POSTER NUMBER: P3-B26

# Machine Learning in Practice: Operational Lessons from South African Healthcare Facilities

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Machine learning (ML) promises transformative change in differentiated care and improvements to patient outcomes. This abstract illustrates the operational journey and lessons learned from deploying an ML tool across various healthcare facilities in South Africa.

## Background and Description

We deployed a back-office support tool built using an ML binary classifier that enriched the upcoming appointment list (UAL) from the local EMR, Tier.net. The outcome modelled is the patient's risk of missing their next appointment (IIT). By segmenting the UAL according to risk, the facility can prioritise the higher-risk patients while gaining efficiencies by treating low-risk patients with a lighter touch.

## Lessons Learnt

Operationalising the tool provided a sobering reality check on how far we still have to go to realise AI's gains.

1) **Model Degradation** is expected when operationalising ML tools but is especially relevant when policies and environments undergo material changes. Recently, a big push has been made to put patients on MMD or CCMDD. When such changes occur, the model's performance naturally declines and would need to be "refreshed" by retraining it.

2) **Data Access and POPIA:** Obtaining data for training (and retraining) ML models can be unnecessarily cumbersome. The regulatory framework, established primarily by POPIA, allows data to be shared with partners to develop value-added services on the data holder's behalf. Unfortunately, because of the limited understanding of POPIA and the lack of maturity in data sharing, many still do not comprehend the permissible criteria for sharing de-identified data.

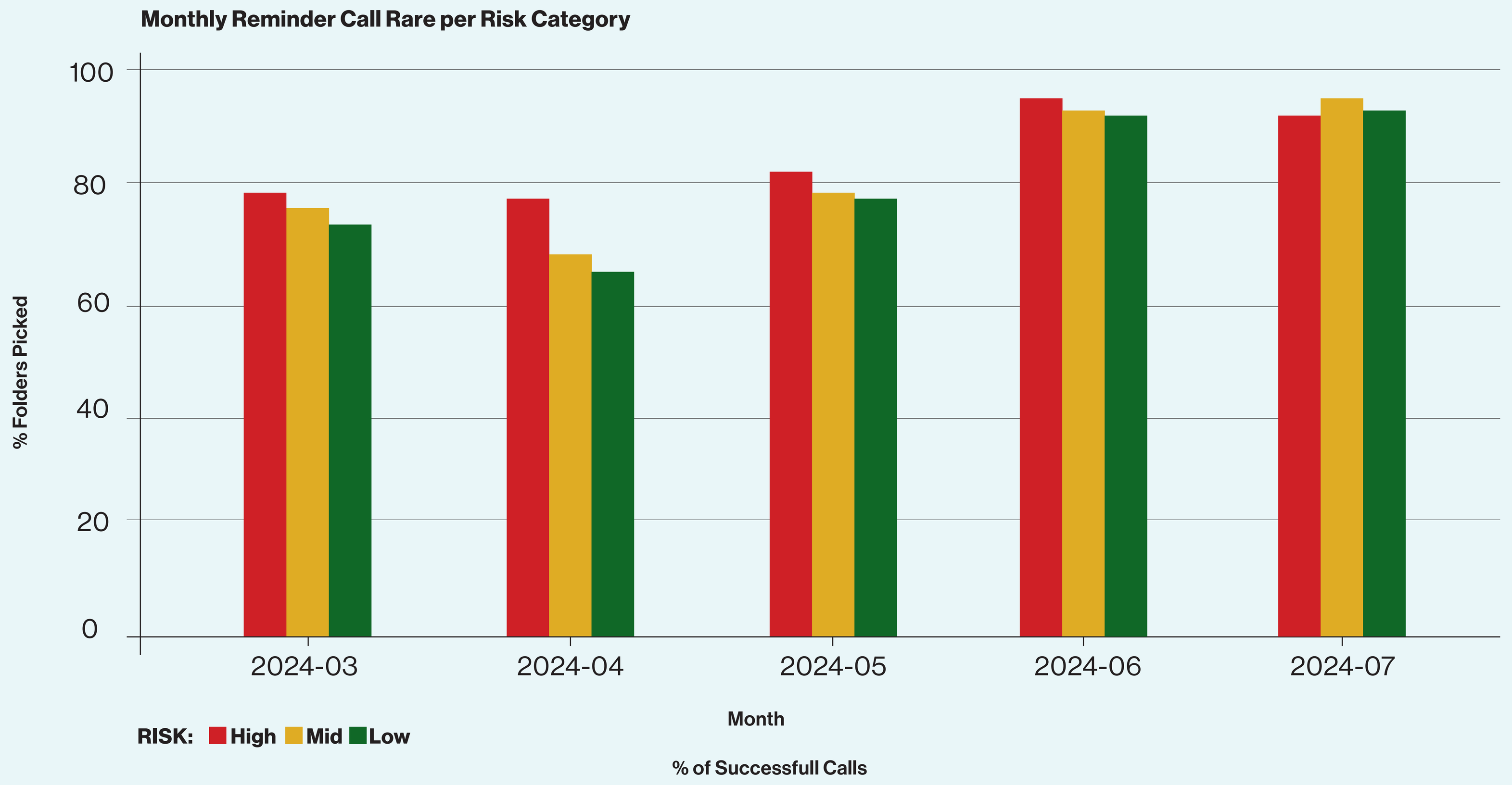
3) **Consistency across Facilities:** The variability of how processes are followed makes it especially difficult to roll out a new tool and workflow. Since facilities have different interpretations of the guidelines, a wide range of management styles, and dissimilarities in resources and equipment, it is essential to consider each facility and its nuances with care.

## Conclusion

Operationalizing ML tools in resource-limited healthcare settings demands flexibility, collaboration, and a deep understanding of the local context. Our experiences underscore the need for adaptive solutions that align with patient care realities. We are excited to share the remediations and strategies we have developed to address the challenges we have encountered.

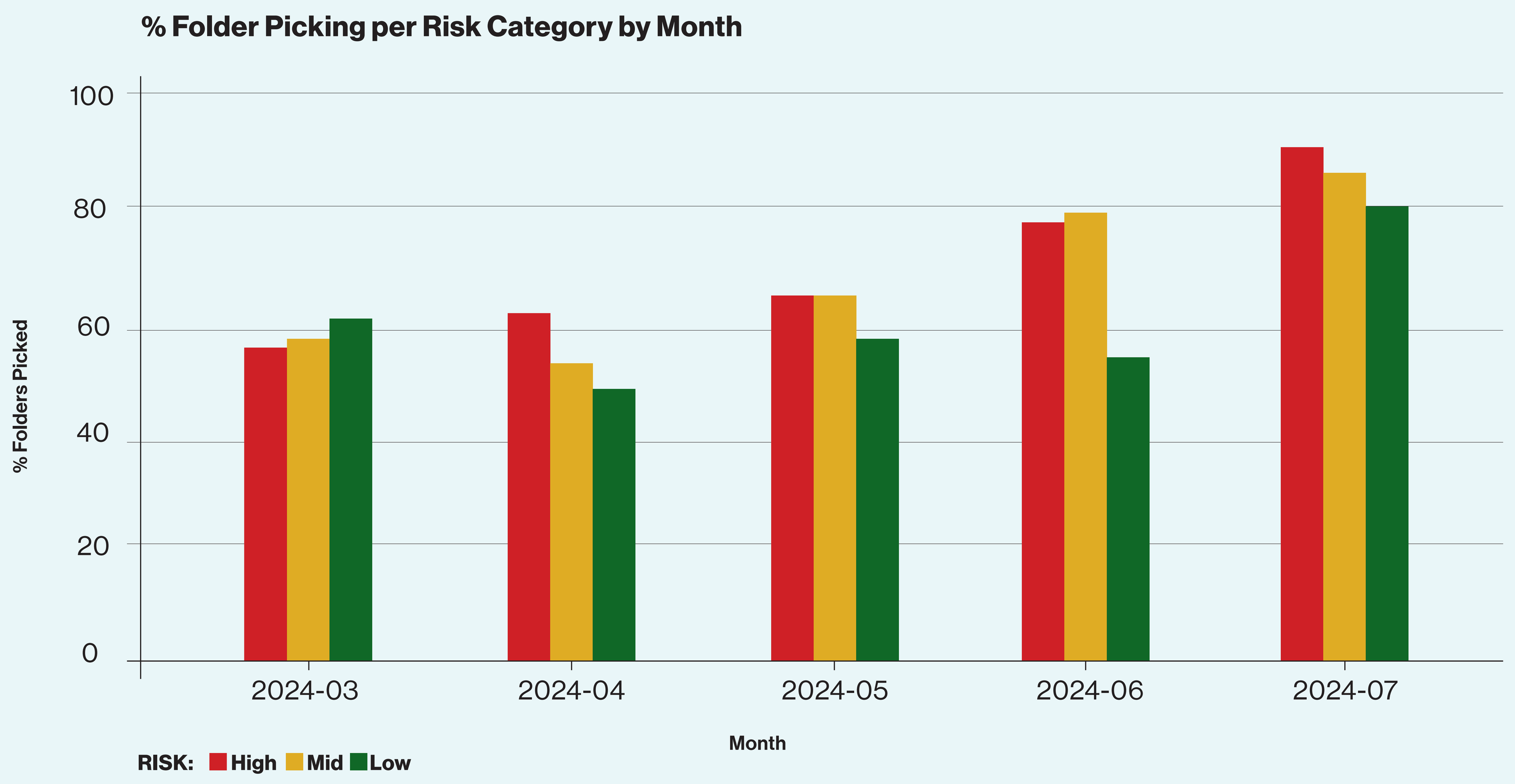
### Intervention 1: Calling Prioritisation

**Limited risk prioritisation & only 60-70% of calls are successful**



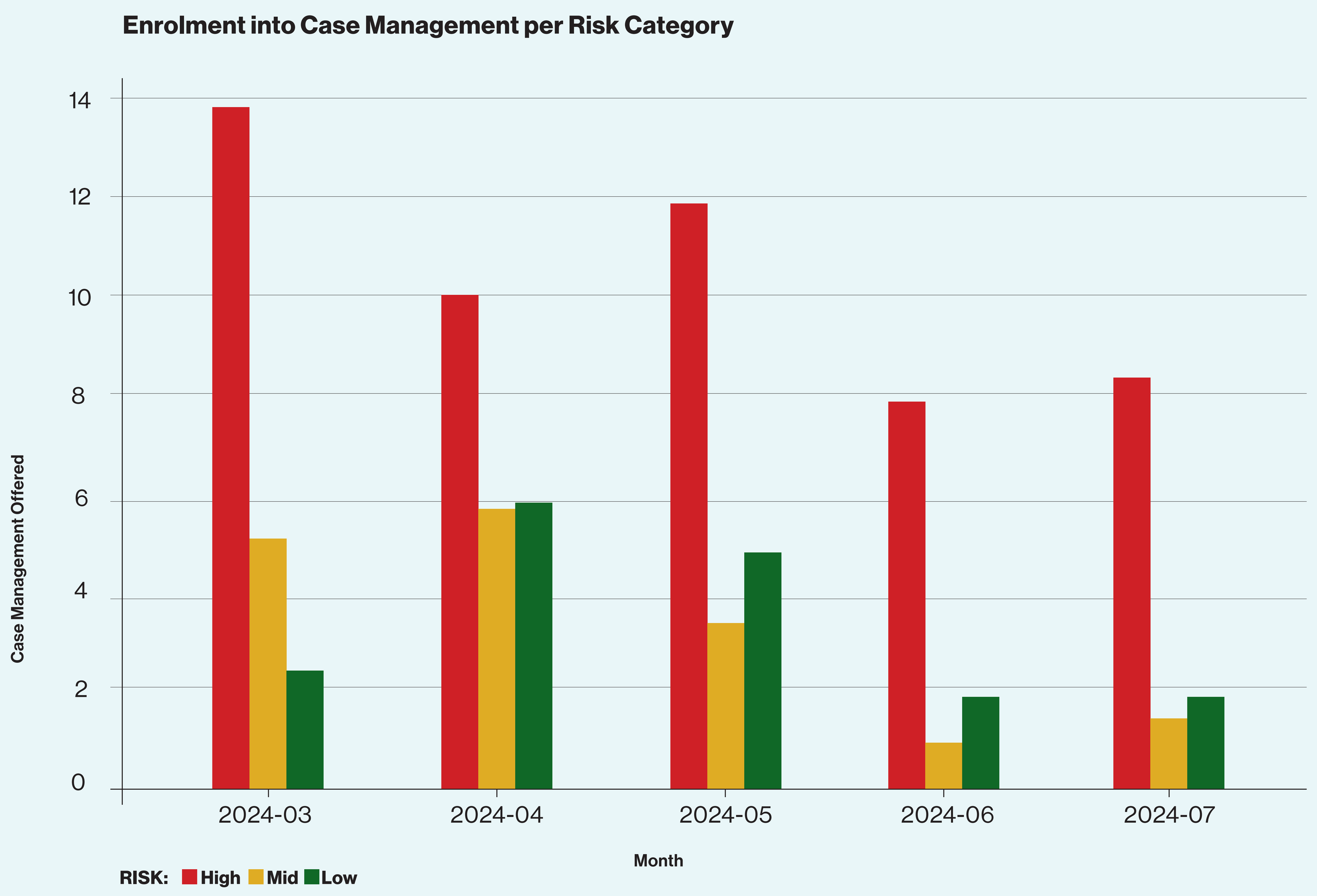

### Intervention 2: Folder Picking

**High & Medium Risk prioritised in folder picking**




### Intervention 3: Case Management Prioritisation

**Significant focus on High Risk patients**

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