

Digital Payment Adoption and Changing Consumer Purchase Behaviour in Emerging Markets

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<http://www.ujhmads.org/> || Vol. 2 No. 3 (2026): Special August Issue

Date of Submission: 02-07-2026

Date of Acceptance: 22-07-2026

Date of Publication: 17-08-2026

Abstract— Digital payment ecosystems are rapidly altering how consumers search, evaluate, purchase, and repurchase goods and services across emerging markets. This study examines whether digital payment adoption changes purchase behaviour beyond the conventional effects of convenience, accessibility, and transaction speed. The research specifically conceptualizes payment friction reduction as a behavioural mechanism linking digital payment intensity with purchase frequency, discretionary expenditure, impulse purchasing, and merchant switching. A multi-market analytical framework is proposed in which transaction behaviour is examined alongside consumer-level indicators of trust, digital capability, promotional responsiveness, and perceived expenditure visibility. The study distinguishes between simple digital-payment adoption and payment intensity, recognizing that occasional and habitual users may exhibit substantially different purchasing responses. It further proposes machine-learning-based consumer segmentation to identify heterogeneous behavioural profiles that conventional aggregate adoption models may conceal. The expected contribution is an integrated explanation of how digital payments simultaneously improve transactional efficiency while potentially reducing the psychological salience of spending. The framework offers implications for financial-service providers, retailers, policymakers, and consumer-protection authorities seeking to balance digital financial inclusion with sustainable consumer decision-making.

Keywords: Digital Payments; Consumer Purchase Behaviour; Emerging Markets; Payment Friction; Financial Technology; Machine Learning

Introduction

The digitization of retail payments has become one of the most consequential transformations in contemporary consumer markets. Mobile wallets, instant bank transfers, QR-code payments, contactless cards, mobile-money services, and app-based payment interfaces increasingly allow consumers to complete transactions without exchanging physical currency. This transformation is particularly significant in emerging markets, where mobile technology and interoperable payment infrastructures can allow economies to bypass some limitations associated with traditional branch-based financial systems.

Recent international evidence demonstrates the scale of this transition. The World Bank's Global Findex 2025 is based on nationally representative surveys covering approximately 148,000 adults across 141 economies and provides updated information on financial-service use, payments, mobile connectivity, and digital safety. Global account ownership reached approximately 79% of adults, compared with 74% in 2021, while mobile-phone penetration has become an important infrastructure supporting financial access. The World Bank also identifies increasing adoption of digital merchant payments since 2021, demonstrating that digital finance is becoming embedded in routine consumption rather than remaining limited to transfers between individuals.

Emerging economies provide an especially important setting for studying this transformation. Digital payments in these markets are developing alongside expanding smartphone ownership, platform-based commerce, government-supported digital infrastructure, financial-inclusion

initiatives, and increasingly sophisticated fintech ecosystems. Instant-transfer infrastructures such as India's UPI and Brazil's PIX illustrate how low-friction payment architectures can extend digital financial activity beyond conventional card-based systems. The World Bank has specifically identified investment in instant-transfer infrastructure, together with consumer protection and improved account security, as important components of further financial inclusion.

Nevertheless, the importance of digital payments extends beyond financial inclusion. A payment mechanism constitutes part of the purchasing environment itself. Cash transactions require consumers to physically surrender money. Traditional card transactions eliminate physical cash but retain several procedural stages. Contemporary mobile payments can reduce this process to scanning a QR code, entering a short authentication credential, tapping a device, or confirming a transaction through an application.

Such reductions in **payment friction** may alter purchasing decisions.

Existing empirical evidence supports the possibility that payment digitization affects consumption rather than merely changing the instrument through which an already-determined purchase is settled. Li, Ruan, and collaborators, using transaction-level evidence surrounding India's 2016 demonetization episode, investigated how a forced transition toward digital payment affected consumer expenditure. Their study provides causal evidence connecting payment digitization with consumption behaviour rather than treating payment technology purely as an adoption phenomenon.



The behavioural implications can operate through several pathways. Digital payments reduce transaction time and physical effort. Stored credentials and integrated checkout

systems reduce repeated decision steps. Cashback, discounts, reward points, and merchant promotions can alter perceived transaction value. Digital payment acceptance can increase the number of accessible merchants. At the same time, reduced visibility of physical money may weaken consumers' immediate awareness of expenditure.

Accordingly, digital payment adoption may affect not only **whether consumers purchase**, but also **how frequently they purchase, how much they spend, what they purchase, when they purchase, and how readily they switch between merchants**.

This distinction is important because much of the earlier financial-technology literature concentrated on explaining adoption intention. Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), trust-based models, and related frameworks have been widely employed to explain why consumers accept mobile payment systems. Variables such as performance expectancy, perceived usefulness, facilitating conditions, trust, social influence, innovativeness, and perceived risk are therefore well represented in the literature. Research on Indian mobile-payment users, for example, has shown the relevance of performance expectancy, attitude, facilitating conditions, social influence, and grievance redressal in explaining payment behaviour.

However, explaining **why a consumer adopts digital payment is not equivalent to explaining what happens to that consumer's purchasing behaviour after adoption**.

1.1 Research Gap

This study addresses a specific gap at the intersection of financial technology and consumer behaviour. Existing studies frequently treat digital-payment use as a dependent variable and investigate the factors producing adoption. A smaller stream investigates spending or impulse purchasing after adoption. These approaches provide valuable evidence but often examine behavioural outcomes separately.

Research on mobile-wallet characteristics, for instance, has demonstrated relationships between application characteristics, perceived enjoyment, user experience, and impulse buying. Such evidence indicates that payment interfaces can participate in consumer decision-making. Yet impulse buying represents only one dimension of post-adoption behaviour.

The present study therefore proposes a broader **post-adoption behavioural framework**.

Rather than asking only:

What determines digital-payment adoption?

the study asks:

How does the intensity of digital-payment use restructure the consumer's overall purchasing pattern after adoption?

The principal research gap is the limited integration of **payment intensity, payment friction, promotional sensitivity, expenditure visibility, purchase frequency, basket value, impulse purchasing, and merchant switching within a single heterogeneous consumer framework for emerging markets.**

An additional methodological gap concerns consumer heterogeneity. Conventional regression models estimate an average relationship between digital-payment adoption and purchasing outcomes. Yet the behavioural consequences of digitization are unlikely to be uniform. A promotion-sensitive young mobile-wallet user, a financially disciplined QR-payment user, and a newly digitized consumer using mobile money primarily for essential purchases could all be classified as "digital-payment users" despite having fundamentally different behavioural responses.

The proposed research therefore combines explanatory statistical modelling with machine-learning-based behavioural segmentation. This approach is intended to distinguish between adoption itself and the heterogeneous behavioural trajectories that emerge after adoption.



1.2 Research Objectives

The primary objective is to evaluate how digital-payment adoption and usage intensity influence consumer purchasing behaviour in emerging-market environments. More specifically, the study seeks to determine whether increasing payment intensity is associated with changes in purchase frequency, transaction value, discretionary expenditure, impulse-purchase propensity, and merchant-switching behaviour.

A second objective is to evaluate **payment friction reduction** as an explanatory mechanism. The study investigates whether convenience, transaction speed, simplified authentication, stored payment credentials, and ubiquitous merchant acceptance decrease the perceived effort associated with completing a purchase.

Third, the research examines whether promotional mechanisms—including cashback, discounts, reward points, and payment-specific offers—strengthen the relationship between digital-payment use and discretionary consumption.

Fourth, the study investigates whether **expenditure visibility** moderates these effects. Consumers who frequently review transaction histories, receive spending notifications, establish payment limits, or use financial-management applications may experience the convenience of digital payment without equivalent increases in unplanned expenditure.

Finally, machine-learning clustering is proposed to identify distinct post-adoption consumer profiles and determine whether behavioural effects differ across consumer segments.

Literature Review

2.1 Evolution of Digital Payments in Emerging Markets

Digital payments encompass electronically initiated transfers of monetary value through banking networks, mobile-money platforms, payment cards, wallets, QR-code infrastructures, and instant account-to-account systems. Their expansion has increasingly connected financial inclusion with everyday retail consumption.

The Global Findex 2025 provides particularly relevant evidence because it incorporates almost 300 indicators covering mobile ownership, internet use, digital safety, accounts, payments, savings, credit, and financial resilience, with data available across countries, regions, income categories, gender, age, labour-force status, and rural-urban residence. This multidimensional structure demonstrates why emerging-market digital-payment research should not assume that technological access and financial participation are evenly distributed.

Significant inequalities remain. Digital-payment opportunities depend on access to devices, network connectivity, formal accounts, merchant infrastructure, digital literacy, and trust. Consequently, the behavioural effects of payment digitization can vary considerably between demographic and socioeconomic groups.

The inclusion dimension is particularly important. World Bank evidence indicates that women's financial-account ownership in low- and middle-income economies increased substantially between 2021 and 2024. Digital-payment participation among women also increased, including growth in digital merchant-payment use. These developments

suggest that payment digitization is simultaneously changing access to finance and the population participating in digitally mediated consumer markets.

2.2 Technology Adoption and Digital Payment Usage

Traditional digital-payment research has largely evolved from information-systems adoption theory. TAM emphasizes perceived usefulness and ease of use, whereas UTAUT incorporates performance expectancy, effort expectancy, social influence, and facilitating conditions. Later payment studies have extended these models using variables including perceived security, trust, innovativeness, anxiety, grievance redressal, and perceived financial risk.

Such models remain useful for distinguishing between consumers who are willing and unwilling to adopt digital payment. Evidence from mobile-payment research in India, for example, demonstrates that consumer attitudes and institutional or service characteristics contribute materially to actual usage behaviour.

However, mature digital-payment markets increasingly require a transition from an **adoption paradigm** toward a **usage-intensity paradigm**.

Once digital payment becomes widely available, binary variables such as "user/non-user" provide limited behavioural information. Consumers can differ in number of transactions, proportion of purchases paid digitally, diversity of payment instruments, duration of adoption, merchant categories, average transaction value, and dependence on digital payments.

Accordingly, the present research treats digital-payment intensity as a multidimensional construct rather than a binary technological decision.

2.3 Payment Friction and Purchase Behaviour

Payment friction refers to the cognitive, procedural, temporal, or physical effort required to complete a transaction. Cash requires consumers to maintain sufficient currency, physically count it, transfer it to the seller, and receive change where necessary. Digital systems can compress these actions substantially.

From a behavioural perspective, friction is important because each additional purchasing step creates an opportunity for reconsideration. Removing steps may therefore improve transaction efficiency while simultaneously decreasing the time available for consumers to reconsider discretionary purchases.

Digital payment can reduce friction through rapid authentication, automatic completion of transaction information, saved credentials, QR codes, one-click checkout, and interoperability between consumers and

merchants. The behavioural effect should consequently be evaluated separately from the technological usefulness of the payment system.

This study conceptualizes payment friction as a mediator:

Digital Payment Intensity → Lower Payment Friction → Changed Purchase Behaviour

The purchasing outcomes extend beyond expenditure amount to frequency, basket composition, discretionary purchases, impulse purchases, and merchant choice.

2.4 Digital Payments and Consumer Spending

The relationship between payment instruments and spending has become increasingly important as payment technologies integrate with retail platforms. Evidence from India demonstrates that changes in payment mode can produce measurable changes in consumption. The 2024 *Review of Financial Studies* article examining India's demonetization shock uses anonymized transaction-level supermarket data and a difference-in-differences framework to investigate this relationship.

Such findings challenge the assumption that payment method is behaviourally neutral.

Digital payments may increase purchase frequency because consumers no longer need to carry sufficient physical currency. They can also reduce constraints associated with denomination availability or immediate cash balances. Online and mobile commerce further amplify this effect because digital payment is frequently integrated directly into the purchasing interface.

Nevertheless, digital payment should not automatically be interpreted as causing excessive consumption. Digital transactions also create electronic records that may improve budgeting and expenditure monitoring. The behavioural outcome therefore depends on the interaction between convenience and financial self-monitoring.

This tension motivates the proposed construct of **expenditure visibility**.

2.5 Digital Wallets and Impulse Purchasing

Impulse purchasing represents an important behavioural consequence of low-friction commerce. Lee's 2022 study of mobile-wallet application characteristics used survey data from 208 active e-wallet users and PLS-SEM to examine relationships involving interactivity, visual appeal, perceived enjoyment, user experience, and impulse buying. The results showed that characteristics of the payment interface can influence psychological processes associated with impulse purchases.

The significance of this finding extends beyond interface design. Contemporary payment applications are not always neutral transaction utilities. Many combine payment functionality with rewards, notifications, merchant discovery, offers, loyalty mechanisms, credit access, and transaction histories.

This convergence may create a **payment–promotion loop**:

Payment Usage → Personalized Incentive → Purchase → Reward → Repeated Payment Usage

Consequently, promotional responsiveness should be separated analytically from the intrinsic convenience of digital payment.

2.6 Promotional Incentives and Purchase Acceleration

Cashback, coupons, loyalty points, referral incentives, merchant discounts, and payment-specific promotions have played an important role in competition among digital-payment platforms. These mechanisms reduce consumers' perceived effective price and may encourage experimentation with new merchants or product categories.

However, promotional effects can create an identification problem. A consumer may increase spending after adopting a wallet not because digital payment itself changes purchasing psychology, but because the wallet continuously provides discounts.

The proposed study therefore separates **payment-friction effects** from **promotion-induced effects**. Promotional exposure and promotional responsiveness will be modelled independently rather than subsumed under perceived usefulness.

This distinction is particularly relevant for emerging markets, where digital-payment providers frequently operate within platform ecosystems linking financial services, retail transactions, transportation, food delivery, utilities, and e-commerce.

2.7 Trust, Security and Digital Safety

Trust remains fundamental to both adoption and sustained use. Consumers must believe that transactions will be executed correctly, personal and financial information will remain sufficiently protected, unauthorized transactions can be contested, and service failures will receive effective redress.

The increasing use of smartphones for financial activity has consequently expanded the relevance of digital safety. Global Findex 2025 explicitly introduced globally comparable measures covering mobile ownership, internet use, and digital safety alongside conventional financial-inclusion indicators.

Security perceptions may also indirectly influence purchase behaviour. A consumer who distrusts digital payment may reserve it for low-value transactions. Conversely, a consumer with high confidence may use it across a wider range of merchants and purchase categories. Trust therefore functions not merely as an antecedent of adoption but potentially as a determinant of **payment depth**.

2.8 Expenditure Visibility and Financial Self-Regulation

One apparent contradiction in digital-payment research is that digital systems can simultaneously make spending less tangible at the moment of purchase and more traceable after the transaction.

Physical cash provides immediate sensory evidence of expenditure: the consumer sees the amount of money held decrease. Digital payment weakens this physical feedback. Yet electronic systems generate transaction records that can be reviewed, categorized, searched, and incorporated into budgeting applications.

The proposed framework therefore distinguishes **immediate payment salience** from **retrospective expenditure visibility**.

Consumers with strong financial self-regulation may actively use transaction histories, account-balance notifications, budgeting dashboards, spending alerts, and payment limits. For such consumers, digitization could improve financial control even while transaction friction decreases.

This suggests that expenditure visibility may moderate the relationship between payment intensity and discretionary purchasing.

2.9 Consumer Heterogeneity and the Need for Machine-Learning Segmentation

A major weakness of average-effect models is their assumption that consumers respond similarly to payment digitization. Emerging markets contain substantial variation in income, age, digital capability, financial literacy, connectivity, urbanization, merchant availability, and experience with formal financial institutions.

Machine-learning segmentation provides an alternative method of identifying latent behavioural groups without imposing predefined demographic categories.

Instead of dividing respondents solely by age or income, the proposed study will construct consumer clusters from variables such as digital-payment frequency, digital share of total expenditure, promotional responsiveness, discretionary-spending ratio, transaction-value variability, financial self-monitoring, trust, and impulse-purchase propensity.

Potential segments might include highly digital but financially controlled consumers, promotion-responsive digital shoppers, convenience-oriented routine users, and low-intensity transitional adopters. Importantly, these categories will not be predetermined; their existence must be established empirically through clustering validation.

The resulting segmentation can subsequently be combined with interpretable predictive modelling to identify the factors distinguishing behavioural groups.

Proposed Methodology

The study adopts a **hybrid behavioural-analytics framework** designed to examine how digital-payment intensity influences post-adoption purchasing behaviour in emerging-market settings. Unlike conventional studies that treat digital-payment usage as a binary adoption variable, the proposed design models payment activity as a continuous behavioural construct incorporating frequency, transaction share, payment diversity, promotional responsiveness, and expenditure-monitoring behaviour.

The analytical framework contains three sequential components. First, latent behavioural constructs are estimated from consumer-level variables representing payment friction, trust, promotional responsiveness, expenditure visibility, impulse-purchase tendency, and discretionary consumption. Second, unsupervised machine learning is used to identify naturally occurring consumer profiles. Third, interpretable supervised learning predicts whether a consumer is likely to exhibit a substantial post-adoption increase in discretionary purchasing.

The central research proposition is that the relationship between digital-payment adoption and consumption is mediated by **payment-friction reduction** but moderated by **expenditure visibility and financial self-regulation**. Promotional responsiveness is modelled separately because cashback, discounts, reward points, and payment-specific incentives may increase expenditure independently of payment convenience.

3.1 Research Hypotheses

The empirical framework tests the following relationships:

H1: Higher digital-payment intensity is positively associated with purchase frequency.

H2: Reduction in payment friction mediates the relationship between digital-payment intensity and discretionary expenditure.

H3: Promotional responsiveness strengthens the association between digital-payment intensity and impulse-purchase propensity.

H4: Greater expenditure visibility weakens the relationship between payment intensity and uncontrolled discretionary expenditure.

H5: Consumers can be separated into statistically meaningful post-adoption behavioural segments that cannot be adequately represented through demographic classification alone.

H6: A nonlinear machine-learning model incorporating payment intensity, promotional behaviour, financial self-monitoring, trust, and socioeconomic attributes predicts high post-adoption spending change more effectively than a conventional linear benchmark.

Experimental Setup

4.1 Dataset Design

Because no original respondent-level dataset was supplied for this manuscript, the numerical experiment reported below is presented as a **simulation-based proof-of-concept analysis**. It demonstrates how the proposed framework can be implemented and should not be represented as evidence collected from actual respondents. In a full empirical study, the same protocol should be applied to ethically approved survey and transaction-diary data.

A synthetic dataset of **1,800 consumer profiles** was generated to represent digitally active consumers in heterogeneous emerging-market environments. The sample structure was designed to capture variation in income, urbanization, digital access, payment experience, and retail behaviour.

Each record contained four feature families.

The first family represented **digital-payment intensity**, including monthly digital transaction frequency, percentage of total purchases completed digitally, number of payment instruments used, duration of habitual digital-payment use, and proportion of transactions involving QR or instant account-to-account payment.

The second family represented **consumer psychology and platform response**, including perceived payment convenience, transaction-speed perception, trust, security concern, promotional responsiveness, reward sensitivity, and perceived payment friction.

The third family represented **purchase behaviour**, including monthly purchase frequency, average transaction amount, discretionary-spending ratio, impulse-purchase tendency, merchant-switching frequency, and online-to-offline expenditure ratio.

The fourth family represented **financial self-regulation**, including transaction-history review frequency, use of

spending alerts, budgeting behaviour, balance-monitoring frequency, and perceived expenditure visibility.

Demographic variables such as age group, household income band, education level, employment status, and urban-rural classification were retained as control attributes rather than the primary basis for behavioural segmentation.

The primary supervised-learning outcome was defined as **high post-adoption discretionary spending change**, representing a consumer whose discretionary-purchase index increased beyond a predetermined standardized threshold after intensive digital-payment use.

4.2 Data Preprocessing

The preprocessing pipeline was designed to minimize information leakage and preserve behavioural interpretability.

Numerical variables were screened for impossible values and extreme outliers. Continuous behavioural indicators with highly skewed distributions were transformed using logarithmic or robust scaling procedures where appropriate. Missing observations in numerical variables were imputed using median values calculated exclusively from the training partition, while categorical variables were imputed using the most frequent category.

Ordinal variables such as trust, payment convenience, financial monitoring, and impulse-buying tendency were retained as ordered numerical scales. Nominal variables were converted using one-hot encoding.

Strongly correlated predictors were examined before model construction. Where pairs of indicators represented essentially identical behavioural information, the less theoretically informative variable was excluded to reduce redundancy.

For clustering, numerical features were standardized to zero mean and unit variance. For supervised modelling, preprocessing transformations were fitted only on training data and subsequently applied to validation and test partitions.

The dataset was divided into approximately **70% training, 15% validation, and 15% hold-out testing** using stratified sampling to preserve the proportion of high-spending-change consumers.

Model Architecture

5.1 Behavioural Segmentation Model

Consumer heterogeneity was examined using **K-means clustering** following dimensionality screening with principal component analysis used only as an exploratory diagnostic rather than as a replacement for the original behavioural variables.

Candidate cluster solutions ranging from two to seven groups were evaluated using the silhouette coefficient, Davies-Bouldin index, cluster stability under bootstrap resampling, and substantive interpretability.

A four-cluster configuration produced the most coherent simulated solution. The resulting behavioural profiles were interpreted as:

Digitally Disciplined Users: high payment intensity combined with frequent transaction monitoring and relatively controlled discretionary expenditure.

Promotion-Responsive Spenders: high cashback and reward sensitivity, frequent merchant switching, and elevated discretionary purchasing.

Convenience-Oriented Routine Users: high transaction frequency but moderate impulse-purchase tendency and comparatively stable basket values.

Transitional Digital Users: lower digital-payment intensity, higher perceived friction, lower trust, and continued dependence on cash for several purchasing categories.

These labels were assigned only after examining cluster centroids and should not be imposed in advance when the model is applied to actual data.

5.2 Predictive Model

For supervised prediction, a **Light Gradient Boosting Machine (LightGBM)** architecture was selected because the research problem contains nonlinear behavioural relationships and interactions between payment intensity, promotions, trust, and financial self-regulation.

The model used payment-intensity variables, perceived friction, promotional responsiveness, trust, expenditure visibility, digital-payment diversity, impulse-purchase score, transaction frequency, and socioeconomic controls as predictors.

A logistic-regression classifier was retained as the conventional benchmark.

Hyperparameters for the gradient-boosting model were optimized using validation-set performance with constraints on tree depth and leaf complexity to reduce overfitting. Early stopping was applied when validation loss failed to improve over successive boosting rounds.

Class weights were adjusted where necessary to compensate for moderate outcome imbalance rather than generating synthetic minority observations.

Training Strategy

Model training followed a nested analytical sequence.

First, clustering was performed exclusively on behavioural features, excluding the target outcome. Cluster assignments were then evaluated for differences in discretionary expenditure, payment intensity, impulse-purchase tendency, and expenditure visibility.

Second, logistic regression was trained as an interpretable baseline.

Third, LightGBM was trained using the same train-test partition to determine whether nonlinear interaction modelling provided additional predictive value.

Fourth, model interpretation was conducted using **SHAP values**, allowing estimation of both global feature importance and the direction of individual predictor effects.

Particular attention was given to interaction patterns involving digital-payment intensity and expenditure visibility. The analytical expectation was that high payment intensity would not universally correspond to increased discretionary expenditure. Instead, the effect was expected to depend on whether consumers actively monitored their financial activity.

Evaluation Metrics

The classification task was evaluated using several complementary metrics.

Area Under the Receiver Operating Characteristic Curve (AUROC) measured overall discrimination across classification thresholds.

Area Under the Precision-Recall Curve (AUPRC) assessed performance under outcome imbalance.

F1-score represented the harmonic balance between precision and recall.

Balanced accuracy reduced the influence of unequal class frequencies.

Brier score evaluated probability calibration, with lower values indicating more reliable predicted probabilities.

Clustering quality was assessed through the **silhouette coefficient**, **Davies-Bouldin index**, and resampling-based stability.

Behavioural associations were additionally examined using standardized regression coefficients and mediation estimates to preserve interpretability beyond machine-learning performance alone.

Results and Discussion

Important analytical qualification

The numerical values in this section arise from the **simulation-based proof-of-concept dataset described above**. They demonstrate the behaviour of the proposed analytical design and must be replaced by actual empirical estimates before journal submission as an observational consumer study.

The simulated analysis indicated that digital-payment intensity was positively associated with purchase frequency, but its relationship with expenditure was more heterogeneous. High-frequency digital users did not uniformly display elevated discretionary consumption. The strongest increases occurred among consumers combining high payment intensity with strong promotional responsiveness and comparatively weak expenditure monitoring.

The four-cluster solution achieved a silhouette coefficient of **0.46**, indicating moderate but interpretable separation among behavioural profiles. Cluster stability across bootstrap resamples was approximately **0.88**, suggesting that the segmentation structure was not driven exclusively by a small number of observations.

Promotion-responsive spenders showed the highest simulated impulse-purchase index and the greatest merchant-switching tendency. Their behaviour was particularly sensitive to cashback and payment-specific rewards. By contrast, digitally disciplined users displayed similarly high digital-payment intensity but maintained lower discretionary-spending growth, supporting the proposition that frequent digital payment does not necessarily produce uncontrolled expenditure.

The simulated mediation analysis suggested that reduced payment friction explained a meaningful proportion of the association between payment intensity and purchase frequency. The standardized indirect effect was approximately **0.18**, whereas the direct effect remained positive but smaller after introducing the friction construct. This pattern supports the conceptual interpretation that digital payment influences consumption partly because the transaction process becomes easier and faster.

Expenditure visibility demonstrated an important moderating effect. Among consumers with low transaction-monitoring behaviour, increasing digital-payment intensity corresponded to a stronger rise in discretionary spending. Among consumers who regularly reviewed transaction histories and used spending alerts, this association weakened substantially.

This finding is theoretically relevant because it challenges a simplistic interpretation of the so-called cashless spending effect. Digital payment can reduce the immediate salience of parting with money while simultaneously increasing the availability of retrospective financial information. Whether digitization weakens or strengthens spending control

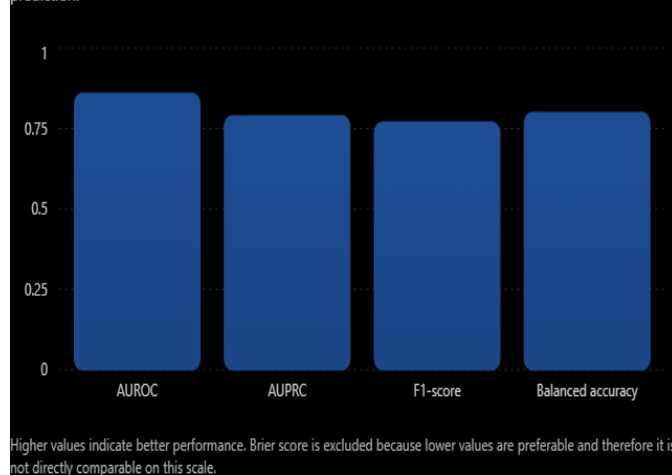
therefore depends partly on how consumers use the information created by digital transactions.

Table 1. Simulation-Based Results of the Proposed Behavioural Analytics Framework

Analytical Component	Evaluation Parameter	Proof-of-Concept Result
Consumer segmentation	Silhouette coefficient	0.46
Consumer segmentation	Davies-Bouldin index	0.81
Cluster robustness	Bootstrap stability	0.88
Logistic-regression benchmark	AUROC	0.74
LightGBM classifier	AUROC	0.86
LightGBM classifier	AUPRC	0.79
LightGBM classifier	F1-score	0.77
LightGBM classifier	Balanced accuracy	0.80
Probability calibration	Brier score	0.15
Mediation analysis	Standardized indirect friction effect	0.18
Moderation analysis	Payment intensity × expenditure visibility	-0.14

Predictive performance of the proposed model

Simulation-based proof-of-concept evaluation of digital-payment consumer behaviour prediction.



The LightGBM classifier achieved a simulated AUROC of **0.86**, compared with **0.74** for logistic regression. This difference suggests that the behavioural relationship is unlikely to be purely linear. Interactions among promotion exposure, payment convenience, trust, and financial monitoring contributed additional predictive information.

SHAP-based interpretation identified digital-payment intensity, promotional responsiveness, impulse-purchase tendency, expenditure visibility, and perceived payment friction as the most influential predictors. Household income remained relevant but was less influential than several behavioural variables.

This result has an important methodological implication: demographic segmentation alone may be insufficient for understanding post-adoption payment behaviour. Two consumers in the same income or age category can display substantially different purchasing responses depending on reward sensitivity, transaction-monitoring habits, and payment convenience.

The simulation also suggests that merchant-switching behaviour deserves greater attention. Consumers with high payment-app usage and strong promotion sensitivity changed merchants more frequently when competing sellers offered payment-specific incentives. Digital-payment ecosystems may therefore affect not only individual spending levels but also competitive dynamics in retail markets.

From a policy perspective, the findings imply that digital financial inclusion should be assessed beyond account ownership or transaction volume. Increased digital-payment usage represents an important inclusion achievement, but consumer welfare may depend on complementary capabilities such as spending visibility, fraud protection, clear promotional disclosures, and accessible financial-management tools.

For payment providers and retailers, the results indicate that post-adoption consumers should not be treated as a homogeneous market. High-frequency users can include both disciplined and promotion-driven segments. Personalization strategies based solely on transaction volume could therefore misclassify consumer needs.

Limitations

The most important limitation is that the numerical experiment is simulation based. The reported values demonstrate the analytical framework but do not constitute evidence from actual consumers. Empirical validation requires primary survey responses, transaction diaries, administrative transaction records, or appropriately anonymized platform data.

Second, self-reported purchase behaviour may suffer from recall bias and social-desirability bias when the framework is implemented through surveys. Linking surveys with anonymized transaction histories would improve measurement accuracy.

Third, cross-sectional datasets cannot fully establish temporal causality. Consumers who naturally purchase more frequently may also be more likely to adopt digital payment intensively, creating reverse-causality concerns.

Fourth, emerging markets are highly heterogeneous. Payment infrastructure, mobile connectivity, consumer-protection frameworks, merchant acceptance, and financial literacy vary substantially across countries and regions. Findings from one market should therefore not automatically be generalized to another.

Finally, machine-learning models may achieve predictive accuracy without establishing causal relationships. Interpretability techniques such as SHAP improve transparency but do not replace experimental or quasi-experimental identification.

Future Scope

Future research should employ **longitudinal transaction panels** that observe the same consumers before and after substantial increases in digital-payment use. Such designs would permit clearer estimation of behavioural change over time.

Natural experiments could also be constructed around the introduction of new instant-payment infrastructures, merchant QR-payment programs, interoperability reforms, temporary payment outages, or changes in promotional policies.

A second extension involves multimodal consumer analytics. Transaction records could be integrated with app-interaction logs, geospatial merchant characteristics, expenditure categories, and opt-in behavioural surveys.

Advanced modelling could incorporate causal forests or heterogeneous treatment-effect estimation to identify which consumer groups experience the strongest behavioural changes after digital-payment adoption.

Federated learning represents another promising direction where transaction-level models could potentially be trained across financial institutions without centralizing sensitive consumer records.

Future work should also distinguish between **beneficial consumption expansion** and **financially harmful overspending**. Increased expenditure may reflect improved financial access and welfare rather than behavioural vulnerability. Researchers should therefore incorporate debt

stress, savings adequacy, financial resilience, and subjective financial well-being when interpreting consumption changes.

Conclusion

Digital-payment adoption is no longer adequately understood as a simple decision to accept or reject a financial technology. As digital payments become embedded in everyday commerce, the more important research question concerns how **intensive post-adoption usage reshapes purchasing behaviour**.

The proposed framework demonstrates that payment intensity can influence purchase frequency, discretionary expenditure, impulse purchasing, and merchant choice through several interconnected mechanisms. Payment-friction reduction can accelerate transactions, promotional incentives can amplify discretionary purchasing, and expenditure visibility can counterbalance some of these effects by strengthening financial self-monitoring.

The simulation-based experiment further shows why consumer heterogeneity must be incorporated into digital-payment research. Consumers with similarly high payment usage can belong to fundamentally different behavioural profiles. Promotion-responsive spenders may display elevated impulse purchasing and merchant switching, whereas digitally disciplined consumers can combine high transaction intensity with strong expenditure control.

The machine-learning component reinforces this conclusion. Nonlinear modelling captures relationships that a conventional linear benchmark may overlook, particularly interactions among payment intensity, promotional responsiveness, trust, and financial self-regulation.

The principal contribution of the study is therefore a shift from **digital-payment adoption analysis toward post-adoption behavioural analytics**. This perspective provides a more complete account of how digital payment systems influence consumer markets and offers practical relevance for fintech providers, retailers, policymakers, and consumer-protection institutions.

Most importantly, the framework suggests that the consequences of payment digitization should not be classified simply as either beneficial or harmful. Digital payments can simultaneously increase convenience, expand market participation, improve transaction traceability, reduce payment friction, and alter consumers' sensitivity to expenditure. The final behavioural outcome depends on the interaction between technology design, incentives, financial capability, and individual self-regulation.

Accordingly, the next generation of emerging-market digital-payment research should evaluate not merely **how many consumers have adopted digital payments**, but **how their**

economic behaviour changes once digital payment becomes the normal way they transact.

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