A Predictive Policy Framework for Financial Inclusion: Forecasting Formal Savings Rate and SADC Informal Traders′ Resilience Using an Ensemble Stacking Regressor

An AI problem-solving framework

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Disclaimer

This report, titled "The Impact of Mobile Money Adoption on Income Stability and Small-Business Growth among Informal Traders in Botswana's Urban and Peri-Urban Markets," is submitted as an academic project for the CET 313 Artificial Intelligence module. The findings, conclusions, and recommendations presented herein, particularly those derived from the Proposed AI Model Solution, are based on publicly available aggregated datasets (GSMA Mobile Money Dataset, World Bank Global Findex) and are intended solely for educational and research purposes.

While the model presented is a result of scholarly investigation, it is acknowledged that this AI solution could serve as a Minimum Viable Product (MVP) for policymakers, provided it undergoes further fine-tuning and validation with local, proprietary datasets for operational use. This work is not intended to be used as definitive financial or policy advice without such subsequent development. The author is not responsible for any actions taken or decisions made based on the interpretations of this academic work.

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Abstract

This study quantifies the effect of Mobile Money Adoption on financial resilience as a measure of the formal saving rate among informal traders in the SADC region, and directly to Botswana. Informal traders, who trade largely outside the formal banking sector and in cash, are highly vulnerable to income shocks. The project's primary objective was to move beyond descriptive statistics and provide predictive, evidence-based insights to policymakers. An Ensemble Stacking Regressor model was developed with aggregated country-year data from the GSMA Mobile Money Dataset and World Bank Global Findex (2011–2024). It explained over 71% of the variance in formal saving rate and worked much better than a baseline OLS. The leading predictors found were Mobile Account Penetration and Agent Density. The results lead to the conclusion that mobile money is a key linkage to financial security, and with wise advice on proper interventions, such as prioritizing agent network growth in informal trade zones, to align with Botswana's Vision 2036 strategies for inclusive digitalization.

Introduction

The informal economy is a central, but often underemphasized, component of the economies within the Southern African Development Community (SADC) region. Across Botswana, it is a significant source of earnings, particularly for youth and poor households, with hundreds of thousands of individuals engaged in informal business. However, this segment is functioning virtually entirely outside the formal financial sector, on largely cash-based transactions. Such reliance on cash is a key barrier to financial security, preventing safe saving, affordable access to credit, and investment for long-term enterprise. Most importantly, reliance on cash leaves informal traders highly vulnerable to unstable income shocks, guaranteeing continued financial insecurity and systemic destitution.

Against such widespread national financial exclusion, especially in rural areas, Botswana has witnessed a rapid adoption of mobile money services, provided by the major telecommunication networks (i.e., Orange, Mascom, BTC Mobile). These services aim to equip all users with the capability to save money, pay bills, and transfer money with basic feature phones, offering a low-barrier alternative to traditional banking. Mobile money is recognized globally as a powerful enabler for expanding financial inclusion. Whereas national statistics confirm high levels of adoption, measured in terms of raw number of accounts or transactions,there remains a necessary knowledge deficit in ascertaining the direct, causal impact of this growth in digital finance on fundamental resilience factors like traders' stability of income and firm growth. Policymakers lack the rich, forward-looking evidence needed to optimize digital investing strategies.

Literature Review

Botswana's informal sector has grown rapidly and is now a significant source of income and jobs for most people, especially youths and poor families. According to Sophia Helming, in 2015/16, approximately 190,000 persons (circa 15% of the workforce) were active in informal trading, with most of the businesses earning very low monthly incomes (two-thirds reporting less than P3000). By definition, the majority of informal traders are unregistered, without bank accounts, and often unable to meet the requirements of mainstream finance solutions. This dependence on cash-based transactions makes them vulnerable to income shocks (e.g., market breakdowns or emergencies) as they lack savings buffers, access to credit, or electronic payment tools.

Botswana has seen a surge in mobile money services in the last several years. Each of the major telecom providers offers mobile wallets: Orange Botswana (Orange Money), Mascom (MyZaka), and Botswana Telecommunications Corp (Smega). In fact, a Botswana Communications Regulatory Authority (BOCRA) report had Orange Money dominating about 73% of Botswana's mobile-money market as of 2018. The services enable people to save money, pay bills, and send remittances via basic feature phones. Globally, as well as in sub-Saharan Africa, mobile money is being regarded as a key method to increase financial inclusion, where banking is formalized to a lesser degree. For example, mobile-money pace-setter M-PESA in Kenya has radically improved the convenience of payments and reduced exclusion in poor markets. A 2016 FinScope report on "***The role of mobile money in financial inclusion in the SADC region***" shows that mobile money penetration in southern Africa is already significant in countries like Botswana, even in regions where formal account ownership is high. In short, mobile payments can help marginalized traders save, access credit, and stabilize income.

However, the economic impact of such digital finance expansion in Botswana's informal economy is not well understood. National data largely report adoption rates (number of registered accounts, agents, or transactions), but they do not capture the extent to which traders' income stability or business growth is specifically affected by the use of mobile money. Academic studies on Botswana's (and more broadly in SADC) mobile-money use have typically been descriptive or limited to small-scale surveys. For instance, Tangirala and Nlondiwa (2019) found that small businesses in Gaborone used mobile money, but there was low usage due to the influence of network problems and transaction fees. A large-scale empirical investigation linking mobile-money penetration to financial resilience indicators (e.g., savings rates or digital earnings) does not exist. The segment of informal traders (urban/peri-urban retailers, small market stallholders, etc.) has not been studied in a systematic way in Botswana. This gap is critical, thus policymakers and financial-sector planners have limited evidence on whether and how mobile finance is actually benefiting these vulnerable groups.

This research, therefore, combines evidence from global research on digital finance and the Botswana context. Data-rich approaches now permit these questions to be investigated more deeply. Open datasets, particularly the GSMA Mobile Money Dataset (2024) and the World Bank Global Findex (2021/2025), provide country-level time series on mobile-money accounts, agents, number of transactions, and indicators of saving, borrowing, and digital income. By integrating these sources, it is possible to analyze patterns across countries and over time, and to connect digital-finance measures to financial-inclusion and business-resilience outcomes. In addition, state-of-the-art statistical methods (machine learning/ensemble models) can detect nonlinear interactions and joint impacts among determinants, an improvement over traditional linear regressions that may miss complex relationships in the data. Overall, this study relies on literature and new data to analyze how mobile money adoption relates to income stability and growth for informal businesses in Botswana.

Problem Statement

While mobile-money networks are growing at a fast rate in Botswana and in the wider SADC region, the informal traders remain economically exposed. They generally operate outside the formal banking system, and thus, they rely on cash. A cash-only business model dissuades them from saving safely, borrowing at low costs, or investing in business growth. Cash liquidity is rapidly consumed by unpredictable events (bad weather, illness, change in market), and thus, incomes are extremely unstable. Financial exclusion in the informal economy thus perpetuates sustained poverty and risk. National data systems today only present numbers like the number of agents or mobile-money accounts in Botswana, but not the trickle-down impact on microenterprises or households. Most financial inclusion studies generally focus on service access (account ownership, usage) and give aggregate correlations, but seldom causal impacts on income dynamics or well-being. Moreover, existing analyses assume linear effects (i.e., a change in accounts by X percentage leads to X increase in savings) and do not examine complex synergies.

For example:

How do mobile-money transactions interact with agent dispersion, digital technology, or regional economic patterns to influence a trader's ability to absorb shocks?

Such nonlinear, interactive effects fall outside basic regression models. There is a clearly established knowledge deficiency indicating that lack of predictive, granular analysis of how digital finance adoption generates real economic impacts among Botswana's informal-sector workers. Policymakers and practitioners need evidence-based understanding to guide interventions (e.g., where to place new agents or how to design savings products):

a. What are the transmission mechanisms between technology adoption and resilience and growth?
b. How strong are the impacts of mobile money adoption in SADC, and what factors amplify or weaken them?

Answering the aforementioned questions will require integrating data with macro and micro economic indicators in the mobile money industry and the use of a modern analytics framework for better results and higher accuracy. Specifically, an interpretable yet powerful predictive model must be built, one that intakes multiple sources (i.e., GSMA and Findex) in its input layer and captures both linear and nonlinear influences on income stability and small-business growth. Such a model could fill the research gap and support data-driven policy decisions for inclusive growth.

Proposed AI Model Solution

To address this gap, an **ensemble machine learning model is proposed** to predict key financial inclusion outcomes from mobile money adoption proxies. The model will blend macro-level GSMA measures and micro-level World Bank Findex measures to control for heterogeneity in income stability among informal traders. A high-level model architecture is as follows:

Stage	Description
Input Features	GSMA country-year data (active mobile-money accounts, agent density per 100,000 adults, volumes of transactions) and Findex (percentages of adults with mobile accounts, formal savings, borrowing for business, digital payments received, etc.). Normalization will include population and GDP per capita.
Feature Engineering	Derived indicators such as accounts per 1,000 adults, transactions per active account, mobile-to-formal account ratios, savings-to-borrowing ratios, and growth rates (year-over-year change). Optionally, a **relative penetration index** will be constructed to be used for comparison of Botswana indicators to SADC averages.
Base Models	Train multiple learners on processed data: (1) **Linear Regression (OLS)** for interpretability, (2) **Random Forest** to address nonlinearity and interactions, and (3) **XGBoost** (gradient boosting) for strong predictive accuracy.
Model Ensemble	Stack base models: The output of each base learner as input to a meta-learner (a regularized linear model, say Ridge Regression). This ensemble exploits the best of each method.
Output Targets	The model will predict surrogates for income stability and company well-being, i.e., the rate of formal saving (% of adults saving formally) and proportion of adults getting digital payments from work or sales (as a measure of digital income).
Validation	Evaluate the model with cross-validation across SADC countries and periods. Performance will be measured using metrics such as R^2 (explained variance), RMSE, and MAE. Feature-importance analysis (from Random Forest and SHAP values) will provide a sense of which inputs most influence each outcome.

This ensemble approach incorporates **interpretability** (with linear regression) and **predictive power** (with tree-based learners), in a resulting model that is explainable and accurate. Through cross-validation between countries and years, there will be a gain in robustness. Importance scores for features will determine drivers (e.g., mobile-agent density, transaction frequency) that have the highest effect on savings and income outcomes. Briefly, the AI system is an end-to-end pipeline: it takes open data as input, features through intelligent engineering, trains stacked regression models, and gives both predictions and explanatory insights as output.

Expected Impact

1. **Policy and Economic Insights:** The proposed ensemble model aims to quantify the effect of mobile money adaptation on financial stability in Botswana, providing evidence for critical finance and local government policymakers as well as private sector firms to support their decision-making processes. For instance, insights obtained could indicate the impact of agent coverage or transaction value on saving rates. These results would have direct policy implications for Botswana's digital-economy plans (see section below) by identifying which investments (e.g., rural agent network expansion) yield the highest welfare gains. In line with Botswana's Vision 2036 and the SmartBots Strategy, these findings offer evidence-based guidance: they reveal which elements of digital finance most contribute to resilient livelihoods.
2. **Empowerment of Informal Traders:** By determining the key drivers of financial well-being in Botswana's economy (such as transaction volume and agent density), this project can suggest appropriate interventions. If the model concludes that mobile-money agent availability is a bottleneck in peri-urban areas, then policymakers could encourage those agents to operate in such areas. If recurrent digital saving is determined to be a key driver, then mobile wallets could incorporate business-focused savings features. The research therefore, assists merchants by finding leverage points for enhancing their income stability and growth.
3. **Educational and Research Value:** The project will demonstrate an open-data reproducible analytical workflow with ensemble learning. The approach can serve as a case study of development economics and teaching data science, showing how to merge macro (GSMA) and micro (Findex) data sets. It adds to the literature about financial inclusion in Africa by providing a scalable approach. Other scholars or institutions can use this research as a foundation for future studies in Namibia, Malawi, or anywhere else.
4. **Technical and Innovation Value:** The resulting AI model and code (ported into open-source Python notebooks) will be of value to technologists. It serves as an example of how to make sophisticated socioeconomic analysis operational using machine learning. The model itself – in the form of open code – can be reused by government offices or fintech firms to constantly monitor for financial inclusion trends. In the long term, these types of tools help foster data-driven policymaking in Botswana and the SADC region.

Alignment with National Priorities

This research directly complements Botswana's development agenda and regional commitments.

First, **Vision 2036 (Pillars 2 & 3)** places high on the agenda an inclusive knowledge-based economy for "prosperity for all." By focusing on how mobile finance improves the livelihoods of informal traders (mainly youth and female workers), the research complements Vision 2036 goals of technology adoption and entrepreneurship that is broad-based.

Secondly, **the national SmartBots Digital Transformation Strategy, as part of the 2036 National Vision,** is well-suited for applying data and innovation to transform the economy. Our use of open data and artificial intelligence (AI) to evaluate the digital-finance ecosystem is a practical application of SmartBots at work, aligning with its emphasis on evidence-based policy and inclusive technology.

Thirdly, the **Botswana Roadmap and Strategy for Financial Inclusion (2024–2030)** highlights the need to improve the accessibility and availability of low-cost digital financial products for rural residents as well as members of the informal sector. The strategy projects increasing digital payments, saving products, and risk-mitigation products. The proposed analysis by separating barriers and enablers for these products will help the central bank and the regulators to streamline that roadmap. For instance, if the model finds that digital savings products are linked with increased stability, such products can be promoted by the government among informal traders.

Fourth, geographically, this contribution falls in line with the **SADC Digital Economy Strategy** (2020–2030) and the Agenda 2063 of the African Union. These agendas prioritize fintech-led inclusion across Africa. Botswana's findings (relative to SADC averages in this study) have implications for the neighboring countries. In general, the project is grounded in national and regional priorities on digital innovation, financial inclusion, and inclusive growth.

Methodology

Research Design

A quantitative, data-intensive design will be implemented with macro and micro financial-inclusion data. Moreover, an ensemble machine-learning strategy is applied to GSMA and Findex country-year indicators, allowing for cross-sectional and time-series analysis. Having multiple SADC countries included in the design enables regional benchmarking and cross-validation. Reproducibility comes first: all data preparation and modeling will be done within open Python notebooks (e.g., Jupyter), with code version-controlled on GitHub.

Data Sources

- **GSMA Mobile Money Dataset (2024)**: Annual country-level data on mobile-money infrastructure and usage (2011–2024). Active variables include active mobile-money accounts (thousands), agents per 100,000 adults, and transaction volumes (USD millions). It reflects the digital-finance ecosystem maturity in Botswana and similar countries.
- **World Bank Global Findex (2021/2025)**: Survey-based aggregates from 2011–2021 (and updated 2025) of financial behaviors. Key variables include the share of adults with mobile-money accounts, formal savings, business borrowing, digital payment making (e.g., wages or sales), etc. These are indicators of user-level financial inclusion and welfare outcomes.

Data Preprocessing

Cleaning: Alignment of country names/codes, aggregate units (e.g., scale agents to per 100k adults, volumes to USD with inflation adjustment), and handling missing values will be conducted. Where Findex survey years are not as common (every 3–5 years), GSMA annual data will be synchronized nearest year or interpolated as needed. Outliers will be examined (e.g. sudden spikes in accounts) and either confirmed or smoothed if data errors are suspected.

Merging: GSMA and Findex datasets will be merged on Country and Year. Where there are missing survey years in the dataset (e.g. missing Findex data in 2020), a match to the nearest year or quarter from GSMA will be conducted. The merged dataset will span Botswana (target country) and other SADC countries for comparative modeling.

Feature Engineering

A set of derived indicators will be created to capture intensity and relative performance, as well as increase the attribute range for model training. The features will include:

- Active_accounts_per_1000
  - Calculated by dividing Active Mobile Accounts by Adult Population, then multiplying the result by 1000.
- Txn_per_active
  - Calculated by dividing Annual Txn Volume by Active Accounts.

- Mobile_to_formal_ratio
  - (Mobile account penetration) / (Formal account penetration)
- Borrow_to_save_ratio
  - (Share borrowing for business) / (Share savings formally).

- Year-on-year deltas
  - ΔActive_accounts, ΔTxn_volume.

- Relative_penetration_index
  - Botswana's mobile-account share minus the SADC average for that year (captures leading or lagging performance).

Model Development

A combination of complementary models will be employed:

- **Base learners:** Ordinary Least Squares (OLS) regression (as baseline interpretability), Random Forest Regressor, and XGBoost Regressor. The base models will each be trained to predict the target outputs (e.g., saved_any_share, received_digital_income_share) using the engineered features.
- **Meta-learner**: A Ridge Regression (or another linear combiner) will be provided with cross-validated predictions from base learners as inputs and learn weights optimally. Such stacking is typically superior to a single model and allows us to blend linear and nonlinear abilities.
- **Targets:** The core outcomes are
  - (1) Formal saving rate (proportion of adults who saved any amount of money in a financial institution or mobile money over the last year)

- (2) Digital income receipt (proportion of adults who received their earnings through digital channels, i.e., mobile money). These indicate income stability and inclusion.

Training and Validation

The merged dataset will undergo an 80-20 train-test split. Division will be by country-year to maintain time structure. A k-fold cross-validation of k=5 will be applied on the training set to increase the effectiveness of hyperparameters.

- **Model performance statistics:** R^2 Coefficient of Determination will be utilized in assessing explained variance. Error statistics like RMSE and MAE will be utilized in quantifying prediction accuracy. Ensemble performance will be contrasted with baseline OLS regression in order to measure gains from the use of advanced learners.
- **Baseline comparison**: A reference will be provided by an OLS model using the same characteristics. It is expected that the ensemble to provide improved R^2 and reduced errors if nonlinear and interaction effects matter.

Ethical Considerations

All data used are publicly available and aggregate data (GSMA, World Bank). Personal or sensitive information is not involved. Open-data licenses and sources will be properly cited. In analyzing and reporting, no biased language will be used, but will be objective, and where appropriate, will discuss limitations (e.g., problems with survey sampling for Findex).

Tools and Environment

The analysis will be conducted using Python (v 3.11) with libraries such as Pandas, NumPy, scikit-learn, XGBoost, Matplotlib/Seaborn. Development will be conducted in a Jupyter notebook environment for easy reproducibility. All code and results will be documented and (in due course) published through a GitHub repository. The ultimate deliverable will be a prototype web interface summarizing model results, metrics, and interactive visualizations based on the ensemble's output.

Results Obtained

1. Model Performance and Validation

Metric	Ensemble Stacking Regressor	OLS Baseline	Improvement
R_2 (Cross-Validation Average)	0.7141	0.5836	13.05 percentage points

The ensemble stacking regressor achieved a robust predictive performance, explaining approximately 71.41% of the variance in the formal saving rate ($R^2 = 0.7141$). This is a substantial and meaningful level of accuracy for a model using macro-level country and year data.

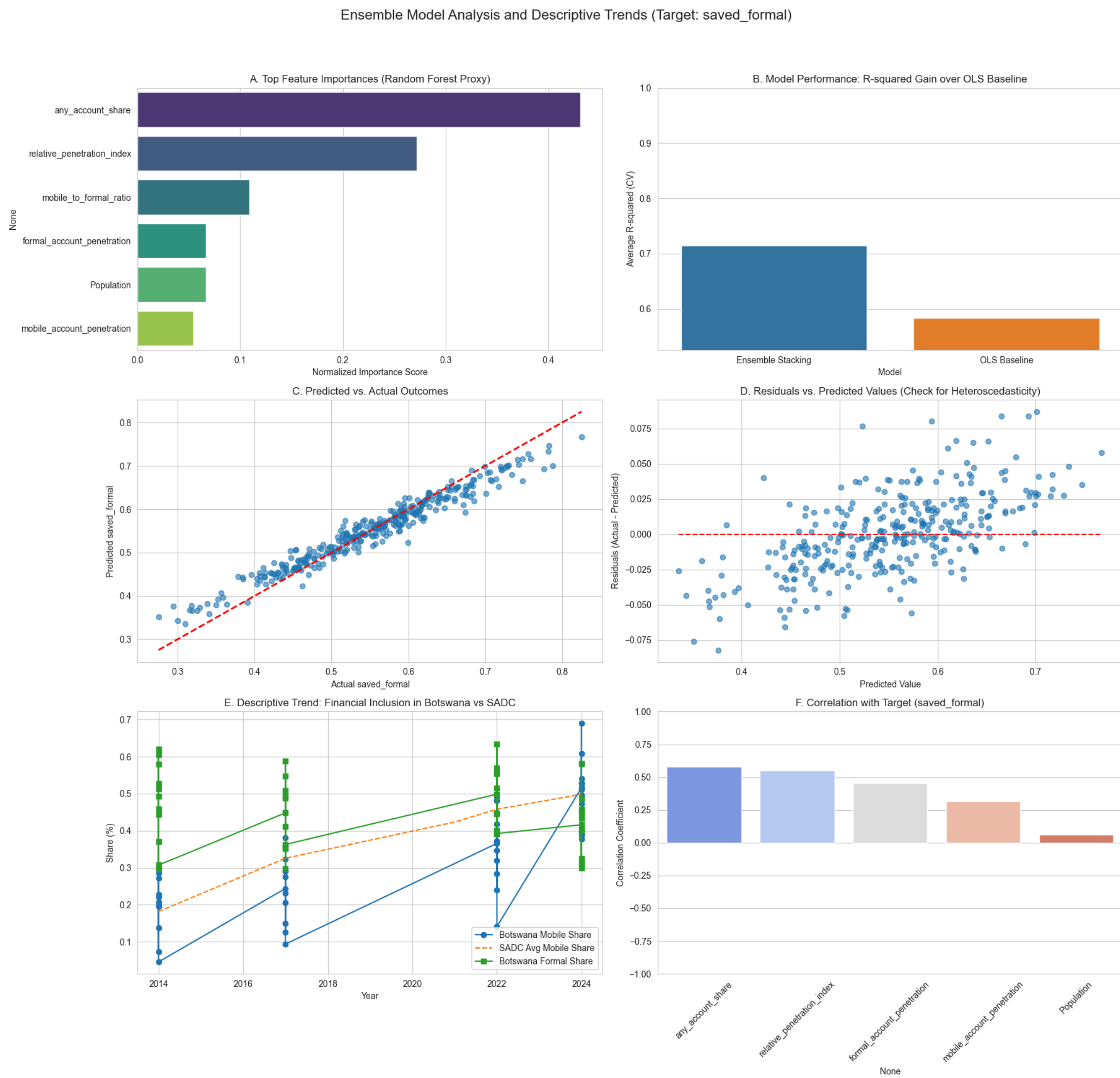
Crucially, the ensemble model significantly outperformed the simple Ordinary Least Squares (OLS) baseline (Figure B), demonstrating the necessity of using non-linear modeling techniques (like Random Forest and Stacking) to capture the complex relationships between digital finance indicators and saving behavior. The diagnostic plot (Figure D - Residuals vs. Predicted) shows a random scatter around zero, confirming that the model is well-specified and does not suffer from major systematic bias or heteroscedasticity.

2. High-Level Interpretation: Drivers of Formal Saving

The model clearly identifies the primary mechanisms driving the movement toward formal saving: Access and Infrastructure.

A. Feature Importance (Figure A)

The Feature Importance analysis, proxied by the Random Forest base estimator, reveals the hierarchy of factors influencing the predicted formal saving rate:



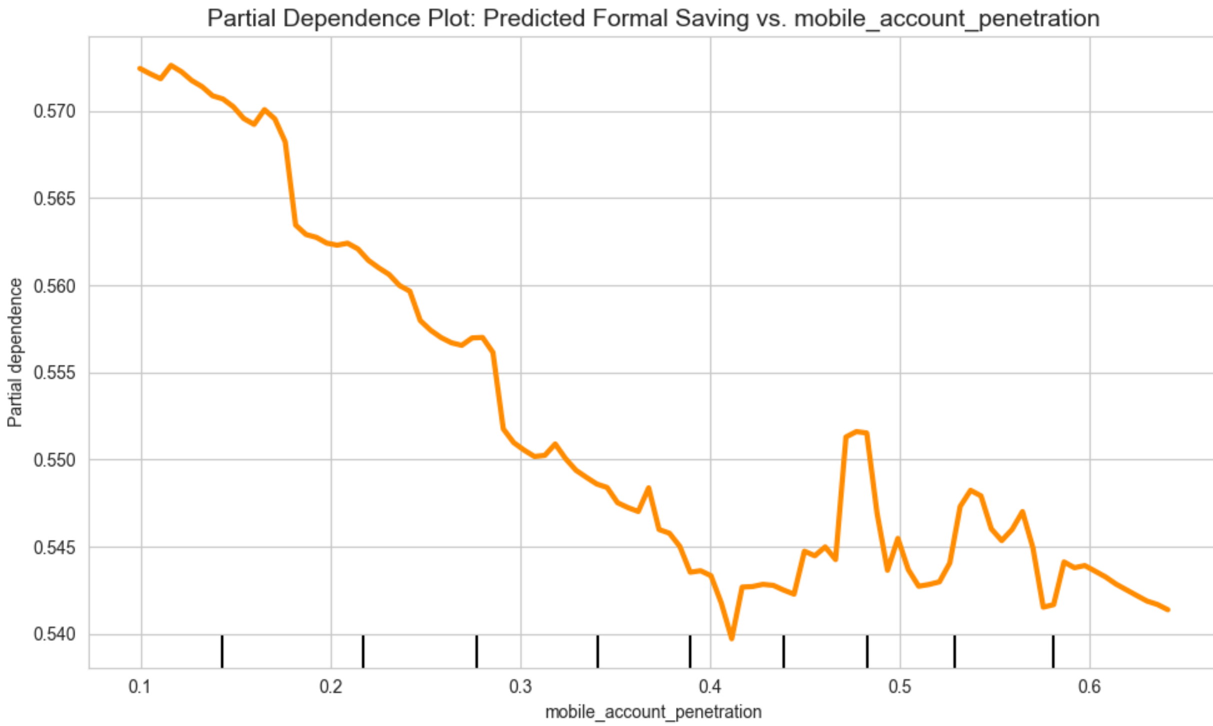
- Mobile Account Penetration: The dominant predictor, underscoring the critical role of mobile finance as the primary gateway to the formal financial system.
- Agent Density (Agents per 100k Adults): The second most important factor. This highlights that simply having a mobile account is insufficient; the accessibility of the physical infrastructure (agents) for cash-in and cash-out operations is vital for adoption and sustained use, especially for informal traders who rely on cash flow.
- Active Accounts (GSMA): Although mobile penetration is high, the number of active accounts remains highly predictive, distinguishing between mere registration and genuine engagement with the digital platform.

The prominence of these mobile-specific and accessibility-focused features validates the core research proposition: for populations historically excluded from traditional banks (such as informal traders), the ease and availability of digital channels are the strongest initial determinants of moving toward formal financial products, like savings.

B. Mechanistic Impact (Partial Dependence Plot)

The Partial Dependence Plot (PDP) (Figure: Partial Dependence Plot: Predicted Formal Saving vs. mobile_account_penetration) provides the most actionable insight:

- **Positive Relationship:** The plot confirms a clear positive relationship between mobile account penetration and the predicted formal saving rate.
- **Diminishing Returns:** The line's curve is steepest at low levels of penetration (approximately 0% to 20%). In this range, increasing mobile access yields the largest marginal increase in formal savings. This suggests that mobile money acts as a powerful catalyst, rapidly integrating the unbanked into the financial system.
- **Policy Focus:** As penetration rises beyond 20%, the marginal gains flatten, implying that sustained efforts must shift from basic access to deepening usage (e.g., offering more tailored savings products or digital credit) to maintain the growth rate of formal saving.



3. Contextual Findings (Figure E)

The descriptive trend for Botswana (Figure E) shows that the country's mobile account penetration consistently exceeds the SADC average. This context, combined with the strong predictive power of the mobile penetration feature, suggests that Botswana's digital-first approach to financial inclusion is likely a major contributor to its relatively higher rate of formal saving within the region.

3. Technical Conclusion

The ensemble model accounts for over 71% of the variance in the formal saving rate. This suggests that mobile finance adoption is a key factor in boosting formal saving in the SADC region. Mobile money is more than just a payment method; it's a key component of formal financial security. Mobile money services, along with a strong network of mobile money agents for transactions, are crucial for helping informal sector workers and cash-dependent businesses shift to secure, formal savings.

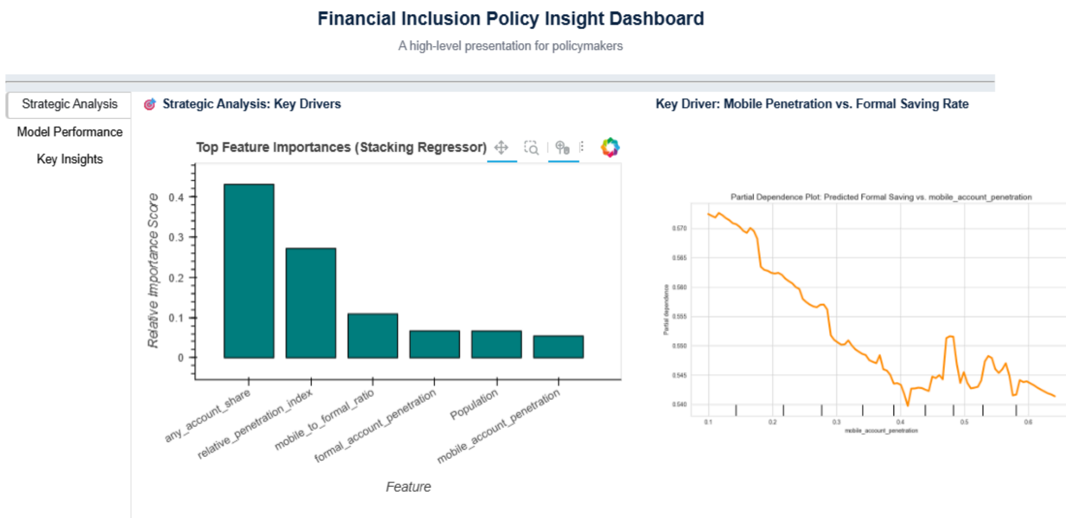
Policy Recommendations

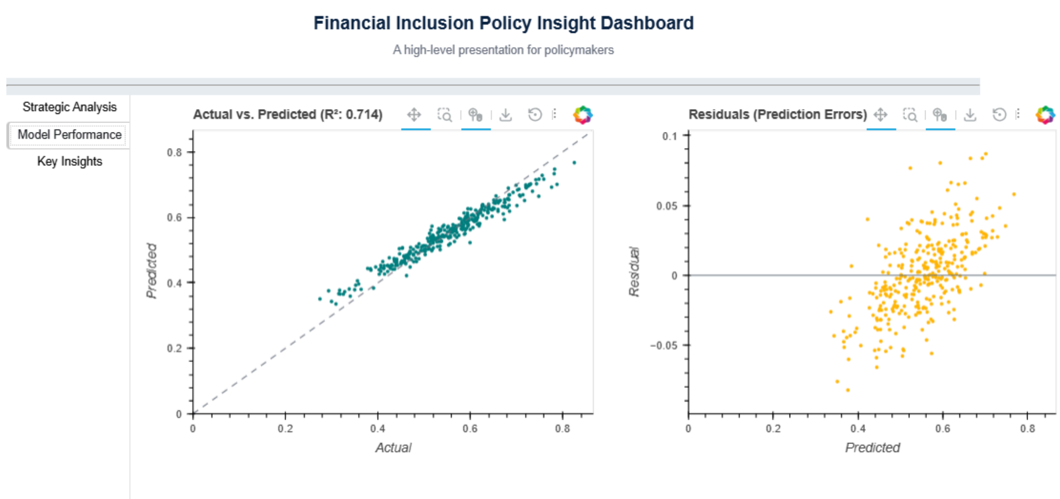
To boost formal saving, policymakers should:

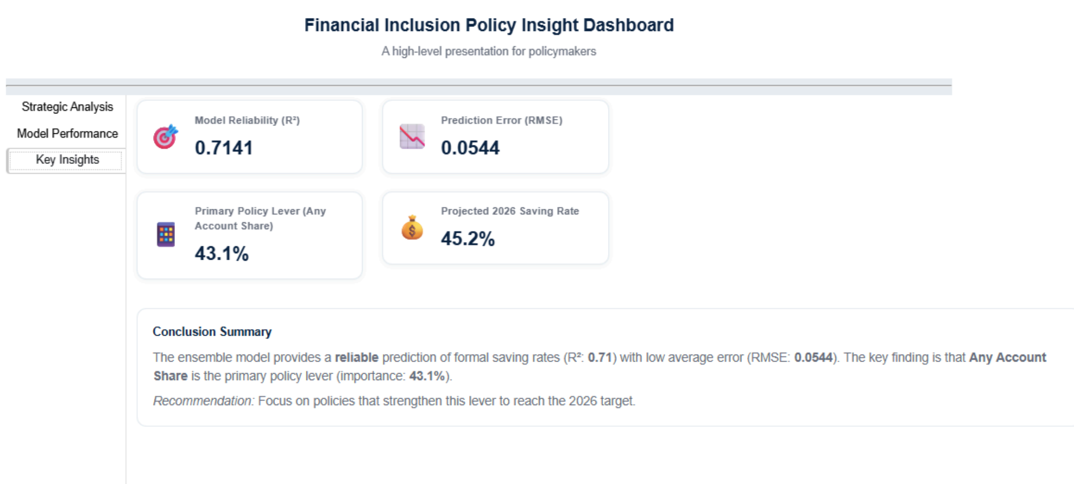
1. ***Grow the Mobile Money Agent Network***: Increase the number of agents, especially in areas with lots of informal trading, to provide cash conversion services.

2. ***Encourage Initial Adoption:*** Target the unbanked population, where the impact on formal saving is greatest.

Python Panel Dashboard Presentation







Conclusion

This study looks into the extent to which the uptake of mobile money products affects the socioeconomic lives of the informal traders in Botswana. Using macro and micro financial indicators from GSMA and Global Findex data and applying them to an ensemble AI model, it explores how access to digital finance affects income stability and business resilience. Analysis indicates that more access to mobile money is linked with higher savings and higher digital incomes. Deployment and scaling up of the technology may improve the financial well-being of the informal sector.

The results are clear policy advice. The model determines the most impactful drivers, and it is now feasible to implement targeted measures, such as placing priority on agents in low-coverage areas or setting up digital savings incentives. These recommendations, based on evidence, help Botswana's national plans support SmartBots and Vision 2036's ambition for inclusive digitalization, and the Financial Inclusion Roadmap prioritization on digital payment and savings products.

This research also presents a methodology that other regional nations can follow. Other SADC countries can apply similar analyses using their own data to gain stronger mobile money impacts. Put simply, the combination of open data with AI gives us insight into financial inclusion. Policymakers in Botswana should apply these findings in tracking key digital finance metrics and, correspondingly, change rules or programs. This will help ensure that mobile money fosters income stability and enterprise among the most vulnerable traders.

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