

From Digital Compliance to Financial Autonomy: Trust, Task Diversity, and Phygital Adoption in Microfinance

ALOK KUMAR YADAV, DR. SHOVARA CHOUDHURY

Abstract: Digitally recorded transactions do not by themselves establish borrowers' independent control of digital financial services. This study re-estimates an interviewer-assisted survey of 662 active microfinance borrowers in Ranchi district, Jharkhand, using constructs drawn from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Descriptively, digital loan repayment was reported by 582 borrowers (87.9%) and fund-transfer use by 369 (55.7%), a paired difference of 32.2 percentage points (95% CI 28.6–35.7; exact McNemar $p < .001$). Across six digital task indicators, respondents reported a mean of 3.71 tasks ($SD = 1.61$; median = 4; IQR = 3–5). Trust in the MFI was high ($M = 4.37$, $SD = 0.49$) and exceeded trust in technology ($M = 3.38$, $SD = 1.16$) by 1.00 scale point (95% CI 0.88–1.11; $t(661) = 17.38$, $p < .001$, $d_z = 0.68$). An eight-predictor behavioural-intention OLS model yielded $R^2 = .9851$ and adjusted $R^2 = .9849$; HC3 robust standard errors were used because heteroscedasticity was present. However, VIFs ranged from 1.86 to 86.89, and only 99 distinct substantive response profiles occurred among 662 records, so the partial coefficients are not interpreted as independent causal effects. Profile-grouped ridge and LASSO models were used as stability and prediction checks, and a ridge-logistic model examined fund-transfer participation directly. These models show strong predictive structure but do not identify transaction need, assistance, or independent execution. Accordingly, the Compliance–Autonomy Gap is interpreted as a task-use contrast rather than a validated autonomy measure, while the Trust-Enabled Phygital Adoption Framework (TEPAF) remains a conceptual framework for future testing of the transition from assisted participation to independent financial agency.

Keywords: Digital Microfinance; Financial Inclusion; Borrower Autonomy; Compliance–Autonomy Gap; Technology Acceptance Model; Utaut; Trust Asymmetry; Regularized Regression; Phygital Finance; Tepaf; Jharkhand

Introduction

Digital financial services have moved from being a supplementary channel of financial service delivery to an important component of contemporary financial inclusion. Mobile applications, instant payment systems, agent networks, digital account management, and electronic repayment mechanisms have changed the way financial institutions interact with customers. For microfinance institutions (MFIs), digitalisation offers operational advantages such as faster processing, lower cash-handling requirements, improved record keeping, and greater transaction traceability. At the borrower level, however, the meaning of digitalisation is less straightforward. A transaction can be recorded as digital even when the borrower does not personally initiate, authenticate, or understand it.

Existing research identifies usefulness, ease of use, trust, risk, literacy, support conditions and social influences as possible correlates of digital financial behaviour (Kajol et al., 2022; Neves et al., 2023). It is important, however, to distinguish behavioural intention, task participation and the agency exercised during a transaction. Neither high electronic repayment nor low transfer activity alone identifies who performed the task, whether use was obligatory, or whether a borrower had any need to transfer money. These unobserved dimensions set the measurement boundary of the present study.

The Indian context is especially relevant because the country combines rapid digital-payment expansion with substantial variation in users' capabilities and usage depth. Research on Indian consumers has shown that trust, facilitating conditions, performance expectancy, financial literacy, grievance redressal, and perceived risk can shape digital-payment adoption (Patil et al., 2020; Kumar et al., 2023; Jacob et al., 2024). Yet much of this literature examines bank customers, young consumers, urban users, or users who are already engaged with digital payment systems. Low-income microfinance borrowers constitute a different population. Their interaction with digital finance can be institutionally mediated, socially embedded, and linked to continued access to credit.

This paper asks what can—and cannot—be inferred about borrower agency from digitally recorded transactions. The Compliance–Autonomy Gap distinguishes institutionally prompted activity from self-directed, independently executed use. In the audited analytical workbook, repayment participation exceeds transfer participation by 32.2 percentage points. That difference is statistically clear as a paired task contrast, but it is not itself a validated autonomy score because the survey does not record transaction need, initiator, authentication or degree of assistance.

A second distinction concerns Trust Asymmetry: confidence in the MFI and confidence in the digital channel are measured separately. The paired data show a 1.00-point mean difference between these trust objects. This establishes a descriptive within-sample asymmetry, but not a causal trust-transfer process or the direction of influence on later independent behaviour (McKnight et al., 2002; Yadav & Kalluru, 2024).

The contribution is both empirical and measurement-oriented. The paper (i) distinguishes institutional transaction completion from independent financial activity; (ii) quantifies the repayment–transfer task gap in the audited respondent file; (iii) tests the within-person difference between institutional and technological trust; (iv) re-estimates behavioural-intention associations using HC3 robust OLS and regularized sensitivity models; (v) models fund-transfer participation directly as a task-specific outcome; and (vi) retains TEPAF as a conceptual framework requiring richer data on need, assistance and independent execution.

A systems-level concern follows from this measurement distinction. If administrative dashboards show only transactions recorded on a digital rail, a supervisory reader could mistake institutionally mediated task completion for independently exercised borrower capability. This possibility is termed algorithmic deference in the present paper: reliance on an aggregate system output beyond what its underlying variables actually measure. The term is a proposed reporting-risk concept; the present survey does not audit regulators, platform motives or coercion.

Literature Review and Theoretical Background

2.1 Technology Acceptance Model and digital financial behaviour

The Technology Acceptance Model (TAM) explains technology acceptance through perceived usefulness and perceived ease of use (Davis, 1989). Its continuing relevance in digital finance is evident from recent systematic reviews, which show that TAM and its extensions remain widely used in research on digital financial transactions and FinTech adoption (Kajol et al., 2022; Bhowal & Shil, 2026). Perceived usefulness captures the extent to which a user expects a technology to improve the effectiveness or convenience of a task, while perceived ease of use concerns the effort required to operate the system.

TAM provides a useful starting point for microfinance because borrowers may evaluate digital services in highly practical terms. If a digital repayment is faster, reduces travel, provides a clear record, or avoids carrying cash, it may be perceived as useful. Yet the same borrower may still hesitate to initiate a fund transfer if the process requires unfamiliar menus, authentication steps, or confidence in a digital interface. In this sense, usefulness can encourage acceptance without necessarily producing autonomous usage.

2.2 UTAUT, social context, and facilitating conditions

UTAUT broadens technology acceptance by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). This extension is valuable in financially constrained settings because digital behaviour is rarely determined by individual cognition alone. Family members, peers, field agents, community practices, network connectivity, device access, and service support can all shape actual opportunities to use technology.

Indian studies support the relevance of these factors. Patil et al. (2020) found that social influence and facilitating conditions were important in explaining mobile-payment intention and use behaviour. Nandru et al. (2023) similarly used an extended UTAUT2 model to examine Indian mobile-payment adoption, while Linge et al. (2023) found facilitating conditions to have a particularly strong role among Indian mobile-payment users. Among low-income Indian

consumers, Jacob et al. (2024) reported positive effects of performance expectancy, effort expectancy, and facilitating conditions and a negative relationship between perceived risk and UPI intention. These findings are consistent with the argument that technology acceptance in low-income environments is partly a matter of whether the surrounding environment makes independent use feasible.

2.3 Trust as an institutional and technological construct

Trust is central to financial technology because digital financial transactions involve uncertainty about system performance, privacy, security, error resolution, and the behaviour of service providers. Trust research distinguishes confidence in an institution or other social actor from trust in the technological system itself (McKnight et al., 2002). In digital finance, this distinction becomes especially important when the user already has a long-standing relationship with a bank, MFI, or field agent but is comparatively unfamiliar with the digital interface.

The distinction is supported by recent evidence. Kumar et al. (2023) found that perceived risk and trust shape mobile-banking adoption in India, while Yadav and Kalluru (2024) show that principal-agent trust and intermediary structures influence the use of digital financial services. More recent research continues to position trust as a central mechanism in FinTech adoption (Dahiya et al., 2026), and meta-analytic evidence indicates that trust and risk have systematic relationships with technological adoption across financial services (Ladeira et al., 2026).

Institutional trust and technological trust are treated as distinct survey constructs: Trust in MFI (TMFI) and Trust in Technology (TTEC). The expectation that these may have different associations with use is theoretical; comparing their aggregate means alone cannot establish whether they covary within respondents, transfer causally, or explain independent transaction completion.

2.4 Perceived risk and the problem of invisible financial loss

Perceived risk refers to the user's expectation that a digital transaction may produce an undesirable outcome, such as monetary loss, failed transfer, privacy exposure, fraud, or inability to reverse an error. Digital financial services can therefore create a different psychological environment from cash-based transactions. Cash is tangible and its exchange is immediately visible; a digital balance or transaction status may be abstract, delayed, or difficult for a low-literacy user to interpret.

The literature consistently treats perceived risk as an inhibitor of digital financial adoption. Kajol et al. (2022) identify perceived risk as one of the most frequently cited barriers to digital financial transactions. Kumar et al. (2023) report a significant role for risk and trust in Indian mobile-banking adoption, while Jacob et al. (2024) report a negative association between perceived risk and UPI intention among low-income Indian consumers. The 2026 meta-analysis by Ladeira et al. further supports the general negative role of risk perception across technological financial services.

2.5 Digital literacy and capability

Digital literacy extends beyond smartphone possession to interface navigation, interpretation of transaction messages, authentication, fraud awareness and error recovery. Ullah et al. (2022) discuss the role of digital and financial skills in mobile financial-services intention; Sharma and Díaz Andrade (2023) relate digital finance to broader human-development questions. As the present items measure self-reports rather than observed performance, they should not be interpreted as demonstrated independent capability.

2.6 From transaction adoption to financial autonomy

A limitation of conventional adoption studies is that adoption is often represented by one intention or usage variable. This is analytically convenient but can conceal differences in task complexity and user agency. Recent research has begun to examine the transition from intention to actual use and the role of contextual constraints. Chamboko (2024), for example, uses time-to-event analysis to examine digital financial service adoption, while Kumar et al. (2023) examine actual use alongside intention. Naeem et al. (2022) show how meanings, materials, and competencies shape the process of mobile-banking adoption. These studies suggest that adoption is better understood as a process than as a single binary event.

The borrower centred outcome of interest is not merely whether a payment reached an MFI but whether borrowers can select, initiate, authenticate and complete a range of relevant financial activities without routine dependence on another person. Behavioural intention, task participation and independently executed activity are separate variables. The present reanalysis measures intention and task participation directly from the analytical workbook, but it does not observe independent execution itself.

2.7 From digital transaction logs to administrative inference

Transaction counts are process indicators: they show that a digital channel registered an event, not necessarily who chose, initiated or understood it. In a relationship-based lending system, institutional processing success and user capability could develop at different rates. A conceptual risk arises when one is used as a proxy for the other. We call this hypothesised substitution algorithmic deference, narrowly defined here as accepting a dashboard or automated reporting metric as sufficient evidence of downstream user independence without auditing its measurement validity. This paper has no observations of actual regulator dashboards, audit decisions or code, so the mechanism is an analytical proposition rather than a demonstrated failure of supervisory oversight.

A two-level assessment would keep institutional outcomes (e.g., successful electronic collections and transaction traceability) separate from user outcomes (e.g., optional task use conditional on need, borrower-controlled initiation and authentication, and effective remedies after errors). Comparing their trajectories could reveal disagreement, but establishing design intent requires system specifications, workflow observation and responsible-user interviews, rather than inferring motives from usage rates. The same distinction frames the policy and architecture-audit proposals in Section 9.

Conceptual Contribution: The Compliance–Autonomy Gap

The Compliance–Autonomy Gap is a proposed distinction between institutionally prompted digital activity and independently chosen, executed financial activity. In group-based microfinance, a digital repayment might be completed by staff, by a borrower with assistance, or independently; an aggregate repayment flag does not distinguish these possibilities. A separate fund-transfer flag establishes only whether that task was reportedly used. It cannot distinguish absence of capability from absence of need, access, opportunity or preference. In the audited workbook, repayment exceeds transfer participation by 32.2 percentage points. This is a statistically clear task-use difference, not a measured prevalence of autonomous use or a validated autonomy index.

Institutionally supported transactions can still improve payment traceability and provide access to services. The measurement question is whether access becomes transferable capability and financial agency. A valid operationalization should record for each relevant task: whether the task was required or desired; who decided to transact; who entered details and authenticated; whether assistance was needed; whether completion and outcomes were understood; and whether the borrower could recover from errors. TEPAF proposes relationships between these dimensions, but its stages and pathways have not been estimated in this study.

An institutional interpretation of the Compliance–Autonomy Gap adds a second unit of analysis. At the transaction level, classify a payment by task purpose, obligatoriness and the actor who decides, enters and authenticates. At the reporting level, test whether any summary metric discloses those classifications or obscures them by aggregating all digital transactions. The proposed supervisory proxy mismatch is therefore a separately testable risk and cannot be inferred solely from the observed 87.9% repayment and 55.7% transfer participation rates.

Figure 1. Trust-Enabled Phygital Adoption Framework (TEPAF; conceptual proposal)

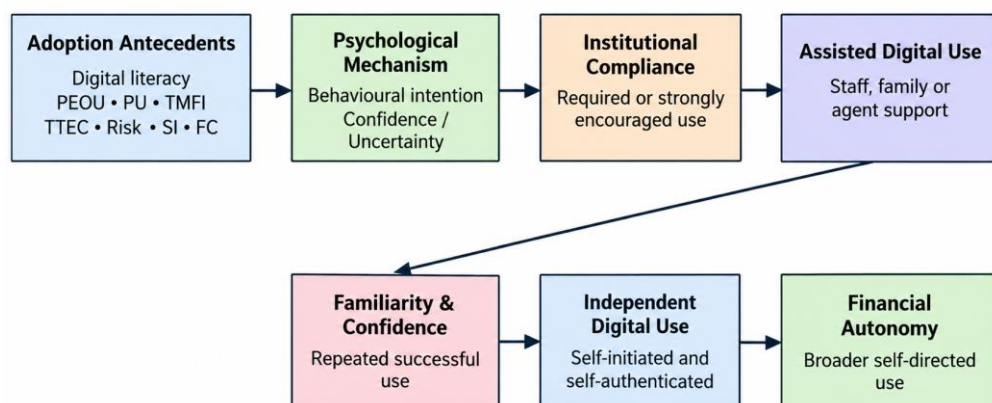


Figure 1. Conceptual pathway: Institutional exposure can progress toward autonomous use when confidence, support and capability accumulate.

Note. Arrows represent proposed transitions, not empirically estimated effects. The current task indicators do not measure the five stages, identify transaction initiators or test a progression

from assistance to autonomy. Supervisory reporting and product-architecture checks are proposed as a parallel evaluation layer, not as measured components of the illustrated individual-level pathway.

The framework makes testable predictions about whether informed assistance can facilitate, rather than permanently substitute for, independent digital use.

Research Objectives and Hypotheses

The study has the following descriptive and conceptual objectives:

- To estimate and compare task-specific digital financial participation, particularly loan repayment and fund-transfer use, in the audited Ranchi borrower sample.
- To distinguish intention toward digital financial services from task-specific participation and independent execution.
- To compare institutional trust and technology trust within respondents and quantify the resulting Trust Asymmetry.
- To identify the additional data necessary to measure compliance, demand, assistance and autonomy rather than assuming these from two use indicators.
- To propose a borrower-centred, empirically testable phygital adoption framework.

The H1–H8 expectations are retained as theory-based directional propositions. Because the predictor constructs are extremely collinear, the study reports robust and regularized estimates without using a simple “supported/not supported” decision table. Coefficient direction and stability across specifications are interpreted cautiously, with emphasis on predictive sensitivity rather than unique causal effects.

- H1.** Perceived financial benefits, used here as the workbook operationalisation of perceived usefulness, are positively associated with borrowers’ behavioural intention to use digital financial services.
- H2.** Perceived ease of use is positively associated with borrowers’ behavioural intention to use digital financial services.
- H3.** Digital literacy is positively associated with borrowers’ behavioural intention to use digital financial services.
- H4.** Trust in the microfinance institution is positively associated with borrowers’ behavioural intention to use digital financial services.
- H5.** Trust in technology is positively associated with borrowers’ behavioural intention to use digital financial services.
- H6.** Perceived risk is negatively associated with borrowers’ behavioural intention to use digital financial services.
- H7.** Social influence is positively associated with borrowers’ behavioural intention to use digital financial services.
- H8.** Facilitating conditions are positively associated with borrowers’ behavioural intention to use digital financial services.

Methodology

5.1 Research design and setting

The study uses a quantitative cross-sectional borrower survey conducted in Ranchi district, Jharkhand, among active microfinance clients. The analytical workbook supplied for re-estimation contains 662 respondent records. Respondent identifiers range from 1 to 663, with identifier 407 absent; 663 is therefore the maximum identifier, not the analytical sample size. The study describes this observed borrower sample and does not treat it as design-weighted evidence for all borrowers in Jharkhand or India.

5.2 Sampling and data collection

The project documentation describes multistage area selection involving Kanke, Namkum and Ratu and interviewer-assisted CAPI at Joint Liability Group centre meetings in locally understandable languages. The analytical file does not contain MFI, centre, JLG or interviewer identifiers, sampling weights, recruitment denominators or response-rate fields. Consequently, cluster-robust standard errors and design-based population estimates cannot be reconstructed from the workbook; row order and respondent identifiers were not used as artificial cluster labels.

5.3 Measures and score construction

The workbook contains 29 five-point items forming nine multi-item constructs: Digital Literacy (DL; 4 items), Perceived Ease of Use (PEOU; 3), Perceived Financial Benefits (PFB; 4), Trust in MFI (TMFI; 3), Trust in Technology (TTEC; 3), Perceived Risk (PR; 3), Social Influence (SI; 3), Facilitating Conditions (FC; 3), and Behavioural Intention (BI; 3). PFB is treated as the empirical operationalisation closest to TAM perceived usefulness. Construct scores are arithmetic means of their component items. Six binary task indicators record balance checking, loan repayment, fund transfer, bill payment, information access and new-loan activity. A task-breadth score is the sum of these six indicators (0–6). The file does not identify whether a task was needed, mandatory, assisted, independently initiated or independently authenticated; task participation is therefore not equated with autonomy.

5.4 Data audit and analytical strategy

The workbook contains no blank cells in the 42 substantive fields. Exact comparison of all substantive fields identifies 99 distinct response profiles among 662 rows; 563 rows repeat a profile already observed elsewhere. Identical profiles do not prove duplicate respondents, but the regularity is material to inferential precision and predictive validation. All 662 records are retained in the primary analysis; a one-record-per-profile analysis is used only as a sensitivity check and is not treated as a corrected sample.

Construct scores are summarised using means and standard deviations, and the six-item task-breadth count is described using the mean, standard deviation, median, interquartile range and observed range. Task proportions are reported with Wilson 95% confidence intervals. The repayment–transfer contrast is evaluated within respondents using the paired difference and an exact McNemar test. Trust Asymmetry is evaluated with a paired-samples *t* test, a 95% confidence interval for TMFI minus TTEC and the paired effect size *dz*. Internal consistency

is assessed with Cronbach's alpha. Multicollinearity is assessed with VIFs, and heteroscedasticity with the Breusch–Pagan test.

Behavioural intention is first modelled by OLS using the eight construct predictors. Because heteroscedasticity is detected, coefficient uncertainty is reported with HC3 robust standard errors and 95% confidence intervals. Holm-adjusted p values are calculated across the eight slopes. The OLS coefficients are not interpreted as isolated causal effects because predictor overlap is extreme.

Two regularized behavioural-intention sensitivity models are then estimated after standardising predictors and the outcome: ridge regression and LASSO. Tuning uses 10-fold group cross-validation in which identical substantive response profiles are assigned to the same fold, preventing exact profile matches from appearing simultaneously in training and validation sets. This profile grouping is a leakage-control device, not a substitute for the unavailable JLG/centre identifiers.

To address the reviewer's request for an outcome closer to actual use, fund-transfer participation is modelled with ridge-penalised logistic regression using standardised predictors and stratified group cross-validation by response profile. Odds ratios are reported per one-standard-deviation change as penalized association summaries rather than classical inferential effects. Task breadth is additionally modelled with grouped-cross-validated ridge regression. SEM/PLS-SEM is not estimated because the observed construct correlations and VIFs indicate that measurement discrimination should be established first; regularization is used here as a transparent stability and prediction sensitivity analysis, not as a cure for measurement overlap.

Results

6.1 Analytical sample and data integrity

Table 1. Analytical sample and data-audit summary.

Audit feature	Observed result	Interpretive implication
Analytical records	662	Use N = 662 in all re-estimated analyses.
Respondent IDs	1–663; ID 407 absent	The highest identifier is not the sample size.
Age	M = 38.06; SD = 11.03; range 21–63	Directly verifiable continuous demographic field.
Substantive fields	42 plus respondent ID	29 scale items and six task indicators are included.
Blank cells	None observed	No item-level imputation was required.
Distinct substantive response profiles	99	Exact profile repetition requires source-form/data-entry review.

Audit feature	Observed result	Interpretive implication
Rows matching an already observed profile	563	Retained in primary analysis; profile-grouped validation used to prevent leakage.
JLG/centre identifiers	Not present	Cluster-robust or multilevel uncertainty cannot be reconstructed.

Note. Exact profile repetition is a data-structure finding, not proof that respondents were duplicated. Demographic category codes are not substantively relabelled here because a separate codebook was not supplied with the analytical workbook.

The reanalysis resolves the sample-count inconsistency in the earlier manuscript: the available analytical file contains 662 records, not 663. The large number of repeated complete response patterns is reported explicitly because it can make nominal-sample precision and random-fold validation look stronger than the independent information in the file warrants.

6.2 Task-use contrast and the Compliance–Autonomy Gap

Table 2. Re-estimated digital-task participation.

Task	n reporting use	Use (%)
Balance checking	636	96.1
Digital loan repayment	582	87.9
Fund transfer	369	55.7
Bill payment	238	36.0
Information access	528	79.8
New-loan activity	106	16.0
Repayment minus transfer	—	32.2 percentage points

Note. Repayment = 582/662 (87.9%; Wilson 95% CI 85.2–90.2). Transfer = 369/662 (55.7%; Wilson 95% CI 51.9–59.5). The paired difference is 32.2 percentage points (95% CI 28.6–35.7).

The paired repayment–transfer table contains 369 borrowers reporting both activities, 213 reporting repayment but not transfer, 80 reporting neither, and no borrower reporting transfer without repayment. The exact McNemar test is significant ($p < .001$), confirming that the two participation rates differ within this sample. Across all six task indicators, borrowers reported an average of 3.71 digital functions ($SD = 1.61$; median = 4; IQR = 3–5; range = 0–6). Balance checking was the most frequently reported task (96.1%), followed by loan repayment (87.9%) and information access (79.8%); new-loan activity was least frequent (16.0%). The repayment–transfer gap is therefore a clear descriptive difference in task participation, but it should not be interpreted as the proportion of borrowers who lack digital autonomy because the dataset does not record whether a transfer was needed, who initiated a task, or whether assistance was required.

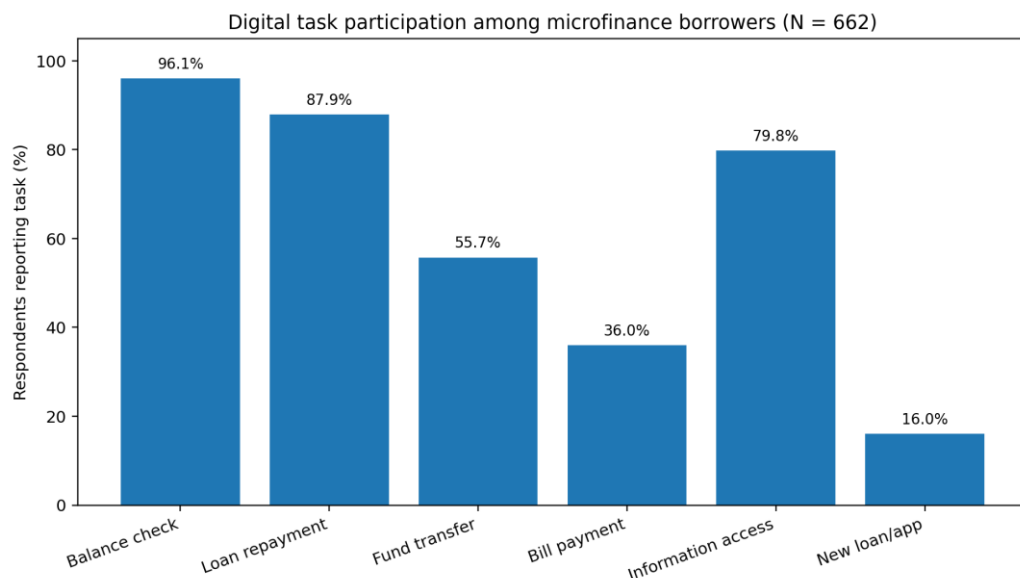


Figure 2. Participation in six digital financial tasks.

Note. Bars show the percentage of respondents reporting each digital task; values are based on N = 662 audited analytical records.

Figure 2 makes the task heterogeneity immediately visible: repayment and balance checking are common, whereas bill payment and new-loan activity are much less frequent. The graph supports the article’s central descriptive claim that digital finance use is not a single, uniform behaviour.

6.3 Construct descriptives, reliability and Trust Asymmetry

Table 3. Construct descriptives, reliability and multicollinearity diagnostics.

Construct	Code	Mean	SD	Cronbach α	VIF
Digital Literacy	DL	3.15	1.29	0.968	59.55
Perceived Ease of Use	PEOU	3.71	1.08	0.931	45.82
Perceived Financial Benefits	PFB	3.58	1.19	0.955	35.05
Trust in MFI	TMFI	4.37	0.49	0.704	1.86
Trust in Technology	TTEC	3.38	1.16	0.946	80.41
Perceived Risk	PR	2.79	1.24	0.954	86.89
Social Influence	SI	3.35	1.24	0.950	37.38

Construct	Code	Mean	SD	Cronbach α	VIF
Facilitating Conditions	FC	3.85	1.15	0.936	55.88
Behavioural Intention	BI	3.55	1.38	0.984	—

Note. VIFs apply to the eight-predictor behavioural-intention model. Very high alpha and VIF values can reflect overlapping item content and should not be interpreted as superior construct validity.

The construct descriptives show meaningful variation across domains. Trust in the MFI is the highest-rated construct (M = 4.37, SD = 0.49), followed by Facilitating Conditions (M = 3.85, SD = 1.15), Perceived Ease of Use (M = 3.71, SD = 1.08), Perceived Financial Benefits (M = 3.58, SD = 1.19), and Behavioural Intention (M = 3.55, SD = 1.38). Trust in Technology (M = 3.38, SD = 1.16), Social Influence (M = 3.35, SD = 1.24), and Digital Literacy (M = 3.15, SD = 1.29) are more moderate, while Perceived Risk has the lowest mean (M = 2.79, SD = 1.24). The relatively small SD for Trust in MFI indicates greater agreement on institutional trust than on the other constructs, whereas Behavioural Intention shows the greatest dispersion. The paired mean difference between Trust in MFI and Trust in Technology is 1.00 point (95% CI 0.88–1.11), $t(661) = 17.38$, $p < .001$, $d_z = 0.68$. This supports a within-sample descriptive Trust Asymmetry, but not a causal process in which institutional trust is transferred to or withheld from technology.

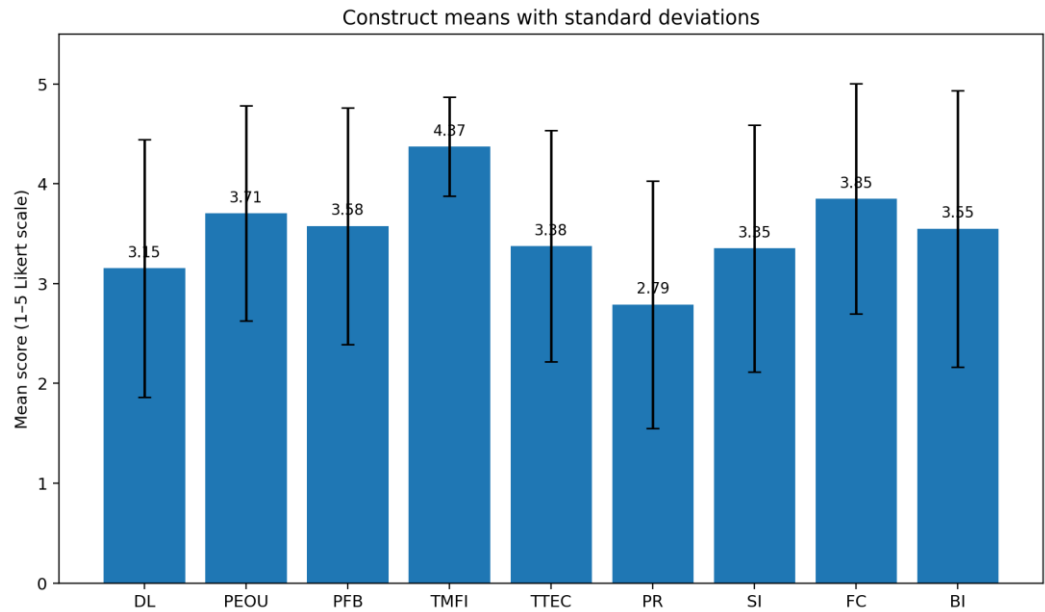


Figure 3. Mean construct scores with standard deviations.

Note. Higher values indicate stronger endorsement on the original five-point response scale. Error bars represent ± 1 SD.

Figure 3 highlights the descriptive pattern visually: institutional trust is highest, technological trust is noticeably lower, and behavioural intention is moderately positive but heterogeneous. This graphical presentation complements the mean and standard-deviation table rather than replacing it.

6.4 Regression diagnostics

The VIFs range from 1.86 to 86.89. Trust in Technology and Perceived Risk are especially collinear, and several other predictors also exceed conventional thresholds by a wide margin. The Breusch–Pagan test rejects homoscedasticity ($LM = 168.55, p < .001$). These diagnostics have two implications. First, HC3 robust standard errors are appropriate for heteroscedasticity. Second, neither HC3 adjustment nor a statistically significant slope can make highly overlapping predictors behave like independent constructs. The regression results are therefore reported as conditional associations and sensitivity evidence, not as clean unique effects. The lack of JLG/centre identifiers also means that cluster-robust or multilevel uncertainty cannot be estimated from the available workbook.

6.5 HC3 robust OLS model of behavioural intention

Table 4. Behavioural-intention OLS with HC3 robust standard errors.

Predictor	B	HC3 SE	95% CI	p	Holm p
Intercept	0.667	0.374	[-0.068, 1.401]	0.075	—
Digital Literacy	0.139	0.049	[0.043, 0.235]	0.004	0.004
Perceived Ease of Use	0.189	0.046	[0.098, 0.280]	< .001	< .001
Perceived Financial Benefits	0.288	0.036	[0.217, 0.358]	< .001	< .001
Trust in MFI	0.065	0.019	[0.028, 0.102]	< .001	0.001
Trust in Technology	-0.261	0.061	[-0.381, -0.141]	< .001	< .001
Perceived Risk	-0.260	0.062	[-0.382, -0.139]	< .001	< .001
Social Influence	0.248	0.030	[0.190, 0.307]	< .001	< .001
Facilitating Conditions	0.313	0.046	[0.222, 0.404]	< .001	< .001

Note. Coefficients are unstandardised. Holm adjustment is across the eight predictor tests. Statistical significance does not imply stable unique construct effects under the observed multicollinearity.

The corrected behavioural-intention model has $R^2 = 0.9851$, adjusted $R^2 = 0.9849$, $F(8,653) = 5401.94$, $p < .001$. Using HC3 robust uncertainty, the conditional slopes are positive for Digital Literacy ($B = 0.139$, 95% CI 0.043–0.235), Perceived Ease of Use ($B = 0.189$, 0.098–0.280),

Perceived Financial Benefits ($B = 0.288, 0.217\text{--}0.358$), Trust in MFI ($B = 0.065, 0.028\text{--}0.102$), Social Influence ($B = 0.248, 0.190\text{--}0.307$), and Facilitating Conditions ($B = 0.313, 0.222\text{--}0.404$), and negative for Trust in Technology ($B = -0.261, -0.381\text{ to }-0.141$) and Perceived Risk ($B = -0.260, -0.382\text{ to }-0.139$). All eight slope tests remain below .05 after Holm adjustment. Nevertheless, the exceptionally high in-sample fit should not be interpreted as near-complete explanatory power, because the predictor set is highly redundant and the file contains repeated response profiles. In particular, the negative Trust in Technology coefficient is not taken to mean that greater technological trust reduces intention; its sign is unstable across model specifications.

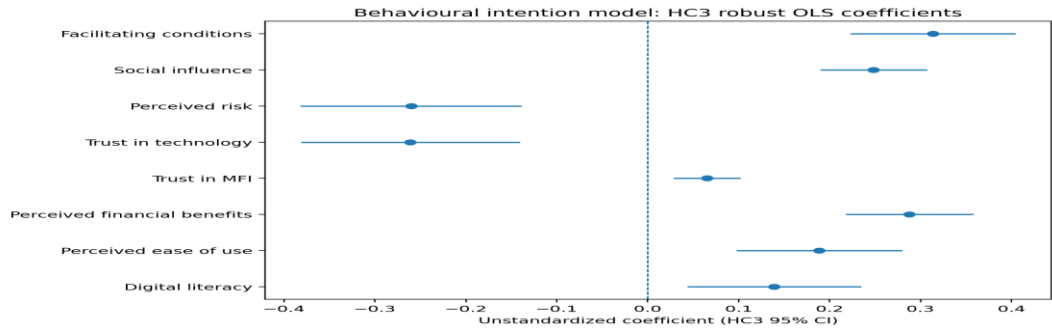


Figure 4. HC3 robust OLS coefficients for behavioural intention.

Note. Points represent unstandardized coefficients and horizontal lines represent 95% HC3 confidence intervals. The figure is descriptive of the fitted model and should be interpreted alongside the documented multicollinearity.

Figure 4 shows that several coefficients remain clearly away from zero after HC3 correction, but the visual separation should not be overread as evidence of unique independent effects because the predictors share extensive variance.

6.6 Regularized behavioural-intention models

Table 5. Profile-grouped regularized sensitivity models for behavioural intention.

Predictor	Ridge β (standardised)	LASSO β (standardised)
Digital Literacy	0.097	0.072
Perceived Ease of Use	0.166	0.125
Perceived Financial Benefits	0.191	0.247
Trust in MFI	0.018	0.000
Trust in Technology	0.037	0.000
Perceived Risk	-0.120	-0.094
Social Influence	0.215	0.284
Facilitating Conditions	0.186	0.171

Note. Predictors and outcome were standardised. Tuning used 10-fold group cross-validation by exact substantive response profile. Ridge $\alpha = 25.12$; mean fold $R^2 = 0.966$ (pooled $R^2 = 0.979$). LASSO $\alpha = 0.01468$; mean fold $R^2 = 0.964$ (pooled $R^2 = 0.978$).

The profile-grouped regularized models provide a stability check on the OLS pattern. Ridge regression retains positive standardised coefficients for Perceived Financial Benefits ($\beta = .191$), Social Influence ($\beta = .215$), Facilitating Conditions ($\beta = .186$), Perceived Ease of Use ($\beta = .166$), Digital Literacy ($\beta = .097$), and a small positive Trust in Technology coefficient ($\beta = .037$), while Perceived Risk remains negative ($\beta = -.120$). The selected LASSO model retains positive coefficients for Perceived Financial Benefits ($\beta = .247$), Social Influence ($\beta = .284$), Facilitating Conditions ($\beta = .171$), Perceived Ease of Use ($\beta = .125$), and Digital Literacy ($\beta = .072$), retains Perceived Risk as negative ($\beta = -.094$), and shrinks both trust coefficients to zero. Mean profile-grouped cross-validated R^2 is .966 for ridge and .964 for LASSO. The change in the Trust in Technology coefficient from negative OLS to near-zero or positive under regularization demonstrates specification sensitivity. Accordingly, the more defensible interpretation is that behavioural intention is associated with a highly overlapping bundle of perceived benefit, usability, social support, enabling conditions, risk and literacy measures rather than with eight cleanly separable effects.

6.7 Task-specific regularized models

Table 6. Profile-grouped regularized models of reported task use.

Predictor	Transfer ridge-logit β	OR per 1 SD	Task-breadth ridge β
Digital Literacy	0.531	1.70	0.026
Perceived Ease of Use	0.635	1.89	0.155
Perceived Financial Benefits	1.051	2.86	-0.050
Trust in MFI	0.772	2.17	-0.023
Trust in Technology	1.354	3.87	0.225
Perceived Risk	-0.844	0.43	-0.412
Social Influence	0.358	1.43	-0.103
Facilitating Conditions	1.030	2.80	0.299

Note. Coefficients are penalized, standardized association summaries and do not have classical OLS-style confidence intervals. Transfer model: ridge-logistic $C = 0.10$; grouped-CV AUC = 0.992, Brier score = 0.035, accuracy = 0.932. Task breadth (0–6): ridge $\alpha = 6.31$; mean fold $R^2 = 0.870$ (pooled $R^2 = 0.916$). Because the file contains only 99 distinct substantive response profiles, these prediction metrics may still overstate generalizability beyond the observed response structure.

The fund-transfer model directly addresses a reported-use outcome rather than behavioural intention. On the standardized ridge-logit scale, the largest positive association summaries are for Trust in Technology (OR per 1 SD = 3.87), Perceived Financial Benefits (OR = 2.86), Facilitating Conditions (OR = 2.80), and Trust in MFI (OR = 2.17), while Perceived Risk is negative (OR = 0.43); the remaining predictors are also positive but smaller. These odds ratios are penalized prediction summaries, not classical causal or hypothesis-test estimates. The very high grouped-CV AUC should therefore be interpreted together with the limited number of distinct response profiles. The task-breadth ridge model similarly predicts the number of

reported functions, with positive coefficients for Facilitating Conditions and Trust in Technology and the largest negative coefficient for Perceived Risk. Neither model distinguishes lack of need from inability to transact, nor assisted use from independent execution.

6.8 Sensitivity to repeated response profiles

As a non-primary sensitivity check, HC3 OLS was re-estimated after retaining one record from each of the 99 distinct substantive response profiles. This changes the weighting of response patterns and is not an assertion that repeated profiles are duplicate respondents. In this reduced profile-level analysis, Perceived Financial Benefits ($p < .001$), Social Influence ($p = .004$), and Facilitating Conditions ($p = .049$) remain below .05, whereas Digital Literacy, Perceived Ease of Use, Trust in MFI, Trust in Technology, and Perceived Risk do not. The loss of apparent precision for several slopes shows that some full-sample inferences depend on the multiplicity of repeated response patterns. This sensitivity result is a major reason for avoiding strong hypothesis-confirmation language.

6.9 Summary of empirical findings

Table 7. Integrated summary of the main empirical findings.

Finding	Result	Interpretation	Caution
Repayment vs transfer use	87.9% vs 55.7%; gap = 32.2 pp	Digital task participation differs substantially by function	Gap is not a direct autonomy measure because need, initiation and assistance were not observed
Trust asymmetry	TMFI M = 4.37; TTEC M = 3.38; paired difference = 1.00	Borrowers trust the MFI more than the technology channel	Cross-sectional paired ratings do not establish trust transfer or causality
HC3 OLS model	$R^2 = 0.9851$; $F(8,653) = 5401.94$	Several constructs are conditionally associated with behavioural intention	VIFs from 1.86 to 86.89 mean partial slopes are unstable
Regularized BI models	Grouped-CV mean $R^2 = 0.966$ (ridge) and 0.964 (LASSO)	Shared predictive signal remains strong under shrinkage	Strong fit reflects structured overlap, not necessarily distinct mechanisms
Transfer ridge-logit model	AUC = 0.992	Constructs predict reported transfer participation well	Outcome is task participation, not verified autonomous use
Repeated profiles	99 unique substantive profiles among 662 rows	Data structure may compress apparent variation	Profile repetition requires source-form verification

Note. “pp” = percentage points; BI = behavioural intention; grouped-CV = group cross-validation. The interpretation column states what the data support, while the caution column states what the result does not by itself establish.

The evidence is strongest for the directly observed descriptive and paired comparisons: task participation differs substantially across digital functions, and institutional trust is higher than technology trust within the same respondents. The behavioural-intention regressions show a strong shared statistical relationship between the measured constructs and intention, but severe multicollinearity prevents confident attribution of unique effects to individual predictors. Regularized and task-specific models are useful as stability and prediction checks, yet they remain sensitive to the structured response patterns in the dataset and do not measure autonomous execution. Thus, the empirical findings support task differentiation and Trust Asymmetry; they do not establish causal pathways, population-wide prevalence of autonomy, or the sequential TEPAF stages.

Discussion

Interpretation follows an evidence hierarchy. Direct descriptive statistics and within-person paired comparisons are treated as the strongest findings because they rely on observed task and trust variables. HC3 OLS coefficients are treated as conditional associations because heteroscedasticity and extreme multicollinearity remain. Regularized models are interpreted as stability and prediction checks rather than inferential tests, and TEPAF and algorithmic deference are presented as conceptual propositions that require new data for validation.

7.1 Digital adoption is not a single behaviour

The clearest empirical finding is descriptive: use varies substantially by task. Digital repayment is reported by 87.9% of borrowers and fund transfer by 55.7%, a 32.2-percentage-point paired difference. Across six tasks, the average breadth is 3.71 functions (SD = 1.61), but use ranges from 96.1% for balance checking to 16.0% for new-loan activity. This heterogeneity supports the argument that digital adoption should not be treated as a single behaviour. It does not establish that the repayment–transfer difference is caused by institutional compulsion, because the survey does not record task need, transaction actor.

The broader six-task profile therefore strengthens a measurement conclusion rather than a causal one: transaction counts should be disaggregated by function, and measures of autonomy should additionally record who initiated and authenticated the transaction, whether assistance was required, whether the task was relevant to the borrower, and whether errors could be resolved. A borrower can report multiple digital tasks without necessarily performing them independently.

7.2 Trust Asymmetry is empirically present but not a causal pathway

Institutional trust exceeds technological trust by 1.00 point on the five-point scale (95% CI 0.88–1.11; $d_z = 0.68$). This is a statistically clear within-sample descriptive difference and supports treating the two trust objects separately in future measurement. However, the cross-sectional design does not establish whether institutional trust precedes, causes,

substitutes for, or eventually transfers to technology trust. The negative bivariate relationship between the two scores in this workbook further cautions against a simple trust-transfer narrative.

7.3 Robust OLS corrects uncertainty, but not construct overlap

The re-estimated OLS resolves the earlier R^2/F inconsistency and uses HC3 standard errors to address heteroscedasticity, but it does not resolve the much more serious problem of construct overlap. VIFs above 80 for Trust in Technology and Perceived Risk indicate that the model is assigning partial slopes to predictors carrying very similar information. The high R^2 should therefore be read as in-sample fit to a strongly structured and redundant predictor set, not as evidence that the model explains almost all behavioural intention in the wider microfinance population.

The regularized models make coefficient instability visible rather than eliminating it. Perceived Financial Benefits, Social Influence, Facilitating Conditions, Perceived Ease of Use and Digital Literacy remain positive across ridge and LASSO, while Perceived Risk remains negative. By contrast, Trust in Technology changes from a negative OLS partial slope to a small positive ridge coefficient and is removed by LASSO; Trust in MFI is also shrunk to zero by LASSO. These patterns suggest that the most stable information lies in the broader direction of benefit/support versus risk, while unique trust effects cannot be separated reliably with the current measurement structure.

7.4 Task-specific modelling advances the Compliance–Autonomy question

Modelling fund-transfer participation directly is more closely aligned with actual reported use than modelling intention alone. The ridge-logistic model shows strong predictive discrimination within the observed response structure, with the largest positive penalized association summaries for technology trust, perceived financial benefits and facilitating conditions and a negative association for perceived risk. However, prediction of a binary transfer flag is not prediction of autonomy. Non-use may reflect no need, no opportunity, access barriers, preference for another channel, or inability to transact; reported use may also be assisted. The model should therefore be interpreted as an exploratory task-participation model, not as evidence that any predictor causes independent digital behaviour.

The task-breadth model provides a complementary summary of how many functions are reported, but breadth is not equivalent to capability or agency. Together, the transfer and breadth models improve alignment between the statistical analysis and the paper's task-differentiation argument, while leaving the stronger autonomy construct for future measurement with actor-, need-, assistance-, safety- and recovery-specific indicators.

7.5 Repeated response profiles limit precision claims

The presence of only 99 distinct substantive response profiles among 662 records is a material feature of the dataset. Exact profile repetition can arise from genuine respondents with identical answers, highly templated responding, copying or data-entry procedures; the analytical file alone cannot determine which explanation applies. Grouping identical profiles during cross-validation prevents direct leakage of the same pattern across training and validation folds, but

it does not replace verification against source forms. The profile-level OLS sensitivity analysis shows that several full-sample p values depend strongly on the multiplicity of repeated patterns.

7.6 Systems-level risk: proxy reporting and implementation friction

The empirical task gap and trust asymmetry motivate a systems-level measurement question: should a digitally recorded transaction be counted as evidence of borrower capability without information on task purpose and transaction actor? The proposed concept of algorithmic deference describes the risk of interpreting an aggregate digital-processing metric beyond what it measures. The present survey does not establish that a regulator or MFI actually makes that error. Testing the proposition would require administrative-reporting templates, platform workflows and actor-level transaction evidence alongside borrower data.

For supervisory and MFI reporting, the practical implication is to separate institutional throughput from borrower-controlled use. Transaction counts can be paired with task diversity, need-adjusted use, independent initiation/authentication, support intensity and recovery from failed transactions. Such indicators would make it possible to test whether digital processing growth is accompanied by greater user agency rather than assuming the relationship.

Trust-Enabled Phygital Adoption Framework (TEPAF)

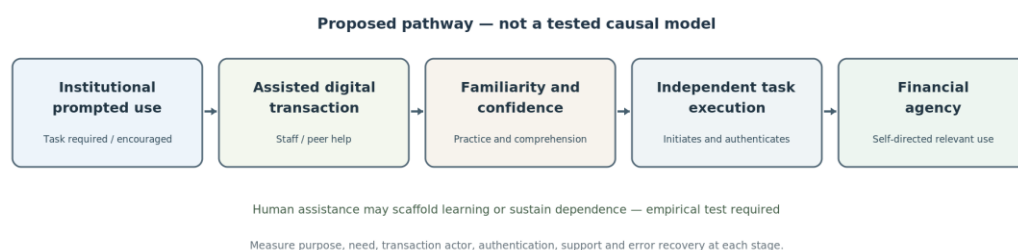


Figure 5. Trust-Enabled Phygital Adoption Framework (TEPAF).

Note. The framework is conceptual. It organises the empirical discussion around a progression from antecedents and psychological assessment to assisted use, familiarity, independent use and financial autonomy.

The model diagram is included to clarify the article’s conceptual contribution. It should be interpreted as a heuristic framework grounded in the observed patterns and prior literature, not as a statistically estimated path model.

TEPAF proposes five conceptual states: (1) institutional compliance, (2) assisted use, (3) familiarity and confidence, (4) independent task execution and (5) self-directed financial agency. The supplied data do not establish who occupies each state, whether the states occur sequentially or whether assistance causes later autonomy. Figure 5 and Table 8 therefore remain conceptual organising devices rather than estimated causal models. They identify the types of borrower-level, product-level and supervisory indicators that future research should collect to test whether digital financial services genuinely support user-initiated and recoverable financial action.

Table 8. Proposed TEPAF stages and candidate indicators (conceptual, not directly measured as stages).

Stage	Core borrower condition	Institutional implication
1. Institutional compliance	Uses digital channel mainly because the institution requires or strongly encourages the transaction.	Measure whether the transaction is mandatory and who initiates it.
2. Assisted digital use	Transaction is completed with help from staff, family, agents, or other intermediaries.	Treat assistance as a transition mechanism, not automatically as autonomy.
3. Familiarity and confidence	User becomes able to interpret screens, confirmations, risks, and routine procedures.	Use repeated demonstrations, vernacular guidance, and low-risk practice.
4. Independent digital use	Borrower can initiate and complete multiple financial tasks without routine assistance.	Measure transaction diversity and independent initiation.
5. Financial autonomy	Digital services are used for self-directed financial management beyond institutional obligations.	Evaluate digital inclusion through agency, choice, and capability.

TEPAF distinguishes a digital transaction from the organisation of the transaction: who decides, enters information, authenticates and handles failure. Human support can plausibly scaffold learning, but it can also preserve long-term reliance. Future repeated observation should test whether assisted practice predicts subsequent independent performance, controlling for demand, access and prior experience, rather than treating the proposed arrows as demonstrated pathways.

A future TEPAF study could link individual borrower observations to a contemporaneous workflow audit: compare staff-mediated and self-initiated transactions, determine whether optional functions are actually accessible to borrowers, and document the information visible to the institution and to the borrower. The stage model would be supported only if repeated evidence indicates change in capability, not merely an increase in the transactions appearing in administrative records.

Managerial and Policy Implications

9.1 Measure autonomy, not only transaction volume

A proposed dual-level evaluation would report institution-level throughput separately from borrower-level agency. An MFI or supervisory dashboard could display transaction counts together with the share of relevant tasks personally initiated and authenticated, support intensity, use conditional on reported need, transaction diversity, and the resolution of failed

operations. The figures in this study do not establish any of those dimensions; Table 8 provides an illustrative data-collection and audit specification rather than findings about existing regulatory dashboards.

9.2 Convert field staff from transaction intermediaries into digital educators

As a proposed practice, field staff can explain steps, invite borrowers to initiate tasks safely and provide support for checking receipts or reporting errors. A well-designed evaluation should measure whether assistance declines as independent competency grows while maintaining safeguards against fraud and unauthorised handling of credentials (Yadav & Kalluru, 2024).

9.3 Design for vernacular and low-literacy use

Digital interfaces serving microfinance borrowers should minimise text density, use familiar terminology, support local languages where feasible, and provide clear audio or visual confirmation. Digital literacy should be treated as a design constraint rather than merely as a user deficit.

9.4 Make transaction confirmation immediate and understandable

For users who are uncertain about invisible digital balances, immediate confirmation is central to trust formation. Confirmation should clearly display the amount, recipient, transaction status, and a reference number. Where literacy is limited, auditory or assisted confirmation can supplement conventional text receipts.

9.5 Strengthen grievance redressal

The literature shows that grievance redressal can influence mobile-payment use (Patil et al., 2020). In microfinance, failed transactions may have disproportionate psychological consequences because the borrower is managing limited financial resources. A fast, accessible, vernacular complaint and reversal mechanism can reduce the perceived consequences of failure and support trust formation.

9.6 Treat cybersecurity as an inclusion issue

Cybersecurity education should be integrated with financial inclusion rather than treated as a specialist technical issue. Borrowers should be taught never to share PINs, passwords, or authentication codes and should be given practical demonstrations of how legitimate support differs from fraudulent requests. The goal is not simply to warn users but to make safe behaviour feasible and understandable.

9.7 Proposed supervisory indicators and product-architecture audit

A reporting template could separate three denominators: eligible borrowers, borrowers with a genuine need for a particular service, and borrowers who attempted it. Transaction success, independent completion and unmet demand would then be reported as different quantities. An aggregate repayment count should not be described as autonomy without actor-level evidence. To inspect whether a platform facilitates borrower choice as well as institutional collections, an evaluation may review user journeys, interface access, supported task types, consent and authentication flows, complaint pathways, and the comparability of administrative and borrower-reported logs. These are candidate audit indicators; the present survey has not

examined software architecture, platform motives, regulator behaviour or the prevalence of coercion.

Table 9. Proposed two-level financial inclusion dashboard and architecture-audit indicators (not measured in this study).

Audit dimension / unit	Proposed measurable indicator	Documentation and interpretive safeguard
Institutional throughput	Completed digital repayments / repayment attempts; report method and observation period.	Reconcile transaction ledgers; report an operational processing measure only, not borrower autonomy.
Task need and choice	Optional transfers undertaken / borrowers reporting a need to transfer; also record no-need and unmet-need categories.	Use explicit need and attempt questions; do not classify non-users as incapable without a relevant denominator.
Actor and independent execution	Borrower-initiated and borrower-authenticated tasks / applicable transactions; stratify fully assisted, partly assisted and unassisted use.	Cross-check consented user reports and workflow evidence; do not infer actors from an account holder's name.
Product architecture and intent	Availability and usability of borrower-initiated transfers, balance checks, service choices and voluntary alternatives, compared with repayment paths.	Audit written requirements, screen flows, access rules and user testing; features alone do not establish developer or regulator motives.
Transaction diversity	Number of distinct relevant services used per borrower, interpreted alongside need and access.	Document task definitions, eligibility and reporting window; breadth is not equivalent to autonomy.
Trust, confirmation and remedy	Separate MFI/technology trust items; comprehension of status; successful complaint and reversal among eligible error cases.	Validate construct separation and follow actual user journeys; aggregate trust means do not establish causal friction.
Reporting transparency and safeguards	Disaggregate institutional compliance, assisted use and borrower-controlled use where valid; document definitions, missingness and privacy protections.	Compare dashboard fields with audit data and obtain appropriate consent; no existing supervisor's practices were audited.

Note. These are prospective indicators, not findings or descriptions of current policy. Distinguish a participant who does not need a transfer from one who attempts a transfer but cannot complete it. Use aggregate, consent-respecting records and avoid publishing identifiable borrowers' transaction trails.

Supervisory metric realignment is consequently framed as a falsifiable measurement proposal: compare inclusion assessments obtained from transaction totals with those obtained from observed need-adjusted and independence-adjusted indicators. Differences would identify a

reporting mismatch only if task definitions, denominators, record quality and user consent are established. Adoption of such indicators entails feasibility, privacy and administrative-burden considerations that the present study has not evaluated.

Theoretical Implications

The paper adds a distinction not directly represented in intention-focused TAM/UTAUT models: the identity and independence of the actor executing a transaction. The re-estimated task-use results show that digital functions are used at materially different rates, but they still do not validate a latent autonomy construct. The theoretical extension is therefore to specify actor, need and independence as additional outcomes rather than to claim that TAM/UTAUT is empirically displaced.

Institutional and technological trust are empirically distinct in this sample: TMFI exceeds TTEC by about one point in paired data. This supports treating trust objects separately in measurement. It does not establish a temporal trust-transfer process, and the unstable multivariate coefficients show why future work should establish discriminant validity before assigning structural paths.

The phygital proposal places in-person assistance alongside digital task execution and asks whether intermediation becomes temporary learning support or durable dependence. This is compatible with accounts of adoption as the interaction of materials, competencies and practice (Naeem et al., 2022), but the transition itself remains untested in the present data.

A further proposition concerns the interface between technology-acceptance theory and administrative measurement: an institution's recorded digital adoption and a borrower's independent capability are outcomes at different levels. The proposed algorithmic-deference mechanism concerns how a reporting system might collapse those outcomes. Testing it would require institutional documents, platform specifications and supervisory decision evidence in addition to borrower records; the present article provides no test of that mechanism.

Limitations and Future Research

The study is cross-sectional and geographically restricted to active microfinance borrowers represented in one Ranchi analytical workbook. The file contains 662 records but no JLG/centre identifiers, sampling weights, recruitment denominator or response-rate information. Consequently, cluster-robust uncertainty, design-based representativeness and population prevalence estimates cannot be reconstructed. Demographic category codes also require the original codebook before coded groups are substantively labelled.

Measurement overlap is unusually high. VIFs reach 86.89 and several construct correlations are extremely strong. HC3 standard errors address heteroscedasticity but not multicollinearity, repeated-pattern dependence or causal identification. Ridge and LASSO improve numerical stability and out-of-sample checking, but they do not establish construct validity. SEM/PLS-

SEM would be appropriate only after item wording, factor structure, convergent validity and discriminant validity are independently verified.

The analytical file contains only 99 distinct substantive response profiles among 662 records. Repeated profiles do not prove duplicate respondents, but their multiplicity can inflate nominal precision and predictive performance if identical patterns are split across training and validation samples. Profile-grouped cross-validation and the one-record-per-profile sensitivity analysis reduce this specific leakage risk and reveal the dependence of some results on repeated patterns, but they cannot replace verification against original questionnaires, CAPI exports and data-processing logs.

The Compliance–Autonomy Gap is operationalised here only as a difference in reported participation between repayment and transfer. The survey does not record whether repayment was mandatory, whether a transfer was needed, who initiated or authenticated the transaction, how much assistance was required, whether the borrower understood the outcome, or whether an error could be resolved independently. For that reason, neither the 32.2-point task gap, the task-breadth score, nor the transfer model should be described as a direct measure of autonomy. Future research should collect transaction-level actor and need variables, identify lending-centre clusters, use longitudinal observations to test TEPAF transitions, and validate a borrower digital-autonomy scale incorporating independent initiation, authentication, task diversity, safety and error recovery. A separate institutional study could compare borrower-level measures with administrative dashboards and product workflows to test the proposed algorithmic-deference mechanism directly.

Conclusion

Re-estimation of the respondent-level workbook materially changes the numerical headline while improving transparency. The analytical sample is $N = 662$. Digital repayment is reported by 87.9% of borrowers and fund transfer by 55.7%, producing a 32.2-percentage-point paired task gap (95% CI 28.6–35.7). Across six digital functions, mean task breadth is 3.71 (SD = 1.61). These results establish substantial task heterogeneity within the observed sample; they do not establish the prevalence of independent financial capability.

Trust Asymmetry is supported as a paired descriptive result: trust in the MFI ($M = 4.37$, $SD = 0.49$) exceeds trust in technology ($M = 3.38$, $SD = 1.16$) by 1.00 point. The behavioural-intention model shows extremely high in-sample fit and statistically precise HC3 slopes, but VIFs up to 86.89, repeated response profiles and unavailable cluster identifiers prevent those slopes from being interpreted as clean unique or causal effects. The regularized models confirm that several coefficient signs are sensitive to specification, especially within the trust/risk block. A ridge-logistic model of fund-transfer participation and a ridge model of task breadth move the analysis closer to observed use, but they still cannot distinguish lack of need from lack of capability or assisted use from independent execution. Accordingly, the study's strongest contribution is measurement-oriented: digital financial inclusion should be assessed using task-specific use together with need, actor, assistance, authentication, safety and error-recovery information rather than transaction volume alone. TEPAF remains a conceptual framework for

testing how assisted participation may or may not develop into independent financial agency in future longitudinal and transaction-level research.

Appendixes

Appendix A. Supplementary Descriptive Tables

Appendix Table A1. Detailed descriptive statistics for digital task use.

Task	n	%	95% CI
Balance check	636	96.1	94.3–97.3
Loan repayment	582	87.9	85.2–90.2
Fund transfer	369	55.7	51.9–59.5
Bill payment	238	36.0	32.4–39.7
Information access	528	79.8	76.5–82.6
New loan/app	106	16.0	13.4–19.0
Task breadth (0–6)	—	Mean = 3.71; SD = 1.61	Median = 4; IQR = 3–5

Note. Confidence intervals for percentages are Wilson 95% intervals. Task breadth counts the number of endorsed digital functions out of six.

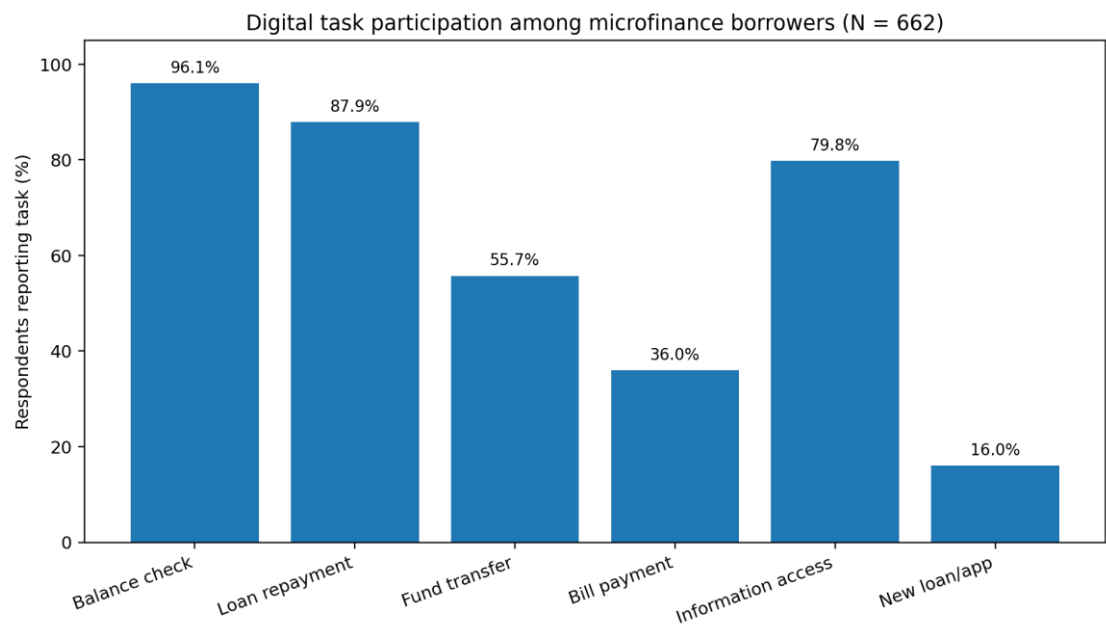
Appendix B. Supplementary Model Diagnostics and Sensitivity Results

Appendix Table B1. Diagnostic and sensitivity statistics for the behavioural-intention model.

Predictor	HC3 OLS p	Holm-adjusted p	VIF	Unique-profile OLS p
DL	0.004497	0.004497	59.55	0.278
PEOU	5.137e-05	0.0001541	45.82	0.09497
PFB	4.496e-15	3.147e-14	35.05	0.0006227
TMFI	0.0005432	0.001086	1.86	0.2232
TTEC	2.258e-05	0.0001129	80.41	0.1446
PR	2.945e-05	0.0001178	86.89	0.1771
SI	4.768e-16	3.815e-15	37.38	0.004051
FC	2.989e-11	1.793e-10	55.88	0.04866

Note. Breusch–Pagan LM = 168.55, $p < .001$. Unique-profile OLS uses one retained record per distinct substantive response profile ($n = 99$).

Appendix C. Additional Graphical Summary



Appendix Figure C1. Digital task participation profile.

Note. Reproduced here for quick reference within the supplementary materials.

Abbreviations

TAM — Technology Acceptance Model; UTAUT — Unified Theory of Acceptance and Use of Technology; MFI — Microfinance Institution; NBFC-MFI — Non-Banking Financial Company–Microfinance Institution; JLG — Joint Liability Group; CAPI — Computer/Tablet-Assisted Personal Interview; DL — Digital Literacy; PEOU — Perceived Ease of Use; PFB — Perceived Financial Benefits; TMFI — Trust in MFI; TTEC — Trust in Technology; PR — Perceived Risk; SI — Social Influence; FC — Facilitating Conditions; BI — Behavioural Intention; TEPAF — Trust-Enabled Phygital Adoption Framework; VIF — Variance Inflation Factor; AUC — Area Under the ROC Curve.

References

Bhowal, P., & Shil, P. (2026). Exploring FinTech adoption: A systematic literature review on user acceptance. *Telematics and Informatics Reports*, 22, 100343. <https://doi.org/10.1016/j.teler.2026.100343>

Chamboko, R. (2024). Digital financial services adoption: A retrospective time-to-event analysis approach. *Financial Innovation*, 10, 46. <https://doi.org/10.1186/s40854-023-00568-1>

Dahiya, P., Gupta, A., Khandelwal, M., Saxena, M., & Sabharwal, S. (2026). Understanding fintech adoption in India: The mediating role of trust and the moderating role of emotional intelligence. *Future Business Journal*, 12, 221. <https://doi.org/10.1186/s43093-026-00928-0>

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.

Jacob, R. C., Jacob, M. E., & Johnson, J. (2024). Understanding factors affecting UPI adoption among low-income consumers in India. *Indian Journal of Finance*, 18(7), 44–59. <https://doi.org/10.17010/ijf/2024/v18i7/174032>

Kajol, K., Singh, R., & Paul, J. (2022). Adoption of digital financial transactions: A review of literature and future research agenda. *Technological Forecasting and Social Change*, 184, 121991. <https://doi.org/10.1016/j.techfore.2022.121991>

Kumar, R., Singh, R., Kumar, K., Khan, S., & Corvello, V. (2023). How does perceived risk and trust affect mobile banking adoption? Empirical evidence from India. *Sustainability*, 15(5), 4053. <https://doi.org/10.3390/su15054053>

Ladeira, W. J., Jafar, S. H., & Santini, F. O. (2026). A meta-analysis of technological adoption of financial services: Investigating risk and trust perception effects. *International Journal of Bank Marketing*, 44(3), 393–421. <https://doi.org/10.1108/IJBM-02-2025-0156>

Linge, A. A., Chaudhari, T., Kakde, B. B., & Singh, M. (2023). Analysis of factors affecting use behavior towards mobile payment apps: A SEM approach. *Human Behavior and Emerging Technologies*, 2023, 3327994. <https://doi.org/10.1155/2023/3327994>

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, 13(3), 334–359. <https://doi.org/10.1287/isre.13.3.334.81>

Naeem, M., Ozuem, W., Howell, K., & Ranfagni, S. (2022). Understanding the process of meanings, materials, and competencies in adoption of mobile banking. *Electronic Markets*, 32, 2445–2469. <https://doi.org/10.1007/s12525-022-00610-7>

Nandru, P., Madhavaiah, C., & Senthilkumar, S. A. (2023). Factors affecting the adoption of mobile payment services during the COVID-19 pandemic: An application of extended UTAUT2 model. *Journal of Science and Technology Policy Management*, 16(3), 405–431. <https://doi.org/10.1108/JSTPM-03-2023-0044>

Neves, C., Oliveira, T., Santini, F., & Gutman, L. (2023). Adoption and use of digital financial services: A meta analysis of barriers and facilitators. *International Journal of Information Management Data Insights*, 3(2), 100201. <https://doi.org/10.1016/j.jjime.2023.100201>

Patil, P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. *International Journal of Information Management*, 54, 102144. <https://doi.org/10.1016/j.ijinfomgt.2020.102144>

Sharma, H., & Díaz Andrade, A. (2023). Digital financial services and human development: Current landscape and research prospects. *Information Technology for Development*, 29(4), 582–606. <https://doi.org/10.1080/02681102.2023.2199189>

Ullah, S., Kiani, U. S., Raza, B., & Mustafa, A. (2022). Consumers' intention to adopt m-payment/m-banking: The role of their financial skills and digital literacy. *Frontiers in Psychology*, 13, 873708. <https://doi.org/10.3389/fpsyg.2022.873708>

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.

Yadav, R. S., & Kalluru, S. R. (2024). Principal–agent trust and adoption of digital financial services: Evidence from India. *Economic Notes*, 53(3), e12247. <https://doi.org/10.1111/ecno.12247>