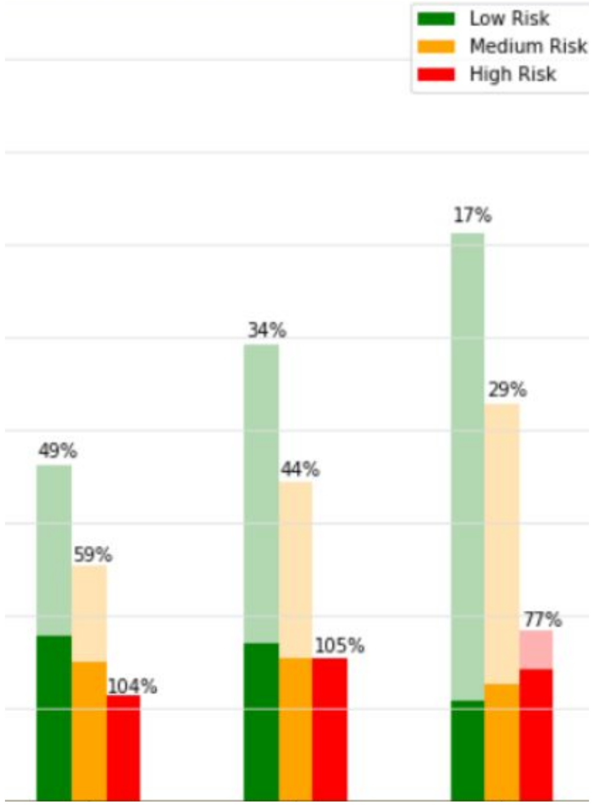
PALINDROME
DATA

Measurable Behavioral Change

Providers Differentiated Care by Risk Profile



High-Risk Patient Files Prioritised when Picked and Filed



Designing for the average patient will result in average results

Contact Us

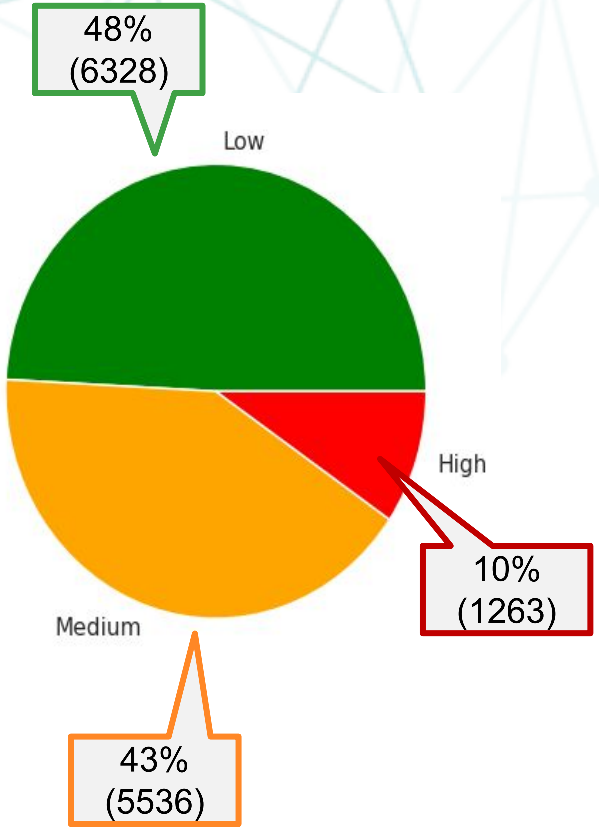
info@palindrome.org.za

linkedin.com/company/palindromedata

Old Results

The risk score was able to effectively predict risk and segment patients

	Outcome N	IIT N	IIT Rate	Increase in Risk*
Low Risk	6,328	1,083	17.11%	-
Medium Risk	5,536	1,520	27.46%	**60.43%**
High Risk	1,263	391	30.96%	**80.89%**
Med & High Risk	6,799	1,911	28.11%	**64.23%**

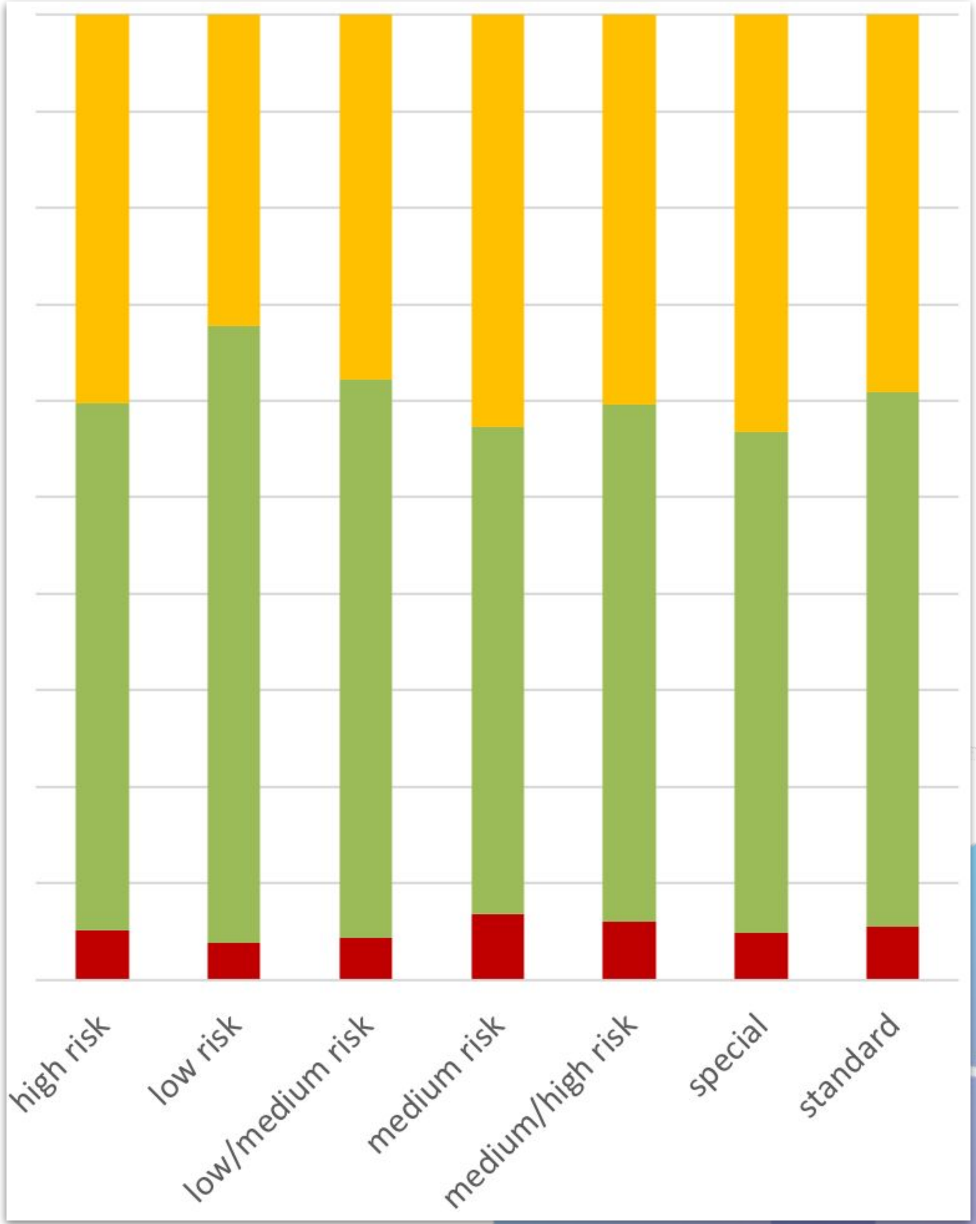


***Compared to low-risk**

Differentiation of Care

1. Low-risk Intervention → Low-risk Individual: Strong

2. High-risk Intervention → High-risk Individual: Weak

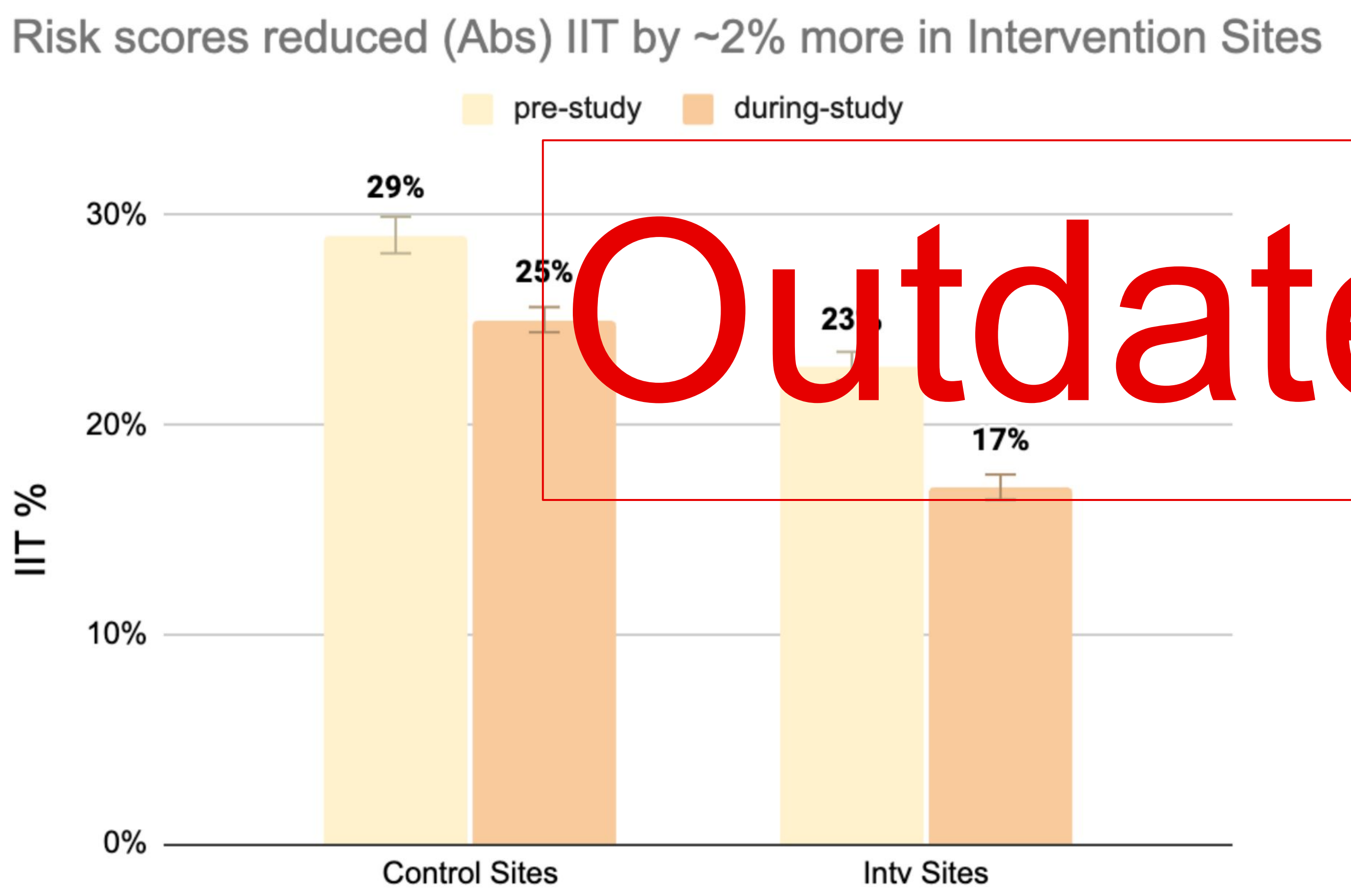


Differentiation of Care

1. Most interventions are weakly differentiated

2. Strong
   a. MMD, Fast Track → Low-risk
   b. Nutrition, Social Services, GBV, Support Group → Med-risk
   c. Disclosure, After Hours → High-risk

When the Risk Scores are Used, Outcomes Improve



Note: Intervention site data represents (a) all visits at intervention sites pre-study and (b) only visits at intervention sites during study where the risk score was engaged with.

Outdated

IIT Reduction by Arm*

- Control: 4%
- Intervention Engagement: 6%

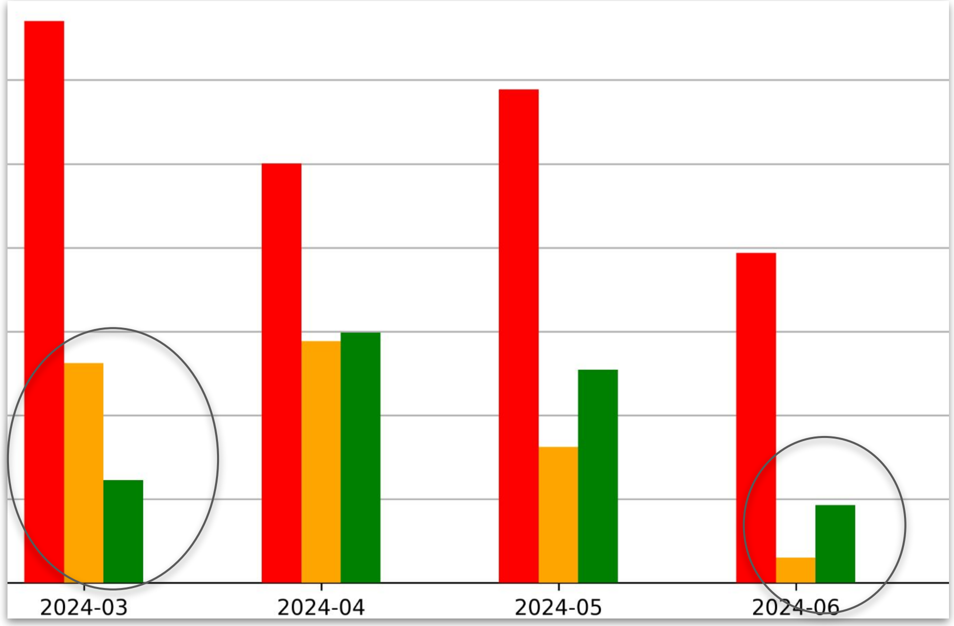
***Difference-in-Difference**

-1.7% ± 0.3%

The Support Planner has assisted in aiding healthcare professionals start to assign intensive interventions, such as case management, to mostly high risk clients

1 Case Management

Strong differentiation across risk profiles



March 2024: High risk patients have always been assigned case management. Medium and low risk patients are also

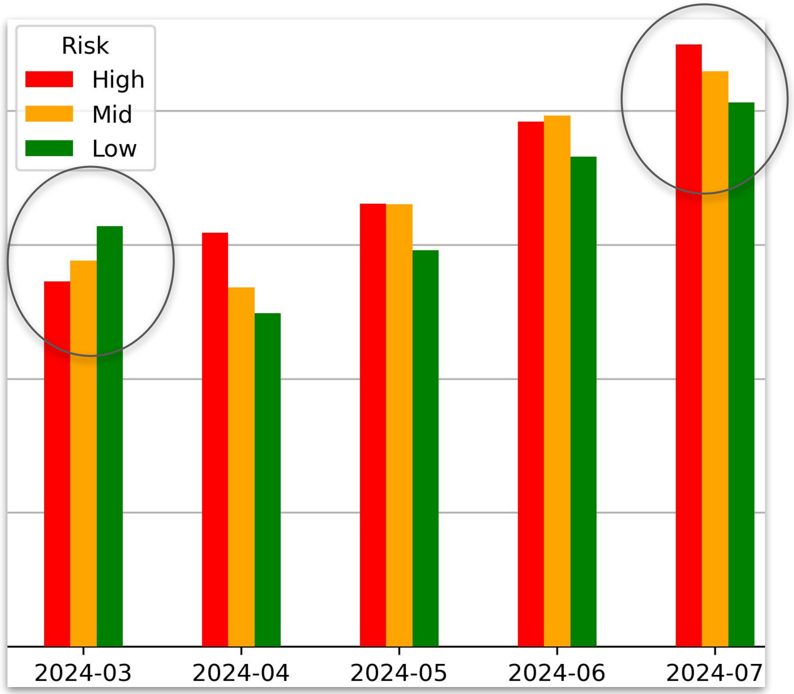
Extensive and frequent in-field user training

June 2024: Case management is starting to be assigned to mostly high risk patients

The Support Planner is enabling healthcare staff to prioritise patients according to their risk of LTFU. This behaviour is improving.

2 **Folder Picking**

Increasing differentiation across risk profiles



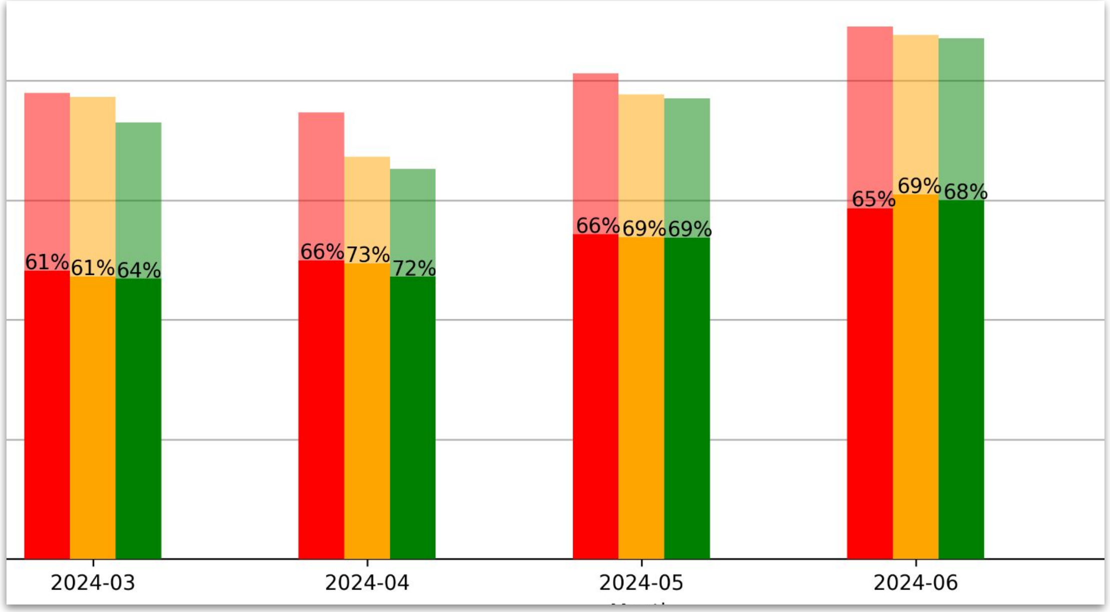
<u>March 2024:</u> Low risk patients were being prioritized over high risk patients

Extensive and frequent in-field user training

<u>July 2024:</u> Improvement in differentiation as high risk patients are being prioritized over low risk patients

We are still seeing persistently weak differentiation of telephonic reminders across risk profiles

3 **Telephonic Reminders** — **Weak differentiation across risk profiles**



<u>March - June 2024:</u> Little to no differentiation for telephonic reminders across the risk profiles

💡Telephonic reminders is an easy and quick intervention in resource-constrained facilities. It can be effective *given* the risk profile

MG Impact

risk_category	Count			Percentage of the intervention (Likelihood of assigning to X risk given intervention)			Percentage of risk group (Likelihood of assigning X given X risk)		
	High Risk	Low Risk	Medium Risk	High Risk	Low Risk	Medium Risk	High Risk	Low Risk	Medium Risk
service									
Adherence Counselling and Treatment Support	651	6344	4453	5.7	55.4	38.9	16.0	14.9	15.2
CBM1 - Community pharmacy ART refill	30	190	176	7.6	48.0	44.4	0.7	0.4	0.6
CBM2 - Community ART Refill Group: Healthcare Worker led	9	110	69	4.8	58.5	36.7	0.2	0.3	0.2
CBM3 - Community ART Refill Group: PLHIV led	6	29	30	9.2	44.6	46.2	0.1	0.1	0.1
CBM4 - Adolescent Community ART/ peer-led groups	1	20	24	2.2	44.4	53.3	0.0	0.0	0.1
CBM5 - Home delivery	16	224	124	4.4	61.5	34.1	0.4	0.5	0.4
CBM6 - One Stop Shop	0	14	14	0.0	[illegible]	50.0	0.0	0.0	0.0
Counselling on Disclosure	415	3377	2589	6.5	52.9	40.6	10.2	7.9	8.9
Enhanced Adherence Counselling for Virally Unsuppressed Clients	189	1517	1205	6.5	52.1	41.4	4.6	3.6	4.1
FBM1 - Fast-track	106	2780	[illegible]	2.6	67.2	30.2	2.6	6.5	4.3
FBM2 - Facility ART group: HCW led	98	880	[illegible]	5.8	52.5	41.7	2.4	2.1	2.4
FBM3 - Facility ART group: Support group led	50	170	168	12.9	43.8	43.3	1.2	0.4	0.6
FBM4 - Decentralization (Hub and Spoke)	[illegible]	24	15	11.4	54.5	34.1	0.1	0.1	0.1
FBM5 - After hours	32	[illegible]	113	9.3	58.0	32.8	0.8	0.5	0.4
FBM6 - Weekends and Public Holidays	4	20	21	8.9	44.4	46.7	0.1	0.0	0.1
FBM7 - Children/Teen/Adolescent Club (Peer managed)	11	19	39	15.9	27.5	56.5	0.3	0.0	0.1
FBM8 - Mother infant pair/Mentor mother led	4	16	16	11.1	44.4	44.4	0.1	0.0	0.1
Identification of Treatment Partners/Support Groups	224	2906	1823	4.5	58.7	36.8	5.5	6.8	6.2
Multi Month Dispensing	343	4475	2763	4.5	59.0	36.4	8.4	10.5	9.5
Provide mental health and Psychosocial support services (MHPSS)	137	1788	1118	4.5	58.8	36.7	3.4	4.2	3.8
Refer for Gender-based Violence Care	85	799	696	5.4	50.6	44.1	2.1	1.9	2.4
Refer for Nutrition Services	99	763	662	6.5	50.1	43.4	2.4	1.8	2.3
Refer for Social Services	90	743	654	6.1	50.0	44.0	2.2	1.7	2.2
Refer to OVC Partner	79	187	370	12.4	29.4	58.2	1.9	0.4	1.3
Revalidate phone number and descriptive address	395	4787	3075	4.8	58.0	37.2	9.7	11.2	10.5
Service Integration and Synchronisation (Viral Load Bleeding Refills and other services)	314	3790	2350	4.9	58.7	36.4	7.7	8.9	8.0
Treatment Preparation	236	2094	1716	5.8	51.8	42.4	5.8	4.9	5.9
Use of Pre-Appointment and Frequent Reminders	441	4384	2986	5.6	56.1	38.2	10.8	10.3	10.2

INCOMPLETE

A Unified Company Vision!

- Villgro has helped Palindrome develop a deep understanding of who we are and what we want to offer the world.
- They helped us create a coherent vision for the company, enabling us to tell our story clearly enough for broader and larger markets.
- The Villgro team has nurtured us to think bigger, providing customised support that directly fits where we are.

Evidence

Published

1. Nature Scientific Reports
   Applying machine learning and predictive modeling to retention and viral suppression in South African HIV treatment cohorts
   [https://doi.org/10.1038/s41598-022-16062-0]
2. JAIDS
   Validation and improvement of a machine learning model to predict interruptions in antiretroviral treatment in South Africa
   [https://doi.org/10.1097/qai.0000000000003108]
3. PLOS
   Historical visit attendance as predictor of treatment interruption in South African HIV patients: Relating linear risk factors to a validated machine learning model
   [https://doi.org/10.1371/journal.pgph.0002105]

www.nature.com/scientificreports

scientific reports

Check for updates

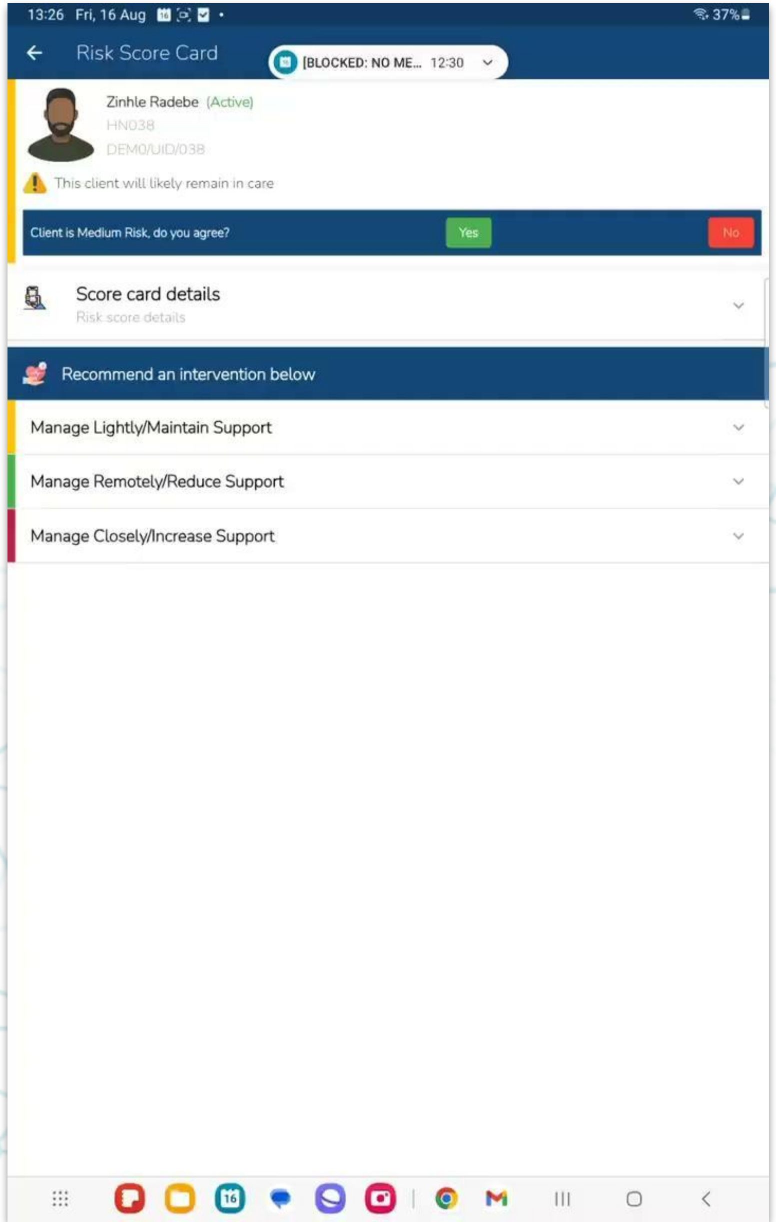
OPEN **Applying machine learning and predictive modeling to retention and viral suppression in South African HIV treatment cohorts**

Mhairi Maskew[1✉], Kieran Sharpey-Schafer[2], Lucien De Voux[2], Thomas Crompton[3], Jacob Bor[1,4,5], Marcus Rennick[3], Admire Chirowodza[3], Jacqui Miot[1], Seithati Molefi[3], Chuka Onaga[3], Pappie Majuba[3], Ian Sanne[1,3] & Pedro Pisa[3,6]

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

Esra R[1,2§], Carstens J[3], Le Roux S[4], Mabuto T[4], Eisenstein M[4], Keiser O[1], Orel E[1], Merzouki A[1], De Voux L[3], Maskew M[5], Sharpey-Schafer K[3]

1 University of Geneva, Institute of Global Health, Chemin des Mines 9, 1202 Genève, Switzerland
2 Imperial College of London
3 Palindrome Data, Cape Town, South Africa
4 The Aurum Institute. 29 Queens Road, Parktown, Johannesburg, South Africa.
5 Health Economics and Epidemiology Research Office, Department of Internal Medicine, School of Clinical Medicine, Faculty of Health Sciences, University of the Witwatersrand


13:26 Fri, 16 Aug
37%
Risk Score Card
[BLOCKED: NO ME... 12:30
Zinhle Radebe (Active)
HN038
DEMO/UID/038
This client will likely remain in care
Client is Medium Risk, do you agree?
Yes
No
Score card details
Risk score details
Recommend an intervention below
Manage Lightly/Maintain Support
Manage Remotely/Reduce Support
Manage Closely/Increase Support

Data Approaches that got us here, won't get us to elimination

Routine / Surveillance Databases

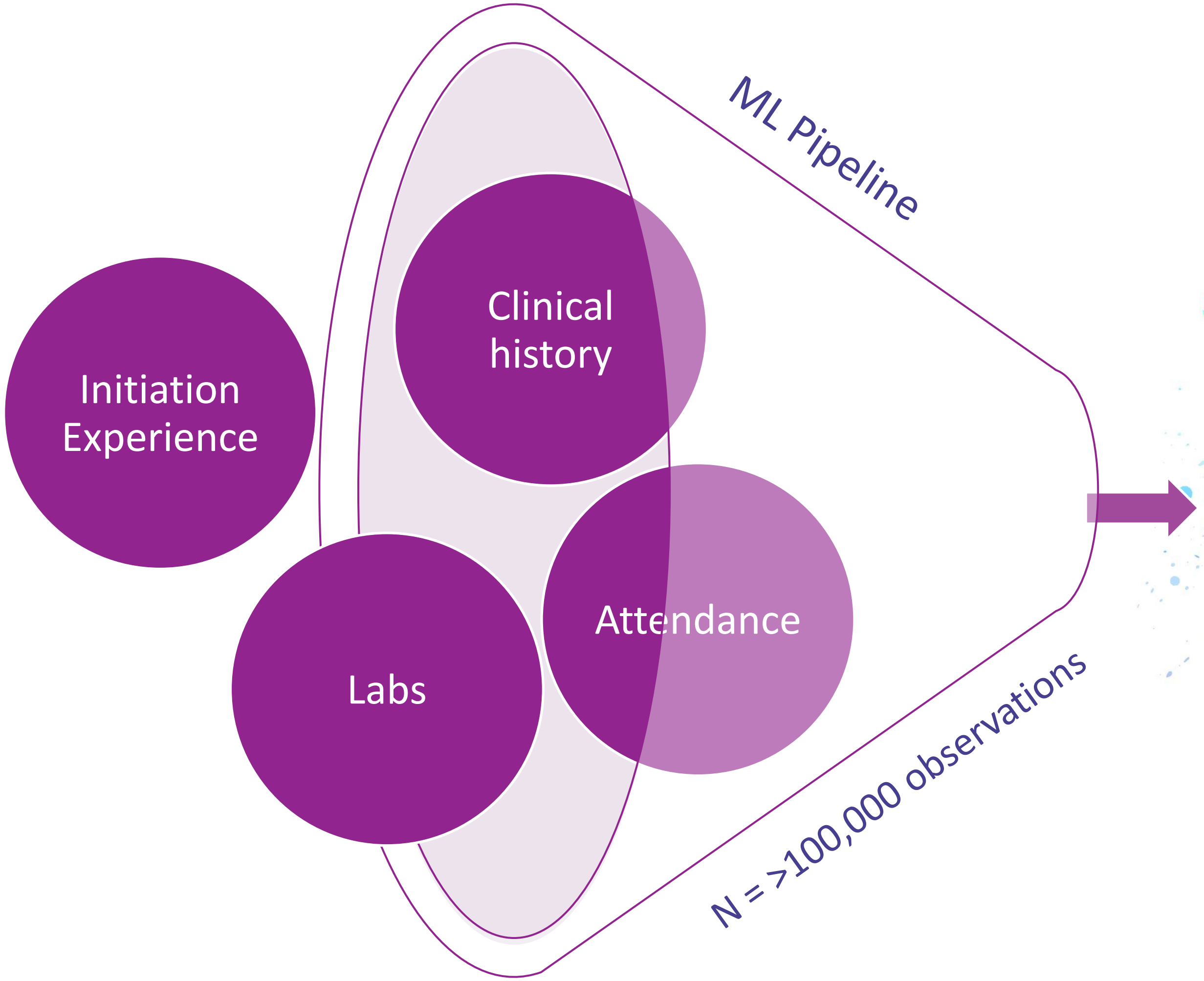
- ✔ Built for targets at scale
- ✖ Few Qs, so scalable, but lacks context

Research Studies

- ✔ Many rich questions
- ✖ Slow & Low (n), so hard to know if it replicate & resonate

PALINDROME DATA

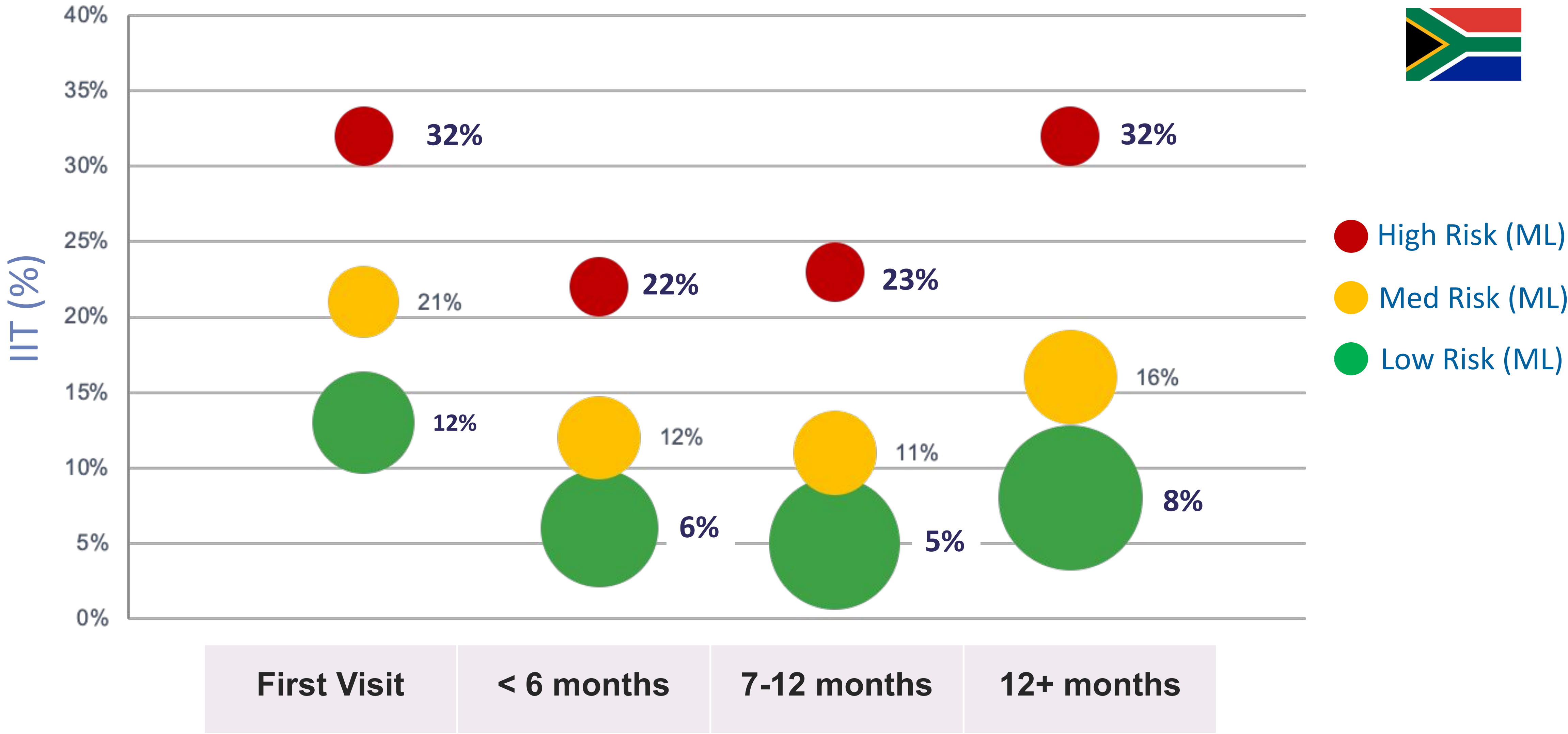
Science & Methodology



IIT Predictions

[Maskew et al, 2022, https://www.nature.com/articles/s41598-022-16062-0]

Interruptions in Treatment (IIT)



Esra et al (2023) https://doi.org/10.1097/qai.0000000000003108

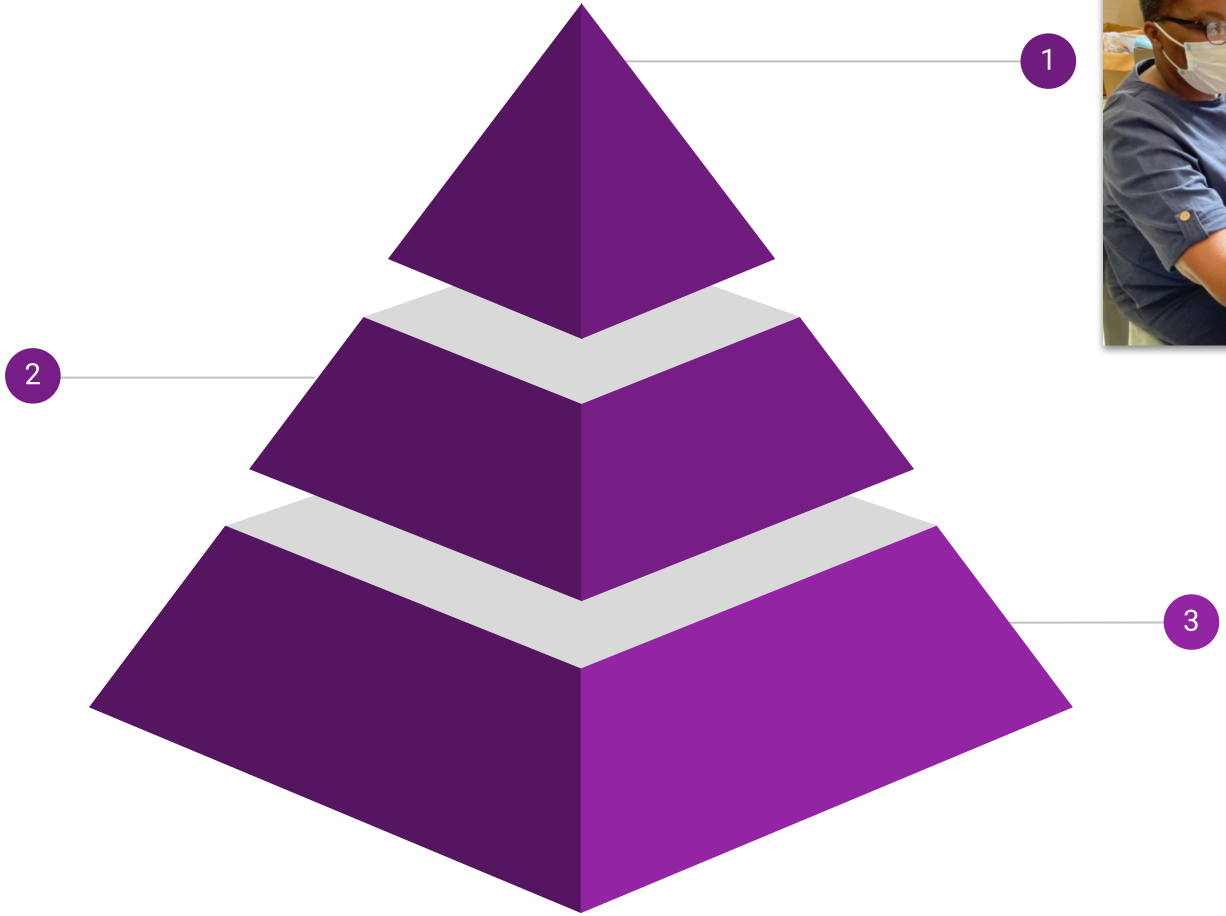
PALINDROME DATA

How do we *operationalise* in our under-resourced clinics?

Feedback From Healthcare Workers

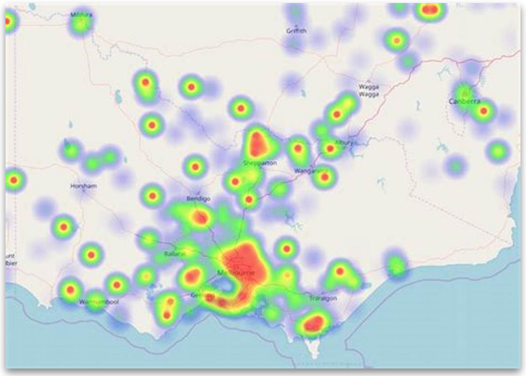
Applied at 3 levels

Facility: Who needs to be prioritised?



Point of Care: What is the client struggling with?

Programme Design: Where are segments over/under served?



PALINDROME DATA

Future Work

Opportunities we're raising funds for next 24 months

Project	Description	months	budget
South Africa	We've built a local scoring service integrated with local EMR, as well as a making paper or app-based algorithm for implementers. We'd like to extend the tools to package them up with 3 models: IIT, VL and pregnancy, for adoption by 3 more partners (serving ~100k patients)	9	$264,375
South Africa	With the change in MMD guidelines, more patients are picking up from 3rd party pharmacies. We've been discussing with the database provider - being able to support wellness and risk scores for this large and growing cohort of patients, being able to evaluate differentiated impact of patient profiles both in and out of the clinic.	12	$352,500
Nigeria Partner Expansion	2nd partner Nigeria implementation & study, leveraging the current integration with the national EMR, and localisation of the intervention matching (up to 100,000 patients). Executing this through local ML partners we can package the solution for futher natural adoption and expansion into integrated programmes.	18	$528,750
New HIV Models For Botswana & Kenya	We're engaging with HIV imp orgs in Botswana and in Kenya, and need to first validate a local model and a tool integration POC before roll out. Per country localisation we can move quickly through our 3 set up phases (discovery, modelling, POC validation) to serve up to ~10k patients.	6	$176,250
LISA Platform Investment	For the Nigeria study, on the side we've begun the work on an automated enterprise platform for both serving predictions, matching interventions as well as measuring impact thereof. The LISA infrastructure would allow us to maintain, monitor and serve models, across programme areas to EMRs across the region.	20	$881,250

Health worker owns the final DSD decision

Does this client need referal to any services?				
Refer to CSTO/social worker	Decant Patients	3 month Repeat	Space & Fast Lane	Choose Appt Date
Other:	Adherence Counseling	Disclosure Assistance	Refer to Case Manager	None

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 ____________________

IAS 2023

Acknowledgments

Acknowledgements of our Research & Funding Partners

THE AURUM INSTITUTE

Health Economics and Epidemiology Research Office

HE²RO

Wits Health Consortium
University of the Witwatersrand

Right to care
Treating Health Seriously

jhpiego
Saving lives. Improving health. Transforming futures.

INDLELA
BEHAVIOURAL INSIGHTS FOR BETTER HEALTH

Johnson & Johnson
Global Public Health

PALINDROME DATA

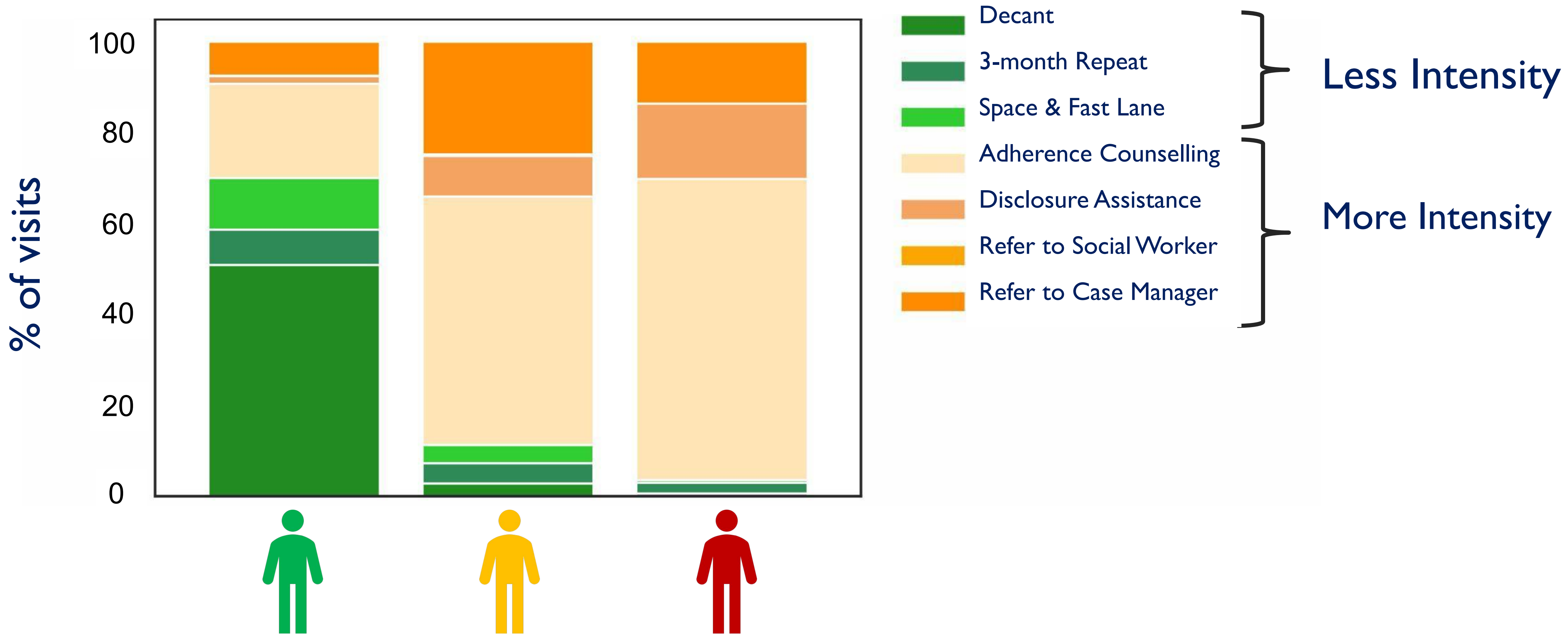
Public Health is often wasteful one-size-fits-all:

Low Yield blanket interventions

We need Personalised Care

Archetyped, Tailored, Targeted Interventions

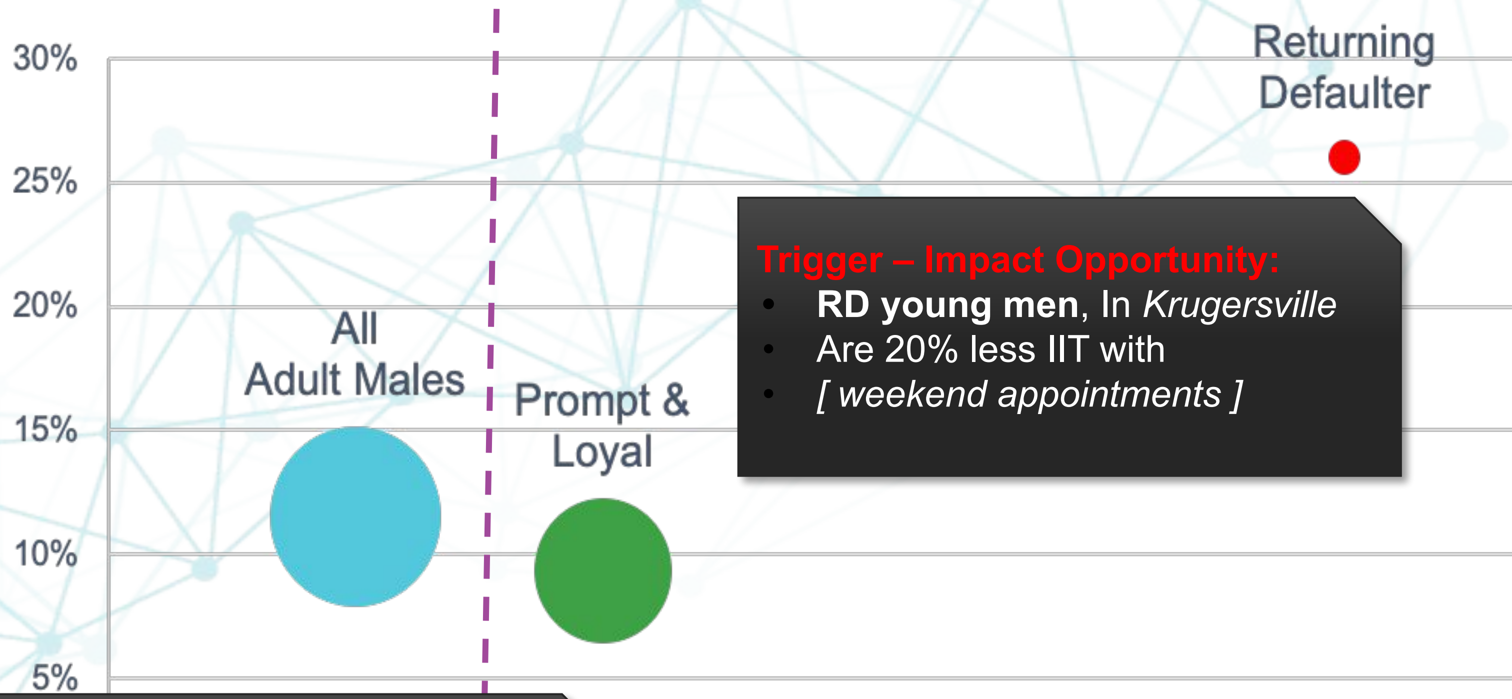
HCW intuitively prescribed Differentiated models by risk profile



Lesedi Recommendation Engine

Using AI to identify opportunities for action

- ***Under***-served groups (impact)
- ***Over***-served groups (costs)



Trigger – Impact Opportunity:

- **RD young men**, In *Krugersville*
- Are 20% less IIT with
- *[weekend appointments]*

Trigger – Effciiency Opportunity:

- **P&L young men**, In *Qwa-Qwa*
- Are 5x less IIT but are 54% of the queues.
- Consider *[increase MMD decanting]*