Predicting Early Exit From a Health Program

Mhlasakululeka Mvubu, Lazola Makhupula [1] Matthew Olckers, Alexander Lam, Toby Walsh [2] Tuba Islam [3]

[1]mothers2mothers, Cape Town, South Africa [2]UNSW Sydney, Sydney, Australia [3]Google London, United Kingdom

Background

mothers2mothers (m2m) is an African NGO that provides integrated primary health care to families who need it most, delivered by women who know them best. m2m trains and employs local women living with HIV as community health workers who provide services in under-resourced health clinics and door-to-door in communities.

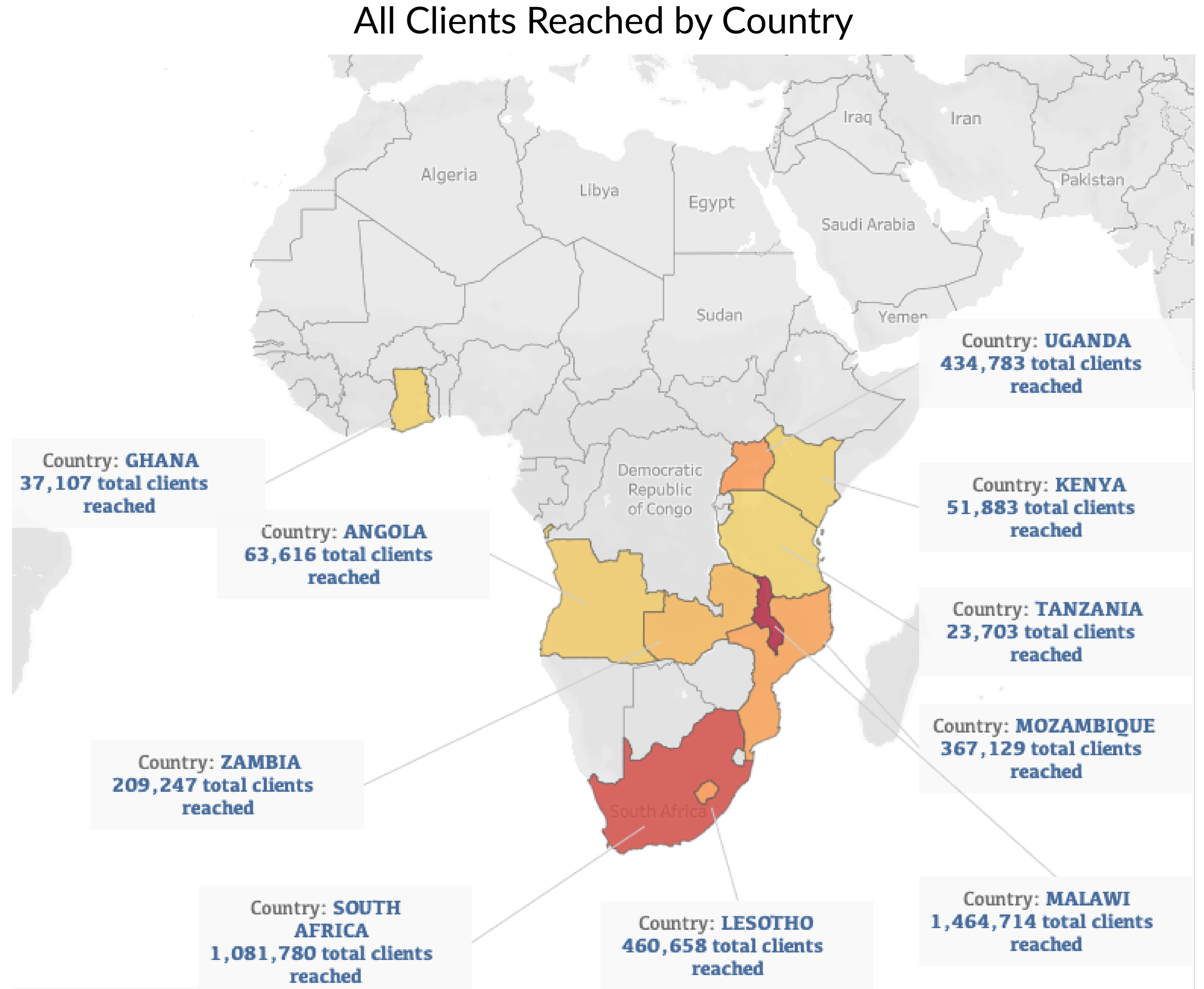
m2m Impact

- **1,630,558** new and returning clients were reached through direct services and technical assistance, a 22% increase over 2020.
- **1,866** women living with HIV were employed directly by m2m as frontline health workers called "Mentor Mothers".
- **544** locations in which Mentor Mothers provided direct services, including health facilities and in the surrounding communities.
- **0.7%** is the mother-to-child HIV transmission rate among enrolled m2m clients—well below the 5% UN benchmark. This makes 2021 the eighth straight year we have achieved virtual elimination.
- **95-95-95** In 2021, m2m met all of UNAIDS' ambitious 95-95-95 Fast Track Targets for ending HIV/AIDS, four years ahead of the 2025 target dates.

Created nearly **12,000** jobs for women living with HIV.

Reached more than **15 million** people with critical health services in sub-Saharan Africa.

All Clients Reached by Country



Abstract

To tackle the spread of HIV in Africa, mothers2mothers (m2m) employs HIV-positive women as Mentor Mothers to counsel HIV-positive mothers and their families. We report on the progress of a project to predict which clients will exit from m2m's health program for preventing mother-to-child transmission of HIV. The project uses two approaches to predict client exit: machine learning predictions from client data and predictions made by the Mentor Mothers.

Relying solely on app data without human involvement, we anticipate an AUC <70, indicating poor performance. The machine learning approach might struggle to capture crucial nuances in human interactions, limiting its effectiveness. Human expertise, provided by the Mentor Mothers, is vital for achieving more accurate predictions.

Method

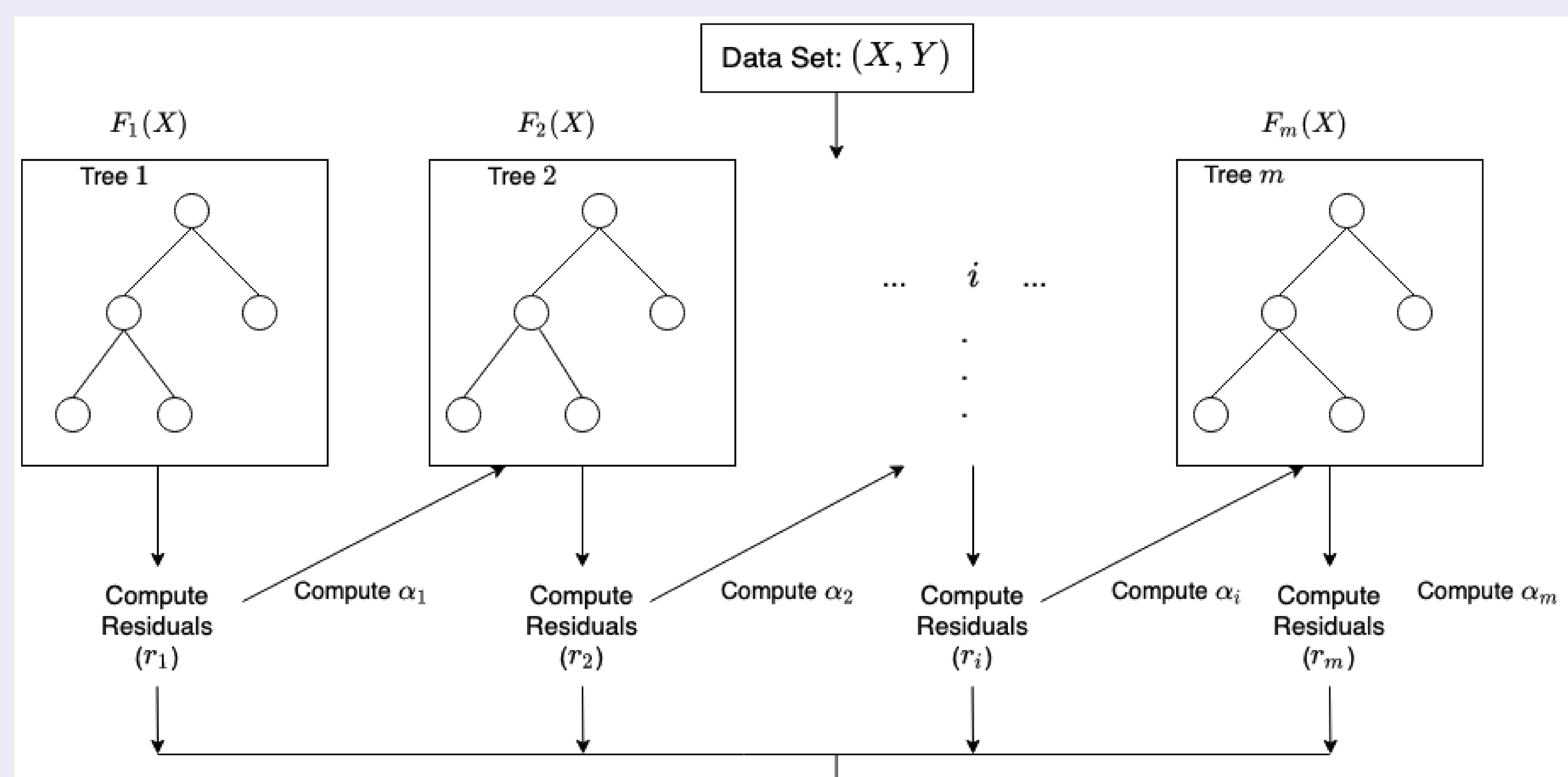
First Target Measure: The first target measure is designed to identify clients who missed their first appointment within seven days of enrollment. Clients who exit the program for reasons unrelated to their appointment attendance are excluded from the data to ensure accurate predictions.

Second Target Measure: The second target measure is used to identify clients who did not attend their most recent appointment within the first 90 days of enrollment. This measure helps to capture a broader range of clients who might be at risk of exiting the program.

XGBoost

In XGBoost, the prediction is obtained by summing the predictions of all the individual trees, and each tree is constructed in an iterative manner to minimize a specific loss function. Additionally, regularization terms are applied to control the complexity of the model and prevent overfitting.

In the context of the described project, where two target measures are used to predict client exit, human experts can provide valuable insights and domain knowledge to improve the model's performance. They can help in feature selection, data preprocessing, and fine-tuning the model to make more accurate predictions based on their understanding of client behavior and exit patterns.



$$F_m(X) = F_{m-1}(X) + \alpha_m h_m(X, r_{m-1}),$$

where α_i, and r_i are the regularization parameters and residuals computed with the i^{th} tree respectfully, and h_i is a function that is trained to predict residuals, r_i using X for the i^{th} tree. To compute α_i we use the residuals computed, r_i and compute the following: $arg \min_{\alpha} = \sum_{i=1}^{m} L(Y_i, F_{i-1}(X_i) + \alpha h_i(X_i, r_{i-1}))$ where $L(Y, F(X))$ is a differentiable loss function.

XGBoost

The general equation for XGBoost can be represented as follows:.

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)$$

where:

- $\hat{y}_i$ represents the predicted output for the i-th instance.
- K is the total number of trees (base models) in the ensemble.
- $f_k(x_i)$ denotes the prediction of the k-th tree for the i-th instance.

Results

The models were trained and tested on data from 20,726 and 8,033 HIV-positive women, respectively, who had their first meeting with m2m between January 2020 and January 2022. The models' predictive performance for missing appointments was found to be poor, with ROC AUC scores of 0.62 and 0.65 for missing the first appointment and missing the most recent appointment within the first 90 days of enrollment, respectively.

It is important to note that the model used in this study had a training data cutoff date of January 2022. However, as part of the next phase, data beyond January 2022 will be incorporated into the training process. This inclusion of more recent data is expected to lead to significant improvements in the model's performance. By utilizing the additional data, there is an expectation of enhancing the model's predictive capabilities in identifying missing appointments among HIV-positive women who engaged with m2m (mothers2mothers) between January 2020 and the updated data cutoff date. The expansion of the training dataset is anticipated to result in more accurate predictions, further benefiting the healthcare support provided to these women.

Train Size	Test Size	ROC AUC	Period
20,726	8,033	0.65	Sep 2021 - Jan 2022

Table 1. Performance

Next Step

To enhance the model's accuracy in predicting missing appointments, we will expand the input feature set to include socio-demographic variables and past appointment history. We'll conduct extensive parameter tuning and explore advanced machine learning techniques, like deep learning and natural language processing, to leverage textual data from clients' interactions and optimize performance. Additionally, we will incorporate other relevant metrics to measure performance, such as precision, confusion matrix, to provide a comprehensive evaluation of the model's predictive capabilities. These strategies aim to provide more effective interventions and improve healthcare outcomes for HIV-positive women.

Emphasizing interpretability and transparency, we'll use techniques like LIME and SHAP to gain insights into the model's decision-making process and provide interpretable explanations for predictions. Additionally, we'll explore ensemble methods like stacking and boosting to boost predictive power by combining multiple models' strengths. With continuous feedback from the Mentor Mother survey, we aim to iteratively refine the model, understand its limitations, and create a more robust predictive tool for supporting future healthcare interventions.

References

[1] Aaron Bohlmann, Javed Mostafa, Manish Kumar, et al. Authors' responses to peer review of "machine learning and medication adherence: Scoping review". *JMIRx Med*, 2(4):e33962, 2021.