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DRIVERS OF DIGITAL FINANCIAL ADOPTION: EVIDENCE FROM GLOBAL FINDEX DATA AND IMPLICATIONS FOR ISLAMIC FINTECH

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Abstract
In this present paper, we examine the factors driving the adoption of digital finance based on microdata from the 2021 Global Findex database. Internet access, mobile phone possession, education, and income are found to be important determinants of digital finance engagement. Digital monetary service use is correlated to strong digital access and greater education levels. A binary logistic regression model was used to estimate digital finance use, whereas the random forest classification model was able to foretell with an accuracy of 74.3% and a 0.792 ROC-AUC score. Results were found to be robust to tests of the sensitivity of the results to model specifications. The paper combines econometric valuation, predictive modelling, and robustness analysis, offering actionable insights for researchers, financial institutions, fintech service providers, and policymakers aiming to foster digitally inclusive financial systems.

1. INTRODUCTION

Digitalization of economic services has made a tremendous impact on modern financial systems in developed and developing countries. The use, access, and management of financial services have significantly changed with the advent of mobile banking platforms likewise electronic payment systems, digital wallets, and fintech applications. The ongoing trend of digitization of financial systems opens up opportunities for financial inclusion, especially in the case of underserved populations. Digital finance is increasingly playing a role in financial inclusion policies and strategies because digital financial services can lower transaction costs, increase access, and expand participation to financial services beyond traditional banks. In areas where there are limited physical banking facilities, mobile connectivity and internet penetration have helped to increase access to financial services.

Knowing what makes digital finance work and what doesn't is thus crucial for policymakers, financial and fintech providers, and development agencies. Based on previous research, the adoption of financial technology is related to demographic, socioeconomic, and technological factors. Internet access, mobile phone ownership, education, income, and demographics are known factors that influence digital finance engagement, as indicated in previous research.

Although the majority of studies use a traditional econometric approach, only a small number of studies incorporate a predictive machine learning framework with econometric inference for financial inclusion. Despite the growing academic interest in digital financial inclusion, there are limited empirical analyses that combine digital connectivity, socio-economic factors, and predictive classification techniques using large-scale international microdata. Moreover, most of the past studies rely exclusively on either explanatory econometric techniques or on predictive machine learning techniques.

In this respect, the current study examines the factors shaping the adoption of digital finance based on individual-level microdata obtained from Global Findex 2021. In the analysis, binary logistic regression is used in conjunction with random forests to identify the demographic, socioeconomic, technological, and geographic characteristics of digitally enabled financial engagement. To improve the empirical reliability, the study also provides odds-ratio estimation, marginal effects analysis, predictive performance, and robustness testing. The empirical findings indicate that Internet connectivity, mobile phone ownership, education, and income have a significant impact on the probability of digital finance engagement, while female respondents demonstrate relatively lower probability of digital finance engagement. The machine learning classification framework is also fairly robust, and comparable explanatory variables are important predictors in the classification.

The paper adds to the growing body of research on digital financial inclusion in a few ways. First, it brings together the econometric estimation and the predictive approach, which are based on machine learning, in an integrated analysis. Second, it provides an evaluation of financial innovation involvement of various demographic and socioeconomic groups, based on large-scale international microdata. Thirdly, the study suggests policy recommendations that are pertinent to the authors and policymakers, fintech providers, and financial institutions to improve the digitally inclusive financial system, including the newly emerging Islamic digital finance ecosystem.

The rest of the paper is organised as follows. The literature review and the theoretical background are presented in Section 2. In Section 3, the hypotheses and conceptual framework are developed. The data description and variable operationalisation are given in Section 4. A methodological framework is presented in Section 5. The results of the empirical work are presented in Section 6, and the robustness and sensitivity analysis in Section 7. The findings and policy implications are discussed in Section 8; the study is concluded in Section 9.

2. Literature Review

2.1 Digital Finance and Financial Inclusion

With the introduction of digitally enabled financial services, the financial landscape has changed drastically, creating greater opportunities for financial inclusion in both developed and developing countries. New digital tools, like mobile banking apps, electronic payment systems, FinTech, and digital wallets have helped to make financial services more accessible by reducing costs and bringing a range of services outside the traditional banking system.

The prevailing view in the literature is that digital finance has the potential for improving financial inclusion, as it increases access to and usage of financial services, makes it easier to use, and streamlines transactions, especially for those who have reduced access to physical branches. Mobile financial services have grown in importance in developing economies, where access to traditional financial services is scarce. Further, prior studies have found that digital finance engagement is linked to other socioeconomic development measures, such as greater financial engagement, financial transaction efficiency and access to formal finance. For this reason, the issue about the determinants of digital financial behavior has become fashionable in the financial inclusion research.

2.2 Determinants of Digital Finance Engagement

Literature has already identified various factors associated with digital finance engagement such as demographic, socioeconomic and technological factors. Internet connectivity and mobile phone ownership have been constant major considerations, because they are essential to accessing digitally-enabled financial services, which typically require strong technological systems and communication access.

Another important factor in literature review on financial technology adoption is education level. The more educated people are more likely to be digitally literate, financially savvy, and technologically proficient, and therefore more likely to be effective in using digitally enabled financial platforms. Income, too, has a relationship with financial technology adoption; higher income people are likely to have better access to formal financial services, the internet, and smartphones.

Digital economics/finance studies also suggest that gender and country of residence are other demographic determinants that may be important in the breakdown, especially for developing economies where access to technology be unlike between men and women and where there are socioeconomic disparities.

Existing literature has generally confirmed the significance of digital connectivity and socioeconomic capability in determining financial technology engagement, but empirical results are sometimes also varied at the institutional and regional levels. In this context, empirical research using large international microdata continues to be important to advance our understanding of the factors determining digitally enabled financial participation.

2.3 Technology Adoption and Human Capital Perspectives

Theories and models of technology adoption and human capital growth are significant foundations for analysing the digital finance engagement behaviour. According to the Diffusion of Innovations Theory (DoIT), the channels of communication, technological exposure, and access to innovation systems play a role in the adoption of innovation. Therefore, mobile access and internet connection are important facilitating factors in the adoption of financial technology in digitalised financial ecosystems. Similarly, the concepts of human capital emphasize the importance of education, digital literacy and information skills in understanding how people interact with financial technologies. The higher educated people may be more technologically confident and show a better understanding of financial issues and thus be better prepared to use digitally enabled financial services. So the technology acceptance perspectives also suggest that perceived ease of access and usefulness can be other factors influencing people's recognition of financial technologies (FTs). These theoretical viewpoints provide a basis for the overall claim that digital connectivity and human capital development are the key pillars of numerically inclusive financial systems.

2.4 Machine Learning in Financial Inclusion Research

Therefor new machine learning skills have been increasingly dominating on research inclusion and financial technology in current years. Synthetic data generation for assessing classification performance identifying the most important predictive variables like improving the accuracy of financial data analyses are increasingly utilizing predictive algorithms resembling Random Forests, Support Vector Machines and gradient boosting techniques in commercial literature. Machine learning methods offer several benefits in financial presence studies, as they can reveal nonlinear relationships, and assess the relevance of variables in large datasets. But in literature it is common to use predictive machine learning methods as an alternative of traditional econometric estimation approaches.

So there is little research that connects explanation in econometrics to the prediction of classifications using machine learning in a single analytical framework. Both approaches can be used together and improve the interpretability and predictive ability of financial technology adoption research, providing analytical robustness.

2.5 Research Gap and Theoretical Positioning

The literature on the adoption of financial technology and digital financial inclusion is growing; however, there are some empirical and methodological gaps. While explanatory econometric and predictive machine learning frameworks are widely used in previous research, few studies have integrated both frameworks in a coherent empirical framework.

Moreover, much of the existing research is based on country-specific data, or on relatively small samples, which makes it difficult to make wide comparisons of the drivers of digital finance engagement across demographic and socioeconomic groups. The use of large-scale international microdata and the use of inference- and prediction-oriented analytic techniques for these data are thus still underdeveloped in the literature.

The present study addresses these limitations by adopting both Logistic regression estimation and random forest classification approach at individual level with the Global Findex data. To augment empirical credibility and analytical completeness, marginal effects analysis, predictive evaluation and robustness testing are also part of the study.

3. Hypotheses Development and Conceptual Framework

Demographic, socio-economic and technological factors affect adoption of digital financial services. The analysis is based upon three theories: Technology Acceptance Model (TAM) for measuring perceived usefulness and ease of use, Diffusion of Innovations (DOI) theory to measure the characteristics of innovations, and Financial Inclusion Theory to measure access and participation. These are frameworks that help to develop hypotheses on what factors affect the adoption of digital financial services. Past studies show that financial behaviour and technology access is influenced by educative variables, income and socio-demographic variables.

3.1 Digital Connectivity and Financial Participation

Digital connectivity is key to access to digital financial services. The adoption of internet and mobile phone enhances the access to technology and the efficiency of communication, which helps to use mobile banking services, electronic payment methods and fintech apps. The majority of the literature on financial inclusion suggests that digital connectivity is highly relevant to the uptake of financial technologies and that the more connected one is, the more likely one is to use them.

H1: Internet usage and mobile phone ownership is positively related to use of digital financial services.

3.2 Human Capital and Digital Finance

Human capital approaches imply that education levels can have a huge influence on access to digitally-enabled financial services. Education provides impacts on digital literacy, technological skills and financial awareness that helps to improve interaction with financial technologies, People with more education tend to show more confidence and awareness of digital platforms, mobile apps and electronic financial systems.

H2: Higher education is positively associated with digital finance.

3.3 Socio-Economic Capability and Digital Finance

Socio-economic capability is also a factor in determining digital finance engagement since better-off individuals with smartphones, Internet services, and access to banking products and financial technologies are more likely to be engaged in digital finance. Financial resources would hence allow to participate in digitally enabled financial ecosystems (DEFE). Amongst the literature available, there is a general suggestion that the wealthier individuals are more likely to adopt financial technologies as they have access to technological infrastructure and formal financial systems.

H3: Higher income levels are a positive factor for the use of digital finance.

3.4 Demographic and Geographic Variables

Demographic and geographic conditions also play a role in accessing digitally enabled financial services. Gender gaps in access to technology, financial knowledge and formal financial systems have been well-established in financial inclusion studies. Likewise, residential geography is a factor in digital finance engagement and different areas may have varying levels of technology, internet connectivity, and access to financial services. But as mobile financial ecosystems proliferate, traditional obstacles to financial access are becoming more and more blurred.

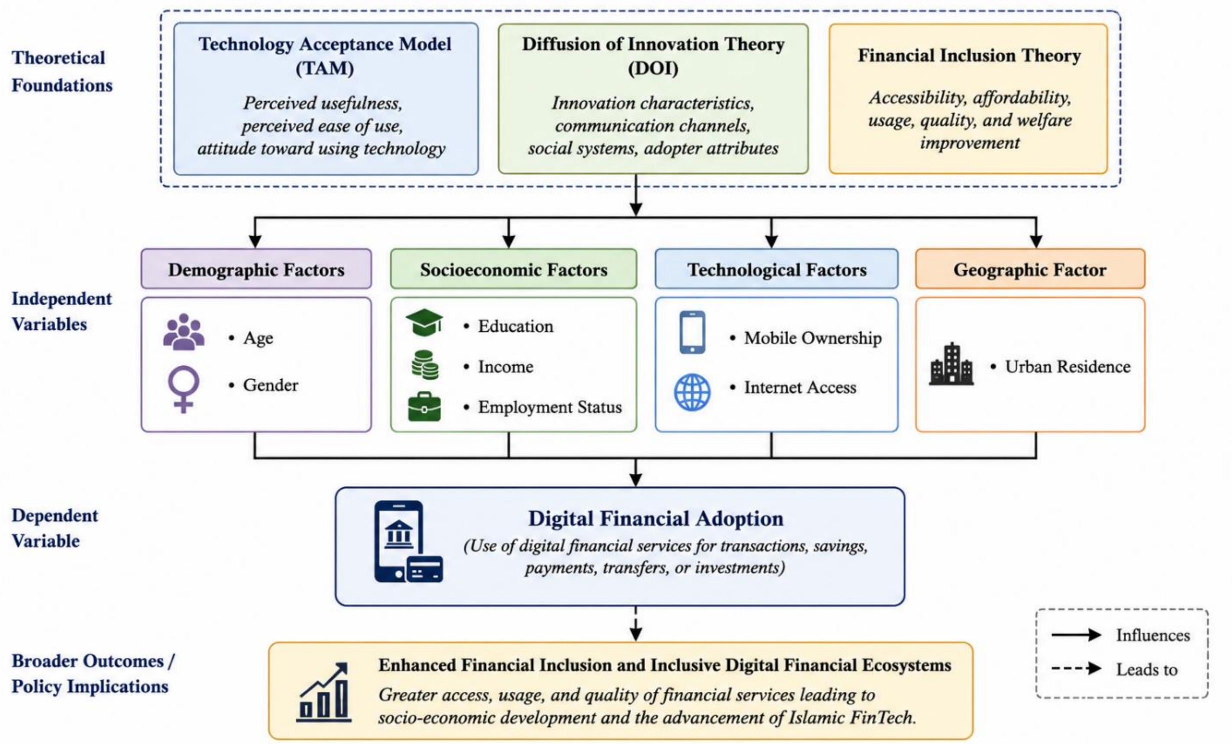
H4: Location and gender have significant effects on the use of digital finance.

3.5 Conceptual Framework

There are several important factors that theoretical foundations and empirical literature suggest impact the adoption of digital financial services. The conceptual framework in Figure 1 helps to illustrate these relationships. The empirical analysis is conducted on the proposed relationships that are summarised graphically in Figure 1.

The diagram depicts the potential links between demographic, socioeconomic, technological, and geographic factors and the adoption of digital finance. It draws on Diffusion of Innovation Theory, Technology Acceptance views and human capital theory, which highlight the impact of digital connectivity, accessibility, education and socioeconomic capacity on financial technology engagement. The model assumes that the use of financial services via the Internet and mobile phones is associated with Internet access, mobile phone ownership, education, income, gender, age and place of residence.

Figure 1. Conceptual Framework for Determinants of Digital Financial Adoption



Source: Authors' illustration.

The diagram depicts the potential links between demographic, socioeconomic, technological, and geographic factors and the adoption of digital finance. It draws on Diffusion of Innovation Theory, Technology Acceptance views and human capital theory, which education and socioeconomic capacity on financial technology engagement. The model assumes that the use of financial services via the Internet and mobile phones is associated with Internet access, mobile phone ownership, education, income, gender, age and place of residence.

4. Data Description and Variable Operationalisation

4.1 Data Source and Sample Construction

It is based on microdata from the Global Findex 2021 database provided by the World Bank (individual level). This dataset offers a complete array of financial access, digital finance engagement, demographic and socioeconomic data for several economies. This first data set was 143,420 observations. Variable selection, binary recoding of categorical indicators, treating missing data and discarding incomplete records were all part of data preprocessing. These procedures resulted in the final analytical sample with 75,580 observations for the econometric estimation and machine learning classification.

The large cross section sample yields more statistically valid and generalizable empirical analysis, which can be used to represent a wide range of demographic and socioeconomic characteristics.

4.2 Dependent Variable

Digital finance usage is measured using a dependent variable operationalised as a binary indicator of the engagement with digitally enabled financial services. The respondents who are digitally financially active are coded 1 and those who do not use it are coded 0.

Logistic regression estimation and machine learning with classification analysis of the dependent variable are appropriate since its binary nature.

4.3 Independent Variables

The explanatory variables for the empirical analysis are drawn from the previous financial inclusion and financial technology adoption literature and include demographic, socioeconomic, technological and geographic indicators.

Demographic factors are age and sex, and socioeconomic factors include level of education and income. Internet access and mobile phone ownership are essential features of digital connectivity and are used as technological variables. Residential location is used to identify geographic characteristics; urban versus rural respondents.

The chosen variables are able to explain the main aspects of digitally enabled financial engagement behavior.

4.4 Variable Operationalization Table

Table 1 offers operational definitions, measurement structure and expected directional relationships of the variables employed in the empirical analysis.

4.5 Descriptive Characteristics of the Sample

Descriptive statistics of the variables in empirical analysis are shown in Table 2. The statistics provide basic information on the demographic, socioeconomic, technological and geographic characteristics of the analytical sample.

5. Methodology

5.1 Research Design

The research used quantitative analysis method in analyzing factors that affect the adoption of digital financial services. The main source of data was individual-level microdata from the 2021 Global Findex database. The analytical framework integrated a mix of econometric and machine learning approaches to assess the determinants of digital financial inclusion, which consider demographic, socioeconomic, technological and geographical determinants.

Adoption of digital financial services is a binary response variable which was estimated using dualistic logistic regression. A random forest classification model was additionally used to assess the predictive ability and explanatory variables. Relating machine learning predictions with econometric inference provides a new way to look at digital financial adoption.

5.2 Data Source and Sample Selection

This data is from the World Bank's 2021 Findex data set, which provides extensive information on financial access, digital financial behaviour, and socio-economic and demographic characteristics for a broad set of economies. First data set contained 143,420 observations. Variables were selected, the presence of missing data was evaluated, categorical data was recoded into binary data and cases with incomplete data were excluded. After these procedures, 75,580 cases remained for the estimation using the econometric and machine learning models. The more participants, the greater is the generalizability of the findings across demographic and socioeconomic groups and the more robust the empirical findings.

5.3 Variable Operationalisation

The dependent variable is digital financial adoption which is a binary indicator (0 = not adopted, 1 = adopted). Independent variables were chosen to cover demographic, technological, socioeconomic and geographical factors in the light of previous studies on financial inclusion and technology adoption.

The operational definitions and the measurement structure used for the variables in the empirical analysis are shown in Table 1.

Table 1

Variable Operationalization and Measurement

Variable	Type	Measurement / Coding	Expected Relationship
Digital Financial Adoption	Dependent Variable	1 = Individual uses digital financial payments; 0 = Otherwise	—
Age	Independent Variable	Respondent age in years	±
Female	Independent Variable	1 = Female; 0 = Male	Negative
Education	Independent Variable	Educational attainment categories	Positive
Income	Independent Variable	Income quintile categories	Positive
Employment Status	Independent Variable	1 = Employed; 0 = Otherwise	Positive
Mobile Ownership	Independent Variable	1 = Owns mobile phone; 0 = Otherwise	Positive
Internet Access	Independent Variable	1 = Has internet access; 0 = Otherwise	Positive
Urban Residence	Independent Variable	1 = Urban resident; 0 = Rural resident	Positive

***Source*:** Author's construction based on the Global Findex Database (2021).

5.4 Econometric Specification

The binary logistic regression model (for dichotomous dependent variables) was used to estimate the determinants of digital financial adoption. Logistic regression is broadly used in financial inclusion and technology adoption studies due to its ability to provide reliable estimates of the probability of a binary variable and deal with the disadvantages of the linear probability models.

Logistic regression predicts the probability of the adoption of digital finance as a function of demographic, socioeconomic, technological and geographic characteristics.

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 Age_i + \beta_2 Female_i + \beta_3 Mobile_i + \beta_4 Internet_i + \beta_5 Education_i + \beta_6 Income_i + \beta_7 Urban_i + \beta_8 Employment_i + \varepsilon_i$$

where (Pi) represents the probability of digital financial adoption for individual (i), (β0) is the intercept term, (β1 to β8) represent the estimated coefficients of the explanatory variables, and (εi) denotes the error term.

Model parameters were estimated with the help of the maximum likelihood estimation method. Z-statistics and p-values were used to evaluate statistical significance whereas pseudo-R-squared and likelihood ratio statistics were estimated to assess goodness of fit.

5.5 Logistic Regression Estimation

The thoroughgoing likelihood approach was used to approximation logistic worsening. coefficient estimates, odds ratios and marginal effects were designed to investigate the effect of the instructive variables on digital financial adoption.

To make the estimated coefficients easier to interpret, odds ratios were reported. marginal effects were computed to assess the impact of descriptive variables on the probability of adoption. Conservative levels of statistical import were used.

5.6 Diagnostic Tests and Model Validation

Model adequacy and estimation reliability were assessed through a number of diagnostic tests. Variable distributions were summarized using descriptive statistics. Multicollinearity of the explanatory variables was checked by the correlation analysis and Variance Inflation Factor (VIF) diagnostics. Predictive performances were assessed by classification accuracy, confusion matrix and ROC curves for the machine learning analysis. To evaluate Random Forest model's ability to discriminate between classification thresholds, AUC statistic was used.

6. Empirical Results

6.1 Descriptive Statistics

Descriptive statistics of the variables used in the empirical analysis are shown in Table 2. The findings give initial information on the demographic, socio-economic, technological and geographical attributes of the respondents in the sample.

Table 2

Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Digital Financial Adoption	0.459	0.498	0	1
Age	37.728	16.568	15	99
Female	0.563	0.496	0	1
Mobile Ownership	0.798	0.402	0	1
Internet Access	0.518	0.500	0	1
Employment Status	0.643	0.479	0	1
Urban Residence	0.581	0.493	0	1

Source: Author's calculations based on Global Findex (2021) data.

Descriptive statistics show that around 64.2% of the respondents were deemed to be digitally financially active in the analytical sample. The mean value of mobile phone ownership is relatively high, indicating that mobile phones are widely accessible to the respondents (GASMA2022). Likewise, there is a high level of prevalence with regard to access to the internet, but there are still some differences between people.

Demographic characteristics suggest that there is a good mix of males and females, with a wide age range of respondents. The results also indicate that there is meaningful variation in educational attainment, income categories, and residential location, allowing for the use of the data for multivariate econometric and machine learning estimation.

6.2 Correlation Matrix and Multicollinearity Diagnostics

To analyse the linear relationship between explanatory variables, correlation analysis and multicollinearity diagnostics were performed to check the suitability of the explanatory variables for multivariate estimation.

Table 3
Correlation Matrix of Principal Variables

Variable	DV	Age	Female	Mobile Ownership	Internet Access	Employment Status	Urban Residence
Digital Financial Adoption	1.000	0.025	-0.083	0.287	0.320	0.171	0.123
Age	0.025	1.000	-0.003	-0.019	-0.150	-0.112	0.026
Female	-0.083	-0.003	1.000	-0.092	-0.071	-0.208	0.008
Mobile Ownership	0.287	-0.019	-0.092	1.000	0.426	0.124	0.144
Internet Access	0.320	-0.150	-0.071	0.426	1.000	0.100	0.233
Employment Status	0.171	-0.112	-0.208	0.124	0.100	1.000	-0.020
Urban Residence	0.123	0.026	0.008	0.144	0.233	-0.020	1.000

Source: Author's calculations based on Global Findex (2021) data.

Table 3 shows the correlation matrix of the explanatory variables which reveals that pairwise correlation between the variables is still relatively moderate. Positive relationships with the dependent variable are provided by the positive associations with digital financial adoption that are found for Internet access and for mobile phone ownership, as well as for the positive relationship between educational attainment and digital financial adoption and income level. Importantly, the pairwise correlations do not seem to be high enough to pose serious problems of multicollinearity. The low pairwise correlation also indicates the appropriateness of the variables for multivariate estimation.

Table 4
Variance Inflation Factor (VIF) Diagnostics

Variable	VIF
Age	3.873
Female	1.997
Mobile Ownership	5.287
Internet Access	2.683
Employment Status	2.469
Urban Residence	2.452

Source: Author's calculations based on Global Findex (2021) data.

Table 4 also shows the Variance Inflation Factor (VIF) results, which also indicate that serious multicollinearity has not occurred. None of the VIF values are significantly high: the explanatory variables are not linearly dependent in an undesirable way which would bias the regression estimates.

6.3 Logistic Regression Results

Baseline logistic regression estimates of digital financial adoption are shown in Table 5. The outcomes assess the effect of demographic, socioeconomic, technological and geographic variables on the probabilities of digital financial participation.

Table 5
Baseline Logistic Regression Results

Variable	Coefficient	Std. Error	z-statistic	p-value
Constant	-2.659	0.043	-61.837	0.000
Age	0.023	0.000	59.991	0.000
Female	-0.211	0.013	-15.944	0.000
Mobile Ownership	1.018	0.022	46.349	0.000
Internet Access	1.113	0.015	76.282	0.000
Secondary Education	0.922	0.015	62.899	0.000
Tertiary Education	1.912	0.023	84.403	0.000
Income (Second Quintile)	0.149	0.022	6.900	0.000
Income (Middle Quintile)	0.214	0.021	10.037	0.000
Income (Fourth Quintile)	0.319	0.021	15.075	0.000
Income (Richest Quintile)	0.513	0.021	24.283	0.000
Urban Residence	-0.672	0.014	-49.519	0.000

Source: Author's calculations based on Global Findex (2021) data.

The logistic regression results show that the technological accessibility variables have a significant positive influence on the adoption of digital finance. Internet access and mobile phone ownership continue to have a positive correlation with digital financial participation with high statistical significance.

There are also positive associations with digital financial adoption and educational attainment, as well as income level, implying that socioeconomic capability and digital literacy plays a meaningful role in engagement in digital financial ecosystems. The probability of digital financial adoption is generally lower among female respondents compared to male respondents, however.

The overall results of the baseline regression models indicate that technological accessibility, education, and socioeconomic capability are significant determinants of the digital financial adoption behaviour.

6.4 Odds Ratio Analysis

For ease of interpretation, the logistic regression coefficients were converted to odds ratios to calculate odds of adoption with the explanatory variables.

Table 6

Logistic Regression Odds Ratios

Variable	Coefficient	Odds Ratio
Constant	-2.659	0.070
Age	0.023	1.023
Female	-0.211	0.810
Mobile Ownership	1.018	2.769
Internet Access	1.113	3.043
Secondary Education	0.922	2.514
Tertiary Education	1.912	6.768
Income (Second Quintile)	0.149	1.161
Income (Middle Quintile)	0.214	1.239
Income (Fourth Quintile)	0.319	1.376
Income (Richest Quintile)	0.513	1.670
Urban Residence	-0.672	0.510

Source: Author's calculations based on Global Findex (2021) data.

The odds ratio estimates suggest strong differences in likelihood of digital financial adoption between the respondents who use the internet and those who don't. Likewise, having a mobile phone has a huge impact on digital financial participation.

Education level shows a strong influence, with respondents with a tertiary education having significantly higher likelihood of adoption than other education groups. There can also be an increasingly positive impact of income categories on digital financial participation.

Female respondents, on the other hand, have a relatively lower chance of digital financial uptake. The negative coefficient for the urban dimension could be due to the greater reach of mobile finance services in the rural and hitherto less-served population.

6.5 Marginal Effects Analysis

The marginal effects were calculated to assess how likely the probability of digital financial adoption changes as the explanatory variables change.

Table 7

Average Marginal Effects from Logistic Regression

Variable	Marginal Effect (dy/dx)	Std. Error	z-statistic	p-value
Age	0.0037	0.000	59.991	0.000
Female	-0.0341	0.002	-15.944	0.000
Mobile Ownership	0.1648	0.004	46.349	0.000
Internet Access	0.1801	0.002	76.282	0.000
Secondary Education	0.1492	0.002	62.899	0.000
Tertiary Education	0.3094	0.004	84.403	0.000
Income (Second Quintile)	0.0242	0.004	6.900	0.000
Income (Middle Quintile)	0.0346	0.003	10.037	0.000
Income (Fourth Quintile)	0.0516	0.003	15.075	0.000
Income (Richest Quintile)	0.0830	0.003	24.283	0.000
Urban Residence	-0.1088	0.002	-49.519	0.000

Source: Author's calculations based on Global Findex (2021) data.

Marginal effects estimates show that internet access and having a mobile phone have economically significant positive impacts on the likelihood of digital financial adoption. Education level also shows significant impact, especially from those with tertiary education.

The results also show that the probability of digital financial inclusion is higher among higher income brackets. On the other hand, the female participants show relatively less likelihood of adopting digital finance, indicating the demographic gap in financial technology uptake.

The overall conclusion from the marginal effects estimates is to support the main results from the baseline logistic regression and odds ratio analysis.

6.6 Machine Learning Classification Results

Along with the econometric analysis, a Random Forest classification model was estimated to assess the relative importance of the explanatory variables related to digital financial adoption and the predictive power of the model.

Table 8

Confusion Matrix for Random Forest Classification

	Predicted No	Predicted Yes
Actual No	5,563	4,495
Actual Yes	2,883	15,737

The overall prediction accuracy of Random Forest classification model was 74.3% and was satisfactory in terms of classification capability to differentiate the digitally financially active individuals from non-adopters.

Within the machine learning framework, feature importance analysis reveals that age, Internet access, mobile phone ownership and education are among the most important. The confusion matrix results also show that the model has a relatively high sensitivity for digital financial adopters.

In general, the machine learning results are broadly similar to the econometric estimates, thus providing support for the stability and reliability of the empirical results.

6.7 ROC-AUC and Predictive Performance Evaluation

The predictive performance of the Random Forest classification model was also assessed using Receiver Operating Characteristic (ROC) curve analysis and Area under the Curve (AUC) assessment.

Table 9

ROC-AUC Evaluation of Random Forest Model

Metric	Value
ROC-AUC Score	0.792

Source: Author's calculations based on Global Findex (2021) data.

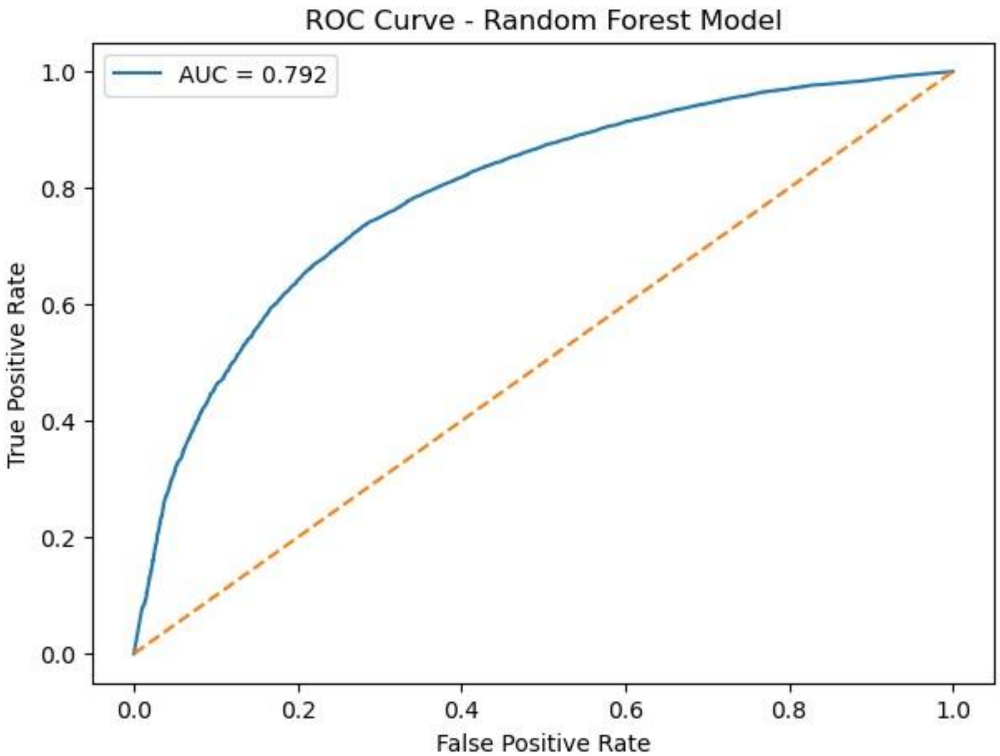


Figure 2: ROC Curve for Random Forest Classification Model

The results show that the Random Forest model has a satisfactory discriminatory ability to differentiate financial adopters from non-adopters based on the ROC-AUC values. So the projected AUC score of 0.792 shows suitable to-strong predictive performance in the classification framework.

The ROC curve stays to be significantly above the diagonal reference line, indicating the random grouping level, and demonstrating the prognostic stability of the machine learning model at different classification thresholds.

7. Robustness Checks and Sensitivity Analysis

7.1 Alternative Model Specification

As a means of assessing the robustness of the findings from the baseline estimates, a different logistic regression specification, which makes use of fewer explanatory variables focusing on demographic characteristics and digital connectivity indicators, was estimated. Objective here is to ascertain if the major determinants finance adoption remain consistent despite using alternative model constructions.

Table 10

Robustness Check: Alternative Logistic Regression Specification

Variable	Coefficient	Std. Error	z-statistic	p-value
Constant	-1.914	0.031	-61.072	0.000
Age	0.010	0.000	19.516	0.000
Female	-0.228	0.016	-14.366	0.000
Mobile Ownership	1.144	0.025	46.502	0.000
Internet Access	1.059	0.017	61.797	0.000

Source: Author's calculations based on Global Findex (2021) data.

Table 10 shows the stability of the alternative specification results with regard to the key explanatory variables. Female respondents have a comparatively lower probability of participating in digital finance and strong positive association with internet access and mobile phone ownership remains.

The reduced specification revealed less explanatory power compared to the base model, but the fact that digital connectivity variables remained statistically significant lends confidence that the access to digital technology is independently associated with financial product adoption behavior. As a whole, the sign and statistical significance of the coefficient estimates indicate the general results of this analysis are not greatly affected by the alternative specifications.

7.2 Stability of Key Predictors

To further test the reliability of the estimates, results from the baseline specification were compared with those from the robustness specification to consider how stable the key explanatory variables were across these two model specifications.

Table 11

Comparison of Baseline and Robustness Model Estimates

Variable	Baseline Model	Robustness Model
Age	0.023	0.010
Female	-0.211	-0.228
Mobile Ownership	1.018	1.144
Internet Access	1.113	1.059

Source: Author's calculations based on Global Findex (2021) data.

Table 11 provides the comparative estimates which show that the specifications are quite directionally consistent. In both models, access to the internet and having a mobile phone are still significant and positively linked to the adoption of digital financial services, and women throughout the models are more likely to have lower adoption likelihood.

While there are some moderate variations between the magnitude of each coefficient, the general stability of the estimates supports confidence in the empirical reliability of the identified relationships. The results thus indicate that the main results of the study are fairly robust to alternative estimation settings.

7.3 Uniformity between econometric and machine learning effects

The paper contribution is the convergence found between the econometric valuations and machine learning organization context. The logistic regression coefficients, the marginal effects and the feature importance in the Random Forest consistently show that education, age, mobile phone ownership and internet access are key factors in determining the adoption of digital finance.

Table 12

Consistency Between Econometric and Machine Learning Results

Variable	Logistic Regression	Marginal Effects	Random Forest Importance	Overall Influence
Age	Positive	Positive	Highest	Strong
Internet Access	Positive	+18.0%	Second Highest	Strong
Mobile Ownership	Positive	+16.5%	Third Highest	Strong
Tertiary Education	Positive	+30.9%	Fourth Highest	Very Strong
Female	Negative	−3.4%	Lower Importance	Moderate
Urban Residence	Negative	−10.9%	Moderate Importance	Moderate

Source: Author's calculations based on Global Findex (2021) data.

The outcomes obtained through the ordering using the Random Forest method also corroborate the results from the econometric method, providing high prediction accuracy and using the same variables from the econometric analysis as the key drivers for predicting digital financial inclusion. The congruence between the various methods of analysis further strengthens the reliability of the results obtained through both methodologies.

In general, the similarities between the outcomes obtained from the econometric method of inference-based analysis and the machine learning analysis of predictions help to strengthen the overall methodological approach and confirm the interpretation that digital connectivity and human capital development remain the key enablers of digital financial attachment.

8. Results Discussion and Policy Implications

8.1 Digital Connectivity and Financial Inclusion

It is evident that the empirical results converge and show that digital connectivity is one of the most compelling enablers of digital finance adoption. In econometric estimates, marginal effects and machine learning classifications, internet access and mobile phone ownership prove to be very powerful determinants of participation in digital financial systems.

The findings indicate that digital infrastructure access is significantly tied to the opportunities for individuals to interact with mobile banking, electronic payment systems and digitally enabled financial services. The large impact of internet connectivity also indicates that financial inclusion efforts are increasingly reliant on technological infrastructure and digital accessibility.

The results are consistent with diffusion of innovation theory, suggesting that communication infrastructure and technological exposure are crucial in explaining the behavior of the innovation uptake process. The findings also mirror earlier financial inclusion studies that found mobile connectivity and internet penetration as fundamental factors in digital financial engagement in developing and emerging economies.

8.2 Education, Income, and Human Capital Effects

Empirical results expose that education levels are a key factor in seminal meeting with digital finance. There seems to be a major relationship between the educated people and their use of digitally financial services, representing that ordinal literacy awareness and technological competence are important permitting factors in the modern financial ecosystem.

The results indicate that the development of human capital may become as significant in the process as the development of technology itself in terms of inclusion into digital finance adoption. Those individuals with a high level of education possess more informational skills and technological readiness in dealing with digital financial tools.

Moreover, there are progressively positive associations between income level and the use of digital finance tools. Those individuals who earn more may benefit from having better access to phones, internet, bank products and financial technologies. Thus, it becomes possible for them to become involved in digital finance. The gradient of income plays an important role in emphasizing the relevance of socioeconomic capability in the financial technology adoption process.

8.3 Gender and Geographic Disparities

Also, it was found that there are also demographic differences related to usage of digital financial products and services. Females are less likely to use digital finance tools as compared to males no matter which estimation approach is used for this purpose.

This gender bias could be associated with already existing gender gap related to financial inclusion, technological knowledge, income levels, and availability of digital services. There could also be cultural and institutional obstacles in females' using of digitally-enabled financial systems, particularly, in emerging markets.

It should be noted that in the regression models under study, the negative correlation between use of digital finance and living in urban areas was observed. While it is somewhat paradoxical, such observation might indicate that financial services based on mobile technology make further progress in reaching the deprived and remote areas.

8.4 Policy Implications

There are several important policy considerations arising from the findings that may guide policymakers, financial institutions, fintech organizations, and development organizations aiming to contribute to financial inclusion.

One is that investments in improving internet connectivity and digital access in affordable ways would be important to complement initiatives in financial inclusion (ITU 2021). Improved broadband penetration and mobile coverage would significantly improve financial inclusion efforts by increasing the inclusion possibilities for underserved groups.

Two is that due to the high impact of education levels on financial inclusion, there is an urgent need to introduce initiatives such as financial capability and digital literacy in tandem with technological inclusion efforts. Increased skills in financial literacy and digital technology would enable individuals to benefit from digitalized financial systems.

Three is the persistence of gender differences, which suggests the importance of designing specific initiatives aimed at ensuring women's inclusion within these initiatives in terms of access to financial knowledge, resources, and digital technology.

Four is that with the growing importance of mobile finance, innovative fintechs could provide a way of expanding inclusion initiatives beyond the boundaries of traditional banking institutions.

8.5 Implications for Islamic Digital Finance

This is applicable to the creation of Islamic digital finance and the fintech ecosystem within the realm of Shariah banking. Both internet connectivity and the accessibility of mobile phones suggest that digitally-based Islamic financial services can provide some significant ways for improving access to finance among the underprivileged.

Islamic banking apps, payment platforms, and fintechs aligned with the Shariah laws will contribute toward achieving this goal by improving financial inclusion in areas lacking conventional banks. In addition, it is suggested that digital literacy and education may prove indispensable in the process of mainstreaming in the Islamic fintech ecosystem. While the paper makes no difference between conventional financial technologies and Islamic ones, the empirical evidence provided in the paper supports the broader idea that technology and human capital are crucial for the development of financially inclusive systems, which includes Islamic fintech systems.

9. Conclusion

9.1 Conclusion

In this case, the study conducted a micro-data analysis on individuals in the Global Findex 2021 data set in order to investigate some of the determinants that affect digital finance adoption. The study used both econometrics estimates and machine learning classifications to examine some of the factors affecting the adoption of digitally-enabled financial services. These factors include demographic, socio-economic, technological, and geographical factors.

The empirical results indicate that the factors of internet connectivity, mobile phone usage, education, and income have played a key role in the adoption of digital finance. From the results, it is evident that the more people have access to digital platforms and have attained a certain level of education; the more likely they are to participate in digital finance.

The results from the machine learning classification method are congruent with the results obtained from the econometric estimates. The predictive capacity of the model used shows good predictive performance with the same explanatory variables. As such, the study finds that the results obtained from each method are robust since they converge on each other.

From a holistic approach, the research helps contribute to the current literature on digital financial inclusion through the use of econometric inference and prediction modeling.

9.2 Policy Recommendations

A number of key points about policy issues relevant to financial system inclusion efforts are implied by these results.

First, due to the importance of internet expansion and low-cost mobile connectivity as facilitators of the participation of the disadvantaged population, the improvements in digital infrastructure appear to be a fundamental aspect of broader financial inclusion efforts.

Second, the correlation between education and the usage of digital financial tools highlights that financial education and classes in digital literacy should be combined with technology courses. Boosting users' knowledge and confidence in finances and technology may be beneficial in terms of using digital financial products.

Third, these gender-based disparities suggest that policies promoting gender inclusiveness in relation to digital technologies and finance literacy are highly important.

Lastly, the increasing role of mobile-based financial platforms in rural areas suggests that fintech innovation may provide valuable opportunities for further expansion of financial service availability beyond traditional banking institutions.

9.3 Limitations of the Study

At the same time, there are several issues related to research limitations. It goes without saying that, although valuable from an empirical point of view, this study has several shortcomings. One of them is that it relies on the findings from cross-sectional surveys.

Second, the study mainly focuses on the measurement of demographic, socio-economic, and digital connectivity variables that have been provided in the dataset. Any other potential variables that can influence the utilization of fintech, including behavioral, institutional, regulatory, or psychological variables, have not been addressed in this study.

Third, prediction has been used as the main target variable of the machine learning algorithm. While the performance of the Random Forest classifier is quite promising, it cannot establish causality, hence making predictions derived from the study need to be interpreted carefully in any policy discussions.

Lastly, this study does not explicitly differentiate between conventional and Islamic fintech services. Additional research using data collected on a particular institution and/or fintech product would help identify the pattern of participation among Islamic fintech users.

9.4 Future Research Directions

It is possible for future research to take advantage of the existing study and employ a panel data approach to better examine the time-based phenomenon of digital finance involvement. It will provide further knowledge and understanding of the sustainability of such digital financial behavior.

Furthermore, it is possible to conduct future research on some other issues concerning financial technology, including personal behaviors, institutions involved, cybersecurity perceptions, digital trustworthiness, and regulatory issues regarding financial technology adoption. Comparative research can also be done by examining developed countries versus developing ones, so that the regional disparity can be understood.

Finally, further research can be carried out based on the Islamic finance ecosystem and Shariah-compliant financial technology services. This will enable us to gain further insight into the various factors that influence Islamic digital finance behavior.

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