Evaluating the effect of dynamic changes in risk profile on subsequent interruption in HIV treatment: A threshold approach to risk triaging

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RETAIN6

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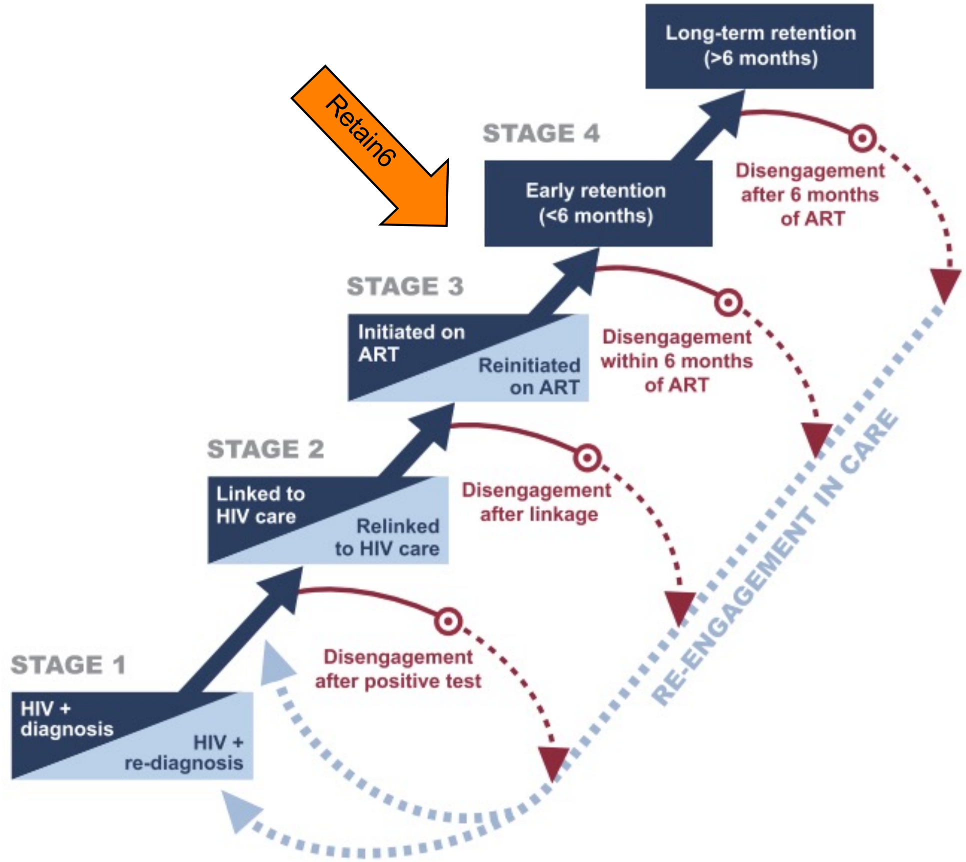
The HIV care journey

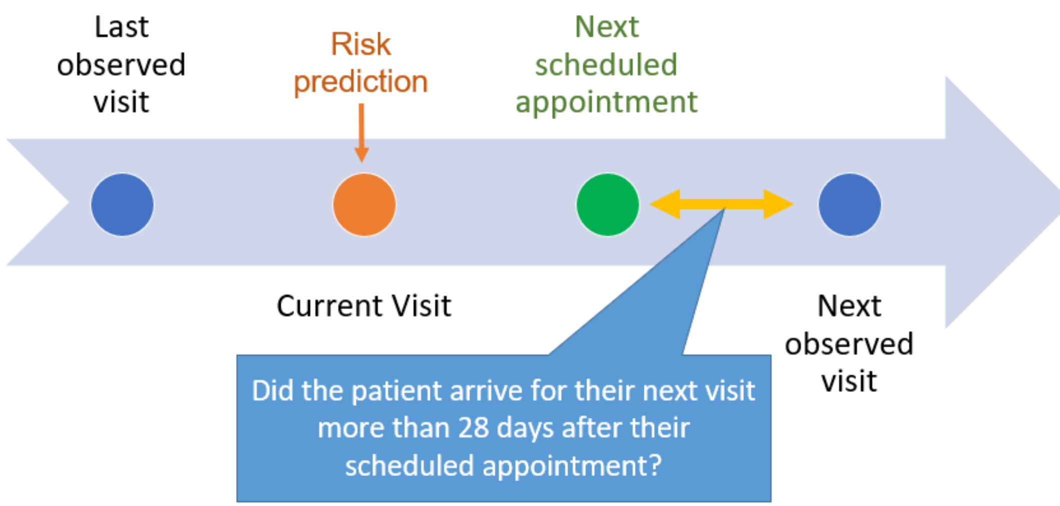
- Continuity of HIV care is critical yet challenging, especially in the early treatment period
- **RETAIN6**: Models of care for the first six months of HIV treatment
- Optimize service delivery during the “early treatment” period
- *About half of initiating clients experience an interruption in treatment during the first 12 months on ART**



Maskew, Benade, RETAIN6 Policy Brief 2023 https://sites.bu.edu/ambit/the-retain6-project

Do we have the methods and tools needed to predict risk of treatment interruptions?

- Machine learning model trained on:
  - Large routinely collected EMR data (>310,000 clients)
  - Clinical trial dataset (881 clients)
- Model predicted risk score for treatment interruption for each observed visit
- Tested against known visit outcomes
- Predicted 2 of 3 treatment interruptions

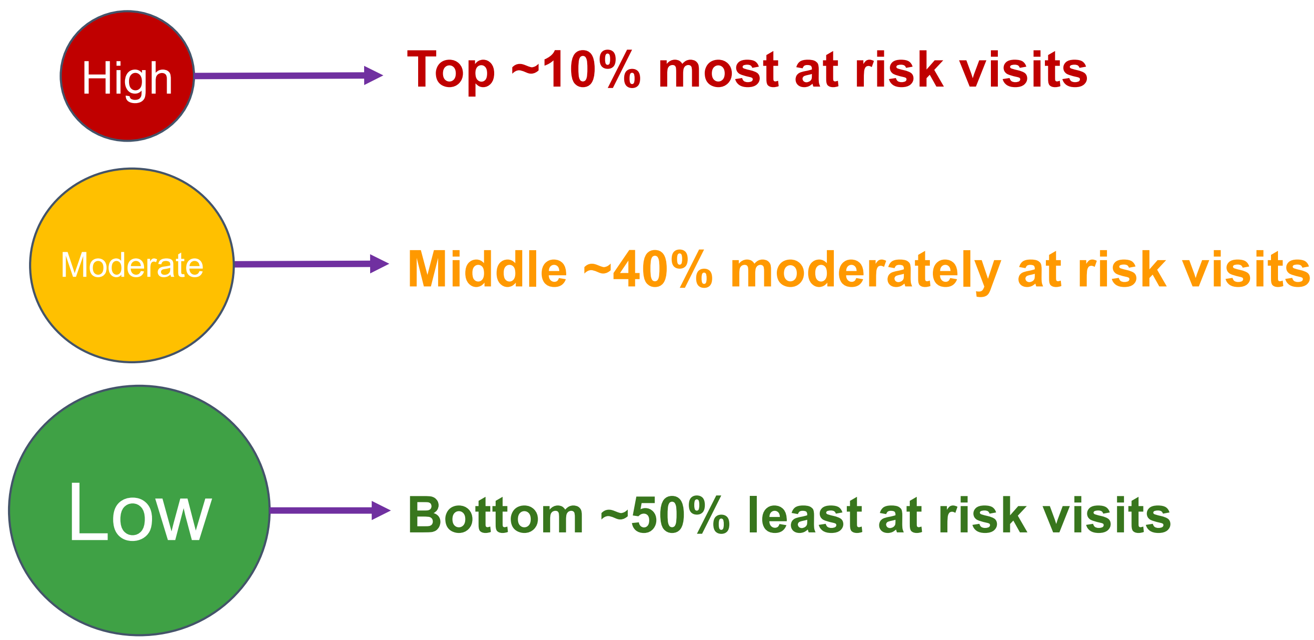


Source: Maskew et al. (2022)

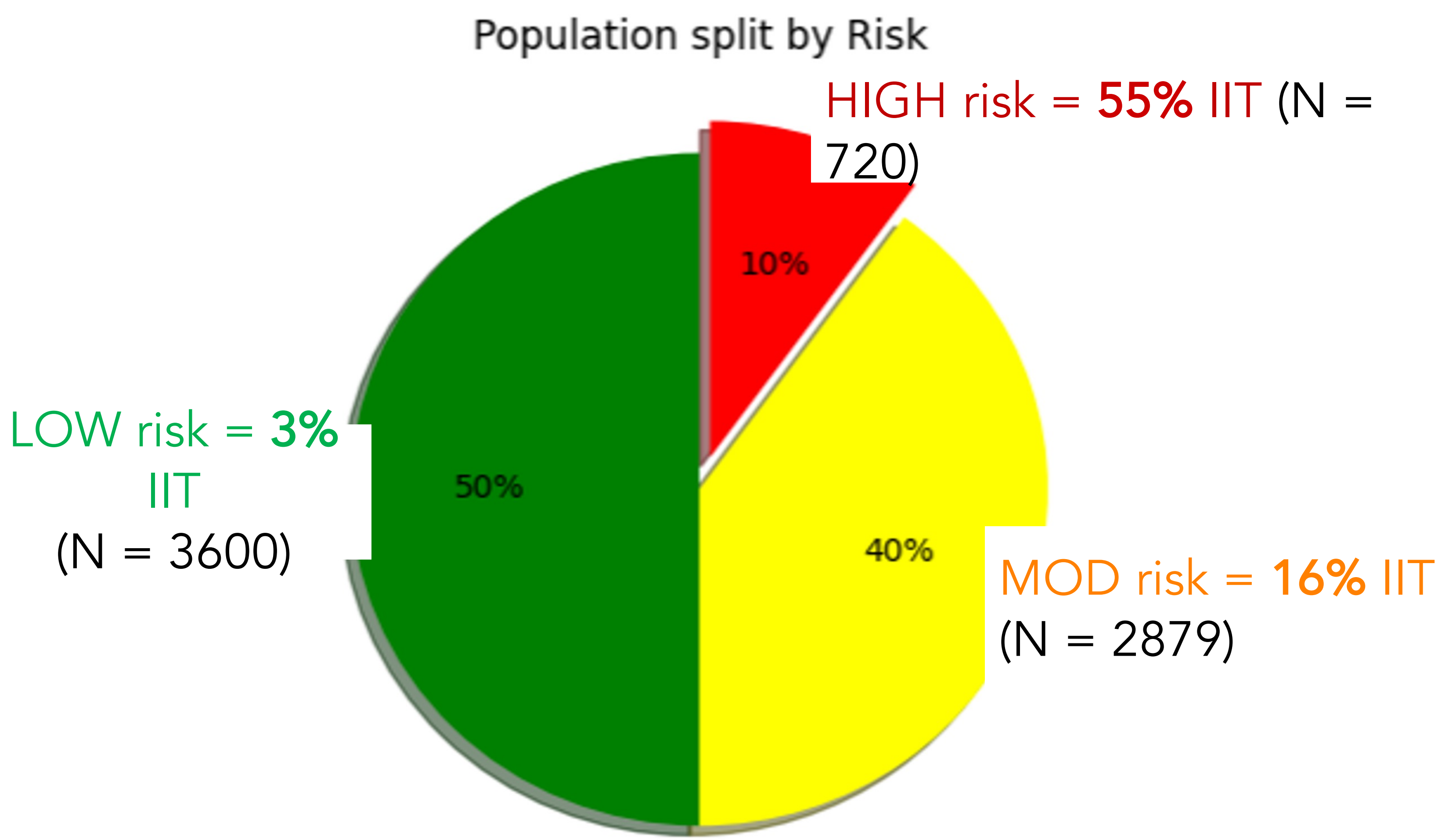
Can risk scores be used to triage patients?

Threshold approach - groups are segmented based on a visit-based risk score

- lowest 50% of scores assigned a “green” or low risk category
- middle 40% of scores assigned a “yellow” or moderate risk category;
- highest 10% of scores assigned a “red” or high-risk category

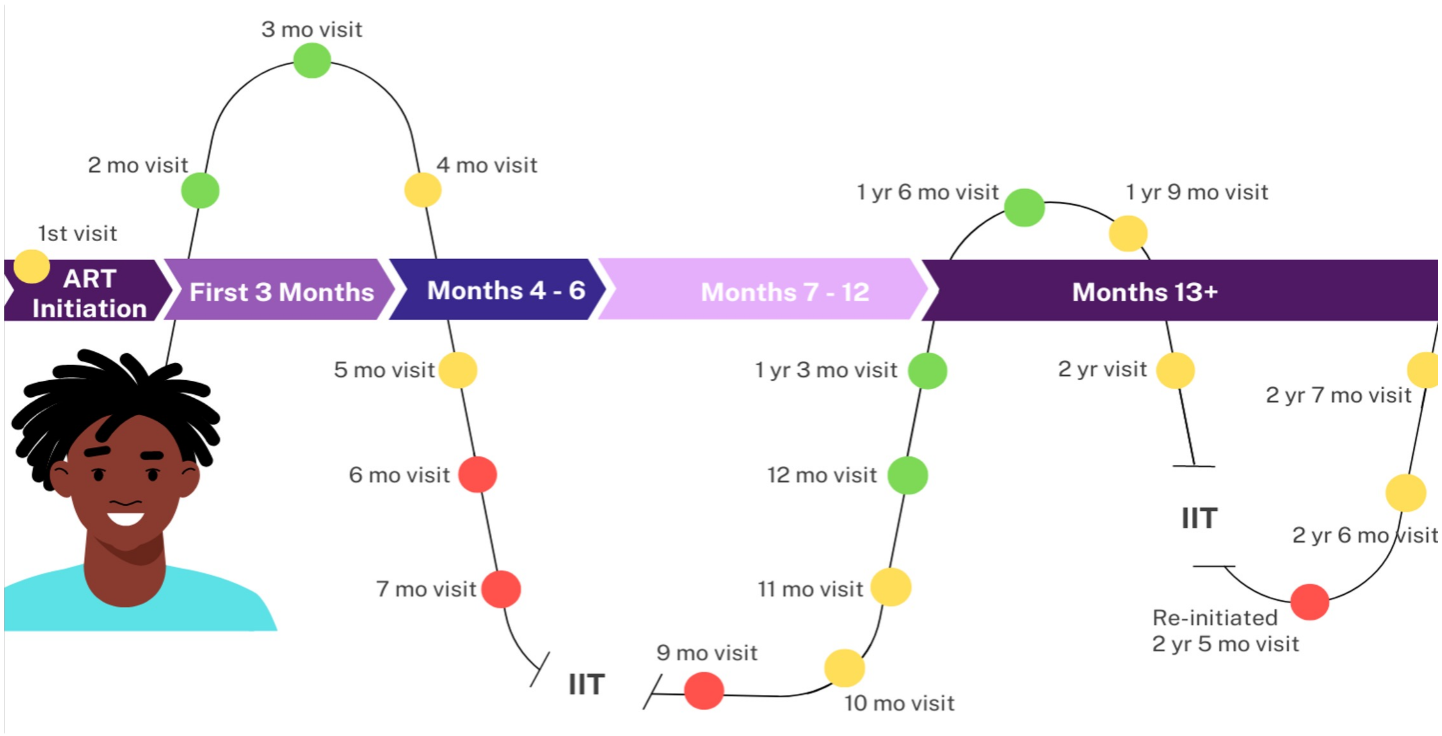


Does risk of IIT differ across predicted thresholds?



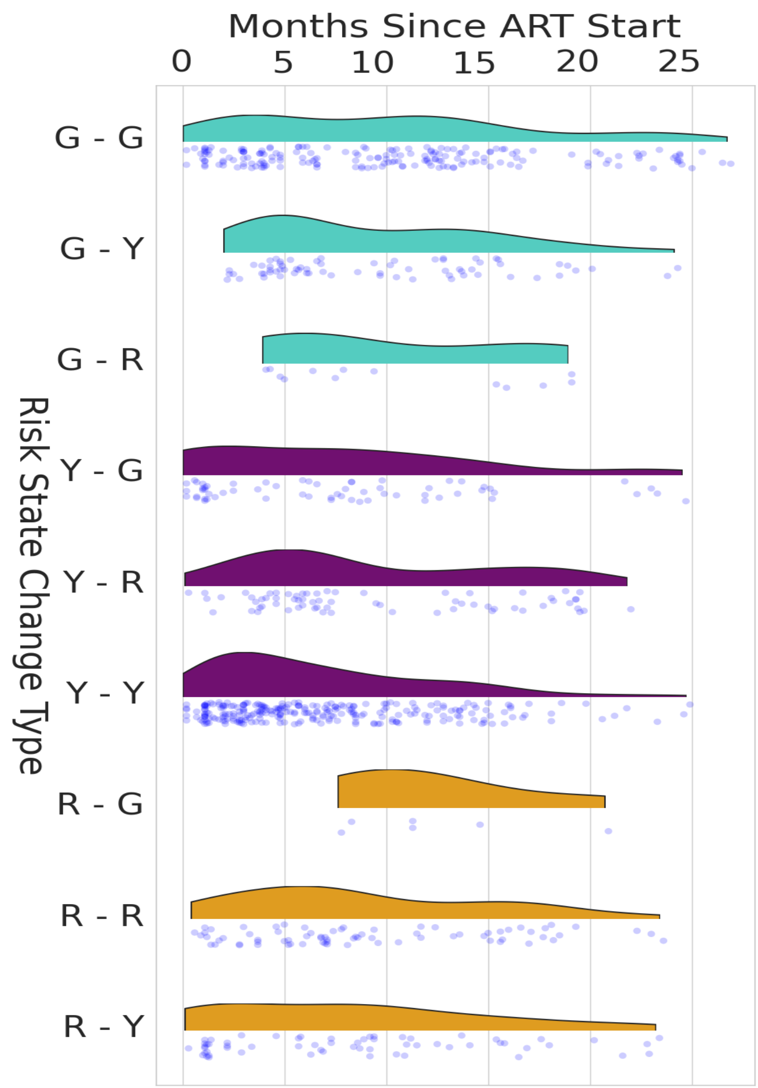
Risk is dynamic

- Individual circumstance, experiences, life events, and perceptions change over time
- This impacts health-seeking behavior and risk of treatment interruption
- Risk score can be estimated at each ART client encounter



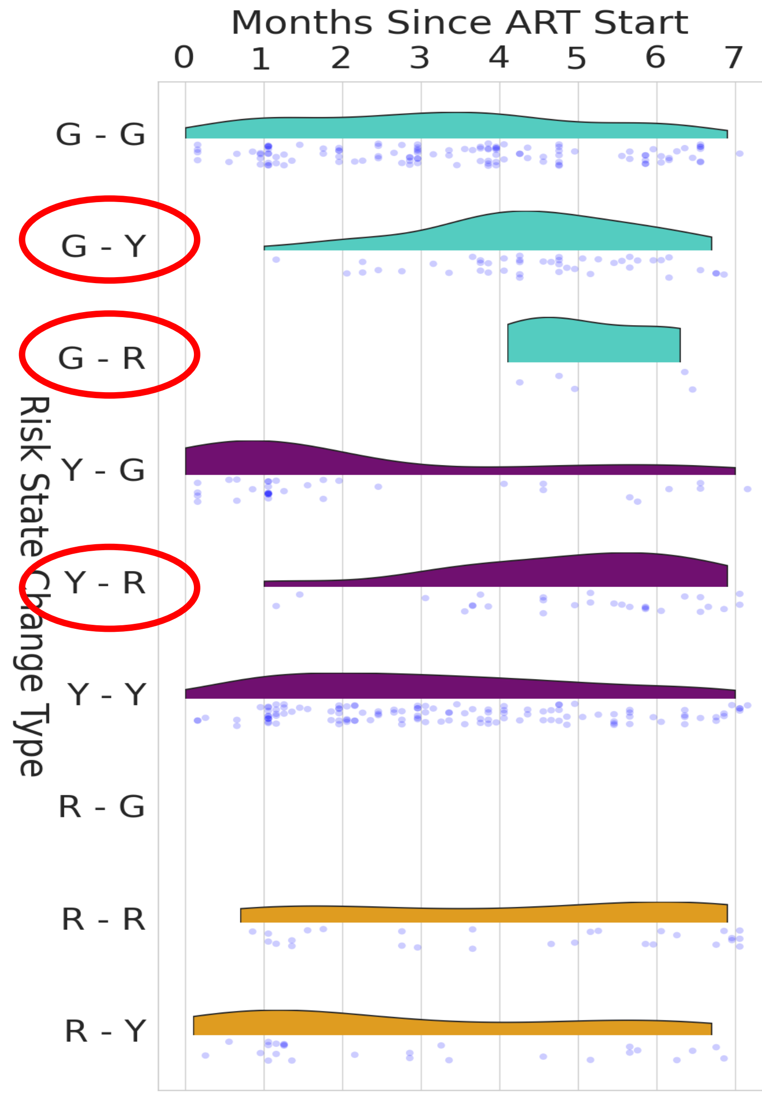
Distribution of change in risk state

- Risk is not static
- Shifts in risk state across visits occur frequently



Distribution of change in risk state

- Risk is not static
- Shifts in risk state across visits occur frequently
- Clustering of shift towards increasing risk state during first 6 months on ART



Risk state changes and IIT

			Current visit risk state classification		
			Low risk	Moderate risk	High Risk
Previous visit risk state	Low risk	N (%) with indicated risk state change between previous and current visit	2,658 (85%)	436 (14%)	37 (1%)
		% Observed current visits classified as treatment interruption (IIT)	IIT=7% (n=185)	IIT=16% (n=69)	IIT=35% (n=13)
	Moderate risk	N (%) with indicated risk state change between previous and current visit	N=736 (28%)	N=1,630 (62%)	N=267 (10%)
		% Observed current visits classified as treatment interruption (IIT)	IIT 8% (n=62)	IIT 16% (n=261)	IIT 26% (n=68)
	High Risk	N (%) with indicated risk state change between previous and current visit	N=43 (7%)	N=352 (56%)	N=231 (37%)
		% Observed current visits classified as treatment interruption (IIT)	IIT 14% (n=6)	IIT 17% (n=61)	IIT 32% (n=73)

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- Change in risk states are important – any ascending risk shift (G → Y → R) doubles risk of IIT
- State changes tend to occur in transition – only 1% of visits switch from low to high risk states
- Observing these shifts can prompt intervention – proactive approach

What does this tell us?

- The first 6 months on ART is a critical period for establishing continuity of ART care – patterns of visit attendance predict treatment interruption
- Risk of treatment interruption is not static; individual risk shifts across time and circumstance
- Change in risk state has an impact on subsequent treatment interruption
- Awareness of change in risk can allow us to engage ART clients proactively before disengagement occurs
- New guidelines in South Africa shift eligibility for differentiated models of HIV service delivery to month 4
  - *Will it be early enough?*

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