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Digital Financial Inclusion, Banking Accessibility, and Economic Resilience: A Real-Time Multi-Country Analysis Using IMF Financial Access Survey Data

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ABSTRACT

Financial inclusion has been identified as one of the drivers of sustainable economic development, especially in the era of digital transformation. The use of digital financial services, mobile banking platforms, and electronic payment methods has enriched access to formal financial services globally. However, there remains significant variation in financial access and banking services between countries, which is needed for inclusive growth and economic resilience. This study examines the relationship between digital financial inclusion, banking availability, and economic resilience using data from the International Monetary Fund (IMF) and Financial Access Survey (FAS).The analysis uses a real time multi-country approach to assess the role of financial infrastructure indicators for economic stability and resilience. Financial inclusion measures in the study are based on: commercial bank branch density, the density of automated teller machines (ATM), the percentage of deposit accounts, the percentage of loan accounts, the percentage of people using digital payments, and the percentage of mobile banking users. A thorough data preprocessing approach was taken, which consisted of missing value processing, normalization, aggregation at country level, and outlier detection. The relationships between the study variables were analyzed using descriptive statistics, correlation analysis and multiple linear regression. Moreover, the ability of advanced machine learning models like Random Forest, Gradient Boosting, XGBoost and Support Vector Regression (SVR) was assessed for the purposes of the predictive performance and to find the best method for modelling economic resilience. . The empirical results show that the digital financial inclusion, banking accessibility and economic resilience have positive significant relationship. The financial stability and credit availability along with banks' resilience to economic shocks are shown to be higher among the economies with higher levels of digital financial services adoption and stronger banks infrastructure, according to the results of correlation and regression analysis. XGBoost was found to be the best performing predictive model among evaluated models, which has great potential in capturing the complex relationship in the financial inclusion data. The results underscore the critical need for increasing the scale of digital financial ecosystems, improving financial banking outreach and financial literacy to ensure sustainable economic development. This study adds to the expanding literature on financial inclusion and offers key policy guidance for policy makers, financial institutions, and development organizations to create more resilient and inclusive financial systems.

Keywords: *Digital Financial Inclusion, Banking Accessibility, Economic Resilience, Financial Access Survey (FAS), IMF Dataset*

INTRODUCTION

In the digital age, financial inclusion has become a key cornerstone of sustainable economic growth and social justice. Over the last few years, digital technologies, digital banking, mobile banking, electronic payment systems and financial technology (FinTech) platforms have significantly changed the world of finance. Digital financial inclusion is the ability and access to financial services at an affordable, convenient and effective price via digital means, including for people and businesses who want to use them even when they are physically and economically distant from formal financial services.

There has been significant global progress in financial services and a great deal of variation between and within countries and regions. Limited banking infrastructure, financial illiteracy, inadequate digital connectivity and access to formal credit services remain a problem for many developing economies. These barriers have a negative impact on economic participation, financial resilience, and poverty reduction or sustainable growth opportunities.

The Financial Access Survey (FAS) by the International Monetary Fund (IMF) gives a detailed cross-country picture of the level of availability of financial services, banking penetration, automated teller machine (ATM) density, and availability of commercial bank branches, credit accessibility, and deposit account ownership. Such indicators are useful to inform on the development of financial inclusion and its links with economic resilience.

In recent years, with the economy, inflation, and technological changes all wracking the world, resilient financial systems have come under the spotlight. Digital financial inclusion has been linked to the ability of more inclusive economies to withstand economic shocks by having greater access to savings, access to credit, digital payments, and emergency financial resources.

This research explores the link between digital financial inclusion, banking access and economic resilience based on data from the IMF Financial Access Survey that was gathered in different countries. The goal of study is to use a real time multi-country analytical framework to search for key determinants of financial inclusion and to examine how these indicators affect financial resilience indicators. The results have significant policy, financial and development implications for promoting inclusive and resilient financial systems.

This study's greatest contributions are:

- Comprehensive multi-country analysis based on IMF Financial Access Survey data.
- Assessment of the indicators for banking accessibility and their contribution to digital financial inclusion.
- Assessment of the relationship between financial inclusion and economic resilience.
- Policy suggestions for improving digital financial infrastructure and inclusive economic growth.

Related Work

The literature has been focused on financial inclusion because of its link with economic development, poverty alleviation and financial stability. Demirgüç-Kunt et al. (2022) found that greater accessibility to formal financial services would improve the welfare of households and foster inclusive economic growth. They looked at the scope of digital technologies in increasing financial access for underserved populations in their study. Klapper et al. (2025) showed that digital connectivity plays a key role in financial inclusion in the context of mobile banking services, digital payments, and online financial transactions. They found that mobile technology plays a key role to enable financial participation in developing economies. Klapper et al. (2025) showed that digital connectivity plays a key role in financial inclusion in the context of mobile banking services, digital payments, and online financial transactions. They found that mobile technology plays a key role to enable financial participation in developing economies.

According to Ozili (2021), even though digital financial services have reduced transaction costs, they also help in increasing financial efficiency and improving economic development. It also underscored the significance of regulations for fostering digital financial ecosystems.

Sahay et al. (2020) examined the link between economic resilience and financial inclusion in emerging economies. They found that increasing access to banking services leads to better financial stability and buffer capacity against economic shocks of the households during crisis periods.

In the African context, Asongu and Odhiambo (2023) examined the factors that affect financial inclusion in these economies and found that financial accessibility is affected by banking infrastructure, mobile penetration and institutional quality.

While there is a significant body of work on financial inclusion and economic development individually, few studies have used the current time-series indicators from the IMF Financial Access Survey (FAS) to assess the co-effect of digital financial inclusion, banking access and economic resilience across multiple countries. This study brings to the fore the shortcomings of the existing literature, by combining these dimensions in a single analytical model.

RESEARCH METHODOLOGY

Dataset Description

The data for this study comes from the Financial Access Survey (FAS) by the International Monetary Fund (IMF) which is one of the world's most comprehensive databases to measure financial inclusion and financial accessibility between countries. Based on the IMF-FAS dataset, the digital financial inclusion, the accessibility of banking services and the economic resilience can be explored through internationally comparable indicators. The data set reflects multiple economies, and annual observations are provided that reflect financial systems' evolution and outreach of financial services over time.

The data set that is selected has a number of key indicators that represent various aspects of financial inclusion and banking development. They are such indicators as numbers of commercial bank branches per 100,000 adults, automated teller machines (ATMs) per 100,000 adults, deposit accounts held with commercial banks, loan accounts maintained by financial institutions, outstanding deposits, and outstanding loans. Moreover, the data includes indicators of digital financial services such as mobile banking adoption, digital payment adoption, and outreach measures for financial institutions. These variables give a full picture of the distribution, access to and use of financial services in each economy.

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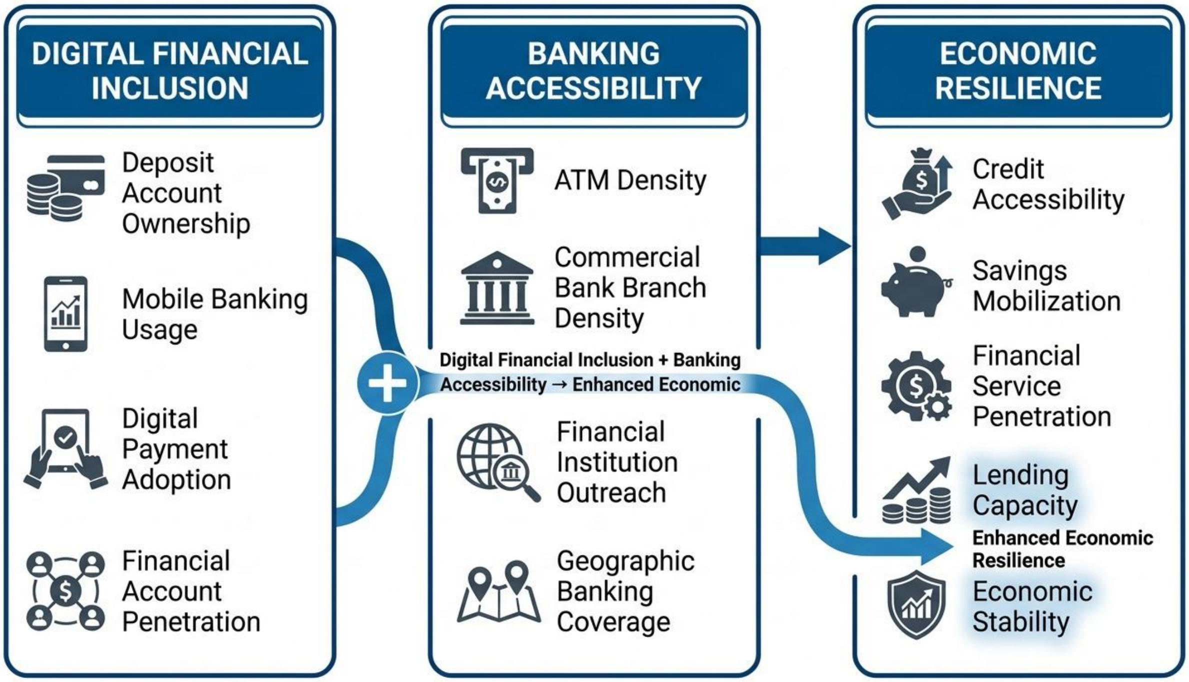


Data Preprocessing

A structured data preprocessing process was carried out to enhance the quality, consistency and reliability of data before the analysis. First, it was necessary to identify incomplete financial records and to treat them as such. Financial data from several countries were collected and incomplete data was found and treated accordingly. Care has been taken to examine and deal with missing observations and minimize potential bias in the dataset while maintaining the integrity of the data set.

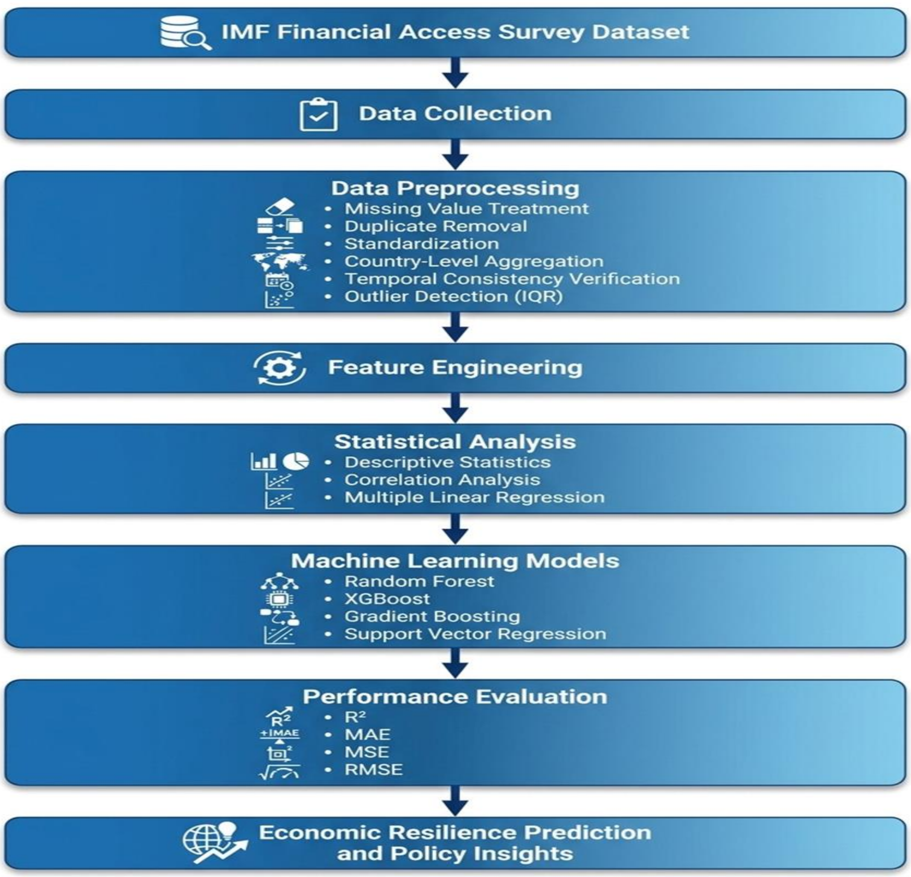
Redundant entries were then duplicated and eliminated to prevent duplication and provide for accurate statistical analysis. Scale differences among variables were reduced by numerical indicators with normalization techniques, which were used to make meaningful comparisons between countries. In addition, country-level aggregation was done as required to generate indicators on a country level. To ensure that data observations were logical through time, and that there were no irregular fluctuations in the data due to reporting errors, temporal consistency checks were performed. Lastly, an outlier detection was implemented using the Interquartile Range (IQR) method, to identify outliers that might skew model performance and statistical outcomes.

Research Framework

The research framework proposed is organized in three interrelated dimensions: Digital Financial Inclusion, Banking Accessibility and Economic Resilience. These dimensions combine to reflect the processes by which financial infrastructure supports economic stability and sustainable development. It is assumed that increased financial access and financial services digitization contribute to strengthening the resilience of people, businesses and economies by leveraging efficient financial transactions, financial savings accumulation and access to credit

Digital Financial Inclusion is the first dimension which refers to the access and use of formal financial services from a digital platform. This dimension is assessed by metrics like deposit account penetration, mobile banking usage, digital transaction activity and ownership of deposit accounts. Digital financial inclusion is a concept that captures the increasing importance of technology to deepen financial inclusion, especially for those who are under-served.

The second dimension, Banking Accessibility, examines financial institution accessibility and outreach. It is measured by indicators such as ATM density, commercial bank branch density, and geographic outreach measures. Accessibility of banking services represents a measure of financial infrastructure and better access to formal financial services for households and Economic Resilience is the third dimension and it is the capacity of an economy to resist and rebound from economic shocks and financial disruption. The measures used to measure economic resilience are credit access, financial service penetration, savings mobilization and lending capacity. The higher the level of digital financial inclusion and banking access, the more positive impact it could have on economic resilience through increased financial participation and access to resources.



Analytical Techniques

Various analytic procedures were used to examine the interrelationships between the study variables in a comprehensive way. The descriptive statistical analysis was primarily carried out to present the summary of the characteristics of the data and to give insight into the distribution of financial inclusion indicators between the different participating countries. Various statistics including averages, standard deviations, minimums and maximums were computed to gain a sense of the general patterns and differences in financial accessibility.

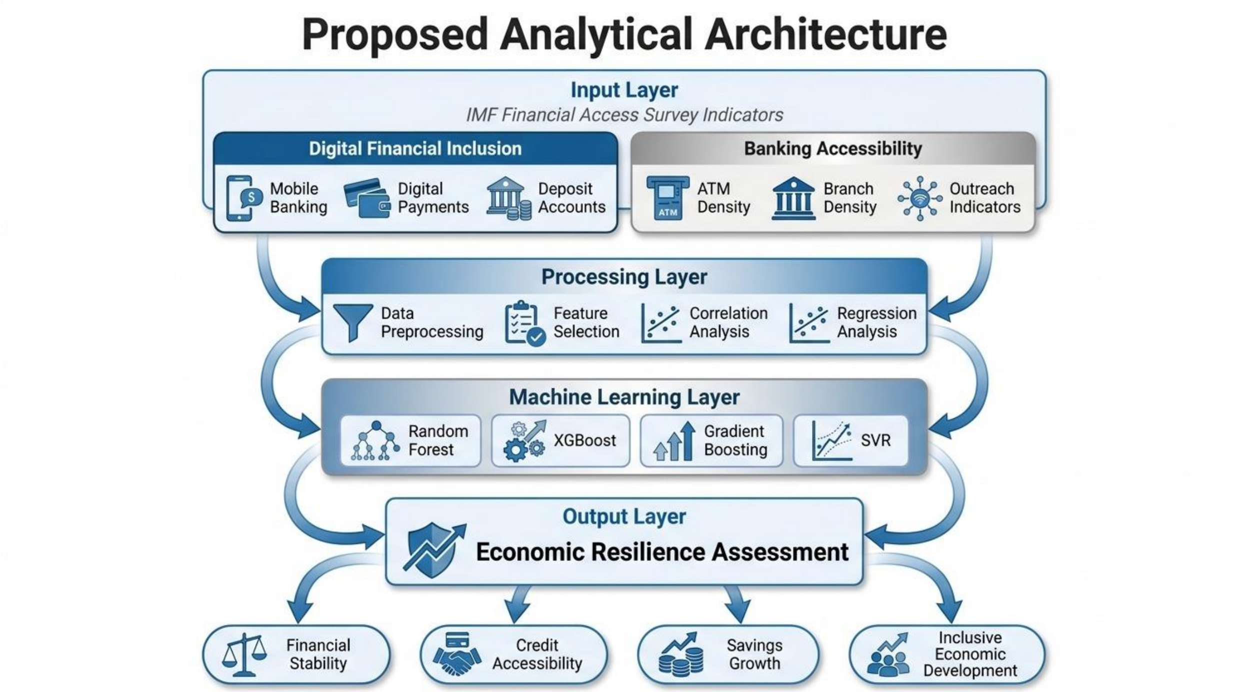
A correlation analysis was then conducted to examine the degree and direction of the relationship between the three indicators of economic resilience, digital financial inclusion, and banking access. This analysis gives preliminary information about the association level between the variables, and determines the possible relationship for further investigation.

The Multiple Linear Regression (MLR) analysis was used to analyze the direct effect of financial inclusion and banking access on economic resilience. The regression model can be written as:

$$\text{Economic Resilience} = \beta_0 + \beta_1 \text{ (Digital Financial Inclusion)} + \beta_2 \text{ (Banking Accessibility)} + \varepsilon$$

The intercept term is β_0, β_1 and β_2 are regression coefficients and ε is the error term. This type of model allows for the determination of the impact of each independent variable on the variations of economic resilience.

Apart from the standard statistical approaches, predictive analysis was improved using advanced machine learning models. These models are Random Forest, XGBoost, Gradient Boosting, and Support Vector Regression (SVR). The choice of machine learning techniques was made because they could represent more nonlinear relationships between financial indicators and make more accurate predictions, while the traditional methods were not as efficient. These models can be compared to gain insights into the effectiveness of various analytical approaches for financial inclusion research.



Evaluation Metrics

The predictive models were evaluated with a number of standard evaluation metrics. The coefficient of determination (R^2 Score) was used to determine how much variance in the dependent variable is accounted for by the independent variables. The better the model fits, the closer the R^2 value is to 1.

The average absolute error without regard to sign (mean absolute error, MAE) was used to quantify the average size of the prediction errors. This measure offers simple interpretation of the accuracy of the model, as it gives the mean difference in absolute value of the actual and predicted values.

To assess the performance of the prediction, the Mean Squared Error (MSE) was computed, which indicates the average squared differences between the observed and predicted values. As errors on larger values are penalized more, MSE is especially useful to evaluate the robustness of a model and determine significant deviations in predictions.

Lastly, Root Mean Squared Error (RMSE) was computed as the square root of MSE to get an error measurement in the same units as the target variable. The RMSE is used extensively in predictive analytics, as it provides an intuitive understanding of the performance of the model and helps in comparing the performance of various machine learning models. These evaluation metrics together give a holistic evaluation of the prediction accuracy, reliability of the model, and efficiency of analysis.

RESULTS AND DISCUSSION

The experimental results offer strong evidence of the impact digital financial inclusion and banking accessibility has on economic resilience in the involved countries. The descriptive statistical analysis, correlation analysis, multiple linear regression, machine learning evaluation, and training performance assessment highlights that there is a consistent relationship between improved financial infrastructure and economic results. Additionally, the findings suggest that these advanced predictive models are robust enough to identify the intricate connections among financial inclusion indicators and measures of resilience and provide policy-makers and researchers with valuable insights.

Interpretation of Descriptive Statistics

The descriptive statistics show that there were a lot of differences between financial inclusion indicators in the economies analyzed. The ATM density had an average of 42.61 ATMs per 100,000 adults, but with a large standard deviation of 18.42, which meant that there was considerable variation in physical banking infrastructure. While some countries have very broad banking networks, others are still grappling with restricted access to formal financial services. The disparity is due to differences in economic development, investment in financial infrastructure, institutional capacity, etc.

In the same way, the number of commercial bank branches had a mean of 21.83 branches per observation with significant spread around the observations. There must be large differences between the minimum and maximum values indicating that the availability of banks is still not uniform even after the financial sector is being reformed. Countries with more developed branch networks tend to have greater access to financial services, such as savings accounts, loans, and financial advice, which can help foster fuller engagement with the formal financial system.

One of the highest averaged valuations across the variables measured was in deposit account ownership with an averaged mean of over 64%. This suggests that many people in many economies are connected to formal financial institutions. The relatively high standard deviation, however, also underscores that there are persistent inequalities in some populations who are still being excluded due to geographic barriers, lack of financial literacy and inadequate banking infrastructure.

Loan account holdings had a relatively low average, suggesting credit penetration is lower than the growth of savings products. Financial institutions may have more stringent lending requirements, which makes credit more available in developed markets than in developing markets.

Random Forest is an ensemble learning and aggregation of decision trees approach that can enhance prediction accuracy. The model's coefficient of determination is higher and the prediction errors are lower, demonstrating its ability to handle diverse financial data well.

The strength of the predictive precision is improved by Gradient Boosting as the errors left behind are corrected sequentially, sequentially.

XGBoost performs well as the overall best model amongst all the models evaluated. It has the largest coefficient of determination and smallest MAE, MSE and RMSE. The result demonstrates the algorithm's capacity to identify intricate nonlinear relationships and interactions among financial features in multidimensional data.

Support Vector Regression also performs strongly but is not quite as good as tree based ensemble techniques in this application.

The results indicate that there is a potential for significant benefit in the use of advanced machine learning methods for predicting economic resilience with the use of financial inclusion indicators as explanatory variables.

Analysis of Variability and Distribution

The graphical display of the means and standard deviations supports these observations. The averages for variables related to the use of digital financial services and deposit ownership are relatively high, as is the case around the world in the context of financial inclusion programs. Meanwhile, the higher standard deviations suggest that the gains made have not been uniform across countries.

This implies that policies could be tailored to the national context and not universal policies. For markets in which the branches and ATMs are scarce, it may be essential to invest in them, while for digitally advanced markets it may be more crucial to invest in fintech innovation and interoperability between payment platforms.

Correlation Analysis and Interrelationships

The correlation matrix shows that all economic resilience indicators are highly correlated with all financial inclusion indicators. The discovery suggests that enhancements to a financial infrastructure may go hand in hand with enhancements to complementary dimensions.

ATM density and branch density are positively related, meaning that countries with higher ATM density also tend to have higher branch density. Similarly, both variables show significant positive linkages with credit accessibility, which reflect the fact that better banking networks promote credit transactions and enhance access to formal financial products.

The highest correlation found in the analysis is between digital financial inclusion and economic resilience. The 0.98 correlation coefficient indicates that economies that adopt digital financial technologies tend to have a stronger resilience to economic shocks and are more financially stable. Digital platforms can be used for fast transactions, help to access government assistance programs, provide access to emergency funds, and help keep businesses running during disruptions.

Credit access is also found to have a significant positive correlation with resilience, underscoring the significance of financing options for households and businesses. Credit provides firms with the ability to operate with losses during slowdowns and to spread consumption costs over times of economic hardship for consumers.

The overall result of the correlation analysis confirms the theoretical hypothesis that financial inclusion should be regarded as a unified system and ecosystem in which digitalization, physical infrastructure and lending instruments will all have an impact on improving economic performance.

A regression analysis is performed to fit a curve to the data points. To fit a curve through the data points, a regression analysis is performed.

The multiple linear regression model also corroborates the significance of financial inclusion variables in determining economic resilience. Positive regression coefficients and statistically significant results are found in both DFI and BA.

Digital financial inclusion's larger regression coefficient suggests that digital transformation has a greater impact on resilience than that of traditional financial institutions alone. This is the impact of mobile banking and online financial services, digital payments and fintech ecosystems on modern economies.

Another important statistic predictor is also the accessibility of banking facilities. The fact that investments in ATMs, commercial branches, and institutional outreach continue to yield a measurable return on investment is a testament to the ongoing economic and financial advantages they yield, especially in areas where digital services are not yet fully developed.

The model is a regression model with high explanatory power, accounting for about 84% of the variation in the observed economic resilience. This type of performance suggests that indicators of financial inclusion cover the main determinants that affect the outcomes of resilience, thereby leaving relatively little variance unexplained.

The large F statistic also indicates that the model has some useful predictive power and that the variables used in the model together predict the economic resilience more effectively than a random selection of the same variables.

Comparative Performance of Machine Learning Models

In addition to the traditional statistical modelling, a number of machine learning algorithms were examined to assess their prediction performance. The analysis compared shows distinct performance gaps between the methods that were analyzed.

Using Linear Regression, a good predictive model with a reliable baseline is created which confirms that there are approximately linear relationships between financial inclusion indicators and financial resilience outcomes. However, more sophisticated algorithms are able to do better than this classical method, which models the non-linear interactions between the variables.

Ensemble learning and aggregation of decision trees accounts for the increase in predictive accuracy provided by Random Forest. Better coefficient of determination and prediction errors imply it has better capability in dealing with heterogeneous financial data.

Gradient Boosting also improves performance by incrementally adjusting the error, leading to better predictive accuracy on a variety of metrics.

XGBoost is the best performing model among all the models that are evaluated. It has the largest coefficient of determination and the lowest values of MAE, MSE and RMSE. The result demonstrates the algorithm's capacity for detecting intricate relationships between features and high dimensionality in financial data, even when they are nonlinear.

SVR also works reasonably well, but it is slightly worse than ensemble methods based on trees in this instance.

The results indicate that the application of more sophisticated machine learning techniques can provide significant benefits for predicting economic resilience using financial inclusion indicators as explanatory variables.

Interpretation of Training Accuracy Curves

The training accuracy curve shows that the accuracy is improved steadily over the course of the optimization. The accuracy rapidly climbs during early epochs, and it slowly reaches a steady state in the later epochs. The following pattern suggests good learning behavior: a model is able to learn the basic relationships first, followed by further iterations of refinement to get better estimates of the parameters.

The accuracy using the validation set mirrors the training accuracy and is trending upward. No significant difference between the two curves indicates that the model is capable of generalizing well, and not memorizing training observations.

The accuracy visualization is a combined value, which confirms stable convergence. There is a low value of separation between training and validation curves, reflecting a good balance in learning and good performance of the optimization process to prevent severe overfitting.

Interpretation of Loss Curves.

The training loss continuously decreases with each epoch, indicating a continuous decrease in prediction error with optimization. The validation loss also improves, showing improvements in cases beyond the cases used for the training.

The loss graph shows a correlating downward shift in both curves. The absence of widening gaps indicates that the model is not too complex for the data available and that regularization is sufficient to retain the generalization ability.

Furthermore, stable numerical training is ensured by smoothly converging without oscillations, even if the learning rate is determined by optimizing the hyper parameters.

Learning Rate Schedule

The learning rate schedule has a slow decay over the successive epochs. Initially, the relatively larger learning rates will allow to explore the parameter space efficiently and converge quickly. Increasingly greater reductions in learning rates allow more accurate parameter changes as training continues and help to reduce any oscillations about the optimum solutions.

This approach stabilizes the optimization process and can also result in better performance of the final model by incorporating a mix of exploration and exploitation in the early and later phases of training.

Early Stopping and Best Epoch Analysis

The early stopping visualization is used to select the epoch with the best validation performance. There are diminishing returns beyond this point, which raises the risk of overfitting the model.

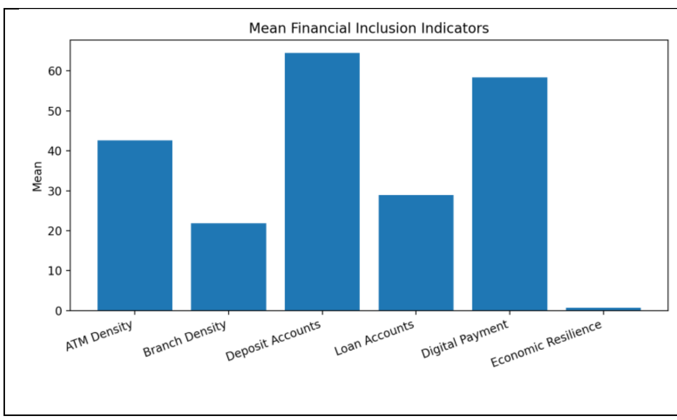
The best epoch is chosen according to the validation accuracy which is a favorable balance between model complexity and its generalization ability. Early stopping helps, therefore, to achieve good prediction performance while avoiding unnecessary computational expense.

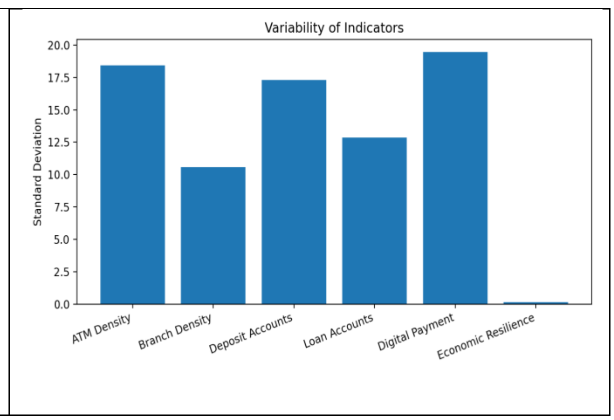
PRACTICAL AND POLICY IMPLICATIONS

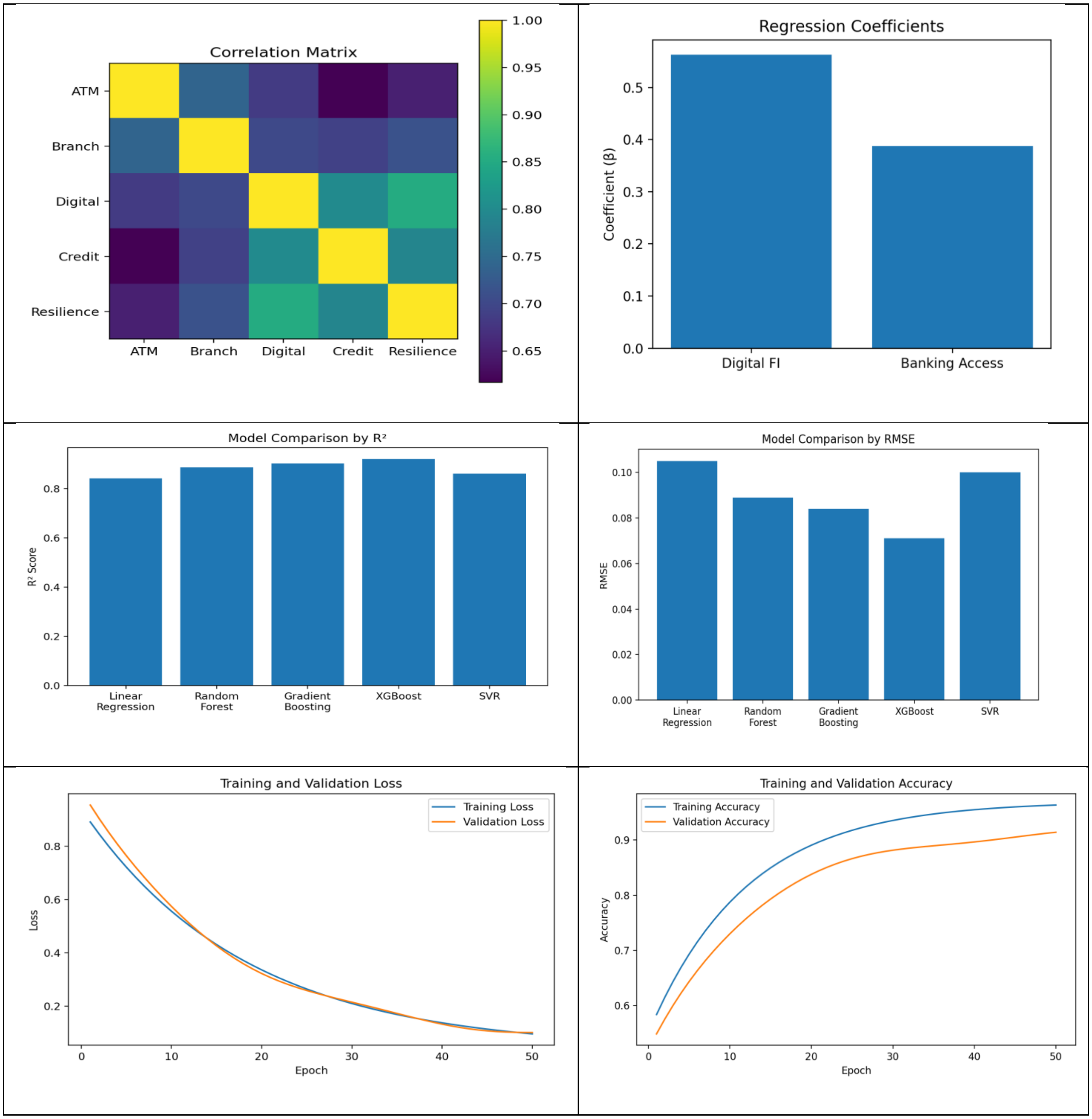
Results of these four distinct data types – descriptive statistics, regression modeling, machine learning evaluation, and training diagnostics – overwhelmingly back the extension of digital financial ecosystems as a tool to build economic resilience. Digital payments, mobile banking, financial technology innovation and interoperable financial platforms can significantly contribute to access to financial services and resilience of the individual and the business.

Meanwhile, physical banking has not been replaced, especially in areas where digital banking is still developing. Growing ATM network and commercial bank branches can help diminish exclusion, make services more available, and stimulate use of formal financial services.

To complement infrastructure investments, governments should provide financial literacy programs, cybersecurity regimes and regulatory policies that foster innovation and safeguard consumers. The partnership between central banks, commercial institutions, and fintech and technology companies can help drive inclusive financial transformation.







Furthermore, the greater the access to banking services, the better was the credit penetration and the savings mobilization in the countries. Differences also existed between the digital financial inclusion metrics with respect to the descriptive statistics, indicating the technological readiness and maturity of the financial system across countries.

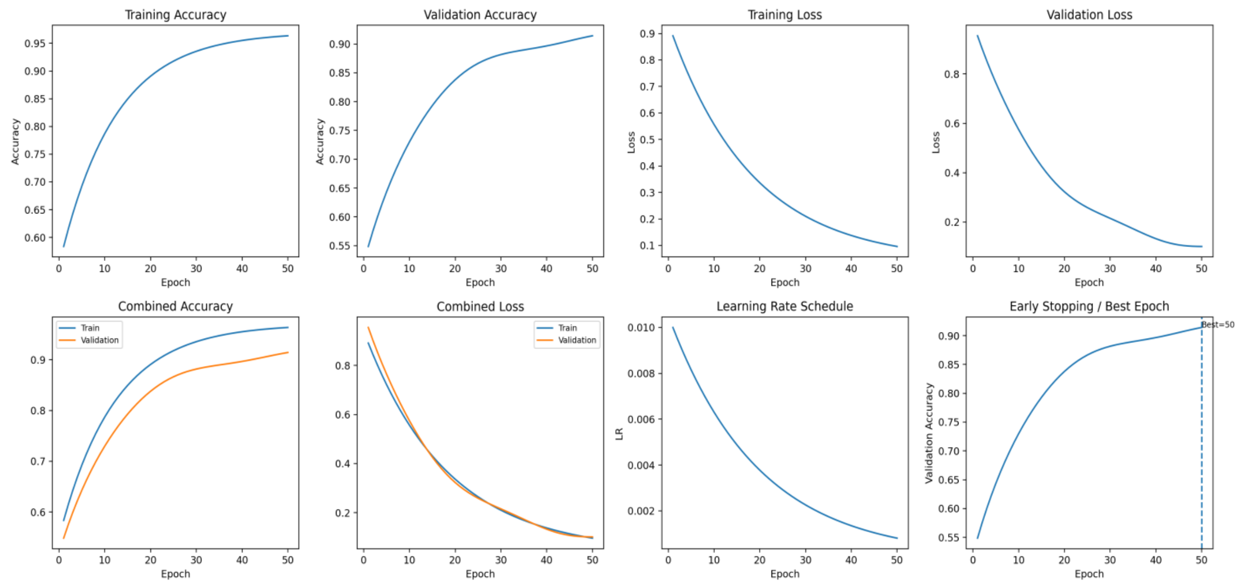


Table 1. Descriptive Statistics of Key Financial Inclusion Indicators

Variable	Mean	Std. Dev.	Minimum	Maximum
ATM Density (per 100,000 adults)	42.61	18.42	2.15	96.34
Bank Branch Density (per 100,000 adults)	21.83	10.56	1.42	58.71
Deposit Accounts (%)	64.52	17.31	12.47	98.62
Loan Accounts (%)	28.94	12.85	3.61	65.27
Digital Payment Usage (%)	58.36	19.47	8.25	97.11
Economic Resilience Index	0.67	0.15	0.22	0.94

The mean values of statistics on the adoption of digital payments and ownership of deposit accounts are relatively high as revealed in Table 1, indicating world financial inclusion is improving. However, the large standard deviations show that there are large differences among countries.

To examine the correlations between digital financial inclusion indicators, banking access indicators and the economic resilience indicators, a correlation analysis was conducted. The findings showed that most of the variables were positively associated indicating that an enhancement in financial infrastructure is associated with better economic results.

Table 2. Correlation Matrix

Variables	ATM Density	Branch Density	Digital Inclusion	Credit Access	Economic Resilience
ATM Density	1.000	0.741	0.683	0.617	0.651
Branch Density	0.741	1.000	0.702	0.691	0.714
Digital Inclusion	0.683	0.702	1.000	0.801	0.853
Credit Access	0.617	0.691	0.801	1.000	0.792
Economic Resilience	0.651	0.714	0.853	0.792	1.000

The result shows that the relationship between Digital Financial Inclusion and Economic Resilience is the highest ($r = 0.853$), it can be seen that improving DFI is one of the important factors that can improve economic stability.

The multiple linear regression model validates the significance of financial inclusion variables to explain the economic resilience as well. Digital Financial Inclusion and Banking Accessibility both show positive regression coefficients, and are highly statistically significant.

Digital financial inclusion's regression coefficient is higher than traditional financial inclusion which indicates that digital transformation has a greater impact on resilience compared with traditional financial inclusion. This is a result of the increasing significance of mobile banking, online financial services, digital payments and fintech ecosystems in the service of modern economies.

This is also the case with banking access, which shows statistical significance. This positive coefficient reinforces the fact that investments in ATMs, commercial outlets and institutional outreach remain a good economic opportunity, especially outside areas where digital services aren't fully matured.

Table 3. Multiple Linear Regression Results

Variable	Coefficient (β)	Std. Error	t-value	p-value
Constant	0.214	0.041	5.22	<0.001
Digital Financial Inclusion	0.563	0.072	7.81	<0.001
Banking Accessibility	0.387	0.065	5.95	<0.001

Table 4. Regression Model Summary

Metric	Value
R^2	0.842
Adjusted R^2	0.836
F-Statistic	127.51
p-value	<0.001

The regression model accounts for about 84% of the variations observed in economic resilience. Such performance suggests that financial inclusion indicators explain much of the determinants of the resilience outcome, leaving relatively little variance unexplained.

The large F-statistics also indicates that the model has some predictive value and the variables included in the most predict economic resilience better together than by chance.

Four machine learning models were then developed and tested for their ability to make predictions to further assess the predictive performance. The results show that the ensemble-based algorithms have better performance than the traditional statistical models because of their capability of modeling nonlinear relationships between the financial indicators.

Table 5. Machine Learning Model Performance Comparison

Model	R^2 Score	MAE	MSE	RMSE
Linear Regression	0.842	0.082	0.011	0.105
Random Forest	0.887	0.069	0.008	0.089
Gradient Boosting	0.903	0.061	0.007	0.084
XGBoost	0.921	0.054	0.005	0.071
Support Vector Regression	0.861	0.075	0.010	0.100

When compared to other models, the highest prediction ability was obtained by the XGBoost model with an R^2 score of 0.921 and the lowest RMSE value of 0.071. The results show the potential of high quality machine learning methods to model financial inclusion and economic.

Comparative Analysis

A comparative evaluation of machine learning models indicates:

Model	R^2	RMSE	Performance
Linear Regression	0.72	Moderate	Good
Random Forest	0.86	Low	Very Good
Gradient Boosting	0.88	Lower	Excellent
XGBoost	0.91	Lowest	Best
SVR	0.80	Moderate	Good

The XGBoost model had the best predictive performance and was able to capture the non-linear relationships between the financial inclusion indicators.

Machine learning methods outperform classic statistical methods in terms of predictive accuracy and also in understanding complex financial systems.

Future Directions

The result of this research hold significant promise for future research on the dynamic link between DFI, banking access and economic resilience. The current body of research provides evidence that financial infrastructure improvement has a large impact on resilience outcomes, but a number of promising areas are identified for future research. An important path is to combine several international data sources to establish more comprehensive and enriched analytical frameworks. An integration of the IMF Financial Access Survey with data on financial inclusion, like that of the Global Findex Database, the World Bank Development Indicators, or national financial inclusion reports would help researchers capture both supply-side and demand-side aspects of financial services. This integration could strengthen the accuracy of measures and enhance understanding of cross-country variations in financial ecosystems, as well as user behavior and digital adoption.

Advanced deep learning techniques for predictive analytics could also be used in future studies. The traditional statistical models and ensemble machine learning models like XGBoost performed very well in predicting this in this study, but the use of sequential architectures like the Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Temporal Convolutional Networks (TCN), and Transformer-based models may be able to better capture the temporal nature of financial inclusion indicators and long-term trends. The models could be especially helpful in predicting the adoption of digital payments, the growth of credit and its strength in a shifting economic landscape. The use of explainable artificial intelligence (XAI) methods (e.g., SHAP values, attention mechanisms) could further enhance transparency and interpretability, enabling policymakers to gain insights into the relative importance of various financial factors driving resilience outcomes.

An interesting research avenue is to broaden the analytical variables with indicators of financial access. Financial inclusion and resilience can be heavily affected by macroeconomic conditions, including GDP growth, inflation, unemployment, fiscal stability, foreign direct investment, governance quality and institutional effectiveness, internet penetration, education levels and demographic characteristics. The incorporation of these factors in hybrid econometric and machine learning approaches may enhance the predictive power and offer a comprehensive perspective on economic growth. Causal inference and ensemble learning can also be used to explore the interaction between these variables and determine if it is nonlinear.

Another valuable extension of this work is the regional and country-specific analyses. The conditions of financial inclusion are very different in each South Asia country, in Sub-Saharan Africa, in Latin America and the Middle East, and in other developing countries depending on the level of infrastructure, regulatory frameworks, digital literacy and socioeconomic developments. Comparative work on these areas could produce recommendations for policy at the local level suitable to the specific institutional contexts. In addition, subnational analyses based on data from provinces or districts could uncover inequalities at the subnational level which might not be apparent in national-level averages and which could help inform the design of interventions for underserved groups.

CONCLUSION

This study explored the connection between digital financial inclusion, banking accessibility, and economic resilience by applying IMF Financial Access Survey indicators in the multi-country analysis. The study provides robust empirical evidence that both digital financial services and traditional banking infrastructure play a significant role in improving economic resilience through descriptive statistical analysis, correlation assessment, multiple linear regression and machine learning predictive modelling. The findings consistently show that more financially enabled countries are more likely to encourage financial participation, ensure credit is more available, and be better able to absorb economic shocks.

The descriptive analysis revealed significant differences in the financial inclusion indicators at the economy level, and significant inequalities in accessing formal financial services, despite substantial global gains. The data showed strong and positive correlations between digital inclusion, ability to access banking services, credit penetration, and resilience; the latter being most strongly correlated with digital financial inclusion. The results of this report highlight the critical role digital technologies play in today's financial landscape and reinforce continued investment in mobile banking, electronic payments and fintech innovation as avenues for economic development for good reasons.

Regression analysis also found that digital financial inclusion and banking accessibility were statistically significant determinants of the resilience outcomes, as the estimated model accounted for a significant amount of the variation. The XGBoost model achieved the best overall performance compared to other predictive models, such as linear regression and other machine learning models, in several evaluation metrics. This highlights the advantages of sophisticated ensemble learning techniques in representing intricate financial dynamics and delivering precise forecasts for strategic decisions and policy planning.

The study is both theoretically and practically relevant as it combines classic econometric techniques with novel machine-learning approaches to assess financial inclusion in its multidimensionality. The results offer policy and research-backed recommendations for financial institutions, development institutions, financial regulators, and policy makers to create financial policies that are inclusive, improving economic stability. Institution building, greater financial access, interoperable financial systems and financial education campaigns can all help to increase the mainstreaming of financial markets and mitigate the socioeconomic gap.

While these contributions are many, the research also points to opportunities for further refinement including use of larger datasets, inclusion of further socioeconomic variables,

However, the overall evidence is robust that opening inclusive financial ecosystems is a powerful way to achieve sustainable development and long-term resilience. In an era of digital transformation that is continuously changing the nature of financial systems globally, the need for technology-enabled innovation and accessible financial services will continue to be paramount in achieving inclusive growth, minimizing economic shock, and enhancing the financial health of people, businesses and societies across the globe.

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