

Barriers and Enablers to Fintech Adoption for Financial Inclusion Among Urban Slum Residents

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Abstract

Fintech can reduce transaction costs, widen access to payments, savings, and insurance, and strengthen resilience for low-income households. Yet adoption and sustained use remain uneven among residents of urban slums. This study investigates the barriers and enablers of fintech adoption and meaningful use through an integrated framework that combines technology adoption theory (UTAUT2) with a capability lens. A sequential mixed-methods design is proposed: qualitative interviews to surface lived constraints and product-fit issues, followed by a representative survey of urban slum residents. Key constructs include perceived usefulness, effort expectancy, trust, perceived risk, social influence, digital and financial literacy, facilitating conditions (devices, data, electricity, connectivity), ecosystem quality (agent density and liquidity, merchant acceptance, interoperability), and policy frictions (ID/KYC). We test six hypotheses using multilevel logistic models, count models for usage intensity, and mediation/moderation analysis. Based on the literature, we anticipate that trust, social influence, low-friction onboarding (digital ID/e-KYC), reliable agent networks, and product fit with irregular cash flows are decisive for sustained use, with stronger effects for women and migrants once access constraints are addressed. The study contributes a practical evidence-informed roadmap for inclusive product design and policy, moving beyond account opening to safe, beneficial use.

Introduction

Rapid digitization has expanded access to financial services through mobile money, e-wallets, and instant payment rails. Despite these advances, residents of urban slums—who face volatile incomes, documentation gaps, device sharing, and high data and electricity costs—adopt and use fintech unevenly. Existing research demonstrates welfare gains from digital payments but is fragmented across disciplines; few studies integrate demand-side factors (trust, literacy, risk), supply-side conditions (agent networks, merchant acceptance, product-market fit), and policy levers (digital ID, tiered KYC, consumer protection) in slum contexts. This paper addresses that gap by proposing and empirically testing a multilevel framework for fintech adoption and meaningful use among urban slum residents. We focus on how perceived usefulness and ease of use translate into behavior only when supported by trust, social influence, facilitating conditions, and robust local ecosystems. We also examine heterogeneity by gender and migration status. The contribution is threefold: an integrated framework, a rigorous mixed-methods research design with testable hypotheses, and actionable recommendations for providers and policymakers seeking to advance safe, sustained inclusion. The paper proceeds with objectives, literature review, methodology, hypotheses, research and sample design, data collection and analysis plans, findings/implications, and conclusions.

Objectives of the study

1. Identify key demand-side barriers and enablers (trust, perceived risk, perceived usefulness, digital/financial literacy).
2. Assess access constraints (device ownership, data affordability, electricity, connectivity) and their impact on adoption and use.
3. Evaluate ecosystem factors (agent density/liquidity, merchant acceptance, interoperability) influencing sustained use.
4. Examine policy frictions and enablers (digital ID/e-KYC, tiered KYC, consumer protection) affecting onboarding and recourse.

Review of literature

1. **Davis (1989) Technology Acceptance Model (TAM):** Davis shows that perceived value and the ease of use are driving the intention to make it a basis for the adoption of fintech by consumers. In slums, utility (e.g., bill pay and payments) is essential, but it is not enough without trust and enabling conditions.
2. **Venkatesh, Thong, and Xu (2012) UTAUT2:** Extends acceptance theory by adding social influence and facilitating conditions. For low-income urban users, social proof (peers/household) and practical supports (USSD, local language, agent help) are often decisive.
3. **Collins, Morduch, Rutherford, and Ruthven (2009) Portfolios of the Poor:** Daily money management among the poor involves irregular cash flows and liquidity juggling. Fintech succeeds when products match these patterns (micro-savings lockboxes, flexible bill pay, small-value transfers).
4. **Jack and Suri (2014):** Evidence from Kenya shows mobile money reduces transaction costs and supports risk sharing. These gains depend on reliable cash-in/out network agent density and liquidity remain core supply-side enablers.
5. **Demirgüç-Kunt et al. (2022) Global Findex:** Digital account ownership rose rapidly, but usage gaps persist, especially among women and low-income urban populations. Trust, literacy, and cost barriers are prominent.
6. **McKee, Kaffenberger, and Zimmerman (2015) – CGAP:** Strong customer protection clear fees, fraud controls, and timely recourse builds trust and prevents drop-off after adverse events, a recurring risk in dense urban markets.

Methodology of the study

- Approach: Sequential mixed methods. Phase 1 qualitative to explore user journeys and refine measures; Phase 2 quantitative to test hypotheses and estimate effect sizes.
- Population: Adults (18+) residing in identified urban slum/informal settlements.
- Constructs: Adoption (binary), usage intensity (count of use-cases), perceived usefulness, effort expectancy, trust, perceived risk, social influence, digital and financial literacy, facilitating conditions (devices, data, power, network), ecosystem quality (agent density/liquidity, merchant acceptance, interoperability), policy frictions/enablers (ID, KYC).
- Instruments:
- Qualitative: Semi-structured interview and FGD guides.
- Quantitative: Structured questionnaire with validated Likert scales (UTAUT2, trust/risk), objective literacy items, and geocoded proximity to agents/merchants.
- Quality controls: Translation/back-translation, pilot test ($n \approx 50$), enumerator training, reliability (Cronbach's $\alpha \geq 0.70$), construct validity (EFA/CFA).

Preparation of hypotheses

H1: Perceived usefulness positively predicts fintech adoption.

H2: Perceived risk negatively predicts adoption.

H3: Trust positively predicts adoption and mediates the effects of usefulness and risk on adoption.

H4: Social influence positively predicts adoption, with a stronger effect among women than men.

H5: Facilitating conditions (device ownership, affordable data, reliable electricity/connectivity) positively predict adoption.

H6: Ecosystem quality (agent density/liquidity and merchant acceptance) positively predicts usage intensity among adopters.

Research design

The study employs an explanation-based survey, which is a cross-sectional one that is incorporated into an exploratory qualitative stage, using a sequential mixed-methods logical approach (QUAL-QUAN). Phase 1 comprises 30-40 in-depth interviews with residents--gender-balanced and inclusive of migrants and youth--alongside 10-12 key informant interviews with agents, merchants, and provider/NGO staff. Thematic analysis will reveal obstacles and enablers, develop concepts, and tailor survey items for multilingual, low-literacy contexts. In order to ensure that the survey is comprehensive and equitable for every subgroup, Phase 2 will conduct an authentic household's study (n600–800) across a range of slum clusters using multi-stage cluster sampling. Hypotheses are evaluated using multivariable and multilevel models to consider individuals who are who are nested within settlements as well as to determine the degree of mediation or moderation in cases where it is relevant. Ethics-related protections comprise informed consent for the local language privacy-by-design methods that reduce personal information that is identifiable and require prior IRB/ethics approval and secure, encrypted data storage that has restricted access.

Sample design

The sampling frame includes the slums/informal settlements identified within the area of study. The multi-stage sampling strategy is used to ensure that the sample is representative and has field effectiveness. In Stage 1, settlements are picked by using an algorithm that is based on probability proportional size (PPS), and thus the probability of inclusion is correlated with the size of the population. The second stage is where, in the selected settlement, the enumeration areas, or blocks, are chosen randomly from lists of updated maps. In Stage 3, households are chosen by random sampling that is systematic with an undetermined start date and a fixed interval. Within each household that is sampled, an adult who is eligible (18plus) is chosen by the Kish grid or the next birthday method to reduce bias by interviewers. The desired number of participants is 600, with the design effect to be around 1.5-1.8 because of clustering, which yields 80percent power at $\alpha=0.05$ to determine odds ratios of 1.4-1.6 for outcomes that have 40% to 60% prevalence (e.g., the adoption of fintech). The stratification process and/or quotas are designed to ensure gender equality and a fair representation of recent immigrants, and post-stratification weights are applied in the event of need.

Collection of data

Primary data will be collected using tablet-based forms (e.g., ODK/Surveyor) with built-in validation, skip logic, and secure syncing; GPS coordinates will record respondent location and nearby agents/merchants to compute proximity, and interviews will be time-stamped to enable quality checks. Enumerators will receive intensive training, including role-plays and ethical protocols, and will use privacy-sensitive interviewing practices especially with women and in device-sharing households to reduce risk and bias; instruments will be translated and back-translated into local languages. A pilot test will refine wording, flow, and expected duration. Field operations will follow a detailed protocol, with daily debriefs and supervisor spot checks, and electronic audit trails documenting sampling steps, edits, and corrections. In addition to providing information on referrals to resolve complaints or issues (e.g. helplines for providers or regulator/ombudsman phone numbers) Respondents will receive standardized consent forms in plain language prior to interviews. These scripts will stress confidentiality and voluntariness.

Data execution

Data execution is a staged schedule: 1 to 2 weeks of enumerator education as well as piloting to establish the calibration of protocols and instruments, followed by four to six weeks of main fieldwork that includes rolling quality controls. Quality checks integrate live-time testing (required fields, ranges and logic check) and ex-post audits. 10% back-checks through call-backs and spot re-interviews with supervisors, as well as paradata review (interview time distributions) in conjunction with GPS consistency to identify fabrication or location mistakes. Data cleaning follows an established procedure: profile missingness and run a MCAR test (**e.g., the Little's test**) to determine the plausibility of MAR; select the appropriate method of treatment (**multiple imputations/FIML instead of. listwise**); Screen univariate and multiple-variate anomalies (with winsorization or more robust methods as required), create scales, and then apply reverse-coding where needed. Quality of measurement is evaluated using the internal reliability (Cronbach's alpha) or the composite reliability (CR), which is followed by an EFA-CFA series to establish convergent as well as discriminant reliability (**e.g., AVERAGE > 0.50 and HTMT > 0.85**). Invariance of measurement across genders is assessed using multiple-group CFA (configural, scale, metric) to allow legitimate subgroup comparisons. Every decision is recorded within an audit trail.

Data analysis

The data analysis process begins with an analysis of the fintech's behaviour in terms of adoption rates, breadth of cases, fee experiences, and adverse events. This is followed by crosstabs based on gender and status of migration to determine the heterogeneity. Quality of measurement is established by the internal coherence (Cronbach's alpha), composite reliability, convergent validity (average variance extracted, AVE), as well as the validity of discriminant variables (e.g., HTMT). Hypotheses are evaluated using multilevel logistic regression models for the adoption of binary models using settlement-level random intercepts and count models to measure the intensity of usage, which Favor positive binomials over Poisson when there is overdispersion. Mediation is evaluated by assessing whether trust is a factor that transmits the effects of perceived value and risk to adoption. This is done using bootstrapped confidence intervals to measure indirect impacts. Moderation is measured by examining interaction terms, particularly gender and social influence, which is then followed by simple-slope and conditional effect interpretation. Robustness checks are made based on variables, LASSO-logit, and Variance Inflation factors (VIF) to establish multicollinearity as well as cluster-robust standard errors at the stage of settlement. Results are presented in odds ratios and as marginal effects, along with pseudo-R², information requirements, and predictive AUCs derived from cross-validation.

Findings and suggestions

Until data are collected, we expect patterns consistent with prior pilots: trust and perceived risk will be decisive, with adverse experiences driving drop-off; therefore, providers should embed proactive fraud warnings, simple dispute channels with 24–48h resolution SLAs, and agent accreditation with visible feedback scores to rebuild confidence. Because facilitating conditions—owning a reliable device, affordable data, and electricity—along with social influence raise adoption, products should offer USSD-first parity with app features, low-data modes, local-language interfaces, offline receipts, and robust error-recovery, complemented by community-led onboarding to harness peer effects. Ecosystem quality will determine usage intensity, so operators and regulators should strengthen agent liquidity management, publish fee caps, expand merchant acceptance, and ensure interoperability across providers. As digital/financial literacy amplifies the usefulness adoption link and women face higher access barriers yet larger gains, implement women-first onboarding, device-access support (e.g., shared-safe accounts, privacy features), and tailored training; migrant-friendly KYC options are essential. Policy enablers—digital ID with e-KYC and tiered KYC—should be deployed with strong privacy safeguards and enforced customer-protection standards and redress reporting. Finally, measure active use and breadth of use-cases (not just registrations), and monitor churn and its causes to iteratively refine products and policy.

Conclusion

Fintech can advance financial inclusion in urban slums, but adoption and sustained, beneficial use depends on more than app availability. An integrated bundle—trust and safety, social proof, affordable access to devices and data, reliable agent networks and merchant acceptance, interoperable rails, and low-friction onboarding through digital ID and tiered KYC—is required to translate intention into meaningful use. This study offers a rigorous mixed-methods plan to identify which levers matter most and for whom, with hypotheses and analytic strategies that can support causal inference where feasible. For providers, designing for irregular cash flows and engineering trust are central; for policymakers, consumer protection and inclusive identity systems are high-impact levers. Future research should provide slum-specific causal evidence and link usage to financial-health outcomes, disaggregated by gender and migration status.

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