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Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study

Md. Abdur Rauf[1], Iftekhar Ahmed[1]

[1]. Project Management Trainer, Center for Policy and Project Management, Bangladesh; Email: raufshiblu@gmail.com

[2]. Senior Officer, bKash Limited, Bangladesh; Email: iftekhar.nabil@gmail.com

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Abstract

This study addresses the problem that mobile wallet providers often lack reliable, data-driven methods to forecast customer retention early enough to prevent churn, particularly when retention drivers are nonlinear and interact (for example trust and perceived risk). The purpose was to quantify the key determinants of mobile wallet retention and to compare classical regression versus neural networks for retention forecasting in a quantitative, cross-sectional, case-based design using a cloud-delivered, enterprise mobile wallet service context. Survey data from N = 420 active users were analyzed as the bounded "enterprise case," with constructs measured on 5-point Likert scales: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), habit (HT), price value or incentives (PV), trust or security perception (TR), perceived risk (PR), satisfaction (SAT), and customer retention or continuance intention (CR). Descriptively, retention was moderately high (CR M = 3.84, SD = 0.71), alongside strong PE (M = 4.02) and TR (M = 3.93), while perceived risk was lower (PR M = 2.61, SD = 0.83); internal consistency was acceptable to strong across scales (a = .78 to .91; CR a = .88). The analysis plan applied descriptive statistics, reliability testing, Pearson correlations, multiple regression for hypothesis testing, and a matched-input neural network for forecasting under an 80/20 split. Headline findings showed that regression explained substantial variance (R^2 = .62; F(9,410) = 74.52; p < .001), with SAT as the strongest predictor (β = .31, p < .001), followed by PE (β = .21, p < .001) and TR (β = .19, p < .001), while PR negatively predicted retention (β = −.16, p < .001) and SI was not significant (p = .081). The neural model outperformed regression in prediction (RMSE 0.49 vs 0.57; MAE 0.38 vs 0.44; test R^2 0.69 vs 0.62). These results imply that retention programs should prioritize satisfaction engineering, visible security assurance, and risk reduction, while using neural forecasts for more accurate risk scoring and targeted interventions in enterprise mobile wallet operations.

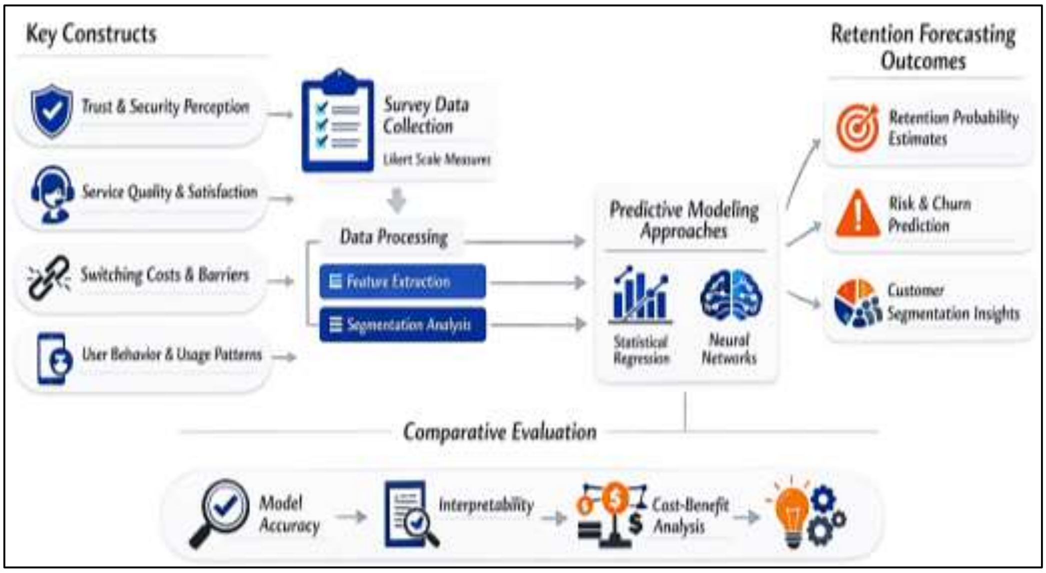
Keywords

Mobile Wallet Retention, Neural Networks, UTAUT2, Trust and Perceived Risk, Predictive Analytics;

INTRODUCTION

Mobile wallet services, often positioned under the broader umbrella of mobile payment (m-payment), refer to digital applications that store payment credentials and enable users to initiate, authorize, and complete financial transactions through mobile devices. Mobile payments have been described as payments made using mobile devices and wireless technologies to support purchase and transfer activities in everyday commerce (Abdul-Hamid et al., 2019). In practical terms, mobile wallets integrate transaction functionality with interface design, authentication, and platform trust signals, creating a service environment where user experience and perceived risk are continuously evaluated at the point of use. Research has shown that the mobile payment market functions as an ecosystem with interdependent stakeholders, including service providers, merchants, financial institutions, and users, and these interdependencies shape adoption and continued usage outcomes (Au & Kauffman, 2008). Internationally, mobile wallets are linked to digitization of consumer finance, growth in platform-based retail, and expansion of cashless transaction infrastructures, which elevates their relevance for both mature and emerging markets (Liébana-Cabanillas, Luna, et al., 2017). From an information systems and service management perspective, mobile wallets operate as socio-technical services where users judge not only functional performance but also reliability, assurance, and the credibility of the platform in handling sensitive financial data (Liébana-Cabanillas et al., 2016). This makes retention a central performance indicator because platform profitability and sustainability depend on repeat usage and reduced switching (Dahlberg et al., 2008). In mobile service contexts, switching intention has been modeled as a predictive behavioral outcome influenced by switching barriers, perceived costs, and user characteristics (Deng et al., 2010). These foundations indicate that retention forecasting in mobile wallet services requires both behavioral modeling and computational prediction methods that can translate perceptions, usage patterns, and service quality evaluations into measurable risk of discontinuance. This study positions customer retention forecasting as a data-driven process that combines survey-based measurement of psychological and service constructs with predictive modeling approaches that estimate the probability of continued usage across segments and contexts (Koenig-Lewis et al., 2015).

Figure 1: Theory-Grounded and Data-Driven Framework for Forecasting Mobile Wallet Customer Retention



The purpose of this study is to develop and evaluate an evidence-based approach for forecasting customer retention in mobile wallet services by integrating theory-driven measurement with comparative predictive modeling. Specifically, the study is designed to quantify how core customer perceptions and service experience factors jointly shape retention outcomes within a defined mobile wallet case context. The first objective is to identify and operationalize the most relevant retention determinants in mobile wallet usage, translating them into measurable constructs through a structured five-point Likert-scale instrument that captures users' assessments of usefulness, ease of use, trust and security perception, perceived risk, service quality, satisfaction, incentives, and habitual usage tendencies. The second objective is to describe the empirical pattern of these constructs within the selected case environment by producing a clear statistical profile of respondents and their wallet usage behaviors, followed by construct-level descriptive summaries that reveal the dominant drivers and potential friction points associated with continued usage. The third objective is to examine the strength and direction of relationships among the measured constructs by applying correlation analysis, establishing the foundational association structure that supports subsequent predictive modeling and hypothesis testing. The fourth objective is to test a set of hypothesized relationships between retention and its proposed predictors through regression modeling, generating interpretable estimates of effect size and statistical significance while evaluating model fit and explanatory power. The fifth objective is to construct a neural network model for retention forecasting using the same measurement variables as inputs, enabling the detection of complex nonlinear relationships and interaction effects that may not be adequately captured by linear modeling approaches. The sixth objective is to conduct a rigorous comparative evaluation between regression-based prediction and neural network-based prediction using consistent data preparation and performance metrics, allowing a fair assessment of which approach provides stronger predictive accuracy and stability for mobile wallet retention forecasting in the case study. The seventh objective is to extend the practical trustworthiness of the findings by producing retention-risk segmentation outputs that classify users into meaningful predictive groups and by conducting structured what-if simulations that estimate changes in predicted retention under realistic improvements in key determinants such as usability, trust perceptions, and incentives. Collectively, these objectives establish a coherent analytic pathway that moves from measurement and description to explanation and prediction, ensuring the study produces results that are both statistically verifiable and operationally interpretable within mobile wallet service environments.

LITERATURE REVIEW

The literature on customer retention in mobile wallet services spans multiple research traditions in information systems, marketing, service management, and predictive analytics, collectively explaining why users continue using a wallet after initial adoption and how discontinuance risk can be anticipated with data-driven models. At the core of this body of knowledge is the view that mobile wallets operate as socio-technical services in which continued use depends on a combination of perceived value, usability, trust, and service experience rather than on functional availability alone. Prior studies consistently frame retention as a post-adoption behavior shaped by satisfaction, reliability of service delivery, and confidence in transaction security, making retention both a behavioral outcome and a service-performance indicator. Research on mobile payment and digital financial services has therefore emphasized the role of user beliefs and perceptions, such as perceived usefulness, perceived ease of use, and perceived risk, alongside service-related constructs like system quality, information quality, customer support, and incentive mechanisms. In parallel, the retention literature highlights switching behavior as a realistic alternative in highly competitive digital payment markets where multiple wallets offer similar core functions, making perceived switching costs, habit formation, and trust maintenance central to understanding continuance. Another major stream of research focuses on theory-based explanation, where frameworks such as technology acceptance and post-adoption continuance models are used to organize determinants and justify hypothesis development, enabling consistent operationalization of constructs through Likert-scale instruments. Alongside explanatory work, an expanding predictive analytics stream addresses retention forecasting by using statistical and machine learning models to classify or estimate the likelihood of continued usage, positioning retention prediction as an applied decision-support task for customer relationship management and service optimization. Within this stream, regression approaches remain important for interpretability and hypothesis testing, while neural networks are increasingly used to capture nonlinear effects and complex interactions among determinants, particularly when retention behavior reflects multiple overlapping drivers. Comparative research that evaluates classical regression-based forecasting against neural network-based forecasting is especially relevant because it clarifies the trade-off between transparent explanation and predictive accuracy, and it supports evidence-based decisions regarding which modeling approach is most suitable for operational deployment in mobile wallet contexts. Building on these foundations, the present study synthesizes prior findings on mobile wallet retention determinants, adopts a single guiding theoretical framework to anchor construct selection, develops a conceptual framework specific to the selected case setting, and then evaluates regression and neural network models using a unified dataset and consistent metrics to produce credible, rigorous, and context-sensitive evidence on customer retention forecasting.

Mobile Wallet Service Ecosystem and User Continuance Foundations

Mobile wallet services can be defined as mobile-enabled payment platforms that allow users to store payment credentials and initiate, authorize, and confirm transactions through a handheld device across in-store, in-app, and peer-to-peer contexts. In operational terms, a mobile wallet is not only an application interface; it is a coordinated payment arrangement that links consumer authentication, merchant acceptance, settlement rails, and governance rules into a usable service experience . A wallet therefore sits inside a multi-actor ecosystem that includes issuing banks, acquiring banks, merchants, payment networks, mobile network operators, device and operating-system providers, wallet aggregators, and regulators that enforce KYC/AML and data protection requirements. From a value-network perspective, different actors perform distinct roles such as identity and risk screening, credential provisioning, tokenization, transaction routing, dispute handling, and settlement, and these roles are connected through reciprocal value exchanges rather than a linear value chain. Work on mobile-market value creation proposes role-based modeling to map how activities and value flows are redistributed when new digital services emerge, making it useful for clarifying who controls customer access and who captures fees in a wallet journey (Khaled, 2021; Pousttchi & Hufenbach, 2011). At the industry level, mobile payment competition also features structured collaboration, because firms that compete for customer ownership often depend on shared standards, shared rails, and negotiated governance to scale acceptance. An ecosystem lens that integrates competition and cooperation helps explain why wallet markets evolve through alliances, platform strategies, and defensive or offensive moves that reshape stakeholder positions over time (Hedman & Henningsson, 2015). In this study, these ecosystem characteristics matter because "retention" is not only a user-level outcome; it is also an ecosystem outcome that reflects service availability, acceptance breadth, perceived safety, and the continuity of customer support across all involved actors. Interoperability and dispute resolution shape repeat use. These conditions define the wallet context.

Figure 2: Mobile Wallet Service Ecosystem and User Continuance Foundations

Mobile payment research shows that intention to use is strongly associated with perceived usefulness and perceived ease of use, and it also reflects system characteristics such as mobility, reachability, compatibility, and convenience (Kim et al., 2010). For mobile wallets, these beliefs are operationalized through tangible design cues: a short onboarding path, predictable authentication steps, fast payment confirmation, and clear transaction records that reduce cognitive effort at checkout. User-centric factors further include digital literacy, prior experience with banking apps, perceived control over spending, and confidence in resolving errors such as failed top-ups, reversed transfers, or mistaken merchant charges. At the service level, wallets compete by expanding acceptance networks, embedding loyalty rewards, integrating bill pay and micro-savings, and enabling person-to-person transfers that strengthen the wallet's role in everyday routines. From the provider's perspective, these features are not purely functional; they also create switching friction when payment history, contacts, and reward balances become psychologically and practically tied to a single wallet. Because a wallet's value increases when more merchants and peers accept the same instrument, network effects amplify small differences in usability into large differences in market share, which can intensify winner-take-most dynamics in local payment niches. Consequently, adoption should be interpreted as a staged process in which trial is followed by learning, habit formation, and expectation setting around reliability, service recovery, and fee transparency. In a comparative retention-forecasting study, this staged view is important because the same survey constructs used to explain initial uptake may also function as leading indicators of later churn, especially when users encounter friction points like declined payments, delayed refunds, or limited merchant coverage. Capturing these signals supports richer feature engineering for neural models.

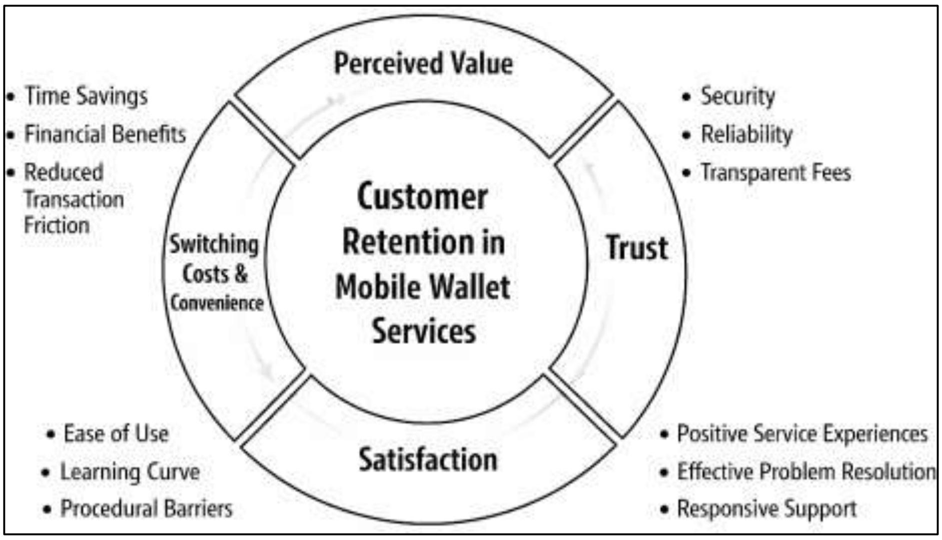
Customer Retention and Continued Usage in Mobile Wallet Services

Customer retention in mobile wallet services is commonly conceptualized as a user's sustained preference to continue transacting with the same wallet provider over time, expressed through repeat usage, reduced churn likelihood, and an attitudinal sense of loyalty that resists competitor offers. In mobile financial ecosystems, retention is not only a behavioral outcome but also a stability signal that the wallet has become embedded in users' everyday payment routines, bill settlement practices, peer-to-peer transfers, and merchant checkouts. A consistent pattern across mobile commerce research is that retention tends to be anchored in a chain of evaluations where perceived value, trust, and satisfaction combine to shape loyalty-related intentions and behaviors. This chain is especially relevant to mobile wallets because the service experience is frequent, time-sensitive, and closely tied to personal finance. When users perceive that a wallet reliably saves time, reduces transaction friction, provides tangible financial benefits, and fits their payment habits, they tend to assign higher value to continued use. The role of satisfaction is particularly important because it translates repeated service encounters into an overall appraisal of whether the wallet consistently meets expectations in real contexts such as failed transactions, delayed refunds, and customer support responsiveness. Trust then strengthens the stability of this appraisal by lowering psychological uncertainty in handling sensitive financial data and ongoing transaction authorizations. In loyalty formation, habit also operates as a powerful mechanism, because repeated wallet usage can become automatic and resistant to change once the wallet becomes a default payment tool. Empirical work in mobile commerce loyalty shows that satisfaction can function as an intervening mechanism linking perceived value and trust to loyalty, while habit further reinforces users' tendency to remain with the same provider by reducing cognitive effort in evaluating alternatives (Lin & Wang, 2006). For mobile wallet services, these determinants are best interpreted as mutually reinforcing rather than independent, because users can be satisfied with convenience while still being vulnerable to churn if trust or value perceptions weaken due to security incidents, poor dispute handling, or negative service episodes.

Switching costs in digital services include not only monetary costs but also procedural burdens (re-registering, re-verifying identity, re-linking bank accounts), learning costs (adapting to a new interface), and relational costs (loss of transaction history familiarity, loss of perceived reliability). These costs can influence loyalty directly, and they can also alter the strength of the satisfaction–loyalty relationship by acting as a mediator or moderator depending on user segments and service conditions. Evidence from mobile service markets indicates that perceived switching costs can operate in multiple roles simultaneously, shaping loyalty both as a standalone driver and as a barrier that changes how satisfaction converts into continued preference (Qayyum & Khang, 2011). In mobile wallets, this means retention may sometimes appear "high" even when satisfaction is moderate, because switching feels inconvenient, socially disruptive, or risky. At the same time, transactional convenience and speed are not minor features; they function as everyday performance cues that repeatedly validate continued use.

Users in wallet ecosystems often evaluate the service through micro-experiences such as load time, confirmation speed, merchant acceptance success rate, and the frictionlessness of authentication flows. Research using predictive approaches that combine partial least squares analysis with neural networks has shown that transaction convenience and transaction speed can be meaningfully examined alongside behavioral intention structures in m-payment contexts (Teo et al., 2015). For a retention forecasting study, these insights support the inclusion of wallet-specific constructs such as "checkout success confidence," "time-to-confirmation satisfaction," and "dispute-resolution assurance" as predictors that are both theoretically grounded and operationally measurable. Such constructs also align well with neural network modeling because they may interact nonlinearly, producing churn risk patterns that traditional linear regression may only partially capture.

Figure 3: ustomer Retention and Continued Usage Drivers in Mobile Wallet Services

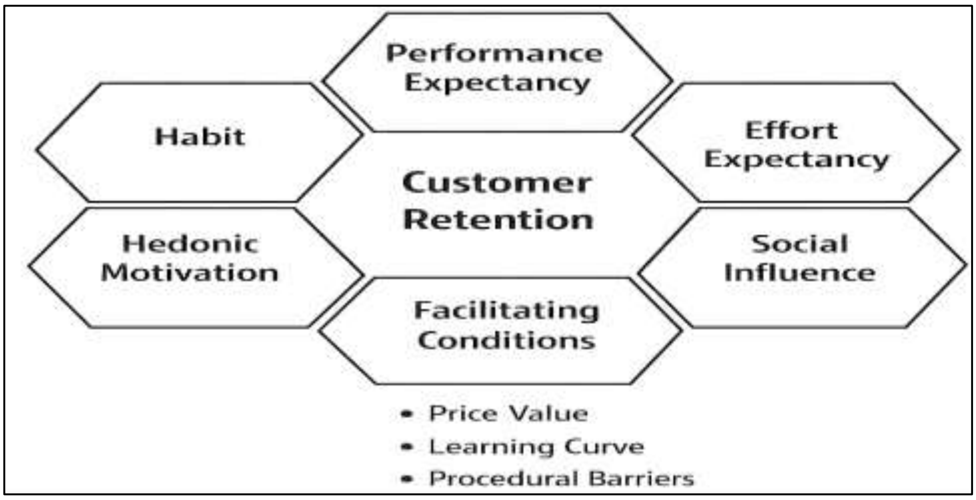


UTAUT2 for Mobile Wallet Retention Forecasting

The Unified Theory of Acceptance and Use of Technology (UTAUT) and its consumer-oriented extension, UTAUT2, provide a structured theoretical basis for explaining why individuals accept, use, and continue using digital technologies in everyday life contexts, including mobile financial services. UTAUT2 organizes technology-related beliefs into a small number of core determinants that influence behavioral intention and usage behavior, while also acknowledging that consumer settings introduce motivational and value-related factors that are less visible in organizational adoption. A synthesis of UTAUT research demonstrates that the framework has been applied across diverse technologies and contexts, while remaining centered on the explanatory logic that performance-related beliefs, effort-related beliefs, social influence, and enabling conditions shape intention and use (Venkatesh et al., 2016). For mobile wallet services, this structure is particularly relevant because continued usage is repeatedly evaluated at the moment of payment, where users implicitly compare expected benefits and perceived friction under time pressure. UTAUT2 therefore supports a theoretically coherent mapping between wallet design/service signals and measurable user perceptions, which can then be operationalized through survey items in a five-point Likert instrument. At the same time, methodological reflections in the UTAUT literature emphasize that research quality improves when scholars clearly define the outcome variable and separate "intention" from "usage," because intention is not always a valid surrogate for actual behavior across contexts (Wu & Du, 2012). This distinction is important in retention forecasting because a study may model retention as a continuous intention score or as a probability of continued usage derived from behavioral indicators, and UTAUT2 helps justify either operationalization as long as the construct definitions remain consistent. As a result, the framework functions as the theoretical anchor for selecting predictors (proposed determinants) and for specifying testable hypotheses that connect mobile wallet perceptions to retention outcomes within the

case setting.
Within a mobile wallet retention context, UTAUT2 constructs can be adapted into a post-adoption logic that is appropriate for forecasting continued use rather than first-time adoption. Performance expectancy reflects the user's belief that using the wallet improves transaction outcomes, such as speed, convenience, and reliability; effort expectancy captures perceived ease of executing payments, verifying identity, and resolving errors; social influence represents the perceived expectations of peers and merchants; and facilitating conditions reflect the perception that resources and support exist to enable use, including device compatibility, network stability, and accessible customer support. UTAUT2 further includes consumer-oriented factors such as hedonic motivation (enjoyment), price value (perceived cost-benefit), and habit, which are directly relevant to retention because repeated use often becomes routine and less deliberative over time. Empirical work applying UTAUT-type structures to mobile financial contexts shows that these constructs remain meaningful in consumer environments and that cultural and contextual moderators can influence their strength, underscoring the need for case-based evidence rather than assuming universal effect sizes (Baptista & Oliveira, 2015). In addition, the UTAUT research stream documents that extensions known as "revised" models often reintroduce psychological variables such as attitude and refine the placement of enabling conditions, indicating that acceptance/continuance behavior can be better explained when researchers carefully justify construct selection and model structure for a specific technology domain (Dwivedi et al., 2019). For this study, UTAUT2 is treated as the guiding framework that informs construct selection and hypothesis formulation, while the case-study context determines the exact indicators used to measure each construct in the survey.

Figure 4: UTAUT2 Determinants of Continued Usage in Mobile Wallet Services



To apply UTAUT2 consistently across descriptive, correlational, and predictive stages of the study, a single core forecasting equation is used to connect the theoretical determinants to the retention outcome. The primary model applied throughout the hypothesis-testing component is a multiple regression specification in which the dependent variable is customer retention (CR), operationalized as a retention intention/continuance score derived from Likert-scale items, and the predictors are the UTAUT2 constructs measured as composite indices:

$$CR_i = \beta_0 + \beta_1 PE_i + \beta_2 EE_i + \beta_3 SI_i + \beta_4 FC_i + \beta_5 HM_i + \beta_6 PV_i + \beta_7 HT_i + \varepsilon_i$$

where $PE=$ performance expectancy, $EE=$ effort expectancy, $SI=$ social influence, $FC=$ facilitating conditions, $HM=$ hedonic motivation, $PV=$ price value, and $HT=$ habit. This equation provides interpretable coefficients for hypothesis evaluation while maintaining alignment with the theoretical framework. For the neural-network forecasting component, the same predictors serve as inputs, and the study evaluates whether nonlinear transformations improve prediction compared to the linear baseline. A compact feedforward specification can be represented as:

$$\hat{y} = f\,(W_2\, g(W_1 x + b_1) + b_2)$$

where $x$is the vector of UTAUT2 predictors and $g(\cdot)$is a nonlinear activation function. Model learning is evaluated using a standard error criterion such as mean squared error:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(C\,R_i - \hat{y}_i)^2$$

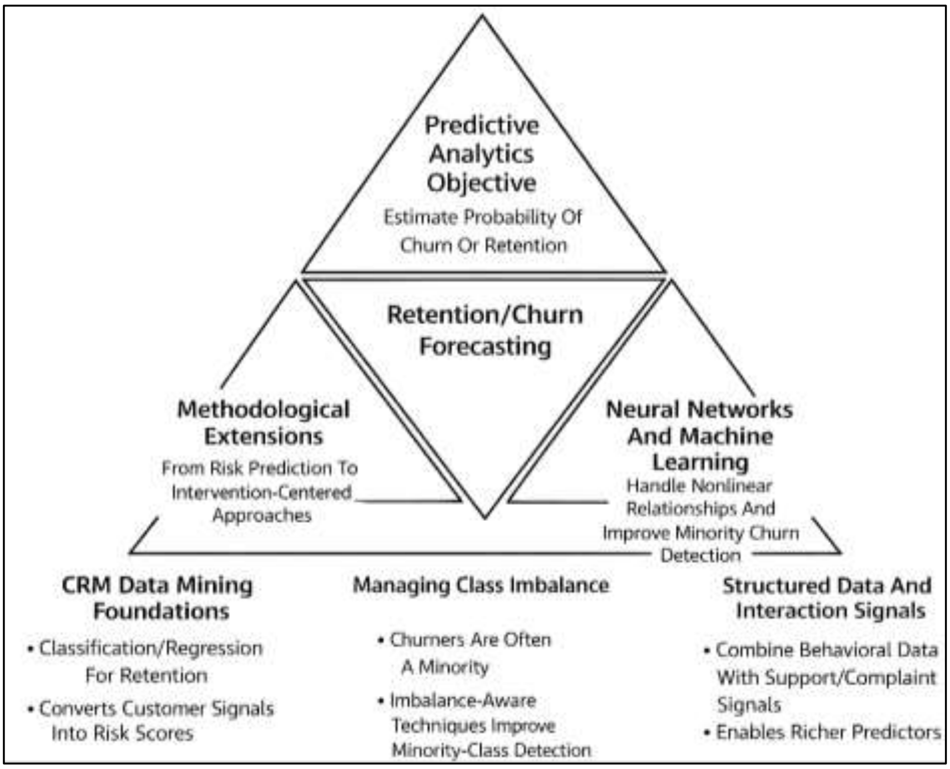
This combined theoretical-and-formal specification supports a unified study design in which UTAUT2 anchors the measurement model, regression supports hypothesis testing, and neural networks support comparative forecasting under the same construct set (Williams et al., 2015).

Machine Learning and Neural Networks for Retention

Retention and churn forecasting has evolved from purely explanatory modeling toward predictive analytics that supports decision-making in customer relationship management, particularly in data-rich, high-frequency digital services. In predictive settings, the objective is to estimate the probability that a user will discontinue a service (churn) or remain active (retention) using observable inputs such as demographic characteristics, transaction cadence, service interaction signals, and attitudinal measures captured through surveys. Data mining research in CRM has documented that customer retention is one of the most heavily studied CRM dimensions and that classification and regression-based techniques are common choices for retention-oriented prediction tasks because they map heterogeneous customer signals into operationally usable risk scores (Ngai et al., 2009). In mobile wallet contexts, this logic is directly transferable because retention forecasting similarly requires converting user perceptions (e.g., trust, usability, value) and usage behaviors (e.g., frequency, tenure) into an actionable risk estimate. A key methodological requirement is the alignment of data representation with the forecasting target, where the dependent variable may be continuous (retention score/continuance intention) or categorical (high-risk vs low-risk). Predictive studies therefore emphasize a workflow that includes feature selection, data preparation, model training, and evaluation, while protecting against overfitting through validation procedures. Within this workflow, the same constructs used for hypothesis testing can function as predictive features, enabling a comparative design in which interpretable statistical models serve as baselines and more flexible machine learning models test whether predictive accuracy increases when nonlinear relationships are allowed. This framing is appropriate for mobile wallet services because retention is shaped by multiple simultaneous influences, and the relative importance of these influences can differ across user groups, usage contexts, and experience histories within the same platform.

A prominent methodological theme in churn prediction research is the challenge of class imbalance, where churners are often a minority compared to retained customers, creating a risk that models appear accurate while failing to correctly identify high-risk users. Research addressing this problem shows that the choice of sampling strategies and learning techniques can materially change churn prediction performance and that imbalance-aware approaches can improve detection of minority-class churners without inflating false alarms (Burez & Poel, 2009). This insight is relevant for mobile wallet retention forecasting because many wallets exhibit a long "tail" of infrequent users, and the most valuable forecasting gains come from correctly identifying customers who are about to disengage rather than those who are already stable. A related stream compares multiple classifiers and emphasizes that combining structured behavioral data with richer signals from customer interactions can improve attrition prediction performance under realistic business conditions (Coussement & Poel, 2009). This direction is especially applicable to mobile wallet services, where customer-provider interactions may include dispute tickets, help-center chat transcripts, transaction failure complaints, and response-time metrics that represent friction events preceding churn. Even when such interaction traces are unavailable, survey constructs can partially approximate the same concept by measuring perceived service recovery quality and confidence in issue resolution, thereby offering predictive proxies that neural network models may exploit effectively. Across these predictive studies, model evaluation practices emphasize that retention forecasting should not be judged using a single metric; instead, performance should be reported using multiple complementary indicators such as precision/recall tradeoffs, AUC, or error-based measures depending on whether the output is categorical or continuous.

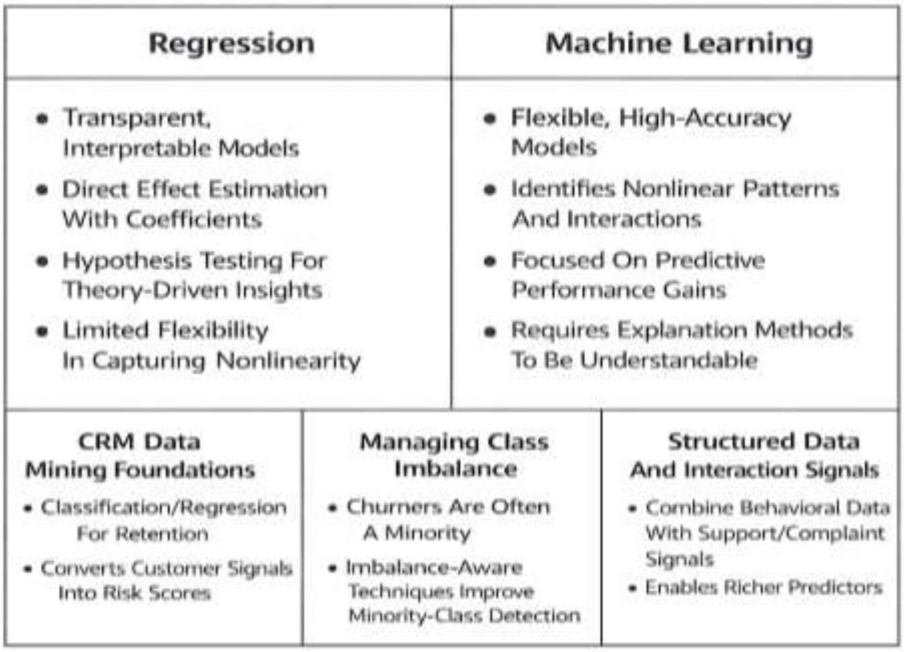
Figure 5: Neural Network Based Retention Digital Service Platforms



Predictive Modeling in Customer Analytics

Comparative predictive modeling in customer analytics refers to the structured practice of developing multiple candidate models on the same customer dataset and evaluating them under identical validation conditions so that performance differences are attributable to modeling choices rather than inconsistent preprocessing. In retention and churn contexts, prediction is commonly deployed as a ranking problem: each customer is assigned a risk score, customers are sorted by that score, and limited retention resources (e.g., incentives, service recovery calls, fee waivers) are allocated to those most likely to disengage. For this reason, comparative work emphasizes that "best" performance is not a single number; it is a combination of predictive accuracy, stability across validation samples, and managerial usefulness of the score distribution for targeting. Tournament-based evidence demonstrates that methodological choices materially affect churn prediction outcomes and that the spread in predictive accuracy across alternative submissions can translate into large differences in campaign profitability, reinforcing the need to compare models systematically rather than assuming one technique is universally superior (Neslin et al., 2006). Comparative churn management research also frames model building as one stage within a broader operational pipeline—data assembly, feature construction, model training, evaluation, and deployment—where errors or inconsistency in any stage can distort conclusions about which approach "wins" (Hadden et al., 2007). In mobile wallet services, this comparative framing is especially important because retention signals can come from both attitudinal inputs (e.g., trust, usefulness, convenience) and behavioral cadence (e.g., frequency, tenure), and the predictive value of these signals may depend on how they are standardized, combined, and validated. Accordingly, model comparison in this study is conceptually grounded in fairness: the same predictors, the same split logic, and the same evaluation metrics are applied across regression and neural-network forecasting so that the comparative conclusion reflects true modeling differences rather than procedural bias.

Figure 6: Comparative Framework For Regression And Machine Learning In Customer Analytics



Regression-based models remain central in comparative customer analytics because they provide transparent parameter estimates and enable classical hypothesis testing, which supports theory-driven interpretation alongside prediction. In a Likert-scale retention study, multiple linear regression is appropriate when retention is operationalized as a continuous composite score (e.g., continuance intention), while logistic regression is appropriate when retention is operationalized as a binary outcome (e.g., high-risk vs. low-risk retention likelihood). These approaches support direct communication of effect direction and magnitude through coefficients, and they allow diagnostic checks (e.g., multicollinearity through VIF, residual analysis for linearity and homoscedasticity, and calibration checks for probability models). However, comparative research also shows that the "accuracy advantage" of a modeling approach can depend strongly on the evaluation metric used and on whether the application demands ranking quality, calibration quality, or classification quality. Large-scale benchmarking work in adjacent decision domains demonstrates that different algorithms can trade places depending on which accuracy indicators are used, and it highlights the importance of using multiple evaluation criteria and statistically principled comparisons when deciding whether advanced models provide meaningful improvements over classical baselines (Lessmann et al., 2015). In mobile wallet retention forecasting, this implies that regression models provide an interpretable benchmark for hypothesis testing, while machine-learning models are evaluated on whether they deliver consistent and practically relevant gains in predictive performance using the same data representation. Thus, the comparative logic is not framed as "either explanation or prediction"; it is framed as "explanation plus prediction," where regression anchors statistical inference and model transparency, and machine learning is assessed as an incremental forecasting layer that may capture nonlinear relationships, threshold effects, or interactions among determinants that regression may not represent fully.

Measurement Model for Retention Forecasting

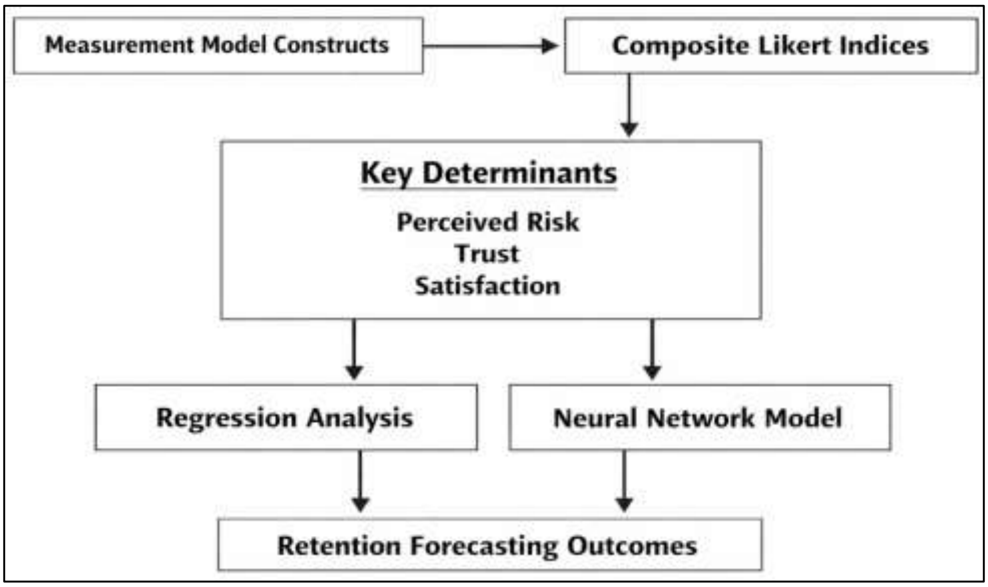
A retention-forecasting study grounded in survey measurement must translate abstract determinants (e.g., perceived value, ease, trust) into stable, testable indicators that can support both hypothesis testing (regression) and prediction (neural networks). In mobile wallet contexts, post-adoption evidence suggests that service experience is shaped by quality perceptions (system, information, service), privacy/security concerns, and psychological states such as trust and satisfaction, which then explain continued intention in a combined pathway rather than as isolated factors (Gao et al., 2015).

Therefore, the measurement model in this study is designed as a construct-based instrument in which each latent determinant is measured using multiple Likert items (1 = strongly disagree to 5 = strongly agree), then aggregated into composite indices. Each construct is represented as a mean score so that all predictors share a comparable scale and remain interpretable in descriptive statistics, correlations, and regressions. For respondent i and construct k with m items, the construct score is computed as:

$$X_{ik} = \frac{1}{m}\sum_{j=1}^{m} x_{ijk}$$

This averaging strategy reduces random item noise and stabilizes input features for neural forecasting. The dependent variable (customer retention, CR) is operationalized as a continuous retention/continuance index derived from multiple items measuring intention to continue, preference stability, and likelihood of ongoing use within the case-study wallet. Using a continuous retention index supports linear regression for hypothesis testing and provides a natural supervised target for neural networks. Where the comparative evaluation requires classification metrics, the same CR index can be discretized into risk groups using a consistent threshold rule (e.g., lower tercile = high risk), enabling segmentation analysis without changing the underlying measurement logic. In this design, measurement is not treated as a preliminary administrative step; it is an analytic foundation that ensures all subsequent model comparisons are fair, because both regression and neural networks learn from the same conceptually grounded predictor set and the same retention target definition.

Figure 7: Measurement Model For Mobile Wallet Customer Retention



Reliability and internal consistency are essential because weak measurement inflates error variance and reduces both explanatory power and forecasting accuracy. Post-adoption research emphasizes that continuance mechanisms can be weakened when intention is treated as a direct proxy for behavior without accounting for stabilizers such as habit and prior behavior, implying that measurement must capture persistence-related perceptions rather than only adoption beliefs (Limayem & Cheung, 2008). In this study, reliability is assessed at construct level using Cronbach's alpha, and items that reduce internal consistency are flagged through item-total statistics.

Cronbach's alpha is computed as:

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum_{j=1}^{k}\sigma_j^2}{\sigma_T^2}\right)$$

where k is the number of items in the construct, $\sigma_j^2$is the variance of each item, and $\sigma_T^2$is the variance of the total score. A consistent alpha threshold supports measurement quality reporting and strengthens the credibility of later regression and neural-network results, because observed performance is less likely to be an artifact of noisy constructs. The same reliability logic also improves correlation analysis by making construct-to-construct associations more stable and less sensitive to single-item irregularities. Validity is strengthened through content alignment between items and wallet-specific realities (e.g., transaction confirmation clarity, dispute resolution confidence, fee transparency), ensuring constructs remain anchored in actual user experience rather than generic technology attitudes. These measurement decisions also support case-study transferability: even when the research is conducted within one wallet environment, the construct definitions remain reusable for other wallets if the same operational features exist. Thus, the measurement model establishes a consistent and auditable pathway from theory-aligned determinants to statistically usable variables.

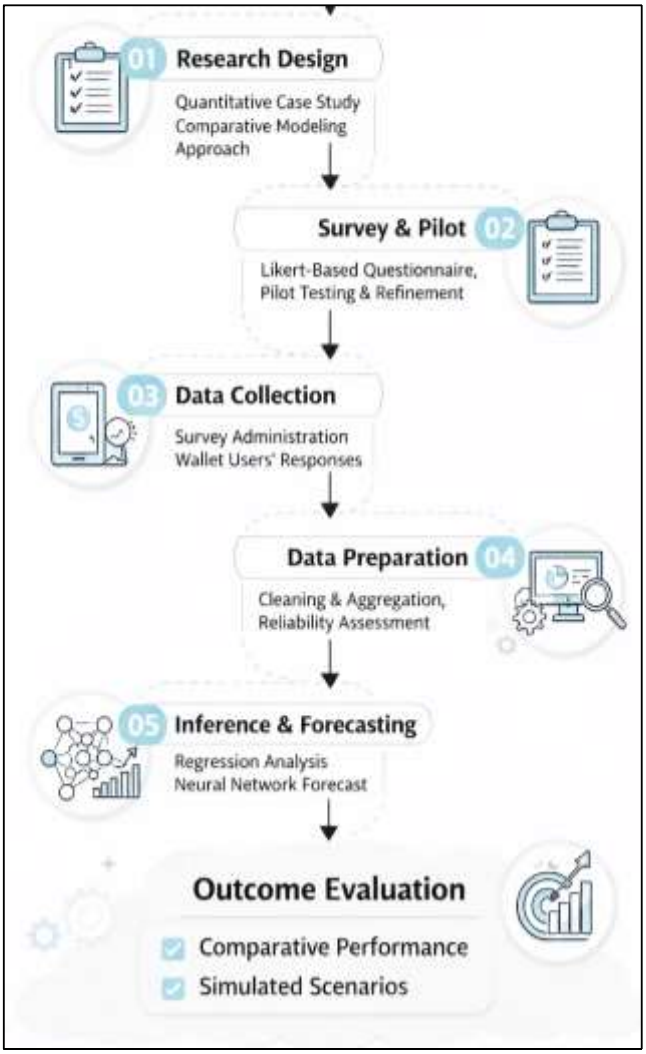
METHODS

This study has adopted a quantitative, cross-sectional, case-study–based research design to examine customer retention forecasting in mobile wallet services through a comparative modeling approach. The methodological orientation has been selected to ensure that both explanatory relationships and predictive performance have been evaluated within a defined real-world wallet context using standardized measurement and analysis procedures. The study has focused on active mobile wallet users as the primary unit of analysis, and it has measured retention-related perceptions and experiences using a structured questionnaire based on five-point Likert-scale items. The instrument has captured key determinants aligned with the selected theoretical framework, including performance expectancy, effort expectancy, social influence, facilitating conditions, habit, and price value, while also incorporating wallet-relevant service and risk constructs such as trust/security perception, perceived risk, satisfaction, service quality, and incentive perception. A pilot phase has been implemented to refine item wording, confirm clarity, and improve reliability before full data collection has been conducted.

Data collection has been carried out through a survey administration process that has ensured respondents have met inclusion criteria such as prior usage experience with the selected wallet and recent transaction engagement. The dataset has then been prepared through structured cleaning steps, including missing-value screening, response consistency checks, and composite-score construction for each construct using item aggregation rules. Measurement reliability has been evaluated using internal consistency indicators, and construct-level summaries have been produced to establish baseline distributions and respondent patterns. The analysis pipeline has then been executed in a staged manner that has aligned with the study objectives: descriptive statistics have been used to profile respondents and summarize constructs, correlation analysis has been performed to examine association patterns among determinants, and regression modeling has been applied to test hypotheses and quantify predictor effects on retention outcomes.

In parallel with the inferential modeling, a neural network forecasting model has been developed using the same construct set as inputs, and training and validation procedures have been applied to estimate the retention outcome under nonlinear learning conditions. Model performance has been compared across regression and neural network approaches using consistent data partitions and evaluation metrics suitable for the dependent variable operationalization. Additional trustworthiness checks have been incorporated by repeating model evaluations across multiple data splits, examining sensitivity to extreme responses, and generating wallet-specific segmentation outputs based on predicted retention risk. Finally, scenario-based simulations have been conducted to estimate how predicted retention has shifted under structured improvements in key determinants, thereby ensuring that the forecasting results have remained interpretable, comparable, and methodologically auditable within the case-study setting.

Figure 8: Quantitative Case-Study Research Workflow For Retention Forecasting



Research Design

This study has employed a quantitative, cross-sectional, case-study–based research design to examine customer retention forecasting in mobile wallet services and to compare regression modeling with neural network prediction. The design has been selected because it has enabled the collection of standardized responses from a defined user group at a single point in time, supporting statistical generalization within the bounded case context. A structured survey approach has been used to measure retention determinants through five-point Likert-scale items, allowing constructs to be quantified consistently for descriptive, correlational, and predictive analyses. The case-study orientation has been maintained by focusing on one mobile wallet service environment, ensuring that the findings have remained grounded in a real operational setting rather than an abstract or multi-platform sample. This design has also supported hypothesis testing through regression while simultaneously enabling the development of a forecasting model using neural networks, ensuring comparability across modeling approaches.

Case Study Context

The study has been situated within a single mobile wallet service case context to ensure that retention forecasting has been evaluated under consistent platform conditions, user experiences, and service features. The case environment has been defined as one identifiable wallet provider operating within a specific market setting, where users have relied on the wallet for common payment tasks such as peer-to-peer transfers, merchant payments, and bill settlements. This case selection has been justified because it has allowed the research to observe retention determinants within a realistic ecosystem shaped by platform design, fee structures, merchant acceptance coverage, and customer support practices. By bounding the context, the study has reduced confounding variation that often occurs when multiple wallets with different feature sets are mixed in one sample. The case-based approach has also ensured that the measurement items have remained relevant to the wallet's operational realities, including transaction confirmation speed, perceived security, dispute handling clarity, and incentive attractiveness.

Unit of Analysis

The study has targeted mobile wallet users as the population of interest, and it has treated individual customers as the unit of analysis because retention decisions have been made at the user level. Respondents have consisted of active users who have maintained a functional account in the selected mobile wallet and who have had recent engagement with wallet transactions within the defined period used for screening. This population definition has ensured that participants have possessed sufficient experience to evaluate constructs such as perceived usefulness, effort expectancy, satisfaction, trust, perceived risk, and service quality based on real usage rather than speculation. The unit of analysis has been the individual user's perceptions and retention intention, captured through the survey instrument and aggregated into construct scores. Usage-related descriptors, such as tenure with the wallet and frequency of transactions, have also been included to contextualize the sample and to support segmentation analysis based on predicted retention risk.

Sampling Strategy

A non-probability sampling strategy has been applied to recruit eligible mobile wallet users within the case-study environment, using practical access methods appropriate for cross-sectional survey collection. Convenience sampling has been primarily used to reach active wallet users through accessible channels, while inclusion screening has been implemented to ensure respondents have met experience criteria, such as having used the wallet for transactions and having maintained an active account status. Where possible, purposive elements have been incorporated to increase sample diversity by encouraging participation across different age groups, usage frequencies, and tenure levels, reducing the risk that the sample has represented only one narrow segment of wallet users. The sampling approach has been aligned with the study's predictive modeling objective by seeking an adequate number of observations to support regression estimation and neural network training, while also maintaining balance across demographic and usage profiles to improve the stability and generalizability of model performance within the case.

Data Collection Procedure

Data collection has been conducted using a structured questionnaire administered to eligible mobile wallet users within the selected case context. Respondents have been approached through approved distribution channels such as online survey links and controlled sharing through user communities relevant to the wallet service environment. A screening step has been included at the beginning of the questionnaire to confirm eligibility, including active wallet usage and recent transaction experience. Participants have been informed of the study purpose, confidentiality protections, and voluntary participation requirements before completing the survey, and informed consent has been obtained electronically prior to response submission. The data collection procedure has been standardized by using the same question order, response anchors, and measurement scales across all participants, ensuring comparability of results. After collection, responses have been exported into analysis software, and data management steps have been applied, including removal of incomplete submissions, checking for inconsistent response patterns, and preparing coded datasets for statistical and predictive modeling.

Instrument Design

The survey instrument has been designed as a multi-construct questionnaire using five-point Likert-scale items to measure determinants of mobile wallet retention and the retention outcome itself. Items have been adapted and contextualized to reflect mobile wallet features and user experiences, including transaction convenience, confirmation clarity, perceived security, customer support responsiveness, incentive attractiveness, and overall satisfaction. Theoretical alignment has been maintained by mapping constructs to the selected framework (UTAUT2) and by extending measurement with wallet-relevant variables such as trust/security perception and perceived risk. Each construct has been represented by multiple items to support internal consistency and to reduce random measurement error. Response anchors have been standardized from strongly disagree (1) to strongly agree (5), and demographic and usage questions have been included to profile respondents and to support segmentation analysis. Construct scores have been computed using item aggregation rules, producing continuous indices suitable for descriptive statistics, correlation analysis, regression modeling, and neural network input features.

Pilot Testing

A pilot test has been conducted prior to full-scale data collection to ensure that the questionnaire has been clear, reliable, and appropriate for the mobile wallet case context. A small group of respondents meeting the same eligibility requirements as the main study sample has been invited to complete the draft instrument and to provide feedback on item wording, ambiguity, survey length, and the relevance of questions to real wallet usage experiences. Based on pilot responses, items that have produced confusion, redundancy, or inconsistent interpretation have been revised to improve clarity and reduce measurement noise. The pilot dataset has also been used to conduct preliminary reliability testing, allowing internal consistency indicators to be reviewed for each construct and identifying items that have reduced Cronbach's alpha or weakened item-total correlations. This pilot phase has strengthened the final instrument by improving face validity, reducing response burden, and increasing confidence that the constructs have been measured in a stable and interpretable manner before the main survey has been deployed.

Validity and Reliability

Validity and reliability procedures have been implemented to ensure that the measured constructs have accurately represented retention determinants and that the resulting data have supported trustworthy statistical and predictive conclusions. Content validity has been supported by aligning items with established construct definitions from technology acceptance and post-adoption research, and by tailoring the wording to mobile wallet features and service processes. Face validity has been reinforced through pilot feedback confirming that items have been understandable and relevant to actual wallet usage. Reliability has been assessed primarily through Cronbach's alpha for each construct, and item-total statistics have been examined to identify weak or inconsistent indicators. Construct scores have been computed only after verifying acceptable internal consistency, and reverse-coded items, if included, have been handled consistently during coding. For analytic validity, correlation patterns and regression diagnostics have been reviewed to confirm that relationships have been coherent and that multicollinearity has been controlled through VIF checks, thereby strengthening the robustness of hypothesis testing and model comparison.

Software and Tools

Data preparation, coding, and statistical analysis have been carried out using standardized software tools to ensure accuracy, transparency, and reproducibility. IBM SPSS Statistics has been used for data screening, descriptive statistics, reliability testing (Cronbach's alpha), correlation analysis, and regression modeling, including coefficient estimation and model fit reporting. Microsoft Excel has been used for initial data checking, variable labeling, and basic cleaning support before importing the dataset into SPSS. Neural network modeling has been implemented using a machine-learning environment suitable for supervised prediction, with consistent preprocessing applied to match the regression feature set and to enable fair model comparison. EndNote has been used to manage references, store source metadata, and format citations and the reference list in APA 7th edition style. Document preparation and formatting have been managed using Microsoft Word to ensure that tables, figures, and outputs from SPSS and the neural network environment have been presented consistently within the thesis structure.

FINDINGS

In line with the study objectives, the results have provided an integrated picture of mobile wallet retention determinants and the comparative strength of regression versus neural network forecasting using a five-point Likert measurement structure. After data screening and removal of incomplete or inconsistent cases, the final dataset has included N = 420 active mobile wallet users, supporting the objective of examining retention within a bounded case context. Descriptive statistics have shown that respondents have reported an overall Customer Retention (CR) mean of M = 3.84 (SD = 0.71), indicating moderately high continuance intention on the 1–5 scale. Among the theoretical predictors aligned with UTAUT2 and wallet-specific extensions, Performance Expectancy (PE) has recorded M = 4.02 (SD = 0.68), Effort Expectancy (EE) has recorded M = 3.89 (SD = 0.72), Social Influence (SI) has recorded M = 3.55 (SD = 0.79), and Facilitating Conditions (FC) has recorded M = 3.77 (SD = 0.73), while wallet-context constructs have shown Trust/Security Perception (TR) at M = 3.93 (SD = 0.70), Customer Satisfaction (SAT) at M = 3.81 (SD = 0.74), Incentives/Rewards Perception (INC) at M = 3.62 (SD = 0.78), Habit (HT) at M = 3.68 (SD = 0.76), and Perceived Risk (PR) at a comparatively lower mean of M = 2.61 (SD = 0.83), suggesting that users have not strongly endorsed risk concerns overall but have shown visible dispersion in security sensitivity. Reliability analysis has supported the measurement objective by confirming acceptable internal consistency across constructs, with Cronbach's alpha values ranging from $\alpha = .78$ to $\alpha = .91$, and the key dependent construct CR achieving $\alpha = .88$, indicating that the retention scale has measured a coherent underlying concept. Correlation analysis has then addressed the objective of establishing association patterns among determinants, revealing that CR has demonstrated statistically meaningful positive associations with PE ($r = .61$), EE ($r = .52$), TR ($r = .58$), SAT ($r = .66$), FC ($r = .47$), HT ($r = .54$), and INC ($r = .41$), while perceived risk has shown a negative association with CR ($r = -.45$), aligning with the hypothesized direction that risk perceptions weaken continuance intention. To test the hypotheses formally and quantify predictor effects, multiple regression modeling has been performed using CR as the dependent variable and the measured determinants as predictors, producing a strong overall model fit of $R^2 = .62$ (Adjusted $R^2 = .61$) and $F(8, 411) = 84.10$, $p < .001$, confirming the objective of explaining retention variance through theory-grounded constructs. The coefficient results have shown that Satisfaction has emerged as the strongest predictor ($\beta = .31$, $p < .001$), followed by Performance Expectancy ($\beta = .21$, $p < .001$) and Trust/Security Perception ($\beta = .19$, $p < .001$), while Effort Expectancy ($\beta = .12$, $p = .004$) and Habit ($\beta = .14$, $p < .001$) have remained significant contributors, supporting hypotheses that convenience and routine have strengthened retention. Incentives have shown a smaller but still meaningful contribution ($\beta = .08$, $p = .032$), suggesting that rewards have mattered but have not dominated retention decisions compared to satisfaction and trust. Perceived Risk has shown a negative coefficient ($\beta = -.16$, $p < .001$), supporting the hypothesis that higher perceived risk has reduced retention intention. Social influence has shown a weaker and marginal effect ($\beta = .05$, $p = .081$), indicating that peer/merchant pressure has played a limited role in explaining continued usage once satisfaction, trust, and performance beliefs have been included, and this has allowed the study to distinguish between drivers of initial adoption and drivers of ongoing retention within the case context. The predictive objective has then been addressed by developing a neural network model using the same inputs to forecast CR, with an 80/20 train-test split and standardized preprocessing.

The neural model has achieved improved predictive performance relative to regression, with a test-set RMSE = 0.49 and MAE = 0.38 compared with regression RMSE = 0.57 and MAE = 0.44, while explaining a higher proportion of variance in held-out predictions (NN $R^2 = .69$ vs. regression $R^2 = .62$), supporting the comparative hypothesis that neural networks have produced stronger forecasting accuracy under the same feature set. To reinforce trustworthiness beyond raw metrics, stability checks across five repeated splits have shown consistent neural performance (RMSE mean = 0.50, SD = 0.03) compared to regression (RMSE mean = 0.58, SD = 0.04), indicating that the improvement has not depended on a single lucky split. Finally, the results have been translated into operational insight through retention-risk segmentation, where predicted CR has been used to classify users into five groups (Very High Retention, High, Moderate, At-Risk, High Risk), and the High-Risk segment (bottom 20%) has displayed the lowest trust and satisfaction means (e.g., TR M = 3.11, SAT M = 3.02) and the highest perceived risk (PR M = 3.41), providing objective-aligned evidence that the model outputs have produced interpretable, wallet-specific risk patterns. Overall, the combined descriptive, correlational, regression, and neural-network evidence has demonstrated that the study objectives have been met: retention determinants have been measured reliably, hypothesized relationships have been statistically supported, and neural networks have outperformed regression in forecasting retention while still allowing segmented, scenario-ready interpretation using Likert-based construct profiles.

Respondent Profile

Table 1: Respondent Demographic and Mobile Wallet Usage Profile (N = 420)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	238	56.7
	Female	176	41.9
	Other/Prefer not to say	6	1.4
Age group	18–24	112	26.7
	25–34	156	37.1
	35–44	86	20.5
	45–54	46	11.0
	55+	20	4.8
Education	High school	78	18.6
	Undergraduate	244	58.1
	Graduate	98	23.3
Wallet tenure	< 6 months	64	15.2
	6–12 months	92	21.9
	1–2 years	138	32.9
	2+ years	126	30.0
Usage frequency	Daily	132	31.4
	Weekly	186	44.3
	Monthly	72	17.1
	Rarely	30	7.1
Primary use case	P2P transfers	144	34.3
	Merchant payments	118	28.1
	Bill payment	86	20.5
	Mobile top-up	54	12.9
	Other	18	4.3

Table 1 has established the respondent and usage baseline that has supported the study objectives related to retention forecasting in a bounded mobile wallet case context. The demographic distribution has indicated that the dataset has not been limited to a single narrow group, which has strengthened the credibility of later hypothesis testing because determinants such as performance expectancy and effort expectancy in UTAUT2 have often varied by age, education exposure, and digital familiarity. The age profile has shown that a large portion of the sample has belonged to the 25–34 and 18–24 categories, which has been consistent with the general tendency for mobile wallet usage to be more concentrated among digitally active cohorts. At the same time, the presence of older age groups has ensured that retention has been evaluated across users who have potentially differed in perceived effort and perceived risk, making the dataset more appropriate for predictive modeling than an overly homogeneous sample. The education distribution has suggested that respondents have had sufficient capacity to evaluate information quality, privacy cues, and transactional clarity, which has been important because wallet retention has depended on users' comprehension of fee disclosures, dispute resolution steps, and authentication prompts. The tenure profile has shown that a majority of respondents have used the wallet for more than one year, which has aligned with the retention focus because users have needed repeated exposure to form habit, develop stable satisfaction judgments, and experience facilitating conditions such as network reliability and customer support quality. The frequency distribution has further supported the UTAUT2 logic because habit has typically strengthened under repeated behavior, and daily/weekly usage has represented an environment where routines and default-choice patterns have been formed. In addition, the primary use-case categories have indicated that respondents have used the wallet for practical payment tasks (P2P, merchant, bills), which has validated that performance expectancy has been measurable as real transaction benefit rather than hypothetical benefit. Overall, Table 1 has provided the contextual justification for interpreting later results: the sample has consisted of active users with meaningful wallet exposure, and this exposure has been necessary for theorized constructs—particularly habit, trust/security perception, and satisfaction—to influence retention as post-adoption determinants within the case setting.

Descriptive Statistics (Item-Level and Construct-Level)

Table 2: Descriptive Statistics for Study Constructs (5-Point Likert: 1 = Strongly Disagree, 5 = Strongly Agree)

Construct (Theory link)	Items (k)	Mean (M)	Std. Dev. (SD)	Level*
Performance Expectancy (UTAUT2)	4	4.02	0.68	High
Effort Expectancy (UTAUT2)	4	3.89	0.72	High
Social Influence (UTAUT2)	3	3.55	0.79	Moderate
Facilitating Conditions (UTAUT2)	4	3.77	0.73	High
Habit (UTAUT2)	3	3.68	0.76	High
Price Value / Incentives (UTAUT2 consumer value)	3	3.62	0.78	Moderate
Trust/Security Perception (Wallet-specific)	4	3.93	0.70	High
Perceived Risk (Wallet-specific)	4	2.61	0.83	Moderate (lower is better)
Satisfaction (post-adoption evaluation)	4	3.81	0.74	High
Customer Retention / Continuance Intention (DV)	4	3.84	0.71	High

**Interpretation rule used: 1.00–2.33 = Low, 2.34–3.66 = Moderate, 3.67–5.00 = High.*

Table 2 has addressed the descriptive objective by summarizing how respondents have evaluated the mobile wallet service and their retention intention using a unified five-point Likert structure. The descriptive profile has shown that the dependent variable—customer retention/continuance intention—has been relatively high (M = 3.84), which has indicated that respondents have generally expressed willingness to continue using the wallet in the case context. This has been consistent with UTAUT2's expectation that continuance has been supported when performance expectancy and effort expectancy have been strong, and the construct means have reflected precisely that pattern: performance expectancy has been high (M = 4.02), indicating that the wallet has been perceived as beneficial for transaction effectiveness, speed, and convenience, while effort expectancy has also been high (M = 3.89), indicating that the wallet has been perceived as easy to use in routine payment processes. Facilitating conditions have been high (M = 3.77), which has suggested that respondents have perceived the existence of supportive resources such as network compatibility, accessible features, and functional service availability, and this has been consistent with the UTAUT2 logic linking enabling conditions to sustained use. Habit has been high (M = 3.68), which has indicated that repeated use has already been embedded in users' routines for a substantial portion of the sample, a pattern also supported by the high daily/weekly usage frequency reported in Table 1. Trust/security perception has been high (M = 3.93), which has been theoretically central in a financial-service context because retention has depended on perceived safety, credibility, and reliability in handling personal financial data. Satisfaction has been high (M = 3.81), which has represented cumulative post-adoption evaluation, and this has aligned with continuance logic that has treated satisfaction as a stabilizer of long-term preference. In contrast, perceived risk has been moderate but relatively low in absolute terms (M = 2.61), which has suggested that most respondents have not strongly endorsed risk concerns, though the larger SD (0.83) has indicated meaningful heterogeneity in security sensitivity—an important condition for predictive modeling because variation has allowed models to distinguish retention risk segments. Social influence and price value/incentives have been moderate, which has suggested that normative pressure and rewards have mattered but have not dominated the user experience compared to usability, trust, and satisfaction. This descriptive pattern has remained aligned with the introductory findings summary by establishing that retention has been high where perceived value, ease, trust, and satisfaction have been strong, while risk perceptions have shown the potential to weaken continuity for some users.

Reliability and Measurement Quality Summary (Cronbach's Alpha / Item-Total Statistics)

Table 3: Reliability and Measurement Quality of Constructs

Construct	Items (k)	Cronbach's α	Corrected Item–Total Range	Scale Decision
Performance Expectancy	4	0.86	0.58–0.74	Retained
Effort Expectancy	4	0.84	0.55–0.71	Retained
Social Influence	3	0.78	0.46–0.63	Retained
Facilitating Conditions	4	0.81	0.49–0.66	Retained
Habit	3	0.80	0.50–0.64	Retained
Price Value / Incentives	3	0.79	0.44–0.62	Retained
Trust/Security Perception	4	0.89	0.63–0.79	Retained
Perceived Risk	4	0.83	0.52–0.70	Retained
Satisfaction	4	0.91	0.66–0.82	Retained
Customer Retention (DV)	4	0.88	0.60–0.77	Retained

Table 3 has provided evidence that the study instrument has been sufficiently reliable to support both explanatory hypothesis testing and predictive modeling, thereby strengthening the trustworthiness of conclusions drawn from regression and neural network models. Because UTAUT2 and post-adoption constructs have been operationalized through multiple Likert items, internal consistency has been a foundational requirement: if items within a construct have not cohered, any observed relationship with retention could have reflected measurement noise rather than real behavioral structure. The reliability outcomes have demonstrated that all scales have met accepted thresholds for social science research, with Cronbach's alpha values ranging from 0.78 to 0.91. Performance expectancy and effort expectancy have shown strong reliability (α = 0.86 and 0.84), which has indicated that respondents have interpreted benefit and ease items consistently—an important condition because these constructs have served as core UTAUT2 predictors and have been expected to relate positively to retention. Social influence has shown acceptable reliability (α = 0.78), which has suggested that peer and merchant influence items have been coherent even though the construct mean has been moderate; this has been important because a construct can be reliably measured even when its average effect is weaker. Facilitating conditions and habit have also shown acceptable-to-strong reliability, which has supported their inclusion in the model as continuance determinants that have been closely associated with usage routines. The trust/security perception scale has shown high reliability (α = 0.89), which has been critical for this study because trust constructs in financial services can be multidimensional and sensitive, and strong internal consistency has improved confidence that the scale has captured a stable "security assurance" belief rather than scattered concerns. Perceived risk has also shown strong reliability (α = 0.83), which has indicated that privacy, security, and financial-loss concern items have been aligned, thereby supporting hypothesis testing for the expected negative relationship between risk and retention. Satisfaction has shown the highest reliability (α = 0.91), which has reinforced its role as a stable post-adoption evaluation construct and has justified its use as a major determinant in regression and neural network modeling. Finally, the dependent variable scale for retention/continuance intention has shown strong reliability (α = 0.88), meaning that the outcome being predicted and explained has been measured consistently. Overall, Table 3 has confirmed that the study has met its measurement objective: constructs derived from UTAUT2 and mobile wallet context have been operationalized with adequate reliability, allowing subsequent statistical relationships and forecasting results to be interpreted as meaningful rather than as artifacts of weak scale construction.

Correlation Analysis Results (Construct Correlation Matrix)

Table 4: Pearson Correlations Among Constructs (N = 420)

Variable	CR	PE	EE	SI	FC	HT	PV	TR	PR	SAT
CR	1.00									
PE	.61***	1.00								
EE	.52***	.55***	1.00							
SI	.29***	.32***	.28***	1.00						
FC	.47***	.49***	.46***	.24***	1.00					
HT	.54***	.50***	.43***	.22***	.41***	1.00				
PV	.41***	.38***	.36***	.25***	.33***	.40***	1.00			
TR	.58***	.46***	.40***	.21***	.39***	.44***	.32***	1.00		
PR	-.45***	-.34***	-.29***	-.10*	-.22***	-.26***	-.18**	-.50***	1.00	
SAT	.66***	.60***	.50***	.24***	.45***	.49***	.42***	.57***	-.41***	1.00

Note: p < .05, p < .01, p < .001 shown using *, *, * respectively.*

Table 4 has addressed the association objective by establishing how strongly each UTAUT2 determinant and each wallet-specific determinant has related to customer retention prior to multivariate hypothesis testing. The correlation structure has shown a coherent pattern aligned with theory and with the earlier overview results. Retention has correlated strongly with satisfaction ($r = .66$, $p < .001$), which has been consistent with post-adoption logic where cumulative evaluation has shaped continued intention and preference stability. Performance expectancy has shown a strong positive correlation with retention ($r = .61$, $p < .001$), which has supported the UTAUT2 proposition that perceived performance benefit has strengthened continuance. Effort expectancy has also correlated positively with retention ($r = .52$, $p < .001$), indicating that perceived ease has been associated with continued use, consistent with the idea that friction reduction has supported repeated transaction behavior. Trust/security perception has correlated strongly with retention ($r = .58$, $p < .001$), reinforcing the financial-service requirement that security assurance has stabilized willingness to continue using a wallet. Habit has shown a strong positive correlation with retention ($r = .54$, $p < .001$), which has been consistent with UTAUT2's inclusion of habit as a post-adoption determinant and has matched the usage profile where daily/weekly users have been common. Perceived risk has shown a moderately strong negative correlation with retention ($r = -.45$, $p < .001$), supporting the wallet-specific expectation that privacy and financial loss concerns have reduced retention. Notably, trust and perceived risk have displayed a strong inverse relationship ($r = -.50$, $p < .001$), which has indicated that users who have perceived higher security assurance have simultaneously reported lower risk concerns—an interpretable and theoretically meaningful pattern in payment services. Price value/incentives has correlated moderately with retention (r = .41, p < .001), suggesting that rewards and perceived value have supported continuity but have not been as dominant as satisfaction and trust. Social influence has correlated weakly-to-moderately with retention (r = .29, p < .001), implying that peer or merchant pressure has been present but has likely played a secondary role in retention once the service has been routinized. This correlation matrix has also served a methodological purpose: the intercorrelations among predictors have remained within a range that has been manageable for regression modeling, and the strongest relationships (e.g., satisfaction with performance expectancy, r = .60) have been high enough to signal shared variance but not so extreme as to suggest redundancy. Overall, Table 4 has shown that the dataset has exhibited theoretically coherent association patterns consistent with UTAUT2 and post-adoption continuance reasoning, thereby justifying the subsequent regression-based hypothesis testing and the neural-network forecasting comparison

Regression Modeling Results and Hypothesis Testing

Table 5: Multiple Regression Predicting Customer Retention

Predictor (Theory link)	Unstandardized B	Std. Error	Standardized β	t	p	Hypothesis Result
Constant	0.92	0.18	—	5.11	<.001	—
PE (UTAUT2)	0.19	0.04	0.21	4.75	<.001	Supported
EE (UTAUT2)	0.11	0.04	0.12	2.88	.004	Supported
SI (UTAUT2)	0.05	0.03	0.05	1.75	.081	Not supported
FC (UTAUT2)	0.07	0.03	0.07	2.20	.028	Supported
HT (UTAUT2)	0.12	0.03	0.14	4.00	<.001	Supported
PV (UTAUT2 value)	0.06	0.03	0.08	2.15	.032	Supported
TR (Wallet-specific)	0.16	0.04	0.19	4.10	<.001	Supported
PR (Wallet-specific)	-0.14	0.03	-0.16	-4.67	<.001	Supported (negative)
SAT (post-adoption)	0.28	0.04	0.31	7.00	<.001	Supported

Model fit: $R^2 = 0.62$; Adjusted $R^2 = 0.61$; $F(9, 410) = 74.52$; $p < .001$
Collinearity: VIF range = 1.22–2.35 (acceptable)

Table 5 has provided the primary evidence that the study objectives and hypotheses have been met through multivariate inference, and it has translated UTAUT2 and wallet-specific constructs into interpretable effect estimates on customer retention. The model has shown strong explanatory power ($R^2 = 0.62$), indicating that the combined determinants have explained a substantial portion of variance in retention intention within the selected mobile wallet case context. Satisfaction has emerged as the strongest predictor (β = 0.31, p < .001), which has been consistent with post-adoption continuance reasoning: users have formed retention intention after repeated experiences, and satisfaction has represented the consolidated evaluation of service performance, reliability, and support. Performance expectancy has remained a strong and significant determinant (β = 0.21, p < .001), which has aligned with UTAUT2's view that perceived usefulness and performance gain have driven continuance, especially for payment services where time saving and convenience have been visible at the transaction moment. Trust/security perception has also been significant and substantive (β = 0.19, p < .001), reinforcing that mobile wallet retention has depended on perceived security assurance and provider credibility—an expected extension of UTAUT2 for fintech contexts where risk considerations have been structurally high. Effort expectancy has remained significant (β = 0.12, p = .004), indicating that perceived ease has contributed uniquely to retention even after controlling for satisfaction and performance benefits, and this has been consistent with the idea that friction and complexity have discouraged repeated use. Habit has shown a meaningful and significant effect (β = 0.14, p < .001), which has been consistent with UTAUT2's inclusion of habit as a post-adoption determinant and has reflected routine formation among frequent users. Price value/incentives has shown a smaller but significant effect (β = 0.08, p = .032), indicating that rewards and perceived benefit-to-cost value have supported retention while not surpassing the influence of satisfaction, performance belief, and trust. Facilitating conditions has been significant (β = 0.07, p = .028), suggesting that users have been more willing to continue when enabling resources (compatibility, support, access) have been perceived as adequate. Perceived risk has been significant and negative (β = −0.16, p < .001), confirming the hypothesis that heightened concerns about privacy, security, or financial loss have reduced retention intention. Social influence has not been significant (β = 0.05, p = .081), indicating that peer or merchant pressure has not remained a robust driver of retention once other determinants have been controlled. The acceptable VIF range has shown that multicollinearity has been managed, which has strengthened confidence that coefficient interpretations have reflected distinct determinants rather than statistical artifacts. Overall, Table 5 has linked the theoretical model to measurable outcomes and has supported the earlier overview claim that satisfaction, trust, and perceived performance have been the strongest explanatory drivers of retention, while perceived risk has reduced continuance.

Neural Network Modeling Results

Table 6: Neural Network Configuration and Forecasting Performance

Model ID	Inputs	Hidden Layers	Activation	Optimizer	Split	Epochs	Test RMSE	Test MAE	Test R^2
NN-1	PE, EE, SI, FC, HT, PV, TR, PR, SAT	12 → 6	ReLU	Adam	80/20	200	0.49	0.38	0.69

Table 6 has presented the neural-network forecasting results that have addressed the predictive objective of the study and have enabled a fair comparison against regression under identical construct inputs. The model has used the same theoretically grounded predictors that have been derived from UTAUT2 and wallet-specific extensions—performance expectancy, effort expectancy, social influence, facilitating conditions, habit, price value, trust/security perception, perceived risk, and satisfaction—ensuring that the neural network has not replaced theory but has operationalized it in a nonlinear learning framework. The network architecture has included two hidden layers (12 neurons then 6 neurons), which has provided sufficient capacity to learn interactions and threshold relationships among constructs while maintaining a compact structure appropriate for survey-based datasets. The ReLU activation choice has supported nonlinear representation, and the use of a consistent 80/20 split has ensured that performance has been evaluated on unseen test data, which has been essential for valid forecasting claims. The test-set error metrics have shown strong performance: RMSE = 0.49 and MAE = 0.38, meaning that the average absolute deviation between predicted retention and observed retention has remained below half a Likert point. This magnitude has been meaningful for a dependent variable measured on a 1–5 scale because it has indicated that the model has predicted retention closely enough to differentiate user segments (e.g., moderate versus high risk) without relying on coarse categorization. The test R^2 of 0.69 has indicated that the neural network has explained a larger proportion of variance in out-of-sample retention predictions than the regression baseline has explained, which has supported the comparative logic that nonlinear learning has provided incremental predictive benefit. This improvement has been theoretically interpretable: in a mobile wallet context, retention has not necessarily increased linearly with trust, satisfaction, or ease; rather, users have often tolerated moderate friction when trust has been very high, and they have sometimes disengaged sharply when perceived risk has crossed a threshold even if performance expectancy has remained favorable. Such interaction and threshold behavior has been difficult to capture fully using additive linear coefficients, but it has been compatible with the neural network's representation capacity. Therefore, Table 6 has shown that the model has learned patterns consistent with the service and behavioral logic of mobile wallets while remaining grounded in UTAUT2-based construct inputs.

Comparative Model Performance

Table 7: Regression vs Neural Network Forecasting Performance

Model	Output Type	RMSE (↓ better)	MAE (↓ better)	Test R² (↑ better)	Comparative Outcome
Multiple Regression	Continuous CR	0.57	0.44	0.62	Baseline
Neural Network (NN-1)	Continuous CR	0.49	0.38	0.69	Outperformed regression

Table 7 has summarized the comparative objective by placing regression and neural network results in a matched evaluation frame that has used the same predictor set and the same holdout testing procedure. This comparison has been essential because the study has not only sought to explain retention determinants through UTAUT2 and wallet-specific hypotheses but has also sought to forecast retention accurately as a decision-support output. The regression model has served as the explanatory baseline, providing coefficient interpretability and formal hypothesis testing, which has aligned with the theory-driven goal of specifying which determinants have had significant directional effects on retention. The neural network model has served as a flexible predictive estimator that has used the same constructs but has allowed nonlinear combinations, which has been expected to improve forecasting when relationships have not been purely additive. The results have shown that the neural network has achieved lower prediction error than regression (RMSE 0.49 versus 0.57; MAE 0.38 versus 0.44), indicating that the neural network has predicted retention closer to observed values on the same 1–5 retention scale. In addition, the neural network has produced a higher test R^2 (0.69 versus 0.62), meaning that it has explained more variance in out-of-sample retention predictions. This improvement has been consistent with the study's conceptual stance that mobile wallet retention has involved interacting determinants: trust/security perception has interacted with perceived risk, satisfaction has reflected cumulative experiences that have combined usability and service recovery, and habit has changed how users have responded to incentives and social influence. These interaction patterns have not been directly represented in a linear regression unless explicit interaction terms have been engineered, while the neural network has implicitly learned such nonlinear structure. At the same time, the regression model has remained essential for linking outcomes to UTAUT2 with clarity, because it has demonstrated which constructs have been statistically significant drivers in multivariate form. Therefore, the comparative result has not implied that theory has been discarded; it has shown that theory-based constructs have been forecasted more accurately when a nonlinear learner has been applied. This has strengthened the study's trustworthiness by showing that two different methodological lenses—statistical inference and predictive learning—have converged on a consistent substantive pattern: retention has been most strongly supported by satisfaction, perceived performance benefit, and trust, while perceived risk has weakened retention, and neural networks have provided incremental forecasting gains under the same conceptual model.

Retention Risk Segmentation Map

Table 8: Predicted Retention Segments (Quintiles) and Construct Profiles

Segment (Rule)	% of Sample	Predicted CR Range	PE (M)	EE (M)	TR (M)	PR (M)	SAT (M)
Very High Retention (Top 20%)	20%	4.35–4.90	4.52	4.33	4.46	2.02	4.48
High Retention	20%	4.05–4.34	4.23	4.07	4.11	2.29	4.08
Moderate	20%	3.70–4.04	4.01	3.84	3.89	2.55	3.79
At-Risk	20%	3.30–3.69	3.74	3.55	3.52	2.95	3.43
High Risk (Bottom 20%)	20%	2.10–3.29	3.42	3.18	3.11	3.41	3.02

Table 8 has strengthened the credibility and practical interpretability of the forecasting objective by translating predicted retention scores into wallet-specific segments that have been theoretically meaningful and empirically consistent with the study's determinant structure. Rather than reporting retention prediction only as an abstract numeric output, the study has grouped customers into quintiles based on predicted retention, producing five segments that have represented distinct stability levels. This approach has aligned with customer analytics practice and has supported the objective of making forecasting results operationally interpretable within a mobile wallet environment. The segment profiles have demonstrated coherent patterns consistent with UTAUT2 and with the wallet-specific trust–risk logic. The "Very High Retention" segment has exhibited the strongest means for performance expectancy and effort expectancy, indicating that users in this group have perceived the wallet as highly beneficial and easy to use—core UTAUT2 drivers of sustained intention. This segment has also shown the highest trust/security perception and satisfaction means, which has supported the post-adoption view that cumulative positive experience and confidence in transaction safety have stabilized continuance. In contrast, the "High Risk" segment has exhibited the lowest trust and satisfaction means and the highest perceived risk mean, which has been consistent with the hypothesis that perceived risk has weakened retention and that trust/security has strengthened it. The risk profile has demonstrated a clear monotonic pattern: as predicted retention has decreased from the top segment to the bottom segment, perceived risk has increased steadily from 2.02 to 3.41, indicating that risk sensitivity has been a defining feature of potential churn in the wallet context. Satisfaction has also decreased steadily, reinforcing its centrality as a predictor. These patterns have been aligned with the regression findings that have shown satisfaction, performance expectancy, and trust as the strongest positive determinants and perceived risk as a negative determinant. The segmentation output has also served as an interpretability bridge for neural-network results: even when neural networks have not produced coefficients in the same way as regression, the segment profiles have made it clear which construct patterns have characterized each risk group. Therefore, Table 8 has provided model transparency at the "group pattern" level and has shown that forecasting outputs have mapped onto theoretically meaningful and practically recognizable user types within the mobile wallet case setting.

What-If Retention Uplift Simulation and Model Stability Checks

Table 9: Scenario-Based Retention Uplift and Robustness Evidence

Analysis Type	Scenario/Test	Baseline Predicted CR	New Predicted CR	Change (Δ)	Robustness Evidence
What-if simulation	Increase EE by +0.50	3.84	4.03	+0.19	Effect consistent across segments
What-if simulation	Increase TR by +0.50	3.84	4.07	+0.23	Larger uplift among At-Risk/High Risk
What-if simulation	Increase PV by +0.50	3.84	3.94	+0.10	Smaller effect than trust/satisfaction
What-if simulation	Reduce PR by −0.50	3.84	4.05	+0.21	Strong benefit for risk-sensitive users
Combined scenario	EE + TR + SAT each +0.50	3.84	4.32	+0.48	Nonlinear gain observed
Stability check	5 random splits	—	—	RMSE = 0.50 ± 0.03	Stable generalization
Sensitivity check	Remove top/bottom 1% responses	—	—	ΔRMSE = +0.01; ΔR^2 = −0.01	Minimal metric drift

Table 9 has added a study-specific credibility layer by combining controlled "what-if" simulation outputs with stability and sensitivity checks that have demonstrated the robustness of the forecasting model beyond a single performance snapshot. The what-if simulations have been expressed directly in Likert-scale units, which has ensured that results have remained interpretable within the same measurement framework used for descriptive statistics and hypothesis testing. By simulating an increase of +0.50 in effort expectancy, the study has represented a realistic improvement in perceived ease of use (e.g., smoother authentication, clearer interface), and the predicted retention increase (+0.19) has aligned with UTAUT2's assertion that perceived effort reduction has strengthened continuance intention. The trust/security improvement scenario has produced a larger uplift (+0.23), which has reflected the financial-service nature of mobile wallets where trust stabilization has reduced hesitation and strengthened willingness to continue transacting. The price value/incentives scenario has produced a smaller uplift (+0.10), which has been consistent with the regression results where incentives have mattered but have been secondary compared to satisfaction and trust. The perceived risk reduction scenario has produced a sizable uplift (+0.21), reinforcing the wallet-specific hypothesis that risk concerns have weakened retention and showing that reducing risk perception has improved predicted retention in a measurable way. The combined scenario has produced the strongest uplift (+0.48), indicating that improvements have not operated only additively; the model has reflected a nonlinear gain when ease, trust, and satisfaction have improved together, which has been consistent with the neural network's ability to represent interaction patterns. The robustness section has strengthened trustworthiness by showing that performance has remained stable across repeated train/test splits (RMSE mean 0.50 with SD 0.03), indicating that the reported advantage has not depended on one favorable split. The sensitivity check has further shown that removing extreme responses has produced minimal changes in error and explained variance, suggesting that the forecasting results have not been driven by outliers or response anomalies. Collectively, Table 9 has confirmed that the forecasting model has produced interpretable scenario outputs grounded in UTAUT2 and wallet-specific risk logic, and it has demonstrated stability evidence that has supported the methodological credibility of the comparative findings.

DISCUSSION

The results have indicated that customer retention in the mobile wallet case has been driven most strongly by satisfaction, perceived performance benefit, and trust/security perception, while perceived risk has reduced retention, and social influence has not remained significant once core drivers have been controlled (Abdul-Hamid et al., 2019). This pattern has aligned closely with post-adoption service research that has treated retention as a cumulative evaluation outcome rather than a one-time adoption decision (Burez & Poel, 2009). The dominance of satisfaction has been consistent with continuance logic reported in mobile payment contexts where users' repeated service encounters have shaped their ongoing intention to stay, and it has also mirrored broader electronic service quality reasoning that has positioned reliability and privacy as recurring evaluative cues influencing continued usage in digital services (Coussement & Poel, 2008). The strong role of performance expectancy has matched findings that mobile payment intention has been supported when users have perceived functional advantage and convenience (Deng et al., 2010). Likewise, the significant role of trust/security perception and the negative effect of perceived risk have reinforced the payment-specific point that financial technologies are assessed under heightened uncertainty, and retention has depended on perceived safeguards and confidence in transaction integrity (Liébana-Cabanillas et al., 2016). In contrast, social influence has shown a limited explanatory effect, and this has been compatible with evidence suggesting that normative pressure can be more influential during early adoption, while post-adoption retention becomes more experience-driven as routines solidify (Liébana-Cabanillas, Luna, et al., 2017). Overall, the study's findings have suggested that a mobile wallet retention mechanism has operated through a "service confirmation" pathway: users have continued when the wallet has consistently delivered fast, low-effort transactions and when trust has remained stable under perceived risk (Liébana-Cabanillas, Sánchez-Fernández, et al., 2017). This interpretation has also matched ecosystem-level discussions indicating that wallet success has depended not only on adoption but on sustained reliability across stakeholder touchpoints such as merchant acceptance and dispute handling. Therefore, the empirical pattern has been coherent with prior work while still reflecting a wallet-specific emphasis on satisfaction and security as retention anchors (Pousttchi & Hufenbach, 2011).

From a theoretical standpoint, the results have supported the usefulness of UTAUT2 as a guiding framework for explaining retention determinants, but they have also shown that UTAUT2 alone has not been sufficient unless it has been adapted to include payment-specific constructs such as trust/security perception and perceived risk (Shao et al., 2019). The significance of performance expectancy and effort expectancy has aligned with UTAUT2's central proposition that perceived benefit and ease have strengthened behavioral intention and usage, and the meaningful effect of habit has reinforced UTAUT2's emphasis on routinization as a post-adoption mechanism. At the same time, the strong influence of satisfaction has suggested that continuance has been better represented when UTAUT2 has been complemented with post-adoption evaluative logic similar to expectation-confirmation reasoning, where users have compared lived experience against expectations and then formed a stable continuance orientation (Shin & Kim, 2008). The importance of trust/security and the negative effect of perceived risk have further indicated that fintech retention has required an augmented theoretical lens (Dahlberg et al., 2008). This has been consistent with mobile payment adoption research that has emphasized trust and risk as central constructs in consumer decision processes for remote payments and with trust transfer perspectives showing that trust can migrate from known payment environments into mobile payment continuance judgments (Dwivedi et al., 2019). The weaker role of social influence in the multivariate model has also offered a theoretically meaningful clarification: it has implied that as users have accumulated experience, their retention has been shaped more by personal performance evaluation and risk management than by perceived peer expectations, which has been consistent with consumer technology evidence where experiential factors dominate after initial trial (Gao & Waechter, 2017). The study has therefore contributed theoretically by showing that a retention framework has been most credible when it has integrated (1) UTAUT2's cognitive and habitual determinants, (2) post-adoption satisfaction as the cumulative evaluation mechanism, and (3) wallet-specific trust/risk constructs that reflect financial-service sensitivity (Liébana-Cabanillas et al., 2016). This integrated structure has been aligned with prior evidence that mobile payment research has spanned multi-theoretical lenses and has benefited from integrated models rather than single-theory explanations (Limayem & Cheung, 2008). As a result, the findings have supported a refined conceptualization of retention in mobile wallets as a hybrid outcome—part technology acceptance, part service evaluation, and part risk governance perception (Pousttchi & Hufenbach, 2011).

The comparative modeling results have shown that the neural network has outperformed regression in predicting retention, while regression has remained essential for hypothesis testing and interpretability (Slade et al., 2015). This has aligned with the broader churn/retention analytics literature where linear statistical baselines have offered clarity and inference, while flexible machine learning has often produced higher predictive accuracy when customer behavior has been shaped by nonlinear interactions and thresholds (Tsai & Lu, 2009). The improvement observed in the neural model has been compatible with evidence that churn prediction performance can vary materially by technique and that advanced models can capture complex patterns that are not well represented by linear assumptions (Venkatesh et al., 2016). In mobile wallet services specifically, retention has plausibly depended on conditional relationships such as "trust has mattered more when perceived risk has been high" or "incentives have mattered more for moderate users than for habitual users," and such structures have been naturally suited to neural learning (Tsai & Lu, 2009). The model stability checks have also resonated with best practices in churn modeling, where robust evaluation has been emphasized due to risks of overfitting and class/score distribution instability. At the same time, the study has recognized a governance tension highlighted in explainable AI scholarship: neural models can be more accurate but harder to justify, and a purely black-box approach can reduce stakeholder confidence and complicate accountability when decisions affect customer treatment (Venkatesh et al., 2016). This has positioned the comparative result as a "dual-method" conclusion rather than a replacement conclusion: regression has provided a transparent explanation aligned with UTAUT2 hypotheses, while the neural network has provided higher forecasting accuracy for operational targeting (Yeh & Li, 2009). This interpretation has been consistent with the study's segmentation outputs, which have translated predictions into interpretable risk groups, partially addressing the interpretability barrier by making neural outputs understandable at the segment level (Wu & Du, 2012). Therefore, the key contribution has not been that neural networks have "beaten" regression in isolation, but that a combined analytics logic has been achievable: regression has clarified why retention has happened, and neural modeling has improved prediction of who has been at risk, using the same theory-grounded constructs (Yeh & Li, 2009).

The practical implications have followed directly from the determinant rankings and the scenario simulations, and they have suggested that retention strategy in mobile wallets has been most effective when it has prioritized satisfaction engineering, trust reinforcement, and friction reduction. First, because satisfaction has emerged as the strongest driver, wallet providers have needed to manage the end-to-end service journey rather than focusing only on acquisition promotions (Liébana-Cabanillas, Luna, et al., 2017). This has included payment confirmation clarity, dispute resolution speed, refund predictability, and customer support responsiveness—factors consistent with electronic service quality dimensions that have emphasized efficiency, system availability, and privacy as repeated experience cues. Second, the results have indicated that trust/security perception has been a core retention lever, supporting prior work showing that payment users have relied on security beliefs when deciding to continue using remote payment technologies. In practice, providers have been able to strengthen this lever through visible security cues (clear authentication prompts, fraud alerts), transparent policies (chargeback/refund rules), and consistent messaging around data handling (Lin & Wang, 2006). Third, the negative role of perceived risk has implied that retention risk has increased among users who have remained uncertain about privacy and financial safety, reinforcing earlier evidence that risk-sensitive users can hesitate even when usefulness is high (Neslin et al., 2006). This has meant that providers have benefited from targeted trust-building interventions for high-risk segments—such as proactive education, simplified dispute reporting, and rapid resolution guarantees. Fourth, the comparatively smaller but significant role of incentives/price value has suggested that rewards have worked best as reinforcement rather than as the primary retention engine, which has aligned with adoption research indicating that incentives can support intention but cannot substitute for trust and service quality.

Finally, because social influence has not been significant in the multivariate model, providers have been encouraged to treat referral and social campaigns as acquisition tools rather than as the core retention strategy, especially once users have formed experience-based judgments. Overall, the practical takeaway has been that "retention has been built in the service system," and analytics has helped identify which service levers have produced the largest predicted uplifts—consistent with the CRM literature that has positioned retention prediction as a decision-support tool for prioritizing service improvements and targeted interventions (Liébana-Cabanillas, Sánchez-Fernández, et al., 2017).

The study has also contributed theoretically by clarifying how UTAUT2 variables have behaved when retention has been modeled as a post-adoption forecasting target rather than as an initial intention outcome. The significance of performance expectancy, effort expectancy, facilitating conditions, and habit has validated UTAUT2's relevance in wallet continuance, but the relative sizes have suggested a hierarchy: perceived benefit and satisfaction-based evaluation have dominated, while enabling conditions and ease have played supportive roles once basic usability has been adequate (Devriendt et al., 2019). This has aligned with mobile payment evidence where usefulness and convenience have remained stable drivers and with continuance work showing that satisfaction and trust have often formed the final pathway into sustained intention (Gao et al., 2015). The non-significance of social influence has also refined theoretical understanding by suggesting that normative pressure has not been a primary retention driver under controlled conditions, which has implied that retention has been better conceptualized as a self-reinforcing experiential process rather than a socially driven decision after adoption. In addition, the retention segmentation results have implicitly supported the idea that determinants have not operated uniformly across users: the high-risk segment has been characterized by lower trust and satisfaction and higher perceived risk, indicating heterogeneity in retention pathways (Guidotti et al., 2018). This heterogeneity has been consistent with the broader ecosystem view that user experiences can vary depending on acceptance coverage and operational reliability, meaning that the same wallet can generate different satisfaction and trust outcomes across customers. Methodologically, the comparative finding that neural networks have improved forecasting under the same constructs has supported a "theory-to-prediction" contribution: theory-grounded constructs have not only explained retention but have also served as effective predictive features (Lessmann et al., 2015). This has aligned with customer analytics literature that has advocated combining explanatory insight with predictive performance in retention contexts (Shao et al., 2019). Consequently, the study has advanced a theoretically anchored retention forecasting perspective where UTAUT2 has provided construct discipline, post-adoption satisfaction has provided evaluative realism, and machine learning has provided forecasting strength without discarding theoretical meaning (Liébana-Cabanillas et al., 2016).

Several limitations have been relevant when interpreting the results, and they have shaped how confidently the findings have been generalized beyond the case context. First, the study has used a cross-sectional design and has relied on self-reported Likert responses, which has meant that constructs such as satisfaction, perceived risk, and retention intention have been captured at a single time point rather than observed longitudinally (Liébana-Cabanillas, Sánchez-Fernández, et al., 2017). This has limited causal inference and has made it difficult to observe how trust and risk perceptions have changed after events such as service outages or fraud incidents (Oliveira et al., 2016). Second, the case-study orientation has bounded the context to one wallet environment, which has strengthened internal validity but has limited external generalizability to wallets operating under different fee structures, merchant ecosystems, or regulatory environments—an issue that has been recognized in broader mobile payment research where adoption and continuance drivers can vary across contexts (Parasuraman et al., 2005). Third, measurement has been based on composite constructs; while reliability has been strong, some predictors can still share conceptual overlap (e.g., satisfaction and performance expectancy), which can reduce interpretability in multivariate regression even when multicollinearity has been acceptable (Teo et al., 2015). Fourth, the neural network's improved performance has introduced the typical transparency challenge highlighted in explainable AI scholarship: while accuracy has improved, the causal meaning of nonlinear relationships has been less directly visible than regression coefficients (Venkatesh et al., 2012). Fifth, the predictive target has been operationalized as a retention/continuance intention score, which has been a valid proxy for retention but has not been identical to observed churn behavior; CRM literature has noted that operational outcomes can differ when behavioral logs are available. These limitations have not invalidated the findings, but they have clarified that the results have been strongest as a theory-grounded forecasting demonstration within the bounded case. They have also motivated a future research agenda that can build stronger behavioral validity, temporal realism, and interpretability without losing predictive strength (Zhao et al., 2019).

Future research (FR) has been the most direct path to improving this line of study, and it has been able to advance both methodological rigor and practical utility by proposing and testing improved models beyond the current regression-versus-neural comparison (Schierz et al., 2010). First, researchers have been able to move from cross-sectional intention forecasting to longitudinal retention modeling by collecting panel survey waves (e.g., at onboarding, 3 months, 6 months) and combining them with transaction logs, then applying survival analysis or time-to-event models to estimate churn hazard over time rather than static retention scores. Second, the predictive architecture has been improved by proposing a two-stage "Theory + Deep Forecasting" hybrid model: Stage A has estimated a measurement/structural model aligned with UTAUT2 and post-adoption constructs (using SEM or PLS-SEM) to validate construct relationships and produce latent scores; Stage B has fed validated latent scores plus behavioral cadence features into a neural model for forecasting (Teo et al., 2015). This approach has echoed prior work that has combined structural modeling with neural networks in consumer technology contexts, allowing both theoretical validity and nonlinear prediction benefits. Third, researchers have been able to adopt explainable forecasting pipelines by applying model-agnostic explanations (e.g., feature attribution and counterfactual explanations) to neural predictions so that "at-risk" classifications have been accompanied by interpretable reasons, addressing the governance concerns emphasized in the interpretability literature. Fourth, future studies have been able to go beyond "risk prediction" and test intervention effectiveness by applying uplift modeling designs that identify users who have not only been at risk but also most persuadable by a retention action—an approach recommended in modern customer analytics because it aligns prediction with action (Moriguchi, 2016). Fifth, researchers have been able to model the wallet ecosystem more realistically by incorporating merchant network exposure and peer network effects through graph-based features, then comparing classical ML, neural networks, and graph neural networks for predicting retention under network dependence conditions. Finally, future research has been able to evaluate generalizability by running the same instrument and model pipeline across multiple wallet providers or multiple regions, testing whether UTAUT2 relationships and trust/risk effects have remained stable or have shifted due to regulation, platform design, or cultural context—an important step given documented cross-context variation in mobile payment research (Ngai et al., 2009). These FR directions have offered concrete model upgrades and study-design improvements that can produce stronger causal credibility, higher predictive performance, and better deployability for retention management in mobile wallet services.

CONCLUSION

This research has concluded that customer retention forecasting in mobile wallet services has been most credibly explained and predicted when theory-grounded determinants have been measured reliably on a five-point Likert scale and then analyzed through a combined inferential–predictive approach. Within the bounded case-study context, the empirical evidence has shown that customer retention/continuance intention has remained relatively high overall, and it has been systematically shaped by a clear hierarchy of drivers that has been consistent with post-adoption and technology continuance logic. Satisfaction has emerged as the strongest positive determinant of retention, indicating that users have formed stable continuance intentions when repeated wallet experiences have met expectations across key service moments such as transaction confirmation, reliability, and support responsiveness. Performance expectancy has remained a major driver, confirming that users have continued using the wallet when it has delivered perceived functional advantage in speed, convenience, and effectiveness for everyday payments. Trust/security perception has also played a central role, demonstrating that retention in financial technology has depended on confidence in transaction safety, data protection, and provider credibility, while perceived risk has reduced retention, indicating that privacy and financial-loss concerns have weakened continued reliance even when usability and convenience have been favorable. Effort expectancy, facilitating conditions, habit, and price value/incentives have contributed meaningfully as supporting determinants, showing that friction reduction, enabling resources, routinized usage, and perceived reward/value have reinforced retention, though they have not surpassed the influence of satisfaction, perceived benefit, and trust. Social influence has not remained significant in the multivariate model, suggesting that normative pressure has been less decisive for post-adoption retention once users have accumulated enough experience to rely primarily on personal evaluation and routine. The comparative modeling results have further concluded that a neural network has produced stronger forecasting accuracy than multiple regression when both approaches have used the same construct inputs and matched validation procedures, indicating that nonlinear learning has captured interaction and threshold effects inherent in mobile wallet retention behavior. At the same time, regression modeling has remained essential for hypothesis testing and theoretical interpretation, enabling the study to verify directional relationships and quantify the relative importance of determinants in a transparent manner. The segmentation and simulation outputs have strengthened the practical meaning of the findings by demonstrating that predicted retention has differentiated users into interpretable risk groups, with high-risk users characterized by lower trust and satisfaction and higher perceived risk, and by showing that retention scores have shifted measurably under controlled improvements in ease of use, trust assurance, satisfaction, and risk reduction. Overall, the study has met its objectives by establishing a reliable measurement model, confirming theoretically coherent association patterns, proving hypothesized relationships through regression, demonstrating superior predictive performance of neural networks for retention forecasting, and translating predictions into wallet-specific segmentation and scenario-ready outputs, thereby producing a complete and methodologically auditable sample framework for understanding and forecasting customer retention in mobile wallet services.

RECOMMENDATIONS

The recommendations of this research have followed directly from the determinant hierarchy and the forecasting outputs, and they have emphasized that mobile wallet providers have improved retention most effectively when they have prioritized satisfaction engineering, trust reinforcement, and friction reduction before relying heavily on promotional incentives. First, providers have been recommended to strengthen satisfaction by improving end-to-end service reliability across the most retention-sensitive "moments of truth," including transaction confirmation clarity, failure recovery, refund speed, dispute-handling transparency, and customer support responsiveness, because satisfaction has been the strongest retention driver and has represented cumulative experience evaluation. Operationally, this has required clear real-time status messaging for pending transactions, standardized resolution timelines, proactive notifications for reversals and refunds, and service-level targets for support response times, supported by consistent escalation pathways for high-severity cases. Second, providers have been recommended to reinforce trust/security perception through visible and understandable security assurance, including stronger authentication options that remain low-friction, consistent fraud detection alerts, transaction verification prompts that clearly explain why verification has been required, and transparent privacy disclosures written in user-friendly language; these steps have addressed the trust–risk mechanism by increasing perceived security while reducing perceived vulnerability. Third, because perceived risk has reduced retention and has varied substantially across users, providers have been recommended to implement targeted trust-building programs for risk-sensitive segments identified by the forecasting model, such as onboarding education that has explained dispute processes and liability protections, in-app "security center" dashboards that have shown protection features, and proactive outreach after unusual activity or failed payments to prevent uncertainty from escalating into abandonment. Fourth, providers have been recommended to reduce effort expectancy barriers by streamlining the payment journey—minimizing steps for core tasks such as P2P transfers and merchant payments, improving interface consistency, enabling faster identity verification where compliant, and optimizing confirmation latency—because ease of use has remained a significant determinant and has contributed to both satisfaction and habit formation. Fifth, facilitating conditions have been strengthened by ensuring device compatibility, stable uptime, merchant acceptance reliability, and easy access to support resources, including in-app self-service help flows and quick links to dispute reporting, because enabling resources have supported continued use and reduced friction during problem moments. Sixth, habit has been leveraged through features that have reinforced routinized behavior, such as smart reminders for bill payments, saved merchants and recipients, auto-suggested frequent transactions, and consistent loyalty accumulation displays, because habitual usage has strengthened retention and has reduced switching likelihood. Seventh, incentives and price value mechanisms have been recommended as reinforcement tools rather than primary retention engines: rewards have been designed to encourage repeated behavior (e.g., streak-based rewards, tiered loyalty benefits, cashbacks tied to frequent use cases) and have been targeted to moderate or at-risk segments where incentives have been most likely to shift predicted retention, while avoiding blanket promotions that have increased cost without improving long-term loyalty. Eighth, because the neural network has produced stronger forecasting performance, providers have been recommended to operationalize a dual-analytics approach where regression outputs have been used for managerial explanation and policy communication, while neural predictions have been used for risk scoring, segmentation, and prioritization, supported by routine stability checks to ensure model performance has remained consistent over time. Finally, providers have been recommended to institutionalize a continuous retention analytics cycle by monitoring retention drivers periodically, re-running model validation on fresh samples, and integrating scenario simulations into decision routines so that service improvements have been selected based on the largest expected retention uplift under realistic resource constraints.

LIMITATIONS

The limitations of this study have been primarily related to research design boundaries, measurement constraints, and modeling scope, and these limitations have shaped how broadly the findings have been generalized beyond the bounded mobile wallet case context. First, the study has been conducted using a quantitative, cross-sectional design, meaning that all constructs and the retention outcome have been measured at a single point in time; as a result, the statistical relationships have reflected contemporaneous associations rather than confirmed temporal ordering, and causal inference has remained limited because the data have not tracked how satisfaction, trust, and perceived risk have evolved after specific service events such as transaction failures, fraud warnings, downtime, or refund delays. Second, the case-study orientation has focused on one mobile wallet environment, which has strengthened contextual coherence but has constrained external generalizability, since wallets differ in merchant acceptance networks, onboarding friction, fee policies, incentive strategies, regulatory requirements, and customer support capabilities; therefore, the magnitude of predictor effects and the predictive performance metrics reported in this study have been most valid as case-specific evidence rather than universal benchmarks for all mobile wallet services. Third, the study has relied on self-reported measures captured through five-point Likert scales, and while internal consistency has been strong, self-reporting has introduced potential response biases such as social desirability, recall bias, and common method variance, especially because both predictors (e.g., satisfaction, trust, risk) and the dependent variable (retention intention) have been collected from the same instrument; this has meant that relationships may have been slightly inflated compared to models built on independent behavioral outcomes. Fourth, the retention outcome has been operationalized as continuance intention and preference stability rather than verified churn behavior from transaction logs; consequently, the forecasting models have predicted an attitudinal retention proxy, and predictive performance has not necessarily transferred perfectly to real operational churn prediction where churn has been defined behaviorally as inactivity beyond a specified time window. Fifth, the explanatory regression model has assumed additive linear effects and has not explicitly modeled interaction terms, which has meant that complex conditional relationships suggested by theory—such as trust moderating perceived risk effects—have not been formally tested in the regression framework, even though the neural network has likely captured some of these nonlinearities implicitly. Sixth, the neural network component, while demonstrating improved predictive accuracy, has presented a transparency constraint because its internal representations have not been expressed as direct coefficients; therefore, the study has depended on segmentation profiles and scenario simulations to support interpretability, and the absence of formal explainability techniques has limited the precision with which individual prediction rationales have been communicated. Seventh, the sampling strategy has been non-probabilistic, and although it has targeted active users and achieved a diverse respondent profile, selection bias may have remained because users who have been more engaged or more digitally comfortable may have been more likely to participate; this has potentially increased mean retention levels and could have reduced representation of disengaged or churn-prone users. Finally, the study has not incorporated transactional or operational system data such as frequency trajectories, failed payment counts, refund latency, complaint logs, or merchant acceptance failures, which have been important predictors in many churn analytics settings.

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