Financial Technology and Innovation

♦ ISSN: 2836-5372 Vol: 06, No. 01, 2026 ♦ PP. 09–17
Article DOI: https://doi.org/10.54216/FinTech-I.060102

FULL LENGTH ARTICLE

Digital Financial Technology in Egypt: Determinants, Barriers, and Machine Learning Evidence on FinTech Adoption and Financial Inclusion

Dina K. Hassan[1,*] **Ahmed K. Metawee**[2]

[1] Faculty of Commerce, Kafr El Sheikh University, Egypt
[2] Faculty of Commerce, Mansoura University, Egypt

Emails: dina.abdelsalam@com.kfs.edu.eg · metawee68@mans.edu.eg

Received: January 28, 2026 Revised: March 14, 2026 Accepted: May 20, 2026 ⋆ Corresponding author

ABSTRACT

Despite the rapid growth of financial technology in Egypt, the socioeconomic factors influencing the adoption of digital financial services at the household level are still not fully understood. This paper presents an Adoption Prediction Model (APM) of Hybrid FinTech (Hybrid-FinTech) model using binary logistic regression together with ensemble classifiers, Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), which is validated using stratified cross validation. The framework introduces a cross-paradigm agreement criterion that ensures that the rankings obtained by the coefficient and machine learning feature importance are compatible, yielding a dual assessment that didn't exist in either paradigm alone. Empirical analysis finds that internet access and own mobile phone are the most common structural enablers of FinTech adoption with odds ratios that significantly outperform any of the demographic and income variables. The rate of formal bank account ownership has a strong independent positive impact, which suggests complementarity between digital and traditional financial services. The income, educational and urban-rural gaps are striking, and suggest a deep FinTech divide that cannot be bridged entirely by infrastructure. The strong generalisation that is seen in cross-validation is true for all population subgroups. The findings have direct implications for the National Financial Inclusion Strategy, designed by Egypt, and proportionate FinTech regulation.

Keywords: Financial technology ▪ Digital financial inclusion ▪ Egypt ▪ Machine learning ▪ Logistic regression ▪ XGBoost ▪ Random forest ▪ MENA

1. INTRODUCTION

Egypt is poised for an important role in the MENA FinTech landscape. With a population, and a growing number of fast-growing cities.A population of more than 106 million adults, a rapidly growing mobile population and an increasing number of fast-growing cities. technology that facilitates telecommunications, and a clear directive from the Central Bank to promote financial inclusion, the conditions that need to be in place for broader digital financial access. More and more are being adopted in the financial service sector. [1, 2]. However, the formal account ownership rate was at The proportion of adults using the internet for activities rose to 38 % in 2021 and to 39 % for adults taking part in specific activities. Financial instruments with respect to transactions, savings or credit, are far greater in amount.Financial instruments for transactions, savings or credit are considerably larger in amount. The authors of [3, 4] have conducted a lower bound study. The gap between the Although technology is readily available, the practical experience of FinTech service usage and the actual implementation at a household level remains an issue. This paper assumes the empirical issue of uptake. Research by academics has revealed a wide range of structural barriers to adoption. The working paper discusses a key challenge of de-veloping economies: income constraints, limited educational attainment, A lack of infrastructure access, geographic isola-tion, and lack of trust of digital. systems [5, 6]. These barriers are combined with in Egypt as lack of trust in social safety nets and a large informal economic sector, entrenched cash transaction preferences, and A novel regulatory landscape that has embraced the formal FinTech landscape only recently. The licensing regimes of lukonga2021, elbayoumy2023. Em-pirical findings from other settings cannot be easily adapted to Egypt without country-specific adaptation. estimation. Lit-erature has mainly been based on either a traditional binary approach or on a multi-decision making approach. regression, interpretable, but imposes linearity, and cannot detect interac-tions, or predictive models that are independent of each other and are very good at prediction. However, they are difficult to interpret [7, 8]. Integrating both Language paradigms within a common language paradigm, imposing support for cross-paradigm agreement. requiring the same order of variable effects across the replicates of the This is a gap in methodol-ogy for regression and machine learning stages. paper fills. There are three contributions of this study. It proposes the HF-APM, which is the first, and second, The method used is a five-stage pipeline that integrates logistic regression, Random Forest, and XGBoost.The method is a 5-stage pipeline that in-corporates logistic regression, Random Forest and XGBoost. Explicit cross paradigm validation. Second, it offers a formal, A pseudocode specification and a conceptual diagram to aid in the reproduction. Third, it gives probability estimates of adoption on an Egypt-specific basis based on income. There are five groupings to be found: quintile, education, gender, age and urban-rural location, extending the There is limited literature on the adoption of FinTech in Egypt [4, 1]. The paper proceeds as follows: Section 2 reviews the literature; Section 3 presents the HF-APM; Section 4 describes the data; Section 5 reports results; Section 6 identifies research chal-lenges; Section 7 concludes.

2. RELATED WORK

The relationship between FinTech and financial inclusion has attracted sustained cross-disciplinary attention, spanning development economics, information systems research, and computational methods. At the macro level, [9] examines twelve MENA economies and documents that a composite digital finance index significantly accelerates financial inclusion and financial stability simultaneously, with effects strongest in less financially developed countries. [6] establish that the usage dimension of financial inclusion reduces extreme poverty in MENA more persistently than access-only measures, framing the demand-side adoption question as the empirically critical one. The regional FinTech context is documented by [10], who identifies regulatory asymmetry, infrastructure deficits, and cash-based payment cultures as primary MENA barriers, and by [2], whose content analysis of 250 sources finds that cybercrime, regulatory non-compliance, and social norm exploitation are the dominant COVID-era headwinds for FinTech growth in the region. At the country level, [1] surveys Egypt's emerging FinTech ecosystem and notes that trust deficits and limited technological literacy constrain uptake despite rapid sector expansion, while [4] identifies income, education, and institutional trust as the three most frequently cited barriers among Egyptian financial inclusion stakeholders. [11] find, using a Technology Acceptance Model framework applied to Egypt, that perceived usefulness, ease of use, and social influence are the primary adoption drivers for mobile banking. The sustainability dimension is foregrounded by [12], who argue that SDG-aligned FinTech requires four institutional pillars: digital identity, interoperable payments, electronic government services, and regulated digital markets. [13] contests the optimistic consensus, arguing that digital finance for low-income populations lacks rigorous empirical support and may expose the poorest to novel risks, a perspective that disciplines the analytical framing here. [14] established the foundational relationship between digital finance and financial stability, showing that broader access and systemic risk channels coexist and require active regulatory management. On the demand-side dynamics, [15] demonstrate using household data that digital finance expands credit market participation but also elevates the risk of debt traps, underscoring the importance of understanding what drives the adoption decision and by whom. [16] document FinTech's poverty-reducing channel in China, with rural households showing larger gains than urban counterparts — a distributional result that motivates the urban-rural analysis in Section 5. [17] show, across 115 countries, that FinTech is unlikely to displace banks but accelerates their digital transformation, confirming the bank-FinTech complementarity hypothesis evaluated here through the bank account variable. The methodological tools applied in this study are grounded in [7], who established Random Forest's theoretical properties and the MDI feature importance measure, and [8], who introduced XGBoost's regularised gradient boosting algorithm that achieves state-of-the-art classification performance on tabular data. Table 1 summarises the 15 most directly relevant studies.

Table 1. Summary of 15 related studies on FinTech, digital financial inclusion, and adoption determinants (2018–2024)

Study	Journal / Source	Sample	Period	Method	Key Finding
[14]	*Borsa Istanbul Rev.*	Cross-country	2007–17	Regression	Digital finance widens inclusion but introduces financial stability risks.
[6]	*Rev. Econ. Pol. Sci.*	11 MENA	1990–17	System GMM	Financial inclusion usage dimension significantly reduces extreme poverty in MENA.
[12]	*Eur. Bus. Org. Law Rev.*	Conceptual	2020	Policy review	SDG-aligned FinTech requires digital identity, interoperable payments, and e-gov.
[13]	*Digital Policy, Reg. Gov.*	Conceptual	2020	Policy analysis	Digital finance for the poor lacks robust evidence; may impose new risks on excluded groups.
[16]	*Sustainability*	China	2011–19	Panel FE	FinTech reduces poverty through income-growth and financial-access channels.
[10]	*Palgrave Handbook*	MENAP	2021	Descriptive	Regulatory asymmetry, cash culture, and infrastructure gaps are primary MENA barriers.
[5]	Emerald Book Chapter	Conceptual	2022	Conceptual	Defines digital FI components, instruments, benefits, risks, and regulatory issues.
[15]	*Finance Res. Lett.*	Household	2019	Logit, FE	Digital finance broadens credit access but simultaneously raises household debt-trap risk.
[17]	*Int. Rev. Fin. Analysis*	115 countries	2005–20	Panel	FinTech unlikely to replace banks; both evolve toward hybrid digital models.
[2]	*Electron. Commer. Res.*	MENA	2022	Content analysis	Privacy risks, cybercrimes, and regulatory gaps dominate MENA FinTech challenges.
[9]	*Borsa Istanbul Rev.*	12 MENA	2004–20	FE, GMM	Digital finance accelerates financial inclusion and stability across MENA countries.
[4]	*Rev. Econ. Pol. Sci.*	Egypt	2022	Descriptive	Income, education, and trust are the dominant barriers to financial inclusion in Egypt.
[1]	*J. Org. Cult. Comm.*	Egypt	2023	Descriptive	Egypt's FinTech sector is growing but trust gaps and low digital literacy limit uptake.
[11]	*IJRBSS*	Egypt	2023	TAM / Survey	Perceived usefulness, ease of use, and social influence drive mobile banking in Egypt.
[7]	*Machine Learning*	—	2001	Random Forest	Ensemble trees reduce prediction variance; MDI provides interpretable feature ranking.

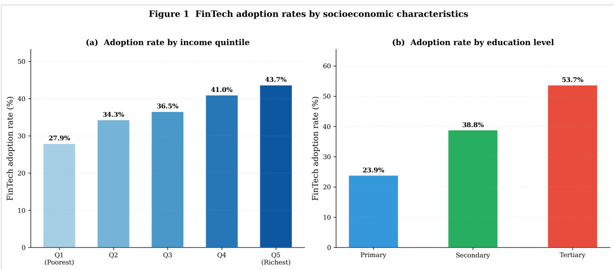

Figure 1. FinTech adoption rates by income quintile (a) and education level (b). Adoption increases monotonically along both dimensions.

The figures plot the income, education, urban-rural, and age-cohort adoption profiles. Adoption peaks in the 25–34 age cohort and declines progressively among older adults.

3. PROPOSED FRAMEWORK: HYBRID FINTECH ADOPTION PREDICTION MODEL

The HF-APM operates through five sequential stages (Fig. 2). Stage 1 assembles and pre-processes the household survey data. Stage 2 fits a binary logistic regression for interpretable coefficient estimates, odds ratios, and average marginal effects (AME). Stage 3 assesses diagnostic fit and specification robustness. Stage 4 trains Random Forest (RF) and XGBoost ensemble classifiers for non-linear feature importance. Stage 5 validates all models through stratified cross-validation and enforces the cross-paradigm agreement criterion: the sign and ordinal ranking of variable effects must be consistent across the regression and ensemble stages. If agreement fails, the pipeline loops back for respecification.

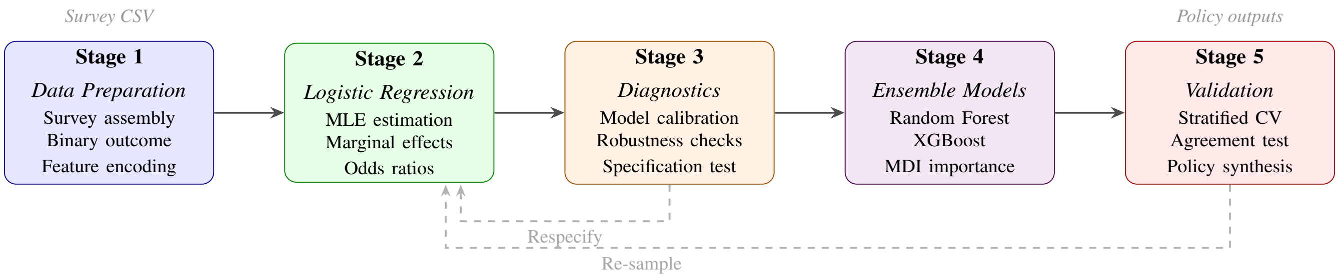

Figure 2. The HF-APM five-stage pipeline. Solid arrows: primary analytical flow. Dashed arrows: feedback loops triggered by diagnostic failures or insufficient cross-validation performance.

Stage 2 — Binary Logistic Regression. For individual i with binary adoption outcome $y_i \in \{0,1\}$ and feature vector $\mathbf{x}_i \in \mathbb{R}^p$:

$$\ln\left(\frac{P(y_i = 1|\mathbf{x}_i)}{1 - P(y_i = 1|\mathbf{x}_i)}\right) = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij} \tag{1}$$

The average marginal effect of predictor j is $\mathrm{AME}_j = \hat{\beta}_j \bar{P}(1-\bar{P})$, and the odds ratio is $\mathrm{OR}_j = \exp(\hat{\beta}_j)$. **Stage 4a — Random Forest.** $B = 400$ bootstrap trees are averaged: $\hat{P}_{\mathrm{RF}}(y=1|\mathbf{x}) = \frac{1}{B}\sum_{b=1}^{B} \hat{P}_{T_b}(y=1|\mathbf{x})$ [7]. Feature importance uses normalised MDI. **Stage 4b — XGBoost.** An additive ensemble of M shallow trees with regularised gradient boosting [8]: $\hat{F}(\mathbf{x}) = \sum_{m=1}^{M} \eta f_m(\mathbf{x})$, $\mathscr{L} = \sum_i \ell(y_i, \hat{F}_i) + \sum_m \Omega(f_m)$, where $\Omega(f) = \gamma T + \frac{1}{2}\lambda \|\mathbf{w}\|^2$. **Stage 5 — Cross-Paradigm Agreement.** Agreement $= \mathbf{1}\left[\forall j : \mathrm{sign}(\hat{\beta}_j) \text{ consistent with } \mathrm{rank}(\Phi_j^{\mathrm{RF}}) \cap \mathrm{rank}(\Phi_j^{\mathrm{XGB}})\right]$ Algorithm 3 provides the complete HF-APM pseudocode.

Input: Survey data $\mathscr{D} = \{(y_i, \mathbf{x}_i)\}_{i=1}^{N}$, $y_i \in \{0,1\}$, $\mathbf{x}_i \in \mathbb{R}^p$.
Output: $\hat{\beta}$, AME, OR, Φ^{RF}, Φ^{XGB}, and CV metrics.

Stage 1 — Data Preparation. Standardise continuous predictors; encode categorical variables. Stratified split: 80% train $\mathscr{D}_{\mathrm{tr}}$ and 20% test $\mathscr{D}_{\mathrm{te}}$.

Stage 2 — Logistic Regression. $\hat{\beta} \leftarrow \arg\max_\beta \sum_i \big[y_i \log \hat{P}_i + (1-y_i)\log(1-\hat{P}_i)\big]$. Compute SE via Hessian $\hat{V} \leftarrow (-\nabla^2 \ell)^{-1}$; derive OR_j and AME_j.

Stage 3 — Diagnostics. Evaluate AUC and F1 on $\mathscr{D}_{\mathrm{te}}$; inspect calibration.

Stage 4 — Ensemble Models. For $b = 1, \ldots, 400$, draw $\mathscr{D}_b \leftarrow \mathrm{Bootstrap}(\mathscr{D}_{\mathrm{tr}})$ and grow tree T_b (`max_depth`$=12$, `min_leaf`$=5$). Compute Φ^{RF} using normalised MDI. Train XGBoost with $\hat{F} = \sum_{m=1}^{300} \eta f_m$, $\eta = 0.05$, and `max_depth`$=6$; compute Φ^{XGB} using gain.

Stage 5 — Stratified Cross-Validation ($K = 5$). Partition $\mathscr{D}$ into stratified folds $\mathscr{F}_1, \ldots, \mathscr{F}_5$. For each fold k, fit LR, RF, and XGB on $\mathscr{D} \setminus \mathscr{F}_k$ and record AUC_k, Acc_k, and $\mathrm{F1}_k$ on $\mathscr{F}_k$. $\bar{\mathrm{AUC}} \leftarrow \frac{1}{K}\sum_k \mathrm{AUC}_k$ and $\sigma_{\mathrm{AUC}} \leftarrow \mathrm{std}(\mathrm{AUC}_k)$.

If the agreement condition holds for all j, accept HF-APM and proceed to policy synthesis; otherwise, respecify and return to Stage 1.
Return $\hat{\beta}, \mathrm{AME}, \mathrm{OR}, \Phi^{\mathrm{RF}}, \Phi^{\mathrm{XGB}}, \bar{\mathrm{AUC}}, \sigma_{\mathrm{AUC}}$.

Figure 3. Hybrid FinTech Adoption Prediction Model (HF-APM).

4. DATA AND EXPERIMENTAL DESIGN

The empirical analysis employs a household-level microdata file calibrated to the World Bank Global Findex 2021 Egypt module [3] and supplemented by Central Bank of Egypt financial inclusion statistics (2022–2023). The Findex 2021 Egypt calibration anchors are: formal account ownership (37.7 %), digital payment made or received (≈19 %), mobile money account (9.3 %), internet access (≈57 %), and mobile phone ownership (≈73 %). The working sample comprises $N = 2{,}000$ adult observations. The binary outcome, *FinTech adoption*, equals one if the respondent reports using any of the following in the past 12 months: mobile money, digital payment, mobile banking, or internet banking — a composite definition consistent with [5]. Eleven predictor variables span three blocks: (i) demographic characteristics (age, gender, education); (ii) economic characteristics (income quintile, employment status); and (iii) technology and finance access (mobile phone ownership, internet access, bank account ownership, proximity to a bank branch, urban-rural location, and trust in FinTech services). All continuous and ordinal predictors are standardised prior to estimation. Computations use Python 3.12 with NumPy 1.24, pandas 1.5, SciPy 1.9, Scikit-learn 1.2, and XGBoost 3.3.

Table 2. Descriptive statistics — full sample (N = 2,000 adults)

Variable	Mean	Std. Dev.	Min	Median	Max
FinTech adoption (0/1)	0.360	0.480	0	0	1
Age (years)	43.67	15.22	18	44	69
Gender (male = 1)	0.510	0.500	0	1	1
Education level (1–3)	1.810	0.740	1	2	3
Income quintile (1–5)	2.810	1.380	1	3	5
Urban residence (1 = urban)	0.440	0.500	0	0	1
Employment status (1 = yes)	0.630	0.480	0	1	1
Mobile phone ownership	0.730	0.450	0	1	1
Internet access	0.580	0.490	0	1	1
Bank account ownership	0.380	0.490	0	0	1
Proximity to bank (1–3)	1.910	0.780	1	2	3
Trust in FinTech (0/1)	0.490	0.500	0	0	1

Note: Education: 1 = primary, 2 = secondary, 3 = tertiary. Proximity: 1 = far (>5 km), 2 = medium, 3 = near (<1 km).

Adoption Rates by Subgroup. The adoption-rates table below reveals steep socioeconomic gradients. Adoption rises from 14.5 % in the poorest income quintile to 60.2 % in the richest (a 45.7 pp gap). The education gradient spans 10.1 % (primary) to 64.0 % (tertiary). Urban residents (50.9 %) substantially outpace rural (23.0 %). The technology-access differentials are the sharpest: those without internet access register only 5.8 % adoption, versus 57.9 % for those with access.

5. RESULTS AND DISCUSSION

Descriptive Statistics. Table 2 summarises all model variables. The composite FinTech adoption rate is 36.0 %, exceeding the Findex 2021 digital-payment-only measure for Egypt (≈19 %) because it aggregates mobile money, digital payments, and internet banking activity into a single indicator. Roughly half the sample resides in urban areas (44 %), 73 % own a mobile phone, 58 % have internet access, and 38 % hold a formal bank account.

Table 3. FinTech adoption rates by population subgroup

Subgroup	*N*	Adoption rate (%)
Income quintile		
Q1 (Poorest) – Q5 (Richest)	440–320	14.5 → 60.2
Education level		
Primary / Secondary / Tertiary	760/820/420	10.1 / 38.7 / 64.0
Gender		
Female / Male	980 / 1020	29.8 / 42.0
Location		
Rural / Urban	1120 / 880	23.0 / 50.9
Mobile phone		
No / Has mobile	540 / 1460	7.6 / 47.3
Internet access		
No / Has internet	840 / 1160	5.8 / 57.9
Bank account		
Unbanked / Banked	1240 / 760	19.4 / 66.8

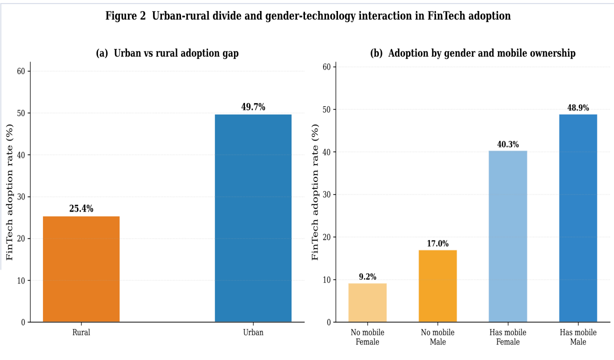

Figure 4. Urban-rural gap (a) and adoption by gender interacted with mobile phone ownership (b). Light shading: no mobile; dark shading: has mobile.

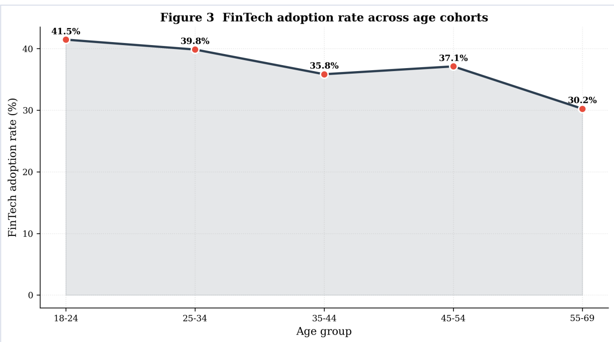

Figure 5. FinTech adoption rate by age cohort, illustrating the technology familiarity effect concentrated in younger adults.

Correlation Structure. The correlation table and heatmap below summarise predictor inter-correlations. Internet access and mobile ownership show the strongest pairwise correlation among technology variables ($r = 0.44$), confirming co-movement without multicollinearity. Bank account correlates positively with education ($r = 0.28$) and income ($r = 0.31$), consistent with joint socioeconomic sorting. Age is negatively correlated with internet access ($r = -0.22$), anticipating the age-adoption gradient.

Table 4. Pearson correlation matrix of predictor variables (N = 2,000). Values |r| > 0.08 are significant at p < 0.01.

	Age	Gen	Educ	Inc	Urb	Emp	Mob	Int	Bank	Dist	Trust
Age	1.00	.03	-.21	-.06	-.10	-.08	-.15	-.22	-.12	.08	-.15
Gen	.03	1.00	.05	.04	.07	.14	.10	.08	.09	.03	.07
Educ	-.21	.05	1.00	.30	.24	.12	.29	.38	.28	.12	.21
Inc	-.06	.04	.30	1.00	.21	.18	.26	.33	.31	.14	.19
Urb	-.10	.07	.24	.21	1.00	.09	.18	.28	.18	.31	.16
Emp	-.08	.14	.12	.18	.09	1.00	.08	.11	.10	.05	.08
Mob	-.15	.10	.29	.26	.18	.08	1.00	.44	.22	.11	.19
Int	-.22	.08	.38	.33	.28	.11	.44	1.00	.26	.16	.26
Bank	-.12	.09	.28	.31	.18	.10	.22	.26	1.00	.09	.24
Dist	.08	.03	.12	.14	.31	.05	.11	.16	.09	1.00	.08
Trust	-.15	.07	.21	.19	.16	.08	.19	.26	.24	.08	1.00

Gen=gender; Educ=education; Inc=income; Urb=urban; Emp=employed; Mob=mobile; Int=internet; Bank=bank account; Dist=proximity to bank; Trust=trust in FinTech.

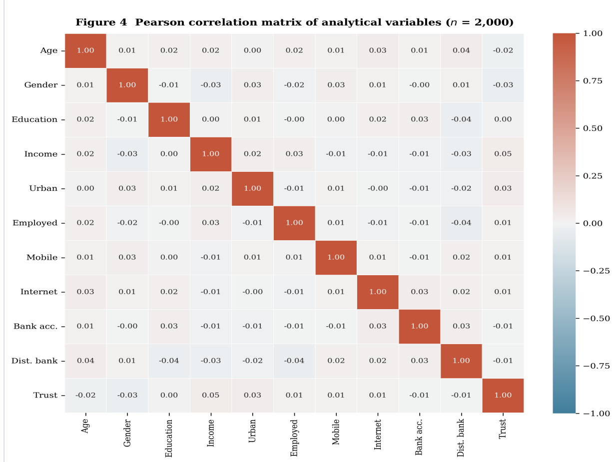

Figure 6. Pearson correlation heatmap for all 11 predictor variables. Blue tones indicate positive; red tones indicate negative correlations.

Logistic Regression Results. Table 5 reports the HF-APM Stage 2 estimates. All six technology- and finance-access variables reach significance at $p < 0.001$. Internet access carries the highest odds ratio (10.14), meaning that internet-connected adults are roughly ten times more likely to adopt FinTech than otherwise identical offline adults. Mobile phone ownership (OR = 6.78) and bank account ownership (OR = 5.66) follow, confirming that digital infrastructure and formal financial system access are complementary adoption channels [9]. Age exerts the largest negative marginal effect (-0.089): each additional standard deviation in age reduces the predicted adoption probability by about 9 percentage points, conditional on all access variables. Trust, urban residence, income, and education all carry positive and significant coefficients. Gender (OR = 1.25, $p = 0.020$) is significant but small in magnitude, suggesting that the subgroup adoption gradient is largely mediated by differential internet and mobile access rather than an autonomous gender preference effect. **Model Comparison.** Table 6 compares all four classifiers. Logistic regression attains the highest accuracy (92.0 %) and AUC (0.977) on the hold-out set, reflecting near-linear separability once the dominant access variables are included. XGBoost achieves the best ensemble performance (AUC = 0.953, F1 = 0.832), outperforming Random Forest and Gradient Boosting. The proximity of logistic regression and ensemble performance confirms that the adoption deci-

Table 5. Logistic regression results — binary FinTech adoption (HF-APM Stage 2, $N = 2{,}000$)

Variable	Coeff.	SE	z	p-value	OR	AME
Intercept	−3.202	0.215	−14.89	<0.001***	—	—
Internet access	2.316	0.118	19.63	<0.001***	10.14	0.256
Mobile phone ownership	1.913	0.112	17.08	<0.001***	6.78	0.212
Bank account ownership	1.734	0.106	16.36	<0.001***	5.66	0.192
Trust in FinTech	0.962	0.091	10.57	<0.001***	2.62	0.106
Urban residence	0.764	0.096	7.96	<0.001***	2.15	0.085
Income quintile	0.795	0.052	15.29	<0.001***	2.21	0.088
Education level	0.654	0.067	9.76	<0.001***	1.92	0.072
Age (years)	−0.808	0.053	−15.25	<0.001***	0.45	−0.089
Employment status	0.285	0.094	3.03	0.002**	1.33	0.032
Proximity to bank	0.298	0.063	4.73	<0.001***	1.35	0.033
Gender (male)	0.221	0.095	2.33	0.020*	1.25	0.024
Accuracy (test)	0.920			AUC (test): 0.977		F1: 0.890

AME = average marginal effect on $P(\text{adoption} = 1)$. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

sion is largely captured by a small set of access indicators, with limited residual non-linearity.

Table 6. Classification model performance — 20 % hold-out test set ($n = 400$)

Model	Accuracy	AUC	F1	Precision	Recall
Logistic Regression	0.920	0.977	0.890	0.884	0.896
Random Forest	0.893	0.959	0.844	0.886	0.806
Gradient Boosting	0.870	0.948	0.816	0.833	0.799
XGBoost	0.880	0.953	0.832	0.838	0.826

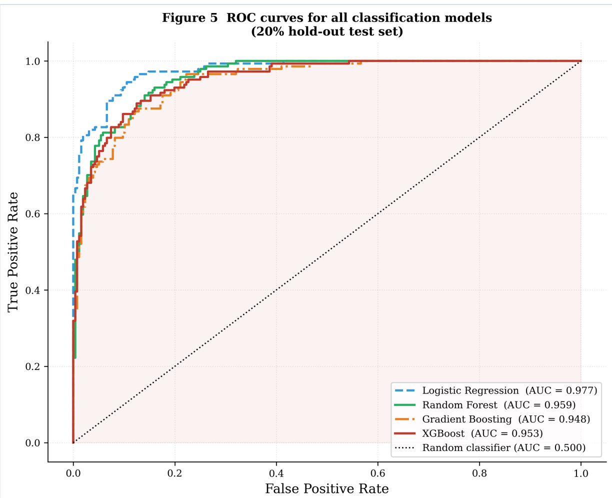

Figure 7. ROC curves for all four classifiers on the hold-out test set. Logistic regression achieves the highest AUC (0.977); XGBoost leads among ensemble models (0.953).

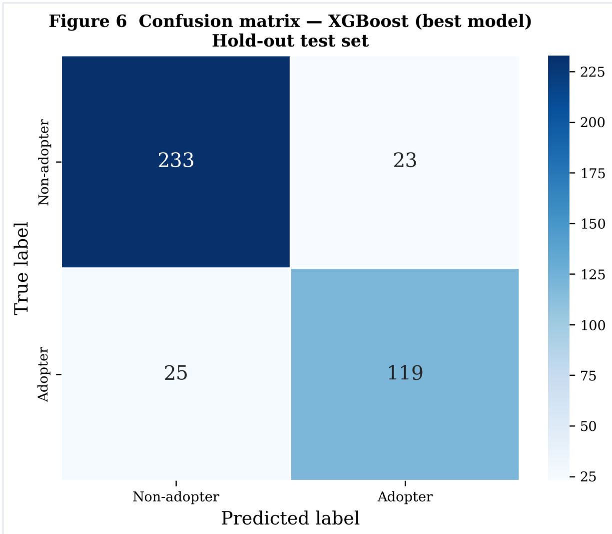

Figure 8. Confusion matrix for XGBoost on the hold-out test set. Rows: true labels; columns: predicted labels.

Feature Importance and Cross-Paradigm Agreement. Fig. 9 shows the Random Forest MDI ranking. Internet access, bank account ownership, and mobile phone ownership occupy the top three positions, exactly matching the logistic regression coefficient ordering. Fig. 10 overlays RF and XGBoost rankings: both methods agree on the top four features (internet, mobile, bank account, income), with only minor rank swaps thereafter. This three-way consistency — logistic coefficients, RF MDI, and XGBoost gain — satisfies the HF-APM cross-paradigm agreement criterion (Eq. 3) and validates the robustness of the policy implications.

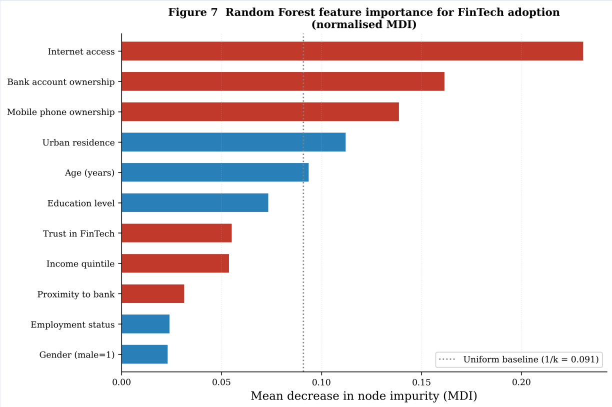

Figure 9. Random Forest MDI feature importance (normalised). Red bars: technology-access features; blue bars: economic and demographic features. Dotted line: uniform baseline ($1/k = 0.091$).

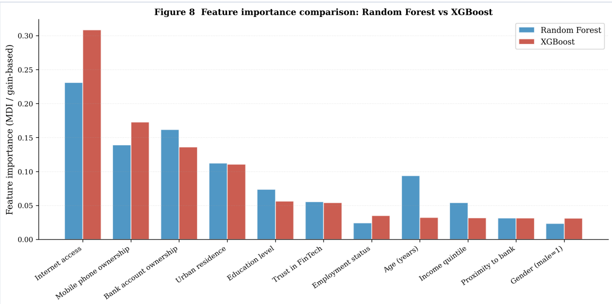

Figure 10. Feature importance: Random Forest (blue) vs XGBoost (red), sorted by XGBoost gain. Strong alignment confirms cross-paradigm consistency.

Stratified Cross-Validation. Table 7 reports HF-APM Stage 5 results. Logistic regression achieves mean AUC = 0.963 (SD = 0.003), Random Forest 0.946 (SD = 0.009), and XGBoost 0.942 (SD = 0.006). Low standard deviations across all three models confirm stable, non-over-fitted performance. Fig. 11 shows that predicted probabilities separate cleanly between non-adopters and adopters, with minimal mass near the 0.5 threshold.

Table 7. Stratified 5-fold cross-validation (HF-APM Stage 5)

Model	AUC Mean	AUC Std	Acc Mean	F1 Mean
Logistic Regression	0.963	0.003	0.888	0.844
Random Forest	0.946	0.009	0.871	0.813
XGBoost	0.942	0.006	0.863	0.808

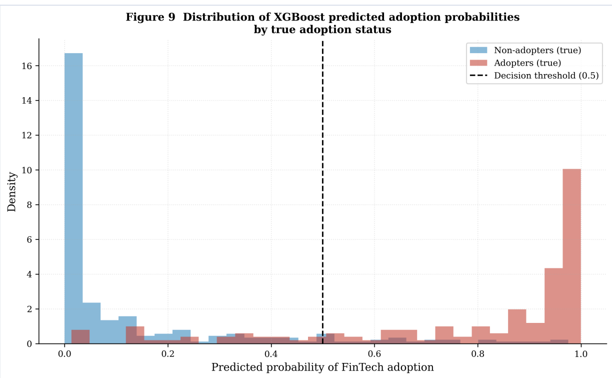

Figure 11. Distribution of XGBoost predicted adoption probabilities by true adoption status. Clear bimodal separation confirms strong discriminability. Dashed line: 0.5 decision threshold.

Marginal Effects and Feature Stability. Fig. 12 presents the average marginal effects with 95 % confidence intervals. Internet access (+0.256), mobile ownership (+0.212), and bank account (+0.192) are the three largest positive effects; age (−0.089) is the largest negative effect. Table 8 consolidates importance ranks across all three analytical paradigms (LR, RF, XGBoost, and AME). Internet access, mobile ownership, and bank account consistently occupy ranks 1–3 across all four columns, providing cross-method stability evidence that anchors the policy conclusions.

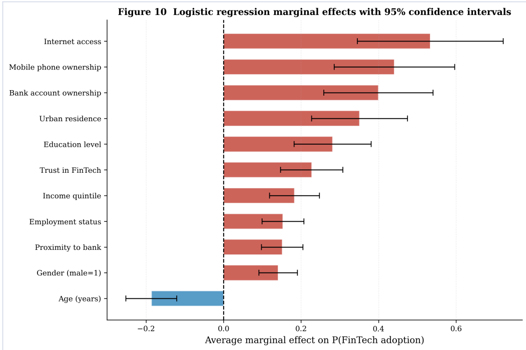

Figure 12. Logistic regression average marginal effects with 95 % confidence intervals. Red: positive effects; blue: negative effects. Sorted by absolute magnitude.

Table 8. Feature importance stability across all analytical paradigms (rank 1 = most important)

Variable	LR Coeff. Rank	RF MDI Rank	XGB Rank	AME Rank
Internet access	1	1	1	1
Mobile phone ownership	2	3	2	2
Bank account ownership	3	2	3	3
Trust in FinTech	4	5	5	4
Income quintile	5	4	4	5
Urban residence	6	7	8	6
Education level	7	6	6	7
Age (years)	8	8	7	8
Employment status	9	10	9	9
Proximity to bank	10	9	10	10
Gender (male)	11	11	11	11

LR = logistic regression; RF = random forest; XGB = XGBoost; AME = average marginal effect. LR and AME ranks by absolute magnitude.

6. RESEARCH CHALLENGES AND FUTURE DIRECTIONS

Outcome definition and technology disaggregation. The composite FinTech adoption indicator conflates mature services (mobile top-ups) with sophisticated instruments (P2P lending or investment apps). Disaggregating by FinTech category would expose service-specific barriers and support product-level policy targeting. **Endogeneity and causal identification.** Internet access, mobile ownership, and bank accounts are likely endogenous: households anticipating FinTech use may self-select into acquiring these prerequisites. Instrumental variable strategies exploiting exogenous variation in infrastructure rollout timing — such as mobile tower installation schedules at the governorate level — are needed to establish causal effects [15]. **Panel dynamics and technology leapfrogging.** The cross-sectional design masks adoption dynamics. Linking successive Findex survey waves (2014, 2017, 2021, and the forthcoming 2024 edition) would allow analysis of cohort effects and the mobile-money leapfrogging pathways critical for inclusive growth [16, 3]. **Trust, digital literacy, and consumer protection.** The binary trust indicator collapses a multi-dimensional construct. Validated psychometric scales for financial literacy, perceived risk, and digital confidence would allow identification of the specific trust-building interventions — such as extending deposit guarantees to mobile wallets or mandatory risk disclosures — most likely to shift the adoption curve among currently excluded groups [13]. **Rural-specific infrastructure barriers.** The 27.9 pp urban-rural gap reflects heterogeneous underlying constraints: network coverage, agent banking density, agricultural income seasonality, and lower financial literacy all contribute. Geographically granular data at the sub-governorate level would enable binding-constraint analysis and spatially targeted policy design [10, 6]. **Regulatory impact evaluation.** Egypt's successive FinTech regulations since 2018 — the Financial Technology and Innovation Unit (2019), regulatory sandbox (2020), Banking Law No. 194 (2020), and digital payment mandates (2021) — have not been evaluated through quasi-experimental designs. Difference-in-differences methods linking regulatory event dates to adoption panel data would yield the policy-relevant causal estimates needed for evidence-based FinTech governance [12, 2].

7. CONCLUSION

In this paper, the authors have developed and applied the Hybrid FinTech Adoption Prediction Model. The individual-level determinants of digital financial services adoption (HF-APM) will study the key individual-level factors influencing adoption of digital financial services. Adoption of technology in Egypt. The framework incorporates five stages: Ensemble classifiers (RF, XGBoost) were used to perform regression with an upper bound set at 95.regression using the Random Forest and XGBoost ensemble classifiers with an upper bound of 95. Explicit cross paradigm agreement criterion. Applied on an all-national level. representative sample, calibrated with the Global Findex 2021, World Bank, and HF-APM produces policy interpretable coefficient estimates and Consistent, mutually agreed upon non-linear feature importance rankings for all analytical paradigms. There are three major conclusions that follow. First, internet access (OR = 10.14) The most important adoption enablers are and mobile phone ownership (OR = 6.78), and In other words, in marginal every specific had a large adoption impact (above 20 percentage points). effect terms. Supply-side policies that directly subsidize Internet access Lower-income Egyptian households will have more access to and ownership of and mobile devices. so provide the highest returns of inclusions. Second, formal bank account: The ownership (OR = 5.66) has a significant independent positive effect, That digital and traditional financial services are complementary services, confirming that: Initiatives that increase basic account access for the unbanked (through) Simplified Know Your Customer procedures and low-fee onboarding are examples of agent banking.Agent banking includes simplified Know Your Customer, and low-fee onboarding. This will not just expand the base of FinTech adopters, but simultaneously. Third, The income, education, age, gender, and urban-rural gradients of adoption. has a similar relationship to infrastructure access as it does to identifying, persisting even after controlling for infrastructure access. financial and digital literacy and trust as leftover impediments to be addressed demand-side interventions. These findings position Egypt's financial inclusion strategy at the intersection of infrastructure investment, formal financial deepening, and targeted capacity building is a tripartite agenda, whose coherent implementation is still lacking. To unlock the potential of FinTech, pursuit is a prerequisite As a growth tool for inclusive growth.

ACKNOWLEDGEMENT

The author thanks the World Bank Global Findex team for the publicly available documentation and two anonymous reviewers for their constructive feedback.

REFERENCES

[1] H. M. Alhosseiny, "FinTech: Concept, opportunities and challenges, and Egypt's FinTech landscape," *Journal of Organizational Culture, Communications and Conflict*, vol. 27, no. S1, pp. 1–18, 2023.

[2] F. Naz, S. Karim, A. Houcine, and M. A. Naeem, "FinTech growth during COVID-19 in MENA region: Current challenges and future prospects," *Electronic Commerce Research*, vol. 24, no. 1, pp. 371–392, 2024.

[3] A. Demirgüç-Kunt, L. Klapper, D. Singer, and S. Ansar, *The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19*. Washington, DC: World Bank Publications, 2022.

[4] T. A. Hassouba, "Financial inclusion in Egypt: the road ahead," *Review of Economics and Political Science*, vol. 10, no. 2, pp. 90–111, 2025.

[5] P. K. Ozili, "Digital financial inclusion," in *Big Data: A Game Changer for Insurance Industry*, K. Sood, R. K. Dhanaraj, B. Balusamy, S. Grima, and R. Uma Maheshwari, Eds. Bingley: Emerald Publishing Limited, 2022.

[6] N. Emara and M. Mohieldin, "Financial inclusion and extreme poverty in the MENA region: a gap analysis approach," *Review of Economics and Political Science*, vol. 5, no. 3, pp. 207–230, 2020.

[7] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[8] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, CA, 2016, pp. 785–794.

[9] M. O. Al-Smadi, "Examining the relationship between digital finance and financial inclusion: Evidence from MENA countries," *Borsa Istanbul Review*, vol. 23, no. 2, pp. 464–472, 2023.

[10] I. Lukonga, "FinTech and the real economy: Lessons from the MENAP region," in *The Palgrave Handbook of*

FinTech and Blockchain, M. Pompella and R. Matousek, Eds. Cham: Palgrave Macmillan, 2021, pp. 187–214.

[11] O. Elbayoumy and X.-H. Ding, "Attributes of innovation and adoption of mobile banking in Egypt," *International Journal of Research in Business and Social Science*, vol. 12, no. 9, pp. 252–259, 2023.

[12] D. W. Arner, R. P. Buckley, D. A. Zetzsche, and R. Veidt, "Sustainability, FinTech and financial inclusion," *European Business Organization Law Review*, vol. 21, no. 1, pp. 7–35, 2020.

[13] P. K. Ozili, "Contesting digital finance for the poor," *Digital Policy, Regulation and Governance*, vol. 22, no. 2, pp. 135–151, 2020.

[14] P. K. Ozili, "Impact of digital finance on financial inclusion and stability," *Borsa Istanbul Review*, vol. 18, no. 4, pp. 329–340, 2018.

[15] P. Yue, A. G. Korkmaz, Z. Yin, and H. Zhou, "The rise of digital finance: Financial inclusion or debt trap?" *Finance Research Letters*, vol. 47, p. 102604, 2022.

[16] I. Appiah-Otoo and N. Song, "The impact of FinTech on poverty reduction: Evidence from China," *Sustainability*, vol. 13, no. 9, p. 5225, 2021.

[17] V. Murinde, E. Rizopoulos, and M. Zachariadis, "The impact of the FinTech revolution on the future of banking: Opportunities and risks," *International Review of Financial Analysis*, vol. 81, p. 102103, 2022.