Journal of Finance and Investment Analysis, Vol. 15, No. 4, 2026, 47-63
ISSN: 2241-0988 (print version), 2241-0996(online)
https://doi.org/10.47260/jfia/1543
Scientific Press International Limited

Financial Technology and Financial Inclusion: Evidence from East African Community Member Countries

Moffat Karo Mwaniki[1], Herick Ondigo[2] and Johnbosco M. Kisimbii[3]

Abstract

This study examines the effect of financial technology on financial inclusion in the eight East African Community member countries over 2014–2023, using a balanced panel of 80 country-year observations. Fintech is measured by penetration rate, usage rate and transaction intensity (mobile-money transactions per adult), with GDP per capita, inflation, financial literacy and bank-branch density as controls. Panel unit root and Kao cointegration tests are reported, and random-effects and fixed-effects estimators are compared with the Hausman test ($\chi^2(5) = 4.79$, $p = 0.441$), with two-way fixed effects, first differences and correlated random effects as robustness checks. Penetration rate ($\beta = 4.965$, $p = 0.002$) and transaction intensity ($\beta = 4.552$, $p = 0.001$) have positive significant effects that survive the controls and fixed effects, whereas usage rate has no significant independent effect; GDP per capita is the strongest control. Fintech advances inclusion through breadth of access and economically meaningful transaction use rather than frequency of use: repeated low-value transfers do not connect users to formal savings, credit or insurance. Because the effects reflect long-run co-movement rather than year-to-year changes, they are interpreted as long-run associations. Policy should prioritise affordable access, interoperable payments and bank–fintech partnerships that convert activity into formal participation.

JEL classification numbers: G21, G23, O16, O33, O55.
Keywords: Financial technology, Financial inclusion, Penetration rate, Usage rate, Transaction intensity, East African Community.

[1] PhD Candidate, Department of Finance and Accounting, Faculty of Business and Management Sciences, University of Nairobi, Kenya.
[2] Department of Finance and Accounting, Faculty of Business and Management Sciences, University of Nairobi, Kenya.
[3] Department of Finance and Accounting, Faculty of Business and Management Sciences, University of Nairobi, Kenya.

Article Info: *Received:* October 10, 2026. *Revised*: November 2, 2026.
Published online: November 12, 2026.

1. Introduction

1.1 Background

Financial technology (fintech) has altered the delivery of payments, savings, credit, insurance, and other financial services by combining mobile connectivity, digital platforms, data analytics, and automated processes (Sangwan et al., 2020; Demir et al., 2022). Its development has particular importance in emerging economies, where distance, branch-maintenance costs, documentation requirements, and low incomes have historically restricted access to formal finance (Kouladoum et al., 2022; Ediagbonya and Tioluwani, 2023). Digital channels can lower transaction costs, extend service hours, improve information flows, and allow providers to reach customers who were previously uneconomical to serve (Kanga et al., 2022; Demir et al., 2022). Fintech is therefore a plausible mechanism for widening financial inclusion, understood as meaningful access to and use of affordable, appropriate, and secure formal financial services (Kling et al., 2022; Ozili, 2023).

Across Africa, mobile money and related digital services have expanded the practical reach of finance beyond conventional banking infrastructure (Chinoda and Mashamba, 2021; Mpofu and Mhlanga, 2022). Empirical evidence links digital technologies with greater account access, payment participation, and opportunities for underserved households and firms, although the magnitude of these gains differs by market structure and institutional setting (Banna et al., 2022; Kouladoum et al., 2022). Fintech can also reduce information and search costs, provide transaction records, and create alternative pathways to formal products (Demir et al., 2022; Ediagbonya and Tioluwani, 2023). However, unequal connectivity, low trust, limited capability, and weak consumer protection can prevent technological availability from becoming meaningful inclusion (Wezel and Ree, 2023; Ozili, 2023).

East Africa provides a compelling setting for assessing this relationship because the region combines internationally prominent mobile-money ecosystems with persistent cross-country exclusion. Kenya and Tanzania have experienced wide mobile-money diffusion, whereas fragile or infrastructure-constrained member countries have substantially narrower digital and formal-finance coverage (World Bank, 2023; Kamau and Aduda, 2024). Agent banking, digital credit, and app-based payments have expanded, but development remains uneven because member states differ in connectivity, institutional capacity, consumer trust, regulatory maturity, and service coverage (Misati et al., 2021; Ozili, 2023). This heterogeneity permits a regional panel analysis of whether differences in fintech breadth and intensity translate into differences in financial inclusion over time.

Fintech is multidimensional and should not be represented by a single proxy. Penetration rate captures the breadth of access to digital-financial accounts or services; usage rate captures how frequently active users transact; and transaction intensity (the number of transactions per adult) captures the scale or intensity of digital-financial activity (Liu and Walheer, 2022). Treating these dimensions as interchangeable can conceal important differences because an account may remain

dormant, frequent low-value activity may not connect a user to broader formal services, and high transaction intensity may reveal deeper integration into the financial system (Sangwan et al., 2020; Liu and Walheer, 2022). The present article therefore estimates their simultaneous effects on financial inclusion.

1.2 Problem Statement

Despite rapid fintech expansion, large segments of the EAC population remain excluded from formal financial systems, and inclusion outcomes remain markedly unequal among member states (World Bank, 2023; Ozili, 2023). Digital access is uneven, transaction activity is concentrated in more mature markets, and effective use continues to be constrained by infrastructure deficits, affordability, limited trust, low financial capability, product relevance, and institutional fragility (Ediagbonya and Tioluwani, 2023; Wezel and Ree, 2023). Consequently, the existence of a mobile account or digital channel does not necessarily mean that households and firms can use a sufficiently broad range of formal services. The coexistence of technological expansion and persistent exclusion raises a substantive question about whether fintech development improves inclusion and which dimension produces the strongest effect.

Existing empirical evidence is positive overall but remains inconclusive in ways that matter for EAC policy. African studies associate fintech with financial inclusion and reduced service barriers (Chinoda and Mashamba, 2021; Kanga et al., 2022; Kouladoum et al., 2022), while other work shows that outcomes vary with institutional quality, market development, financial capability, and the particular technology or service examined (Banna et al., 2022; Ediagbonya and Tioluwani, 2023). Evidence from India and individual African countries cannot automatically be generalized to a region whose member states differ sharply in digital infrastructure, regulation, income, conflict exposure, and financial-system maturity (Asif et al., 2023; Muthengi, 2022). This leaves a contextual gap in comparable region-wide evidence.

A further methodological and measurement gap arises because many studies are cross-sectional, single-country, or user-level and frequently rely on one fintech proxy (Muthengi, 2022; Misati et al., 2021). Such designs may not capture unobserved country differences or changes through time, while single indicators can obscure the distinction between access, repeated activity, and economic intensity (Liu and Walheer, 2022). A longitudinal multi-country test is therefore required to estimate penetration rate, usage rate, and transaction intensity jointly while accounting for country-level heterogeneity and for the macroeconomic and structural conditions - income, price stability, financial capability and traditional banking infrastructure - that drive inclusion independently of technology (Kouladoum et al., 2022; Ozili, 2023). Accordingly, this study determined the effect of financial technology on financial inclusion in the eight EAC member countries from 2014 to 2023.

2. Literature Review

2.1 Theoretical Review

The Diffusion of Innovations Theory provides the anchor explanation for the spread of fintech. Rogers (1962) argues that adoption is shaped by perceived relative advantage, compatibility, complexity, trialability, and observability. Digital finance should diffuse more rapidly when it is cheaper than conventional alternatives, compatible with everyday exchange, easy to learn, and supported by visible agent and communications networks (David-West et al., 2022; Kanga et al., 2022). At the system level, penetration indicates that adoption has moved beyond early users, while transaction volume indicates that the innovation has become embedded in economic activity. The theory therefore predicts a positive relationship between fintech diffusion and financial inclusion, particularly where digital channels extend formal services to previously excluded groups (Kelikume, 2021; Kanga et al., 2022). The Technology Acceptance Model complements diffusion theory by explaining individual acceptance through perceived usefulness and perceived ease of use (Davis, 1989). A digital service is more likely to be adopted and sustained when users believe that it improves the speed, convenience, cost, or quality of financial activity and when the service requires limited effort to learn (Aldammagh et al., 2021; Baber, 2021). Access alone may not lead to sustained participation if platforms are difficult to navigate, expensive, unreliable, unsafe, or poorly matched to users' needs (Ediagbonya and Tioluwani, 2023). This reasoning is particularly relevant to usage frequency: repeated interaction is not necessarily equivalent to deeper inclusion when activity is narrow, low-value, or confined to basic transfers. Financial Inclusion Theory views affordable and appropriate financial access as a means of enabling underserved households and firms to participate in the formal economy (Polillo, 2011; Kling et al., 2022). From this perspective, fintech can reduce geographic and cost barriers, increase service-point density, and produce digital records that support payments, saving, insurance, and credit (Kandpal and Mehrotra, 2019; Kouladoum et al., 2022). The theory also emphasizes meaningful participation rather than registration alone; inclusion requires that services be usable, responsive to client needs, and connected to economic opportunity (Kling et al., 2022; Ozili, 2023). Taken together, the three theories predict positive effects from access breadth and transactional depth while leaving open whether usage frequency has an independent effect after the other dimensions are controlled.

2.2 Empirical Review and Hypotheses

Empirical work across Africa and other emerging markets generally associates digital finance with wider inclusion. Chinoda and Mashamba (2021) found a positive fintech-inclusion relationship in Africa, while Demir et al. (2022) showed that fintech can improve inclusion although distributional effects vary. Kanga et al. (2022) connected fintech diffusion with financial inclusion and income outcomes, and Kouladoum et al. (2022) identified digital technologies as important inclusion drivers in Sub-Saharan Africa. These studies support the proposition that lower

delivery costs and wider digital reach can bring underserved users into formal finance.

Evidence outside the region reinforces this association but also demonstrates contextual variation. Asif et al. (2023) reported that fintech and digital-financial services supported inclusion in India, while Goswami et al. (2022) found that fintech improved rural inclusion. Banna et al. (2022) showed that fintech-based inclusion affected the behavior of microfinance institutions in Sub-Saharan Africa, illustrating that fintech can alter both access and provider incentives. However, differences in regulation, market depth, infrastructure, income, and consumer capability limit the direct transferability of these findings to the EAC (Ediagbonya and Tioluwani, 2023; Ozili, 2023).

Regionally relevant studies provide useful but incomplete evidence. Misati et al. (2021) found that financial innovation enhanced financial deepening and growth in Kenya, and Muthengi (2022) reported a significant relationship between financial technology and inclusion in a Kenyan setting. Their country-specific and, in the latter case, cross-sectional designs do not establish whether the association holds across heterogeneous EAC countries over time. Kamau and Aduda (2024) also highlighted the importance of financial technologies in Kenya, but a regional panel is needed to separate common effects from country-specific conditions.

Measurement further explains why findings may differ. Digital accounts may remain inactive, users may rely on limited cash-in/cash-out functions, and transaction frequency may follow income cycles rather than the depth of financial participation (Liu and Walheer, 2022). Transaction volume can better reflect the practical integration of digital tools into commerce, transfers, saving, and payments, while penetration captures how widely the opportunity to participate is distributed (Sangwan et al., 2020; Liu and Walheer, 2022). The present study consequently tested H01a: penetration rate has no significant effect on financial inclusion; H01b: usage rate has no significant effect on financial inclusion; and H01c: transaction intensity has no significant effect on financial inclusion in EAC member countries.

3. Methodology

3.1 Research Design and Data

The study adopted a positivist philosophy and an explanatory longitudinal panel design. The unit of analysis was the country-year. The population comprised the eight EAC member countries at the end of the study period - Burundi, the Democratic Republic of Congo, Kenya, Rwanda, Somalia, South Sudan, Tanzania and Uganda - and all eight were observed over ten years from 2014 to 2023, yielding a balanced panel of 80 observations. The longitudinal design captured both cross-country differences and changes over time.

Secondary data were compiled from the World Bank Global Findex and World Development Indicators (WDI), national central banks, national statistics agencies, and official financial-sector reports. Financial inclusion was measured using a composite Financial Inclusion Index that captured the availability, accessibility, and

utilization of formal services. Fintech penetration was measured as the proportion of adults with access to mobile-money or digital-financial accounts; usage rate represented the share of adults who transact digitally at least monthly, taken from national financial access surveys; and transaction intensity was measured as the annual number of mobile-money transactions recorded by each central bank. Because raw transaction counts are dominated by population size - Kenya, Tanzania and Uganda each record several billion transactions a year while Burundi and South Sudan record tens of millions - the series was expressed per adult (transactions divided by the population aged 15–64 from WDI) so that the variable is scale-free and comparable across countries and over time. The resulting measure ranges from 1.1 to 183.7 transactions per adult per year. Penetration, usage and transaction intensity enter the model in natural logarithms, so that coefficients are read as the change in the inclusion index per 1% (×0.01) change in the regressor.

Four control variables were added to address omitted-variable bias. GDP per capita (constant 2015 US dollars, WDI; in logarithms) controls for the level of economic development; for South Sudan, where WDI reports no constant-price series after 2015, the 2015 value was extended with the country's real GDP growth rate net of population growth. The inflation rate (annual CPI inflation, WDI) controls for macro-financial stability; where CPI inflation is not published (Somalia, and seven country-years for the Democratic Republic of Congo) the GDP-deflator growth rate was used. Financial capability was controlled for with a financial literacy index compiled from national financial-capability surveys and World Bank/OECD reports, available for all 80 country-years, in place of the adult literacy rate, which WDI reports for only 8 of the 80 country-years. Traditional financial infrastructure was captured by commercial-bank branches per 100,000 adults (IMF Financial Access Survey via WDI), which is unavailable for Somalia; models including this variable are therefore estimated on 70 observations, with the 2019 value carried forward for the Democratic Republic of Congo for 2020–2023.

3.2 Model Specification and Estimation

The direct-effects model was specified as:

$$FII_{it} = \beta_0 + \beta_1 \ln PEN_{it} + \beta_2 \ln USE_{it} + \beta_3 \ln TPA_{it} + \beta_4 \ln GDPPC_{it} + \beta_5 INF_{it} + \beta_6 FLIT_{it} + \beta_7 BRANCH_{it} + u_i + \varepsilon_{it} \quad (1)$$

where FII is the financial inclusion index of country i in year t; PEN, USE and TPA are penetration rate, usage rate and transactions per adult; GDPPC, INF, FLIT and BRANCH are the controls; ui is the country effect and εit the idiosyncratic error. The model was estimated by random-effects (RE) generalized least squares and, as a robustness check, by the fixed-effects (FE) within estimator. The choice between them was made with the Hausman (1978) test, whose χ^2 statistic and p-value are reported in full; because country-specific unobservables such as institutional quality may be correlated with the regressors, FE estimates are presented alongside RE in

every table. Usage rate is measured at the survey wave and does not vary within countries over the sample period, so it is absorbed by the country effects in FE and is identified only in RE; this is noted where relevant and is itself informative about the variable. A correlated random-effects (Mundlak, 1978) specification, which adds the country means of the time-varying regressors to the RE model and yields FE-equivalent slopes while retaining the time-invariant usage rate, was also estimated. Two further checks address the risk of spurious regression in a short macro-panel: a two-way FE model with year effects to absorb common trends, and a model in first differences.

Before estimation, stationarity was assessed with panel unit root tests appropriate to an unbalanced or short panel—the Fisher-type ADF test of Maddala and Wu (1999) and the Choi (2001) inverse-normal Z test, which combine country-level ADF p-values—at levels and first differences, and the Kao (1999) residual-based ADF test was used to test for panel cointegration. Multicollinearity was assessed with variance inflation factors. Conventional GLS standard errors are reported because, with only eight countries, cluster-robust standard errors are unreliable (Cameron and Miller, 2015); the sensitivity of inference to clustering is reported in the robustness section. Hypotheses were evaluated at the 5% significance level.

4. Results and Discussion

4.1 Descriptive Results

Table 1 summarises the variables. Financial inclusion averaged 41.03 on the index, ranging from 5.60 to 83.70 (SD = 23.05), reflecting persistent regional disparities. Fintech penetration averaged 0.537 (range 0.07–0.98), compared with a usage-rate mean of 0.241 (range 0.03–0.46). The raw number of mobile-money transactions averaged 978 million a year and was extremely dispersed (CV = 1.26), ranging from 6.8 million in South Sudan to 4.8 billion in Uganda; once expressed per adult the dispersion falls (CV = 1.09) but remains wide, from 1.1 transactions per adult in South Sudan to 183.7 in Tanzania, confirming that transaction intensity, not merely market size, differs sharply across the region. GDP per capita averaged USD 833 (constant 2015 prices), inflation 16.7% with an extreme maximum of 380% (South Sudan, 2016), the financial literacy index 28.1 and bank-branch density 2.9 branches per 100,000 adults.

Table 1: Descriptive statistics

Variable	N	Minimum	Maximum	Mean	SD	CV
Financial inclusion index	80	5.60	83.70	41.03	23.05	0.56
Penetration rate	80	0.07	0.98	0.54	0.27	0.49
Usage rate	80	0.03	0.46	0.24	0.16	0.65
Transactions (number, millions)	80	6.76	4,817.89	977.64	1,233.20	1.26
Transactions per adult	80	1.09	183.67	39.36	42.94	1.09
GDP per capita (constant 2015 USD)	80	254.40	1,811.22	832.88	407.95	0.49
Inflation (%)	80	−6.69	380.00	16.69	48.12	2.88
Financial literacy index	80	6.00	44.47	28.05	10.77	0.38
Bank branches per 100,000 adults	70	0.63	6.20	2.95	1.59	0.54

Transactions per adult = annual number of mobile-money transactions ÷ population aged 15–64.
Source: Authors' computation.

Financial inclusion displayed substantial regional inequality. Its mean of 41.03 was accompanied by a range of 78.10 index points and a standard deviation of 23.05, showing that the typical country-year was far removed from both the most and least inclusive observations. The coefficient of variation of 0.56 indicates moderate relative dispersion. The pattern is consistent with differences in financial infrastructure, institutional stability, income, regulation, and the maturity of digital-finance ecosystems across the EAC (Ozili, 2023; World Bank, 2023).

Fintech penetration averaged 0.537 and reached a maximum of 0.980, indicating near-universal digital-finance access in the most developed observations. Its minimum of 0.071 nevertheless confirms that access remained extremely limited in some country-years. The moderate coefficient of variation (0.49) suggests that penetration was less uneven than transaction activity. This result reflects the expansion of mobile accounts and agent networks while also revealing persistent infrastructure and adoption gaps (Kanga et al., 2022; Kouladoum et al., 2022).

Usage rate averaged only 0.241, less than half the mean penetration rate, and varied from 0.030 to 0.461 across countries; within each country it is constant over the sample period, because it is measured at the national financial-access survey wave rather than annually. Its coefficient of variation of 0.65 shows greater relative heterogeneity than penetration. The difference between penetration and usage indicates that service availability advanced faster than recurring engagement. Accounts may remain dormant or be used only intermittently because of transaction charges, unreliable networks, limited income, lack of trust, or products that do not address users' priorities (Ediagbonya and Tioluwani, 2023; Wezel and Ree, 2023).

Transaction intensity recorded wide dispersion even after normalisation, with a mean of 39.4 transactions per adult and values ranging from 1.1 to 183.7. The standard deviation exceeded the mean, indicating that a small number of mature markets and high-activity years dominated the regional distribution. This variability supports treating transaction intensity separately from penetration and frequency: countries can achieve broad account access without generating comparable economic intensity. Overall, the descriptive evidence justified the simultaneous

estimation of breadth, frequency and transaction intensity, with controls for the macroeconomic environment.

4.2 Panel Unit Root and Cointegration Tests

Table 2 reports the panel unit root tests. At levels, only the log of penetration rate is stationary on both statistics; the inclusion index, transactions per adult, GDP per capita, financial literacy and branch density are non-stationary, and inflation is borderline. In first differences all regressors are stationary at the 5% level; the inclusion index itself is a smooth, slowly trending series for which the first-difference test does not reject ($p = 0.524$), which with $T = 10$ reflects the very low power of the test rather than evidence of an I(2) process. The Kao residual ADF test does not reject the null of no cointegration for either the baseline (ADF = 0.60, $p = 0.726$) or the controls specification (ADF = 0.30, $p = 0.618$). Two implications follow. First, with ten annual observations per country, both the unit root and the cointegration tests have little power, and their results should be read as inconclusive rather than as decisive evidence for or against a long-run relationship. Second, the level regressions reported in Section 4.3 cannot be assumed to be free of spurious-regression risk on the strength of the cointegration test alone; the two-way FE and first-difference models in Section 4.4 are therefore reported as the direct safeguard, and the level estimates are interpreted as long-run associations.

Table 2: Panel unit root tests (Fisher-type ADF and Choi Z) and Kao cointegration test

Variable test	Level: Fisher χ^2	p	Level: Choi Z	p	1st diff.: Fisher χ^2	p
Financial inclusion index	13.2	0.657	1.67	0.952	15.0	0.524
ln Penetration rate	190.8***	0.000	−8.75***	0.000	197.5***	0.000
ln Transactions per adult	17.3	0.369	0.04	0.517	29.0**	0.024
ln GDP per capita	12.2	0.730	1.30	0.904	30.0**	0.018
Inflation	20.6	0.194	−0.56	0.287	75.6***	0.000
Financial literacy index	0.2	1.000	7.61	1.000	65.8***	0.000
Bank branches per 100,000 adults	11.3	0.662	0.57	0.717	51.3***	0.000
Kao cointegration ADF, baseline (FII on ln PEN, ln TPA)	0.60	0.726				
Kao cointegration ADF, with controls	0.30	0.618				

Country-level ADF with constant and one lag; N = 8 countries (7 for branches), T = 10. Fisher χ^2 has 2N degrees of freedom. Usage rate is time-invariant within countries and cannot be tested. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Source: Authors' computation.

4.3 Hypothesis Testing: Random-Effects and Fixed-Effects Estimates

Table 3 reports the estimates. Column 1 is the baseline RE model with the three fintech indicators only, re-estimated with transactions per adult in place of raw counts; column 2 adds the macroeconomic and structural controls; column 3 is the FE counterpart of column 2; columns 4 and 5 add bank-branch density on the 70-observation sample for which it is available. The Hausman test comparing FE and RE on the time-varying fintech regressors alone gives $\chi^2(2) = 6.09$, $p = 0.048$, marginally rejecting RE at the 5% level; with the controls included it gives $\chi^2(5) = 4.79$, $p = 0.441$, so that once income, inflation and financial capability are controlled for the RE assumption that country effects are uncorrelated with the regressors is not rejected. RE with controls (column 2) is therefore the preferred specification, and FE is reported alongside it throughout; the two give the same signs and significance for every fintech coefficient.

Table 3: Financial technology and financial inclusion: random-effects and fixed-effects estimates

Variable	RE baseline	RE + controls	FE + controls	RE + GDP pc + branches	FE + controls + branches
ln Penetration rate	6.266***	4.965***	5.362***	7.724***	8.720***
	(1.509)	(1.559)	(1.521)	(1.523)	(1.716)
ln Usage rate	5.945	3.157	—	18.741**	—
	(5.243)	(4.238)		(8.109)	
ln Transactions per adult	5.170***	4.552***	3.614***	2.700**	2.568**
	(1.350)	(1.349)	(1.269)	(1.244)	(1.241)
ln GDP per capita	—	17.974***	29.730***	28.010***	40.803***
		(5.043)	(7.188)	(6.984)	(9.795)
Inflation (%)	—	0.020*	0.021*	—	0.019*
		(0.011)	(0.010)		(0.010)
Financial literacy index	—	0.233	0.015	—	−0.328
		(0.330)	(0.388)		(0.388)
Bank branches per 100,000 adults	—	—	—	0.044	1.011
				(0.960)	(1.146)
Constant	−14.719	−125.370***	—	−241.154***	—
	(16.078)	(32.712)		(52.823)	
Estimator	RE	RE	FE	RE	FE
Model F-statistic (p)	26.68	19.74	21.34 (0.000)	27.04	22.20
	(0.000)	(0.000)		(0.000)	(0.000)
R^2 within	0.490	0.597	0.614	0.660	0.700
R^2 between	0.655	0.687	—	0.865	—
R^2 overall	0.646	0.682	—	0.854	—
Observations	80	80	80	70	70
countries	8	8	8	7	7

Dependent variable: financial inclusion index. Conventional GLS/within standard errors in parentheses. Usage rate is time-invariant within countries and is absorbed by the fixed effects in FE columns (—). Column 4 omits inflation and literacy because RE with seven regressors cannot be estimated on seven countries. Hausman FE vs RE: $\chi^2(2) = 6.09$, $p = 0.048$ (fintech regressors only); $\chi^2(5) = 4.79$, $p = 0.441$ (with controls). Between and overall R^2 are not meaningful for FE and are omitted. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Source: Authors' computation.

Penetration rate has a positive and significant effect in every specification: $\beta = 6.266$ ($p < 0.001$) in the baseline, $\beta = 4.965$ ($p = 0.002$) with controls and $\beta = 5.362$ ($p = 0.001$) under FE. A 10% increase in the share of adults with digital-financial access raises the inclusion index by about 0.5 points, holding income, inflation and literacy constant. H01a is rejected. The finding supports diffusion theory: when access points, accounts, mobile connectivity and agent networks reach a larger share of the population, previously excluded users enter formal financial channels, consistent with Kouladoum et al. (2022) and Kanga et al. (2022).

Transactions per adult likewise has a positive and significant effect in every specification: $\beta = 5.170$ ($p < 0.001$) in the baseline, $\beta = 4.552$ ($p = 0.001$) with controls and $\beta = 3.614$ ($p = 0.006$) under FE, leading to rejection of H01c. The effect is smaller once income is controlled for—part of the raw association between transaction intensity and inclusion reflects the fact that richer economies transact more—but it is robust to the removal of scale effects, to the controls and to country fixed effects. Transaction intensity captures the economic embedding of fintech, and the result accords with research showing that digital-financial ecosystems extend the reach and functionality of formal finance (Demir et al., 2022; Chinoda and Mashamba, 2021).

Usage rate is positive but statistically insignificant in the baseline ($\beta = 5.945$, $p = 0.260$) and with controls ($\beta = 3.157$, $p = 0.459$), so H01b is not rejected. In the FE columns it is absorbed by the country effects. It is significant only in column 4, which drops Somalia—an outlier with the region's lowest usage rate (3%) but a mid-range inclusion score—and omits two controls; the result is not robust and is not relied upon. The substantive interpretation of this finding is developed in Section 4.5.

Among the controls, GDP per capita is the strongest single predictor of inclusion ($\beta = 17.97$, $p = 0.001$ in RE; $\beta = 29.73$, $p < 0.001$ in FE): a 10% rise in real income per head raises the index by 1.8–3.0 points. Inflation is positive and marginally significant ($p = 0.08$ in RE, $p = 0.05$ in FE), a result driven by South Sudan's hyperinflation years, during which mobile money substituted for a collapsing cash economy. The financial literacy index and bank-branch density are insignificant once the fintech variables and income are included, indicating that in the EAC digital channels, not branch networks, are the margin on which inclusion is expanding. Overall R^2 rises from 0.646 to 0.682 and within R^2 from 0.490 to 0.597 when the controls are added, and the model remains jointly significant ($F(6, 73) = 19.74$, $p < 0.001$), confirming that the baseline model omitted relevant variables; importantly, the fintech coefficients retain their signs and significance.

4.4 Robustness: Year Effects, First Differences and Correlated Random Effects

Table 4 reports three further specifications. The correlated random-effects (Mundlak) model (column 1) reproduces the FE slopes for the time-varying regressors while retaining usage rate, which remains insignificant ($\beta = 8.471$,

$p = 0.360$); the joint test on the country means is significant ($\chi^2(5) = 19.9$, $p < 0.001$), driven by the inflation mean, so the model offers a useful bridge between RE and FE. The two-way FE model (column 2) adds year effects, which absorb the strong common upward trend in both fintech and inclusion across the region: with the trend removed, penetration ($p = 0.816$) and transactions per adult ($p = 0.124$) are no longer significant, and the model's explanatory power collapses. The first-difference model (column 3) tells the same story: year-to-year changes in fintech indicators do not predict year-to-year changes in inclusion ($F = 0.66$, $p = 0.654$).

These results are reported in full because they bound the interpretation of the main estimates. The fintech effects in Table 3 are identified from the long-run co-movement of penetration, transaction intensity and inclusion within and across countries over a decade, not from short-run fluctuations. Given that the panel unit root tests find most series non-stationary and the Kao test does not confirm cointegration, the Table 3 coefficients are best read as long-run associations consistent with the diffusion mechanism rather than as short-run causal effects. Inclusion is a stock that accumulates slowly as accounts are opened and habits form, so the absence of a contemporaneous first-difference effect is not surprising; but the limitation is real, and a longer panel is needed to resolve it. Finally, with only eight countries cluster-robust standard errors are unreliable (Cameron and Miller, 2015); under clustering by country the control coefficients remain significant but the fintech coefficients are imprecisely estimated ($p = 0.30$ for penetration, $p = 0.15$ for transactions per adult), which is a further reason to treat the magnitudes with caution.

Table 4: Robustness checks

Variable	Correlated RE (Mundlak)	Two-way FE	First differences
ln Penetration rate	5.362*** (1.521)	−0.664 (2.849)	1.436 (2.868)
ln Usage rate	8.471 (9.186)	—	—
ln Transactions per adult	3.614*** (1.269)	2.388 (1.530)	−0.074 (0.719)
ln GDP per capita	29.730*** (7.188)	8.991 (10.620)	8.690 (5.968)
Inflation (%)	0.021* (0.010)	0.010 (0.012)	0.002 (0.004)
Financial literacy index	0.015 (0.388)	−1.476** (0.677)	−0.288 (0.343)
Estimator	RE + country means	FE + year effects	OLS in first differences
Model F-statistic (p)	14.77 (0.000)	3.03 (0.017)	0.66 (0.654)
R^2 (within overall)	0.614 0.963	— —	— 0.048
Observations	80	80	72

Dependent variable: financial inclusion index (first difference in column 3). Country-mean terms in column 1 not shown. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Source: Authors' computation.

4.5 Why Frequency of Use Does Not Translate into Inclusion

The insignificance of usage rate, alongside the significance of penetration and transaction intensity, is the study's most distinctive result and deserves a structural explanation. Three features of the EAC digital-finance ecosystem account for it.

First, the dominant use case is narrow. In every EAC market the bulk of mobile-money activity consists of person-to-person transfers, airtime purchase and cash-in/cash-out at agents (Misati et al., 2021; Kamau and Aduda, 2024). A user who sends a remittance home every week interacts with the system frequently but never leaves the payments layer: the transaction generates no credit history that a lender will accept, no savings balance, and no insurance cover. The Financial Inclusion Index used here weights availability, accessibility and utilization of formal services - account ownership, savings, credit and insurance - so repeated use of a single payments function raises frequency without moving the index. Transaction intensity, by contrast, rises when users add merchant payments, bill payments, bulk disbursements and digital savings and credit products to transfers; it therefore tracks the breadth of financial functions in use, which is what the index measures. This is the distinction the Technology Acceptance Model draws between use and perceived usefulness: frequent use of a tool that solves one problem does not imply that the user perceives, or has access to, its broader functionality (Davis, 1989; Aldammagh et al., 2021).

Second, the regulatory architecture of the EAC separates payments from deposit-taking and credit. Mobile-money providers in Kenya, Tanzania, Uganda and Rwanda are licensed as payment service providers under national payment system laws; they may hold e-money float in trust accounts but may not intermediate it. Savings and credit products delivered over mobile channels (M-Shwari, KCB M-Pesa, Fuliza, M-Pawa, MoKash) exist only where a bank partners with the provider, and these partnerships have developed unevenly—extensively in Kenya, more narrowly in Tanzania and Uganda, and scarcely at all in Burundi, South Sudan and Somalia, where the formal banking system is thin and the regulatory frameworks for digital credit, tiered KYC and agent banking are recent or absent (Ediagbonya and Tioluwani, 2023; Wezel and Ree, 2023). In such settings the ceiling on what frequent use can deliver is set by regulation, not by user behaviour: a Burundian who transacts weekly has no formal savings or credit product to graduate into. Frequency therefore varies across countries without a corresponding variation in inclusion.

Third, affordability and trust limit the conversion of activity into formal participation. Transaction fees, mobile-money taxes (introduced in Uganda in 2018 and Tanzania in 2021), unreliable networks, fraud exposure and weak redress mechanisms push users toward the smallest number of transactions needed to move cash, and discourage the leaving of balances on the platform that would make savings and credit products viable (Mpofu and Mhlanga, 2022; Ozili, 2023). Low financial capability - the regional literacy index averages 28 on a 100-point scale - compounds the problem, because users are unaware of, or unable to assess, the

formal products that frequent use could unlock.

A measurement point reinforces the substantive one. Usage rate is drawn from periodic national financial-access surveys and is constant within each country over the sample period, so its effect is identified only from eight cross-country differences; with so little variation the variable cannot be expected to be precisely estimated, and it is absorbed entirely in the fixed-effects models. The result should therefore be read as a statement that, across EAC countries, differences in how often adults transact are not associated with differences in inclusion once access breadth, transaction intensity and income are held constant - rather than as a precise estimate of a null effect. Taken together, the findings resolve part of the mixed evidence in earlier research by showing that conclusions depend on the fintech proxy selected: breadth of access and economically meaningful transaction intensity are what move inclusion; repeated use of a narrow payments function is not.

5. Conclusion

This article examined the direct effect of financial technology on financial inclusion in eight EAC member countries between 2014 and 2023. Random-effects and fixed-effects evidence, with controls for income, inflation, financial literacy and bank-branch density, shows that the fintech dimensions jointly explain a substantial share of financial-inclusion variation. Penetration rate and transaction intensity have positive significant effects, whereas usage rate does not have a statistically significant independent effect. The study therefore concludes that fintech promotes inclusion when digital-financial infrastructure reaches more people and supports substantial transaction activity. Access that does not translate into useful, affordable, and sufficiently valuable activity is unlikely to close inclusion gaps by itself. Two qualifications apply. Real income per head is the strongest single driver of inclusion in the region, so fintech policy complements rather than substitutes for growth; and the fintech effects are identified from long-run co-movement rather than from short-run changes, so they should be interpreted as long-run associations pending evidence from longer panels.

The study contributes empirically by separating breadth of access, frequency of use, and transaction intensity, and by showing that the effects of breadth and intensity survive macroeconomic controls and country fixed effects within a regional panel. It contributes theoretically by showing that diffusion and perceived usefulness are complementary: the diffusion of access is necessary, but the economic usefulness expressed through transactions determines whether technology becomes a pathway to inclusion.

6. Recommendations

EAC governments and regulators should prioritize affordable mobile and internet coverage, reliable electricity, agent-network expansion, digital identification, and interoperable payment infrastructure, particularly in rural and fragile settings. Regional harmonization of rules for payments, data protection, cybersecurity, and cross-border transactions would allow fintech providers to scale while protecting consumers.

Financial institutions and fintech providers should design beyond account acquisition. Products should solve recurring financial needs, disclose fees clearly, work on low-cost devices, support local languages, and provide dependable redress for fraud and failed transactions. Providers should monitor active, meaningful use and transaction value alongside registration counts. Consumer education, transparent pricing, and trust-building measures should accompany infrastructure investments so that access converts into sustained participation.

Regulators should also address the structural reasons why frequency of use does not deepen inclusion: licensing frameworks that allow regulated bank–fintech partnerships to offer digital savings, credit and insurance over mobile channels; tiered know-your-customer rules that let transaction histories count toward credit assessment; interoperability mandates that move users from closed-loop transfers to merchant and bill payments; and restraint in mobile-money taxation, which pushes activity back to cash. Future research should extend the panel beyond ten years so that cointegration and dynamic effects can be tested with adequate power, obtain annual usage data, test country-specific dynamics, use household-level or transaction-level data, and distinguish between types of digital activity. Longer panels and quasi-experimental designs would help address possible reverse causality between fintech development and financial inclusion.

ACKNOWLEDGEMENTS. The authors thank the Department of Finance and Accounting, University of Nairobi, for institutional support, and the anonymous reviewers for comments that improved the paper.

References

[1] Aldammagh, Z., Abdeljawad, R. and Obaid, T. (2021). Predicting mobile banking adoption: An integration of TAM and TPB with trust and perceived risk. Financial Internet Quarterly, 17(3), pp. 35-46.

[2] Asif, M., Khan, M.N., Tiwari, S., Wani, S.K. and Alam, F. (2023). The impact of fintech and digital financial services on financial inclusion in India. Journal of Risk and Financial Management, 16(2), 122.

[3] Baber, H. (2021). Examining the intentions to use crowdfunding platform: An extended technology acceptance model. International Journal of Services, Economics and Management, 12(2), pp. 149-163.

[4] Banna, H., Mia, M.A., Nourani, M. and Yarovaya, L. (2022). Fintech-based financial inclusion and risk-taking of microfinance institutions (MFIs): Evidence from Sub-Saharan Africa. Finance Research Letters, 45, 102149.
[5] Cameron, A.C. and Miller, D.L. (2015). A practitioner's guide to cluster-robust inference. Journal of Human Resources, 50(2), pp. 317-372.
[6] Chinoda, T. and Mashamba, T. (2021). Fintech, financial inclusion and income inequality nexus in Africa. Cogent Economics and Finance, 9(1), 1986926.
[7] Choi, I. (2001). Unit root tests for panel data. Journal of International Money and Finance, 20(2), pp. 249-272.
[8] David-West, O., Oni, O. and Ashiru, F. (2022). Diffusion of innovations: Mobile money utility and financial inclusion in Nigeria. Insights from agents and unbanked poor end users. Information Systems Frontiers, «24»(5), pp. 1753-1773. https://doi.org/10.1007/s10796-021-10196-8
[9] Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), pp. 319-339.
[10] Demir, A., Pesqué-Cela, V., Altunbas, Y. and Murinde, V. (2022). Fintech, financial inclusion and income inequality: A quantile regression approach. The European Journal of Finance, 28(1), pp. 86-107.
[11] Ediagbonya, V. and Tioluwani, C. (2023). The role of fintech in driving financial inclusion in developing and emerging markets: Issues, challenges and prospects. Technological Sustainability, 2(1), pp. 100-119.
[12] Goswami, S., Sharma, R.B. and Chouhan, V. (2022). Impact of financial technology (fintech) on financial inclusion (FI) in rural India. Universal Journal of Accounting and Finance, 10(2), pp. 483-497.
[13] Hausman, J.A. (1978). Specification tests in econometrics. Econometrica, 46(6), pp. 1251-1271.
[14] Kamau, L. and Aduda, J. (2024). The effect of financial technologies on financial inclusion in Kenya. Journal of Economics, Finance and Business Analytics, 2(1), pp. 45-57.
[15] Kandpal, V. and Mehrotra, R. (2019). Financial inclusion: The role of fintech and digital financial services in India. Indian Journal of Economics and Business, 19(1), pp. 85-93.
[16] Kanga, D., Oughton, C., Harris, L. and Murinde, V. (2022). The diffusion of fintech, financial inclusion and income per capita. The European Journal of Finance, 28(1), pp. 108-136.
[17] Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. Journal of Econometrics, 90(1), pp. 1-44.
[18] Kelikume, I. (2021). Digital financial inclusion, informal economy and poverty reduction in Africa. Journal of Enterprising Communities: People and Places in the Global Economy, 15(4), pp. 626-640.
[19] Kling, G., Pesqué-Cela, V., Tian, L. and Luo, D. (2022). A theory of financial inclusion and income inequality. The European Journal of Finance, 28(1), pp. 137-157.

[20] Kouladoum, J.C., Wirajing, M.A.K. and Nchofoung, T.N. (2022). Digital technologies and financial inclusion in Sub-Saharan Africa. Telecommunications Policy, 46(9), 102387.
[21] Liu, F. and Walheer, B. (2022). Financial inclusion, financial technology, and economic development: A composite index approach. Empirical Economics, 63(3), pp. 1457-1487.
[22] Maddala, G.S. and Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and Statistics, 61(S1), pp. 631-652.
[23] Misati, R.N., Osoro, J. and Odongo, M. (2021). Does financial innovation enhance financial deepening and growth in Kenya? (KBA Centre for Research on Financial Markets and Policy Working Paper No. 49). Kenya Bankers Association.
[24] Mpofu, F.Y. and Mhlanga, D. (2022). Digital financial inclusion, digital financial services tax and financial inclusion in the fourth industrial revolution era in Africa. Economies, 10(8), 184.
[25] Mundlak, Y. (1978). On the pooling of time series and cross section data. Econometrica, 46(1), pp. 69-85.
[26] Muthengi, W.M. (2022). Financial inclusion and economic empowerment of women in rural area projects in Mwingi West, Kitui County, Kenya [Doctoral dissertation, University of Nairobi].
[27] Ozili, P.K. (2023). The future of financial inclusion. In Economic inclusion in post-independence Africa: An inclusive approach to economic development pp. 167-177. Springer Nature Switzerland.
[28] Polillo, S. (2011). Wildcats in banking fields: The politics of financial inclusion. Theory and Society, 40(4), pp. 347-383.
[29] Rogers, E.M. (1962). Diffusion of innovations. Free Press of Glencoe.
[30] Sangwan, V., Prakash, P. and Singh, S. (2020). Financial technology: A review of extant literature. Studies in Economics and Finance, 37(1), pp. 71-88.
[31] Wezel, T. and Ree, J. (2023). Nigeria—Fostering financial inclusion through digital financial services (IMF Selected Issues Paper No. 2023/016). International Monetary Fund.
[32] World Bank. (2023). World Development Indicators database. World Bank.