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Trust, Security, and Nonlinear Retention Dynamics in FinTech Neobanking: An Explainable Machine Learning (XAI) Approach

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Abstract

This study examines customer retention intention in neobanking environments using a theory-informed explainable machine learning framework. Existing digital banking research typically relies on linear modelling approaches to explain retention behaviour, potentially overlooking nonlinear, value-range-dependent, and interaction-based predictive patterns. Using a publicly available survey of 305 neobank users, this study compares regularized linear models, a partial least squares structural equation modelling (PLS-SEM)-inspired benchmark, and XGBoost under repeated nested cross-validation. SHapley Additive exPlanations (SHAP)-based explainability, SHAP interaction analysis, generalized additive model (GAM) diagnostics, construct-level aggregation, and construct-sensitivity checks are used to interpret model behaviour and assess robustness. The results show that XGBoost substantially outperforms the linear benchmarks, achieving the lowest average RMSE and highest average R^2 across 100 out-of-sample test-fold estimates. Trust-related indicators provide the largest share of model-based predictive importance, followed by perceived security and switching costs. SHAP and GAM diagnostics suggest that trust and switching costs may contribute to retention intention in heterogeneous and nonlinear ways, while perceived security displays a more stable positive predictive pattern. Age-related nonlinearities appear weak and should be interpreted cautiously given the young sample profile. The analysis also suggests possible non-additive relationships between trust and perceived security. The study contributes to digital banking and FinTech research by showing how explainable machine learning can complement theory-driven retention models, identify potentially nonlinear predictive patterns, and preserve interpretability. The findings offer practical insight for trust-building, visible security assurance, and retention diagnostics in neobanking contexts.

Keywords: neobanking; customer retention; trust; perceived security; switching costs; explainable artificial intelligence; XAI

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1. Introduction

The rapid expansion of financial technology (FinTech) has fundamentally transformed the global retail financial services landscape. Among the most prominent manifestations of this transformation is the emergence of neobanks, fully digital financial institutions that operate without physical branch infrastructure and deliver services exclusively through mobile platforms and cloud-based ecosystems. Global neobank customers exceeded 140 million users worldwide in 2021 and are expected to reach 350 million users in 2026, reflecting one of the fastest adoption rates observed in modern financial services (Bhalla, 2025). Market projections suggest that the global neobanking sector will surpass USD 2 trillion in transaction value by 2030, supported by increasing digital payment penetration and declining reliance on traditional branch-based banking models (Grand View Research, 2023).

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Unlike conventional banks, neobanks operate entirely through digital interfaces, relying on mobile applications, algorithmic decision systems, and cloud-based infrastructures to deliver financial services. While this digital-first architecture enables lower operational costs, rapid onboarding, and enhanced accessibility, it simultaneously intensifies customer sensitivity to psychological and institutional risk factors. Surveys indicate that over 60% of digital banking users identify security concerns and institutional trust as primary determinants of continued platform usage, exceeding the importance of pricing or functional convenience (Mossburg et al., 2024). In the absence of face-to-face interaction, physical reassurance mechanisms, or established institutional legacy, customers must rely almost exclusively on perceived trustworthiness, platform security, and technological reliability. Consequently, customer retention in neobanking environments is shaped not merely by transactional efficiency but by complex psychological and structural mechanisms governing perceived risk and confidence (Ali et al., 2025).

Trust has long been recognized as a foundational determinant of relationship continuity in digital environments. In online financial contexts, trust reduces perceived uncertainty, mitigates perceived vulnerability, and facilitates long-term relational commitment. This role becomes particularly critical in digital-only banking ecosystems, where financial transactions involve sensitive personal and monetary information transmitted through intangible technological channels. However, trust in digital banking is unlikely to operate through simple linear increments. Behavioural decision theory suggests that individuals respond asymmetrically to perceived gains and losses in confidence. Empirical evidence from digital platform markets shows that negative trust shocks, such as perceived data breaches or service disruptions, generate disproportionately large customer attrition relative to equivalent positive improvements in service quality (Boehm et al., 2022). Accordingly, extremely low trust may sharply suppress retention, whereas high trust may disproportionately accelerate loyalty formation. Trust may therefore function as a nonlinear retention accelerator rather than a uniformly additive predictor.

Closely intertwined with trust is perceived security, defined as the belief that financial information and transactions are adequately protected against fraud, misuse, or unauthorized access. Cybersecurity concerns have become increasingly salient as digital financial adoption expands. Global financial cybercrime losses exceeded USD 10 billion annually in 2023, reinforcing consumer awareness of digital vulnerability (Federal Trade Commission, 2025). Perceived security provides institutional assurance that reduces perceived transaction risk and stabilizes user confidence in technology-mediated financial interactions. Unlike relational trust, which may exhibit asymmetric or threshold effects, security perceptions may operate more steadily by producing incremental reductions in perceived vulnerability. Importantly, trust and security are conceptually complementary constructs: trust reflects relational confidence in institutional intentions, whereas security signals technological competence and systemic reliability. It is therefore plausible that the effect of trust on retention strengthens when security perceptions are high, implying interaction-driven complementarity rather than purely additive influence.

Beyond relational and institutional drivers, switching costs represent structural constraints capable of stabilizing customer retention. In digital banking ecosystems, switching barriers arise from procedural complexity, habit formation, ecosystem integration, automated payment arrangements, and platform personalization. Industry evidence suggests that digitally integrated users linking payroll deposits, subscriptions, and investment services exhibit significantly lower churn probabilities than users employing standalone banking functions (Accenture, 2024). Unlike trust, which promotes voluntary commitment, switching costs discourage exit through behavioural inertia. Behavioural economics further suggests that switching costs may operate through threshold mechanisms, preventing churn only when perceived exit barriers exceed a meaningful level rather than generating gradual loyalty increases across all users.

Despite extensive research examining trust, security, and retention in digital finance, most empirical investigations rely on linear structural equation modelling frameworks that assume additive, symmetric, and constant marginal effects. Such approaches implicitly presume that

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incremental improvements in trust or security produce proportionally equivalent retention responses across customers. However, digital financial behaviour may inherently involve nonlinear response patterns, behavioural tipping points, and cross-construct amplification effects. For instance, high trust may fail to translate into sustained usage when security perceptions remain weak, while strong technological security alone may be insufficient in the absence of relational confidence.

The dataset used in this study was originally analysed by Puente et al. (2025), who developed a stimulus-organism-response (S-O-R) mediation model in which perceived financial security operates as the stimulus, trust functions as the organism, and customer retention and switching costs represent behavioural responses. Using PLS-SEM and bootstrapping, their study showed that perceived financial security positively affects trust and retention, while trust mediates the relationships between perceived financial security and both retention and switching costs. The present study acknowledges and complements this prior research by extending the analysis beyond conventional linear mediation frameworks. More broadly, existing neobanking and digital banking retention studies have predominantly relied on regression- and SEM-based linear approaches, which may overlook heterogeneous, nonlinear, and interaction-based predictive structures. Building on this literature, the present study examines whether neobanking retention intention contains nonlinear, value-range-dependent, and interaction-driven predictive patterns that are not directly observable from linear path coefficients alone.

To address this extension, this study uses explainable machine learning methods within the broader Explainable Artificial Intelligence (XAI) framework. Specifically, it evaluates neobanking retention intention using regularized linear benchmarks, a PLS-SEM-inspired benchmark, nonlinear gradient-boosted modelling, and SHapley Additive exPlanations (SHAP)-based explainability. This integrated approach enables out-of-sample validation while providing exploratory diagnostic insight into possible nonlinear functional relationships and interaction structures beyond traditional additive assumptions. Thus, by integrating behavioural theory with explainable predictive modelling, this study offers a cautious and methodologically extended account of how psychological, institutional, and structural forces may jointly shape retention intention within rapidly evolving FinTech-driven neobanking ecosystems.

1.1. Research Objective

This study is guided by three interrelated research objectives, each examined through a corresponding set of hypotheses developed in Section 3.

The first objective is to examine whether customer retention intention in neobanking environments is better captured by nonlinear predictive structures than by conventional linear specifications. This objective responds to an important methodological limitation in the existing literature, where retention drivers are commonly modelled as additive and constant in effect. To address this issue, the study compares the out-of-sample predictive performance of regularized linear models, a PLS-SEM-inspired benchmark, and a nonlinear XGBoost model using repeated nested cross-validation. This objective is formalised through Hypothesis 1, which predicts that the nonlinear model will achieve stronger predictive performance than linear alternatives.

The second objective is to examine the relative predictive importance and functional behaviour of the main retention determinants, namely trust, perceived security, switching costs, and demographic characteristics. Rather than focusing only on whether these variables are statistically associated with retention intention, the study investigates how their predictive contributions vary across observations and value ranges. Specifically, the study explores whether trust-related variables emerge as the strongest predictors of retention intention, whether trust exhibits nonlinear predictive behaviour, whether perceived security displays a more stable positive pattern, whether switching costs show value-range-dependent effects, and whether demographic characteristics display heterogeneous predictive variation. These issues are explored through Hypotheses 2 to 6 using SHAP-based interpretation, generalized additive model (GAM) diagnostics, and robustness analyses.

 doi:10.20944/preprints202605.1452.v1

The third objective is to examine whether trust-related and security-related perceptions jointly contribute to retention-intention prediction in neobanking environments. The theoretical argument is that trust reflects relational confidence, whereas perceived security reflects institutional and technological assurance. Accordingly, the study explores whether the predictive contribution of trust becomes stronger when perceived security is high. This objective is examined through Hypothesis 7 using SHAP interaction analysis and retention-surface interpretation. However, because some trust indicators overlap conceptually with perceived security, the interaction findings are interpreted cautiously as exploratory model-based evidence rather than causal confirmation of behavioural complementarity.

1.2. Findings, Contribution and Paper Structure

This study reports several important findings. First, the nonlinear XGBoost model consistently outperforms the linear benchmarks under repeated nested cross-validation, suggesting that retention-intention prediction in neobanking environments may involve nonlinear and interaction-based structure beyond standard additive specifications. Second, trust-related indicators emerge as the most influential contributors to model-based retention predictions, although this interpretation is qualified by conceptual overlap between trust and perceived security measures. Third, the explainable machine learning analyses reveal heterogeneous predictive patterns across trust, perceived security, switching costs, and demographic variables, including possible nonlinear and interaction-based relationships that are not fully captured by linear path-based approaches.

This research contributes to the digital banking and FinTech literature in four main ways. First, it extends the existing S-O-R/PLS-SEM literature by examining whether retention-intention prediction contains nonlinear and interaction-based patterns beyond conventional linear mediation structures. Second, it demonstrates how repeated nested cross-validation, SHAP interpretation, GAM diagnostics, construct-level benchmarking, and construct-sensitivity analysis can be integrated into a theory-informed explainable machine learning framework. Third, it provides exploratory evidence that trust-related and security-related perceptions may jointly contribute to retention-intention prediction, while also explicitly addressing conceptual overlap concerns through robustness analyses. Fourth, the study illustrates how explainable machine learning can complement theory-driven digital finance research by identifying potentially nonlinear predictive patterns while maintaining interpretability and transparency.

From a practical perspective, the findings suggest that neobanking retention may depend not only on transactional convenience but also on trust-building, visible security assurance, and ecosystem integration. More broadly, the study demonstrates how explainable predictive modelling can support customer segmentation, retention diagnostics, and theory-informed FinTech analytics while still requiring cautious interpretation regarding causality and behavioural mechanisms.

2. Literature Review

Customer retention has long been recognized as a critical determinant of firm performance in service industries (Orantes-Jiménez et al., 2017; Qiwen et al., 2026). In financial services, retention is particularly consequential due to high customer lifetime value, cross-selling opportunities, and switching frictions. In digital banking environments, retention depends not only on economic utility but also on psychological confidence in the platform (Garzaro et al., 2021; Levy, 2022; Naeem et al., 2026).

Unlike traditional banking, neobanks operate without physical branches, face-to-face interaction, or tangible reassurance mechanisms (Indra and Mohan, 2023; Bolar et al., 2026). As a result, retention decisions are heavily influenced by users' perceptions of trust, institutional reliability, and technological security. Prior research in e-commerce, fintech, and online banking consistently identifies trust and perceived risk as central determinants of continued usage intentions (Dewi and Ketut, 2020; Bergmann et al., 2026). However, most studies model these relationships using linear structural frameworks, assuming additive and symmetric effects across constructs (Alnoor et al., 2022;

 doi:10.20944/preprints202605.1452.v1

Rana et al., 2025). Yet digital user behaviour may exhibit nonlinear response patterns, threshold mechanisms, and interaction effects, particularly in contexts involving perceived financial risk (Harris, 2025; Liao et al., 2026). This suggests that retention in neobanking environments may not be fully captured by linear additive models.

This literature review explores the existing literature on the key drivers of customer retention in digital banking, with a specific focus on trust, perceived security, and switching costs. It synthesizes theoretical perspectives and empirical findings to establish a foundation for the current study's conceptual framework. The review is structured into five parts. First, it examines the role of trust as a central, and potentially nonlinear, determinant of retention in digital financial services. Second, it explores the concept of perceived security and its complementary relationship with trust. Third, it discusses switching costs as structural barriers to customer churn. Fourth, it investigates the role of Demographic Heterogeneity, particularly age, in digital adoption. Finally, it synthesizes these streams of research to identify critical gaps in the literature, particularly the reliance on linear modelling techniques, which this study aims to address.

2.1. The Centrality and Nonlinearity of Trust in Digital Finance

Trust is widely conceptualized as a multidimensional construct reflecting confidence in a partner's integrity, reliability, and competence (Mayer et al., 1995; Dikaoui, 2026). In the context of relationship marketing, trust is consistently identified as a cornerstone of long-term exchange continuity, particularly in environments characterized by uncertainty and risk (Lewin and Johnston, 1997; Morgan and Hunt, 1994; Arruda Filho et al., 2026). Trust reduces perceived vulnerability by serving as a heuristic that simplifies complex decisions and mitigates concerns about opportunistic behaviour.

In digital environments, the salience of trust is amplified. Online exchange is marked by information asymmetry and spatial separation, where physical cues and face-to-face reassurance mechanisms are absent (Sriram, 2005; Zhu and Zhang, 2026). Here, trust becomes a crucial mechanism for reducing social complexity and perceived vulnerability, enabling consumers to engage in transactions despite a lack of direct control (Gefen et al., 2003; Wusko, 2026). This dynamic is particularly pronounced in the financial services sector, where the sensitivity of monetary transactions and personal data makes trust a foundational prerequisite for engagement (Mukherjee and Nath, 2003; Junior Ladeira et al., 2026).

For neobanks, which operate entirely through digital interfaces without physical branches, this mechanism is even more critical. A customer's trust in a neobank encompasses their confidence in the institution's ability to fulfill its promises, safeguard assets, and act with integrity, thereby reducing perceived risk and encouraging continued interaction (Sirdeshmukh et al., 2002; Zhou, 2012). Prior research in e-commerce and online banking has robustly established this positive link between trust and behavioural outcomes such as loyalty, repurchase intentions, and customer retention.

However, behavioural decision theory suggests that the relationship between trust and retention may not follow a simple, linear path where each unit increase in trust produces a constant marginal gain in loyalty. Concepts from Prospect Theory (Kahneman and Tversky, 2013) imply that individuals are inherently more sensitive to losses than to equivalent gains (Abdellaoui et al., 2013; Pavleska and Jerman, 2017; Zheng et al., 2026). This loss aversion suggests a potential asymmetry in the trust-retention link: a drop from high to moderate trust (a perceived loss of confidence) could have a disproportionately larger negative impact on retention than a corresponding increase from moderate to high trust (a perceived gain) would have a positive impact. Furthermore, trust might need to reach a certain threshold before it effectively mitigates risk perceptions and fosters the level of commitment required for true loyalty (Hart and Saunders, 1997; Ostrom, 2003; Jamil et al., 2026). Below such a threshold, customers may remain perpetually wary and prone to switching, while above it, retention could accelerate. In essence, extremely low trust may trigger sharp churn responses, whereas high trust may disproportionately accelerate loyalty formation. Thus, trust may

 doi:10.20944/preprints202605.1452.v1

function as a nonlinear retention accelerator rather than a simple additive predictor. Despite this theoretical plausibility, most empirical studies in banking have modelled trust as a linear construct (See Table 1 below) with constant marginal influence, potentially overlooking these dynamic, asymmetric, and threshold-based effects. This suggests that the role of trust as a nonlinear construct is underexplored. This is a clear methodological gap.

Table 1. Prior digital finance trust studies and their modelling approach.

Study	Context	Methodology	Trust Role	Modelling Assumption
Mukherjee and Nath (2003)	Online banking	SEM	Mediator between antecedents and commitment	Linear structural paths
Casaló et al. (2007)	Online banking	SEM	Trust → commitment	Linear additive effects
Pi et al. (2012)	Online financial services	PLS-SEM	Cognitive → affective trust → adoption	Linear path coefficients
Rajaobelina et al. (2014)	Financial services	SEM	Installed trust → loyalty dimensions	Linear relationships
Yu et al. (2015)	Internet banking	PLS	Trustworthiness → trust → continuation	Linear structural paths
Rouibah et al. (2016)	Online payment systems	PLS	Trust → usage intention	Linear beta coefficients
Punyatoya (2018)	Online retail	Linear	Trust → loyalty intention	Linear regression
Mondego and Gide (2020)	Mobile payment (Australia)	PLS-SEM	Trust → adoption	Linear structural model
Sa'diyah and Soegoto (2021)	Digital payments	Multiple regression	Trust mediates security → intention	Linear mediation
Poudel et al. (2023)	E-payment	Path analysis	Trust → usage intention	Linear path model

Note: PLS- Partial Least Square, SEM-Structural Equation Modelling. '→' indicates positive relationship.

2.2. Perceived Security: Institutional Assurance and Relational Complementarity

Closely related to, yet distinct from, trust is the concept of perceived security. While trust is a relational and psychological construct reflecting confidence in a partner's intentions and integrity, perceived security is an institutional and functional construct reflecting the user's belief that a digital platform has adequate technical safeguards to protect financial data, prevent fraud, and ensure transaction integrity (Flavián and Guinalíu, 2006; Hartono et al., 2014; Wusko, 2026). In the neobanking context, where financial assets and sensitive personal data are entirely digital and remote, perceived security encompassing data protection, privacy policies, and fraud management is a primary and salient concern for customers.

The literature consistently demonstrates that perceived security plays a foundational role in shaping user evaluations of online financial services. By reducing perceptions of risk and vulnerability, security perceptions enhance overall confidence in the service provider's institutional competence (Almaiah et al., 2023; Basurto-Cedeno and Pennington-Gray, 2026). This institutional assurance has a well-documented, direct, positive influence on trust itself (Suh and Han, 2003; Chen et al., 2026b). When customers believe a bank possesses and maintains robust security measures, their relational confidence in the institution's reliability and good intentions is bolstered.

The direct effect of perceived security on retention, however, may operate through a distinct mechanism. It is often characterized as a "hygiene factor" in the tradition of Herzberg's (1966) two-factor theory. In this view, high levels of security may not actively and progressively drive loyalty or delight; instead, they establish a baseline of necessary functionality (Simon et al., 2025; Rosenbaum et al., 2025). A perceived lack of security, conversely, will almost certainly trigger negative evaluations and drive customers away (Yu and Davis, 2025). This suggests a monotonic, though perhaps satiating, influence on retention. Unlike relational trust, which may exhibit asymmetry and threshold effects, security perceptions may operate more uniformly. Improvements in perceived security from low to moderate levels may steadily reduce risk perceptions and increase confidence without the dramatic nonlinear shifts predicted for trust. Thus, security may function as a comparatively stable, monotonic driver of retention.

More importantly, a growing stream of research points to a complementary, or synergistic, relationship between trust and security (Shin, 2010; Greulich et al., 2024; Chang et al., 2025). They are not merely additive drivers that independently contribute to retention. Instead, institutional assurances (security) may provide the necessary foundation upon which relational confidence (trust) can be effectively built and translated into loyalty. A customer may hold a high degree of trust in a neobank's intentions and integrity, but if they simultaneously perceive its security infrastructure as weak or vulnerable, that relational trust may be insufficient to overcome the perceived risk of transacting. The positive disposition is undermined by the lack of institutional protection. Conversely, even the most robust and objectively secure technological measures may fail to retain a customer who fundamentally doubts the bank's honesty or reliability. This points towards a positive interaction effect, where the marginal impact of trust on retention is amplified in the presence of high perceived security, and vice versa. Despite this theoretical plausibility, the interaction between security and trust remains underexplored in empirical research, particularly within predictive models that move beyond linear and additive assumptions to test for such complementarity. As shown in Table 2, prior research overwhelmingly employs linear structural modelling approaches to examine the complementary relationship between trust and security in digital finance. Although these studies consistently demonstrate that security enhances trust and trust promotes adoption, none explicitly investigate nonlinear, threshold, or asymmetric dynamics in the trust–security relationship. This methodological uniformity suggests that important behavioural complexities may remain unobserved.

Table 2. Trust–Security Relationship in Digital Finance.

Study	Context	Model Type	Trust–Security Relationship	Modelling Structure
Ong and Lin (2015)	Internet banking	SEM	Security → Trust → Adoption	Linear structural paths
Stewart and Jürjens (2018)	FinTech adoption (Germany)	SEM	Data Security → Trust → Adoption	Linear additive paths

 doi:10.20944/preprints202605.1452.v1

Study	Context	Model Type	Trust–Security Relationship	Modelling Structure
Okello Candiya Bongomin and Ntayi (2020)	Mobile money	SEM / PLS	Trust mediates security/risk → adoption	Linear mediation
Kaur and Arora (2021)	Online banking	SEM with interaction term	Trust moderates Risk → Intention	Linear interaction within SEM
Zhang et al. (2023)	FinTech services (Pakistan)	PLS-SEM	Data Security → Trust → Adoption	Linear path coefficients
Almaiah et al. (2023)	Mobile banking	SEM	Security and Trust → Adoption	Linear structural model
Hassan et al. (2025)	Decentralized fintech	PLS-SEM	Security and Trust → Adoption	Linear cause–effect paths
Tan et al. (2025)	Mobile payments	PLS-SEM	Security → Trust → Intention	Linear additive structure
Zeng and Hu (2025)	Digital finance development	Econometric regression	Social Trust → Financial Stability	Linear regression

Note: PLS- Partial Least Square, SEM-Structural Equation Modelling. '→' indicates positive relationship.

2.3. Switching Costs and Retention Stability

In contrast to the psychological and relational drivers of trust and security, switching costs represent structural and economic constraints that bind customers to a service provider (Burnham et al., 2003; Chen et al., 2026a). Switching costs are broadly defined as the perceived effort, inconvenience, disruption, or loss that a customer associates with changing from one service provider to another (Vives, 2019; Jose et al., 2022; Bağcı, 2026). In digital financial ecosystems like neobanking, these costs are particularly multifaceted. They arise from procedural burdens, such as the time and administrative effort required to close an existing account and open a new one, as well as the tedious task of updating linked payment details for bills and subscriptions. Financial costs may also be present, including the potential loss of integrated services like direct salary deposits, standing orders, or benefits tied to account tenure. Furthermore, relational and psychological switching costs emerge from the disruption of established habits, the loss of a familiar and personalized app interface, and the termination of a relationship with a known entity (Burnham et al., 2003; Xu et al., 2025).

Switching costs are widely recognized as a key mechanism for customer retention, primarily by creating inertia that discourages defection even when satisfaction with the current provider wanes (Ribeiro et al., 2024). From a strategic management perspective, the Resource-Based View (Barney, 1991) would categorize well-established switching costs as a valuable source of competitive advantage. They create a form of "lock-in" that is not easily replicated by competitors, thereby providing an incumbent firm with a structural buffer against customer churn.

Crucially, switching costs differ conceptually from trust. Whereas trust fosters voluntary relational commitment based on positive beliefs about a partner's intentions and competence, switching costs discourage exit through external or structural constraints. A customer may stay with a neobank not because they deeply trust it, but because the perceived hassle of leaving is simply too great. This distinction has important implications for how switching costs influence retention.

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Behavioural economics suggests that the effect of switching costs may not be linear or gradual. Their ability to prevent churn may only become active once they surpass a subjective threshold (Lin et al., 2026; Ouyang and Mak, 2026). Minor procedural inconveniences are easily overlooked or overcome if a competing offer is sufficiently attractive. It is only when the cumulative perceived effort, risk, or loss associated with switching reaches a critical tipping point that it acts as a genuine psychological deterrent to exit. Below this threshold, switching costs may exert limited influence on retention; above it, they may significantly stabilize customer behaviour.

This implies a nonlinear, threshold-based function for switching costs in predicting retention, a nuance that additive linear models fail to capture. Prior studies have often modelled switching costs as linear predictors of retention, assuming that each incremental increase in perceived barrier produces a constant marginal increase in retention likelihood. However, this assumption may oversimplify their true functional form. It is more plausible that switching costs operate through a threshold mechanism: exerting limited influence at low to moderate levels, but substantively stabilizing retention once perceived burdens exceed a critical breakpoint. As shown in Table 3, prior research on switching costs and customer retention in digital finance overwhelmingly relies on linear modelling frameworks. Switching costs are consistently treated as additive predictors, mediators, or moderators, implicitly assuming constant marginal influence. Even moderation effects are estimated within linear interaction structures. None of the reviewed studies explicitly investigate nonlinear dynamics, threshold effects, or asymmetric retention responses to switching costs. This methodological uniformity suggests that potential nonlinear retention mechanisms in digital financial environments remain underexplored.

Table 3. Switching Cost and Customer Retention in Digital Finance.

Study	Context	Model Type	Role of Switching Costs	Modelling Structure
Colgate and Lang (2001)	Financial services	Regression / Survey analysis	Switching barriers directly affect retention	Linear predictors
Chen and Hitt (2002)	Online brokerage	Random Utility Model	Switching costs reduce probability of switching	Linear predictors
Wong and Mula (2009)	Internet banking (HK)	Regression	Switching costs → Retention	Linear regression
Augusto de Matos et al. (2009)	Banking	SEM	Switching costs as antecedent, mediator, moderator	Linear SEM paths
Afandi (2020)	FinTech lending	OLS	Switching costs as mooring factor	Linear regression
Yoon and Lim (2021)	Internet-only banks	PPM + SEM	Switching cost → Switching intention	Linear structural model
Tanuwijaya and Oktavia (2023)	Digital banks	PPM + SEM	Switching costs influence switching behaviour	Linear structural paths
Ngau et al. (2023)	Banking switching review	Systematic review	Identifies SEM as dominant method	Predominantly linear models

 doi:10.20944/preprints202605.1452.v1

Study	Context	Model Type	Role of Switching Costs	Modelling Structure
Mackay et al. (2025)	Digital banking	PLS-SEM	Switching costs as moderator of loyalty	Linear moderation in SEM

Note: PLS- Partial Least Square, SEM-Structural Equation Modelling, OLS-Ordinary Least Square. '→' indicates positive relationship.

2.4. Demographic Heterogeneity in Digital Adoption

Beyond the psychological and structural drivers of trust, security, and switching costs, demographic characteristics, particularly age, have been recognized as important covariates in technology adoption and customer retention research. However, the role of demographics in digital banking retention is often treated as a secondary consideration, with age, gender, income, and education routinely included as control variables in linear models rather than investigated as potential nonlinear drivers in their own right (Dwivedi et al., 2019; Malik et al., 2024).

Age has long been identified as a significant determinant of technology adoption and usage patterns. The digital divide literature consistently documents that younger users exhibit higher levels of digital literacy, greater familiarity with mobile interfaces, and lower anxiety toward technology-mediated transactions (Niehaves and Plattfaut, 2014; Menon et al., 2026). In the context of digital banking, younger cohorts, often characterized as "digital natives" demonstrate higher propensity to adopt neobanking services, greater comfort with app-based financial management, and higher frequency of mobile transactions (Laukkanen, 2016; Aliakhbar et al., 2026).

However, adoption is not equivalent to retention. While younger users may adopt neobanking services more readily, their retention patterns may differ substantially from older cohorts. Prior research suggests that younger consumers exhibit lower brand loyalty, higher price sensitivity, and greater propensity to switch providers in response to novel features or competitive offers (Lambert-Pandraud and Laurent, 2010; Chaouali and Souiden, 2019; Shrestha et al., 2026). This "promiscuity" in digital services consumption reflects lower switching costs born of digital fluency, i.e., younger users face fewer procedural barriers when migrating between platforms and may derive positive utility from exploring new interfaces.

Conversely, older users, often characterized as "digital immigrants", may face higher adoption barriers initially, including perceived complexity, lower self-efficacy, and heightened risk perceptions (Magsamen-Conrad et al., 2015; Liu and Ahmad, 2026; Yue et al., 2026). However, once adoption occurs, older users may exhibit stronger retention patterns. This stability may arise from several mechanisms: higher habit persistence, greater loyalty to trusted providers, lower propensity for exploratory switching, and higher perceived switching costs due to lower digital fluency (Morris and Venkatesh, 2000; Lissitsa and Kol, 2016; Moxley et al., 2022).

These opposing forces, i.e., higher adoption but lower retention among the young, versus lower adoption but higher retention among the old suggest that the relationship between age and retention may not be monotonic. Instead, retention may be relatively high among the youngest users (who are digitally embedded), decline among middle-aged users (who face complex financial portfolios and competitive offers), and rise again among older users (who value stability and face higher switching barriers). This implies a potential U-shaped relationship between age and retention in neobanking contexts.

In consumer behaviour research, Lambert-Pandraud and Laurent (2010) and Xu et al. (2022a) report that older consumers tend to exhibit stronger brand loyalty in repeated purchase contexts. However, these studies suggest that the relationship may be nonlinear, with loyalty increasing more sharply after a certain age threshold. In contrast, Phua et al. (2020) find that older individuals do not necessarily prefer older or more established brands over newer ones. This divergence in findings suggests that the relationship between age and loyalty may be complex and potentially nonlinear,

 doi:10.20944/preprints202605.1452.v1

implying that linear modelling approaches may fail to fully capture the underlying behavioural patterns.

In financial risk tolerance research, Grable and Lytton (1999) and Finke and Huston (2003) documented U-shaped patterns in risk tolerance across the lifespan, with risk aversion peaking in middle age and declining slightly in later years. Frank et al. (2025) found that overconfidence can partly explain increased financial risk-taking among older adults, independent of their cognitive condition. Since, retention in financial services is partly driven by risk perceptions, these patterns may translate into corresponding nonlinearities in customer stability.

In technology adoption research, Morris and Venkatesh (2000) found that age moderated the influence of attitude and subjective norms on technology usage, but the moderation patterns were complex and not reducible to simple linear interactions. More recently, Yoon and Lim (2021), in their study of internet-only banks, included age as a control variable in a linear structural model and found non-significant effects, potentially because the true relationship was nonlinear and thus undetectable with linear specifications.

In neobanking specifically, preliminary evidence from user behaviour analytics suggests that churn rates may follow a U-shaped age distribution, with youngest and oldest users exhibiting lower churn than middle-aged cohorts (CIGI, 2019). However, these patterns remain under-explored in academic research and have not been systematically tested within predictive retention models that account for nonlinearity. Despite this theoretical and empirical basis for expecting nonlinear demographic effects, the dominant practice in digital banking retention research is to include demographic variables, such as age, gender, income, education as linear control variables within structural equation models or regression frameworks (Dwivedi et al., 2019). This practice carries two significant limitations.

First, linear specifications impose a constant marginal effect assumption. If the true relationship is U-shaped, an inverted-U shape, or exhibits threshold effects, a linear term will average out these patterns and may produce a statistically non-significant coefficient, leading researchers to erroneously conclude that demographics do not matter (Haans et al., 2016; Phua et al., 2020; Yoon and Lim, 2021). This may explain why many studies report weak or inconsistent demographic effects on retention.

Second, treating demographics solely as controls precludes investigation of their potential interactions with psychological and structural drivers. If age moderates the trust-retention relationship, for example, if trust matters more for older users than younger users, this interaction effect can only be properly estimated if the functional form of age itself is correctly specified. Misspecification of the main effect can bias estimates of interaction effects (Aiken et al., 1991).

2.5. Artificial Intelligence, Trust, and Customer Behaviour in Digital Decision Systems

Recent research in computing and information science highlights the expanding role of artificial intelligence in supporting digital decision-making, customer analytics, and trust management in technology-driven environments. For instance, Wang and Ding (2024) examine the influence of explainable artificial intelligence on human–AI interaction and decision performance. Using a quasi-experimental design in a sales prediction context, their findings show that algorithmic explanations can improve human decision accuracy and enhance behavioural trust in AI systems, even though self-reported trust perceptions may not significantly increase. Their study also highlights that the effectiveness of explanations may depend on users' task-related capabilities, suggesting that explainability interacts with human cognitive capacity in shaping trust and decision outcomes. Similarly, Cheng et al. (2026) develop a graph neural network-based trust evaluation model (DLGTrust) that enhances robustness and interaction security by capturing complex relational structures in digital networks. Complementing this perspective, Chahoud et al. (2025) propose a trust-driven federated learning architecture that dynamically evaluates client trustworthiness to prevent malicious participation and improve system stability in distributed AI environments.

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Beyond trust mechanisms, several studies demonstrate how machine learning techniques can support customer analytics and marketing intelligence. Pustokhina et al. (2021) introduce a dynamic customer churn prediction framework that combines deep learning and metaheuristic optimization to improve retention prediction accuracy in business intelligence applications. In a similar vein, Wang (2022) develops a deep-learning-based customer segmentation approach that leverages swarm intelligence to identify behavioural clusters and enhance marketing decision strategies. Xu et al. (2022b) further explore the use of machine learning in evaluating brand equity from a customer perspective, highlighting how marketing ethics and corporate behaviour influence customer satisfaction and loyalty. In the financial services domain, van Braak et al. (2025) apply ensemble machine learning techniques to assess creditworthiness among consumers with limited credit histories while addressing dataset imbalance and algorithmic fairness considerations.

Collectively, these studies demonstrate that contemporary information-processing research increasingly integrates machine learning, trust modelling, and customer behaviour analytics to support digital decision environments. However, despite these advances, limited attention has been given to applying explainable machine learning to uncover nonlinear customer retention dynamics in neobanking platforms, particularly in relation to trust, perceived security, switching costs, and demographic heterogeneity. This study addresses this gap by applying explainable machine learning techniques to model and interpret the behavioural mechanisms underlying customer retention in digital banking environments.

2.6. Limitations of Linear Modelling Approaches

The majority of prior retention research relies on structural equation modelling or linear regression frameworks. While theoretically informative, these approaches assume:

- Additive effects
- Constant marginal influence
- Symmetric responses
- Linear interactions

Digital financial decision-making, however, may involve nonlinear accelerations, threshold effects, asymmetric risk responses, and interaction-driven complementarity.

Recent advances in explainable machine learning enable the identification of nonlinear functional forms while maintaining interpretability. Gradient boosting models can capture complex structures, and SHAP-based analysis allows decomposition of feature contributions, nonlinear dependence patterns, and interaction effects.

Yet few studies integrate theory-driven retention frameworks with explainable nonlinear predictive modelling.

2.7. Research Gap and Study Contribution

This study addresses three related gaps in the digital banking literature and develops a theory-informed explainable machine learning framework for examining retention intention in neobanking environments.

First, the study responds to the dominance of additive linear modelling in prior retention research. Existing studies commonly rely on regression, SEM, or PLS-SEM frameworks that estimate average linear relationships among trust, perceived security, switching costs, and retention outcomes. While these approaches are theoretically useful, they may not fully capture heterogeneous or value-range-dependent predictive patterns in digital financial behaviour. This study therefore evaluates whether nonlinear predictive models provide incremental out-of-sample explanatory value relative to regularized linear models and a PLS-SEM-inspired benchmark.

Second, the study examines the functional behaviour of key retention predictors. Rather than asking only whether trust, security, switching costs, and demographic characteristics matter, the analysis explores how their predictive contributions vary across observed value ranges. SHAP-based interpretation, GAM diagnostics, and construct-level robustness checks are used to investigate

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whether the fitted models learn nonlinear, asymmetric, or heterogeneous patterns. These analyses are interpreted as exploratory model-based diagnostics rather than causal or confirmatory tests.

Third, the study investigates possible non-additive relationships between trust and perceived security. Prior studies often model trust and security as sequential, parallel, or linearly moderated constructs. The present framework allows the relationship to be examined through SHAP interaction values and predicted retention surfaces. However, because some trust indicators, particularly T4, overlap conceptually with perceived security, the interaction findings are interpreted cautiously and supplemented with construct-sensitivity checks.

Beyond its theoretical positioning, the study offers practical value for neobank managers. If nonlinear predictive patterns are observed, explainable machine learning may help identify customer segments where trust, security, or switching-cost perceptions are especially relevant for retention-intention prediction. Such insights can support more targeted retention diagnostics, although they should not be interpreted as causal evidence that a specific intervention will automatically increase retention.

The study also has implications for predictive analytics in digital finance. By comparing nonlinear models against regularized linear and PLS-SEM-inspired benchmarks, the analysis shows whether machine learning adds predictive value beyond established theory-driven specifications. Explainability tools then provide interpretable diagnostics about how the model uses trust, security, switching costs, and demographic variables in prediction.

Overall, this study contributes by extending an established S-O-R/PLS-SEM framework into a cautious explainable machine learning setting. It challenges neither the value of linear theory-driven models nor the original dataset study, but instead examines whether additional nonlinear and interaction-based predictive information can be identified through robust, interpretable modelling.

3. Hypotheses Development

3.1. Nonlinear Predictive Structure in Digital Retention

Customer retention in digital financial services is shaped by complex behavioural and psychological mechanisms. Unlike traditional linear models that assume constant effects, digital banking decisions often involve asymmetric responses, thresholds, and interactions among trust, security, and switching costs. Consequently, nonlinear models are expected to better capture retention dynamics and deliver superior predictive performance.

Hypothesis 1(H1): *A nonlinear predictive model demonstrates superior out-of-sample performance in explaining customer retention relative to linear additive specifications.*

3.2. Trust as the Primary Retention Driver

Trust represents confidence in the reliability, integrity, and competence of a digital financial provider. In environments characterized by information asymmetry and absence of physical reassurance, trust reduces perceived risk and enhances relational commitment. Relationship marketing theory posits that trust forms the foundation of long-term exchange continuity, particularly in service contexts involving financial vulnerability. Given the fully digital nature of neobanking platforms, where interactions are mediated by technology rather than physical presence, trust is expected to exert a dominant influence on customer retention relative to other constructs.

Hypothesis 2 (H2): *Trust constitutes the strongest predictor of customer retention in neobanking environments*.

3.3. Nonlinear and Threshold Effects of Trust

While trust is expected to positively influence retention, its functional form may not be linear. Prospect theory and risk asymmetry arguments suggest that losses (e.g., very low trust) exert stronger behavioural impact than equivalent gains. Extremely low trust may dramatically increase churn risk, whereas high trust may accelerate loyalty formation disproportionately.

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Thus, trust may operate as a retention accelerator rather than a simple additive predictor.

Hypothesis 3 (H3): *The relationship between trust and customer retention is nonlinear and convex, such that retention gains accelerate at high levels of trust and decline sharply at low levels.*

3.4. Perceived Security as A Monotonic Driver

Perceived security reflects users' assessment of data protection, fraud prevention, and transaction integrity. In digital banking, security perceptions reduce uncertainty and perceived vulnerability. Unlike relational trust, which may exhibit asymmetry and threshold effects, institutional security signals may operate more uniformly by steadily increasing confidence and reducing perceived risk. Accordingly, security perceptions are expected to exert a consistently positive influence on retention.

Hypothesis 4 (H4): Perceived security has a positive and predominantly monotonic relationship with customer retention.

3.5. Switching Costs as A Stabilization Mechanism

Switching costs refer to the perceived effort, complexity, or inconvenience associated with changing service providers. Unlike trust and security, which foster positive relational commitment, switching costs operate through inertia and exit barriers. Behavioural economics suggests that switching barriers may not gradually increase loyalty but instead prevent defection once a certain threshold is reached. In digital financial ecosystems, integration with payment systems and established routines may create stabilizing effects only when perceived switching burdens exceed a meaningful level.

Hypothesis 5 (H5): *Switching costs influence customer retention through a threshold mechanism, such that retention increases meaningfully only when switching barriers exceed a critical level.*

3.6. Demographic Nonlinearity

Demographic influences on digital service adoption are often heterogeneous rather than linear. Age-related differences in technology familiarity, financial risk tolerance, and platform preferences may produce nonlinear retention patterns. Middle-aged users may exhibit different engagement sensitivities relative to younger or older users. Thus, demographic variables may demonstrate nonlinear retention effects.

Hypothesis 6 (H6): *Age exhibits a nonlinear (U-shaped) relationship with customer retention.*

3.7. Complementarity Between Trust and Security

Trust and perceived security are conceptually distinct but theoretically complementary constructs. Trust reflects relational confidence in the provider, while security reflects institutional assurance regarding platform safety. Complementarity theory suggests that when two factors reinforce each other, the marginal effect of one increases as the level of the other increases. In digital-only financial contexts, users may require both relational trust and institutional security to sustain long-term commitment. High trust may not fully convert into retention when security perceptions are weak, and strong security alone may be insufficient without relational confidence. Therefore, a positive cross-partial interaction is expected between trust and security.

Hypothesis 7 (H7): *Perceived security positively moderates the relationship between trust and customer retention, such that the effect of trust on retention is stronger when perceived security is high.*

4. Data and Methodology

This study adopts a theory-driven predictive modelling approach to examine the determinants of customer retention in neobanking. Rather than estimating linear structural relationships, we employ supervised machine learning techniques to evaluate the predictive relevance, nonlinear dynamics, and interaction effects among perceived security, trust, switching costs, and retention.

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The objective is not to replace theory with algorithmic modelling, but to validate and extend theoretically derived relationships using explainable machine learning. This approach enables detection of nonlinearities, threshold effects, and synergistic interactions that traditional linear models may fail to capture.

4.1. Data Description

The dataset used in this study originates from a structured survey on neobanking behaviour initially collected by Puente et al. (2025) and subsequently made publicly available on the Kaggle database under the Creative Commons Attribution–Non-commercial–Share Alike 4.0 (CC BY-NC-SA 4.0) license. The dataset captures users' perceptions of digital financial platforms, focusing on key behavioural constructs including Trust (T), Perceived Security (PS), Ease of Payment (EP), Switching Costs to Traditional Banks (SCTB), and Customer Retention (CR), as well as demographic characteristics such as age, gender, and educational level.

During the original data collection process, questionnaires were administered both directly in commercial areas of the cities of Puebla and Mexico City and indirectly through social media platforms, including email, WhatsApp, and Facebook. Participation in the survey was voluntary, and respondents required approximately 8–10 minutes to complete the questionnaire. Fieldwork was conducted between September and November 2023.

The dataset contains 305 observations, representing individuals who reported holding an account with at least one neobank. To avoid brand-related bias and prevent potential promotional implications, the specific financial institutions used by respondents were not recorded in the dataset. The survey instrument measures five behavioural constructs using multiple indicators evaluated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

User perceptions of neobanking services were assessed using measurement scales derived from established studies in the digital finance and service marketing literature. The constructs of trust and customer retention were operationalized using the instruments proposed by Islam et al. (2020). Ease of Payment and Perceived Security was measured using the scale of Harris and Goode (2010). Additionally, switching costs related to migrating from a neobank to a traditional banking institution were measured using the scale developed by Clemes et al. (2010).

Each construct is measured using multiple indicators evaluated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In total, the dataset contains 23 behavioural indicators, including five items measuring Ease of Payment (EP1–EP5), five items measuring Switching Costs to Traditional Banks (SCTB1–SCTB5), three items measuring Customer Retention (CR1–CR3), four items measuring Trust (T1–T4), and five items measuring Perceived Security (PS1–PS5). A detailed description of the measurement items is provided in Table 4.

Table 4. Survey Measurement Items.

Construct	Item Code	Measurement Item
Ease of Payment (EP)	EP1	The payment procedures of this application are efficient.
	EP2	Financial transactions (e.g., sending money, payments, purchases) in this application do not take a lot of time.
	EP3	Financial operations (e.g., sending money, payments, purchases) in this application are user-friendly.
	EP4	Financial operations through this application are easy to use.

Construct	Item Code	Measurement Item
	EP5	Financial transactions through this application do not require extensive data entry.
Switching Costs to Traditional Banks (SCTB)	SCTB1	It would take me too long to switch from this neobank to a traditional bank.
	SCTB2	Switching from this neobank to a traditional bank would require considerable effort.
	SCTB3	It would take me too long to become familiar with the policies of a traditional bank.
	SCTB4	Completing the procedures to switch to a traditional bank would take a long time.
	SCTB5	I am not sure whether switching to a traditional bank would provide additional benefits.
Customer Retention (CR)	CR1	I frequently recommend that other people use the services of this neobank.
	CR2	In the future, I will continue to make financial transactions through this company.
	CR3	I would recommend this neobank to friends, family, and acquaintances.
Trust (T)	T1	I trust this company.
	T2	I trust this company's advice.
	T3	I consider this company to be honest.
	T4	This company's application is safe to use.
Perceived Security (PS)	PS1	It seems that this neobank is very secure.
	PS2	I feel confident performing financial transactions through this application.
	PS3	The security systems of this application appear to be rigorous.
	PS4	When performing financial transactions on this application, I am reassured by its security procedures.
	PS5	In general, this application appears to be concerned about security.

Note: All items were measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

In addition, the dataset includes demographic variables such as age, gender, and educational level. Age is recorded as a numerical variable, while gender and educational level are categorical

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variables coded using ordinal scales. The coding scheme for demographic variables is presented in Table 5.

Table 5. Coding of Demographic Variables.

Variable	Coding	Description
Age	Numeric	Respondent age in years
Gender	1	Female
	2	Male
	3	Other
Educational Level	1	Primary school
	2	Lower Secondary
	3	Upper Secondary
	4	Bachelor's degree
	5	Postgraduate

Table 6 presents the descriptive statistics of the study variables, summarizing their central tendency and dispersion across the sample. The average age of respondents is 26.99 years (SD = 10.58), indicating that the sample is relatively young, which is consistent with the typical user base of digital banking platforms. Gender has a mean of 1.56 (SD = 0.50), suggesting a fairly balanced distribution between male and female respondents. The mean education level is 3.86 (SD = 0.69), indicating that most respondents possess at least a high school or bachelor-level education.

Among the behavioural constructs, Ease of Payment records the highest mean value (4.32, SD = 0.88), suggesting that respondents generally perceive neobanking platforms as convenient and user-friendly. Trust and Perceived Security also exhibit relatively high average scores (4.27 and 4.20, respectively), indicating strong user confidence in the reliability and security of the digital banking services. Customer Retention shows a high mean of 4.15 (SD = 1.01), reflecting a generally strong intention among users to continue using and recommending the neobank services. In contrast, Switching Costs display a comparatively lower mean (3.02, SD = 1.44), suggesting that perceived barriers to switching to traditional banks are moderate and more heterogeneous among respondents. Overall, the descriptive statistics indicate generally favourable perceptions of neobanking services, particularly in terms of usability, trust, and security, while switching barriers appear less uniformly perceived across users.

Table 6. Descriptive Statistics of Study Variables.

Variable	Mean	Std. Dev.	Min	Max
Age	26.99	10.58	18	78
Gender	1.56	0.50	1	2
Education Level	3.86	0.69	1	5

 doi:10.20944/preprints202605.1452.v1

Variable	Mean	Std. Dev.	Min	Max
Ease of Payment (EP)	4.32	0.88	1	5
Switching Costs (SCTB)	3.02	1.44	1	5
Customer Retention (CR)	4.15	1.01	1	5
Trust (T)	4.27	0.84	1	5
Perceived Security (PS)	4.20	0.92	1	5

Note: Construct values represent averages of corresponding measurement items.

4.2. Measurement Reliability and Validity

Table 7 confirms strong measurement reliability and validity. The Kaiser–Meyer–Olkin (KMO) value (0.92) indicates excellent sampling adequacy, while Cronbach's alpha values above 0.70 demonstrate high internal consistency across constructs. Factor loadings support convergent validity, and minor overlap between Trust and Customer Retention items reflects their expected theoretical linkage. Tests for common method bias suggest (CMB) no dominant single-factor influence, indicating limited CMB concerns, although residual bias typical of cross-sectional survey data cannot be fully ruled out.

Table 7. Reliability and construct validity assessment.

Construct	Factor Loading	Cronbach's α	KMO Range	Interpretation
EP	0.619 – 0.894	0.908	0.91 – 0.94	Strong reliability and convergent validity
SCTB	0.679 – 0.866	0.889	0.78 – 0.87	Good construct consistency
CR	0.665 – 0.769	0.846	0.91 – 0.96	Reliable behavioural outcome construct
T	0.714 – 0.768	0.901	0.93 – 0.97	High internal consistency
PS	0.505 – 0.689	0.911	0.93 – 0.95	Acceptable factor separation
Overall KMO = 0.92				

4.3. Predictive Modelling Strategy

The present study employs a predictive modelling framework tailored to a structured tabular survey dataset with a moderate sample size $(N = 305)$. Although this sample is smaller than those typically used in large-scale machine learning applications, tree-based ensemble methods such as XGBoost have been shown to perform effectively in structured tabular settings of comparable scale when supported by appropriate regularization, validation, and out-of-sample testing procedures. To enhance generalizability and reduce the risk of overfitting, the modelling strategy incorporates several safeguards, including regularized linear benchmark models, 10-fold cross-validation, early stopping during boosting, and final evaluation on an untouched hold-out test set. In addition, SHAP-based explainability is used to interpret model behaviour transparently and to assess whether the uncovered nonlinear patterns are consistent with the study's theoretical expectations.

The dependent variable is a continuous customer retention score, defined as the arithmetic mean of the three retention indicators:

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$$Retention_i = \frac{CR1_i + CR2_i + CR3_i}{3}.$$

To prevent target leakage, CR1–CR3 were excluded from the feature set in all predictive models.

Predictors comprised Age, Gender, edu_level, and all non-retention item indicators (EP1–EP5, PS1–PS5, T1–T4, SCTB1–SCTB5). The modelling strategy entailed the following phases: Phase 1 and Phase 2 investigate H1; Phase 3 investigates H2, H3, H4, H5, and H6; Phase 4 investigates H7; and Phase 5 provides a robustness analysis of H1 through H7.

Because the present research focuses on structured tabular survey data rather than unstructured textual inputs, large language models and NLP-oriented architectures were not selected as the primary benchmark family for this study. Instead, benchmark selection was aligned with the data modality and prediction task. In tabular prediction settings, regularized linear models and tree-based boosting remain strong and widely used reference approaches. Accordingly, the empirical benchmark compares XGBoost with Ridge, Lasso, and Elastic Net using the same predictor set, the same preprocessing procedure, the same train–test split, and the same evaluation metrics, thereby ensuring a fair out-of-sample comparison across models. The baseline comparison is therefore based on direct empirical implementation within the present dataset rather than on performance values reported in prior studies.

4.3.1. Phase 1: Linear Baseline Estimation

To establish a benchmark against which nonlinear performance could be assessed, and to test H1, three regularized linear regression models were first estimated: Ridge ($L2$), Lasso ($L1$), and Elastic Net ($L1/L2$). Regularized estimation was preferred to ordinary least squares for two reasons. First, regularization reduces the risk of overfitting by shrinking coefficient estimates, which is particularly important given the moderate sample size relative to the number of predictors. Second, Lasso and Elastic Net provide implicit feature selection, which improves model parsimony and helps identify the most influential additive predictors. In addition to the regularized linear models, a PLS-SEM-inspired linear benchmark was included to directly compare the models against a theory-driven specification based on the original S-O-R framework proposed by Puente et al. (2025). This benchmark used construct-level scores for ease of payment, perceived security, and trust to predict customer retention intention.

The dataset was partitioned into 70% training and 30% test subsets. All preprocessing steps, including centring and scaling of continuous predictors, were fitted exclusively on the training data and then applied to the test data to avoid data leakage. For each regularized model, the optimal tuning parameters ($\lambda$for Ridge and Lasso; $\lambda$and $\alpha$for Elastic Net) were selected through 10-fold cross-validation on the training set by minimizing cross-validated root mean squared error (RMSE). The tuned models were then evaluated on the untouched hold-out test set using RMSE, MAE, and R^2, so that performance comparisons reflect genuine out-of-sample predictive accuracy rather than in-sample fit.

To examine whether the initial hold-out findings were sensitive to a single train-test partition, a repeated nested cross-validation procedure was subsequently conducted across the regularized linear models and the PLS-SEM-inspired benchmark o ensure comparable and robust out-of-sample performance evaluation. The outer evaluation used repeated 10-fold cross-validation, with 10 folds repeated 10 times, generating 100 out-of-sample test-fold estimates for each model. Within each outer training fold, an inner 5-fold cross-validation procedure was used for hyperparameter tuning. In addition, uncertainty estimation was incorporated through the reporting of standard deviations and 95% confidence intervals across the 100 resamples, while statistical comparison of model performance was conducted using pairwise Wilcoxon signed-rank tests and win-rate comparisons across resampled folds.

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4.3.2. Phase 2: Nonlinear Gradient Boosting

To capture potential nonlinearities and interaction effects that linear models cannot accommodate, we estimated an XGBoost regression model (Chen and Guestrin, 2016; Ali et al., 2025). XGBoost is an ensemble learning method that sequentially adds decision trees, each correcting the errors of its predecessors, and has demonstrated strong predictive performance across diverse domains.

Model specification followed best practices for predictive modelling. The same 70/30 train-test split was maintained to ensure comparability with the linear baselines. Hyperparameters, including learning rate (η), maximum tree depth, subsampling ratio, and column sampling ratio were tuned within the training set only, using early stopping with a separate evaluation watchlist to prevent overfitting. Specifically, training progressed until performance on a validation subset (20% of the training data) failed to improve for 30 consecutive boosting rounds. This early stopping procedure ensures that the final model captures genuine predictive structure rather than noise. The tuned XGBoost model was then evaluated on the hold-out test set, and its performance was compared against the regularized linear baselines. To further assess robustness and reduce sensitivity to a favourable single split, the XGBoost model was also evaluated using the same repeated nested cross-validation framework (discussed in section 4.3.1) along with uncertainty estimation and 95% confidence intervals.

4.3.3. Phase 3: Shap-Based Interpretability

While XGBoost provides strong predictive performance, its ensemble tree structure precludes direct coefficient-based interpretation. To address this limitation, we employed SHAP, a game-theoretic framework for model interpretability (Lundberg and Lee, 2017; Ali et al., 2025; Perwej et al., 2025). SHAP expresses model predictions within an additive explanation framework satisfying local accuracy, missingness, and consistency properties.

For each observation i and feature j, the SHAP value $\varphi_{i,j}$ represents the contribution of feature j to the deviation of prediction $f(x_i)$ from the expected model output $E[f(X)]$. Formally:

$$f(x_i) = E[f(X)] + \sum_j \varphi_{i,j}$$

SHAP values therefore provide local explanations of individual predictions and, when aggregated across observations, enable global assessment of feature importance.

Three complementary SHAP-based analyses were conducted:

Mean Absolute SHAP Importance

Overall predictor importance was assessed using mean absolute SHAP values computed across all observations. This metric captures the average magnitude of a feature's contribution irrespective of direction and avoids cancellation effects inherent in signed importance measures.

Signed SHAP Directional Analysis

To examine directional tendencies, mean signed SHAP values were calculated. Because positive and negative contributions may offset across observations, these values should not be interpreted as measures of importance but rather as indicators of whether a feature tends, on average, to increase or decrease predicted retention relative to the baseline prediction.

SHAP Dependence Plots

To characterize functional relationships between predictors and retention, SHAP dependence plots were generated by plotting SHAP values against corresponding feature values across observations. These visualizations reveal nonlinear effects, threshold behaviour, and interaction patterns. Locally weighted scatterplot smoothing was applied solely for visualization purposes to aid interpretation of underlying trends.

4.3.4. Phase 4: Construct-Level Aggregation and Shap Interaction Analysis

To assess the relative importance of theoretical constructs rather than individual indicators, item-level SHAP values were aggregated to the construct level. For each observation, construct-level

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SHAP contributions were obtained by summing SHAP values across all indicators belonging to the same construct. Mean absolute construct-level SHAP values were then computed across observations, and each construct's relative share of predictive importance was calculated by normalizing its mean absolute SHAP value by the total across all constructs.

To investigate interaction effects, specifically the hypothesized complementarity between Trust and Security, we computed SHAP interaction values. The SHAP interaction value $\varphi_{i,j,k}$ represents the joint contribution of features j and k to the prediction for observation i, beyond their individual main effects, and satisfies $\varphi_{i,j,k} = \varphi_{i,k,j}$. The contribution of feature j can therefore be decomposed as:

$$\varphi_{i,j} = \varphi_{i,j}(main) + \sum_{k \neq j} \varphi_{i,k,j} +$$

where $\varphi_{i,j}\text{^}(main)$ denotes the main effect independent of interactions. Mean absolute SHAP interaction values were computed across observations to identify structurally meaningful interaction patterns with particular attention devoted to Trust × Security interaction. To visualize their joint influence on customer retention, a three-dimensional retention response surface was generated by predicting model outputs across a grid of Trust (T4) and Security (PS2) values while holding all remaining features at their median levels.

4.3.5. Phase 5: Robustness Check Via Binary Classification

To assess whether the predictive structure generalizes beyond continuous regression assumptions, we reformulated retention as a binary classification problem. Observations in the bottom 40% of the retention distribution were classified as Low Retention (0), while those in the top 40% were classified as High Retention (1). The middle 20% were excluded to create clearer separation between groups and to reduce classification ambiguity. This approach tests whether the model can reliably distinguish high-retention from low-retention users in a segmentation-based framework more closely aligned with managerial targeting applications.

An XGBoost binary classifier was estimated using the same training/test partition and early stopping procedure described for the regression model. The classifier was specified with the binary:logistic objective function, and performance was evaluated using Area Under the Receiver Operating Characteristic (ROC) Curve (AUC), precision, recall, and F1-score on the hold-out test set. Strong classification performance would indicate that the nonlinear relationships identified in the continuous model are robust to alternative outcome specifications and are not artifacts of distributional assumptions.

4.4. Preliminary Statistical Analysis

Prior to model estimation, preliminary statistical analyses were conducted to examine associations among study constructs and to assess the potential presence of multicollinearity among predictors. Correlation analysis provides an initial understanding of relationships between behavioural variables, while variance inflation factor (VIF) diagnostics evaluate whether predictor interdependence may adversely affect subsequent modelling procedures.

4.4.1. Correlation Analysis

Pearson correlation coefficients were calculated using construct-level composite scores derived from the average of measurement items for each variable. Table 8 reports the correlations among Perceived Ease of Payment, Switching Costs, Trust, Perceived Security, and Customer Retention. All constructs show positive and statistically significant relationships, with Trust demonstrating the strongest association with Customer Retention ($r = 0.762$, $p < 0.001$). Perceived Security and Ease of Payment also exhibit notable positive correlations, whereas Switching Costs display relatively weaker relationships. None of the correlations exceed the multicollinearity threshold ($r > 0.90$), confirming adequate discriminant validity among predictors.

Table 8. Correlation Matrix of Study Constructs.

Variable	EP	SCTB	CR	T	PS
Ease of Payment (EP)	1.000				
Switching Costs (SCTB)	0.099*	1.000			
Customer Retention (CR)	0.547***	0.234***	1.000		
Trust (T)	0.540***	0.186***	0.762***	1.000	
Perceived Security (PS)	0.670***	0.178***	0.646***	0.727***	1.000

Note: *** and * indicate statistical significance at 1% and 10% level respectively.

5. Empirical Results

5.1. Model Comparison and Repeated Cross-Validation

5.1.1. Hold-Out Model Comparison

Table 9 reports the initial hold-out model comparison based on the 70/30 train-test split. The regularized linear models achieved moderate predictive performance, with R^2 values ranging from 0.490 for Lasso to 0.519 for Ridge. The PLS-SEM-inspired benchmark achieved a higher R^2 of 0.598, suggesting that the theory-driven construct specification captures meaningful predictive information. However, XGBoost produced the strongest hold-out performance, with the lowest RMSE of 0.572, the lowest MAE of 0.357, and the highest R^2 of 0.644. This initial result suggests that nonlinear boosting may capture additional predictive structure beyond both regularized item-level linear specifications and the theory-driven construct-level benchmark.

Table 9. Model comparison.

Model	RMSE	MAE	R^2	Model Class
XGBoost	0.572	0.357	0.644	Nonlinear Boosting
Ridge	0.666	0.511	0.519	Linear (L2)
Elastic Net	0.677	0.519	0.502	Linear (Hybrid)
PLS-SEM-inspired benchmark	0.597	0.479	0.598	Linear
Lasso	0.685	0.526	0.490	Linear (L1)

5.1.2. Repeated Nested Cross-Validation

The repeated nested cross-validation results (see Table 10) show that XGBoost consistently outperforms all linear benchmarks. XGBoost achieved the lowest average RMSE of 0.4669, compared with 0.5851 for Ridge, 0.5863 for Elastic Net, 0.5885 for the PLS-SEM-inspired benchmark, and 0.5916 for Lasso. It also produced the lowest MAE of 0.3399 and the highest average R^2 of 0.7243. The PLS-SEM-inspired benchmark performed similarly to the regularized linear models, suggesting that the theory-driven linear structure captures meaningful predictive information but does not match the predictive accuracy of the nonlinear boosting model. Overall, the confidence intervals show a clear separation between XGBoost and the linear specifications, indicating that the improvement is not driven by a favourable single split. This supports the view that nonlinear modelling provides

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incremental predictive value beyond both generic regularized linear models and the original S-O-R-inspired linear structure.

Table 10. Repeated nested cross-validated model performance.

Model	N	RMSE Mean	RMSE SD	RMSE 95% CI	MAE Mean	R^2 Mean	R^2 95% CI
XGBoost	100	0.4669	0.0868	[0.4497, 0.4841]	0.3399	0.7243	[0.7020, 0.7466]
Ridge	100	0.5851	0.0814	[0.5689, 0.6012]	0.4578	0.5756	[0.5484, 0.6028]
Elastic Net	100	0.5863	0.0782	[0.5708, 0.6018]	0.4625	0.5744	[0.5479, 0.6009]
PLS-SEM-inspired benchmark	100	0.5885	0.0839	[0.5719, 0.6052]	0.4518	0.5679	[0.5385, 0.5973]
Lasso	100	0.5916	0.0792	[0.5759, 0.6073]	0.4651	0.5662	[0.5390, 0.5934]

5.1.3. Pairwise Predictive Accuracy Comparison

Pairwise Wilcoxon signed-rank tests were conducted using fold-level RMSE values to compare XGBoost with each regularized linear benchmark. Table 11 reports the mean RMSE differences and win rates across the 100 resamples.

The pairwise comparisons show that XGBoost significantly reduces prediction error relative to all three regularized linear models. The mean RMSE reduction ranges from 0.1182 to 0.1247, and the Wilcoxon signed-rank tests are statistically significant at the 1% level. XGBoost also outperformed Ridge, Lasso, and Elastic Net in 96%, 98%, and 97% of the resamples, respectively. Overall, these results provide robust support for H1, indicating that nonlinear boosting offers incremental predictive value over additive linear specifications. However, the result should be interpreted as evidence of improved predictive performance rather than causal confirmation of nonlinear behavioural mechanisms.

Table 11. Pairwise RMSE comparison between XGBoost and linear baselines.

Comparison	Mean RMSE Difference	Wilcoxon Statistic	p-value	XGBoost Win Rate
XGBoost vs Ridge	0.1182	24.0	< 0.001	96%
XGBoost vs Lasso	0.1247	11.0	< 0.001	98%
XGBoost vs Elastic Net	0.1194	18.0	< 0.001	97%

5.1.4. Predictive Interpretation

Overall, the repeated nested cross-validation results provide robust support for H1. Across 100 out-of-sample test-fold estimates, XGBoost consistently outperformed the regularized linear models in terms of RMSE, MAE, and R^2. The pairwise Wilcoxon signed-rank tests further indicate that the predictive improvement of XGBoost over Ridge, Lasso, and Elastic Net is statistically significant. These findings suggest that nonlinear specifications capture predictive structure that is not fully represented by additive linear models. However, the results should be interpreted as evidence of improved predictive performance rather than causal confirmation of nonlinear behavioural

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mechanisms. Accordingly, the subsequent SHAP-based analysis is treated as an exploratory interpretation of model-learned patterns rather than a confirmatory test of causal nonlinear effects

5.2. Linear Baseline Structure (Lasso Selection)

The Lasso model provides insight (see Table 12 below) into the dominant additive predictors under a linear specification. Trust indicators (particularly T4 and T3) exhibit the largest coefficients, followed by Switching Costs and Security items. This confirms that trust and security perceptions are central drivers of retention even within an additive framework. However, as shown in Table 1, the nonlinear boosted model substantially outperforms the linear baselines, suggesting that additive effects alone are insufficient to fully capture retention behaviour. The next section examines these nonlinear dynamics using SHAP-based analysis.

Table 12. Top Lasso-Selected Predictors.

Rank	Feature	Coefficient	Direction
1	T4	0.322	Positive
2	T3	0.159	Positive
3	SCTB5	0.153	Positive
4	PS4	0.148	Positive
5	PS2	0.122	Positive

5.3. Mean Absolute Shap Ranking

To assess the relative importance of constructs, SHAP values were computed. Table 13 reports feature importance based on mean absolute SHAP values, representing the average magnitude of each variable's contribution to predicted retention across all observations. Trust indicators dominate the ranking, with T4 emerging as the single most influential predictor, followed by T1, T2, and T3. This confirms that trust perceptions constitute the primary driver of customer retention in the model. This finding is consistent with H2. Security indicators (PS2, PS4, and PS1) appear prominently, indicating that perceived platform security plays a substantial secondary role. Switching cost items also contribute meaningfully, suggesting that retention is partially reinforced by perceived barriers to switching. Ease of payment indicators exhibit moderate but consistent influence, while demographic factors, particularly age, display non-trivial heterogeneity effects. Overall, the ranking indicates that retention is primarily trust-driven, reinforced by security perceptions and switching barriers, with convenience and demographics playing supportive roles.

Table 13. Top 15 Features Ranked by Mean Absolute SHAP Values.

Rank	Item	Construct	Mean ∣SHAP∣	Interpretation
1	T4	Trust	0.240	Strongest single driver of retention
2	T1	Trust	0.151	Trust consistently dominant across items
3	PS2	Security	0.109	Security perceptions critically influence retention
4	PS4	Security	0.087	Reinforces importance of perceived security
5	Age	Demographic	0.086	Meaningful demographic heterogeneity effect

Rank	Item	Construct	Mean ∣SHAP∣	Interpretation
6	SCTB5	Switching Cost	0.075	High switching barriers contribute to retention
7	SCTB3	Switching Cost	0.072	Switching cost effects distributed across items
8	T2	Trust	0.062	Additional trust dimension contributes materially
9	T3	Trust	0.058	Trust influence is multi-dimensional
10	PS1	Security	0.058	Security effects spread across indicators
11	EP2	Ease	0.056	Ease contributes moderately to retention
12	SCTB2	Switching Cost	0.049	Switching barriers exhibit consistent influence
13	EP3	Ease	0.041	Ease contributes but less strongly than trust/security
14	EP4	Ease	0.037	Ease effects comparatively smaller
15	SCTB1	Switching Cost	0.034	Switching costs remain relevant but secondary

5.4. Shap Construct Aggregation

To assess how the trained XGBoost model allocated predictive importance across theoretical constructs, item-level SHAP values were aggregated at the construct level. Table 14 reports the mean absolute SHAP values and relative shares. Trust-related indicators accounted for the largest share of model-based predictive importance (37.7%), followed by perceived security (21.4%) and switching costs (19.0%). Ease of payment and demographics contributed smaller shares of predictive influence.

These results suggest that the XGBoost model relied most heavily on trust-related information when predicting retention intention. However, the findings should be interpreted as model-based importance rankings rather than causal or confirmatory evidence. Importantly, the most influential "trust" item, T4, refers to whether the application is safe to use, which overlaps conceptually with perceived security. Therefore, the dominance of trust is interpreted cautiously and further assessed through construct-sensitivity robustness checks. Overall, the SHAP aggregation results are consistent with H2 in a predictive sense, indicating that trust-related indicators provide the strongest contribution to the model's retention-intention predictions.

Table 14. Construct-Level SHAP Aggregation.

Construct	Mean Absolute SHAP	Share (%)	Rank	Interpretation
Trust	0.510	37.7%	1	Largest model-based predictive contribution
Security	0.290	21.4%	2	Important secondary predictive contribution
Switching Costs	0.258	19.0%	3	Meaningful predictive contribution
Ease of Payment	0.171	12.7%	4	Modest predictive contribution
Demographics	0.126	9.3%	5	Smaller but non-zero predictive contribution

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5.5. Directional Effects (Signed Shap)

Mean signed SHAP values (reported in Table 15 below) were examined to assess the overall directional tendency of each variable across the full sample. Because SHAP values are centred around the model's expected prediction, positive and negative contributions across observations tend to offset each other, resulting in mean signed values that are close to zero. Consequently, mean signed SHAP values should not be interpreted as measures of variable importance, but rather as indicators of net directional influence relative to the baseline prediction. The results indicate that higher Trust items generally exert a positive directional effect on retention, while higher Perceived Security perceptions similarly contribute to upward retention predictions. Switching cost indicators exhibit positive but comparatively moderate directional tendencies. Age displays a nonlinear pattern (discussed in the following section), which explains its near-zero average signed contribution despite meaningful predictive importance. Importantly, no major predictor demonstrates a strong negative average directional effect, supporting theoretical consistency across constructs and indicating that the model does not produce substantively contradictory signals relative to established retention theory.

Table 15. Mean Signed SHAP Values (Directional Tendency).

Rank	Variable	Construct	Mean Signed SHAP	Interpretation
		Panel A: Strongest Positive Directional Tendencies		
1	EP2	Ease	+0.000674	Slight upward push on retention
2	PS2	Security	+0.000670	Small positive directional contribution
3	PS4	Security	+0.000631	Reinforces security-driven uplift
4	EP4	Ease	+0.000251	Moderate positive tendency
5	EP1	Ease	+0.000220	Minor positive directional effect
6	Gender	Demographic	+0.000045	Very small net effect
7	SCTB1	Switching	+0.000045	Near-zero positive contribution
8	edu_level	Demographic	−0.000055	Essentially neutral effect
		Panel B: Strongest Negative Directional Tendencies		
1	T4	Trust	−0.001452	Largest net downward tendency (average effect near zero due to nonlinearity)
2	Age	Demographic	−0.000380	Slight net downward tendency overall
3	T1	Trust	−0.000365	Mild negative average direction
4	SCTB4	Switching	−0.000239	Small downward tendency
5	SCTB5	Switching	−0.000230	Minor negative directional effect
6	EP5	Ease	−0.000219	Small downward net contribution

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Rank	Variable	Construct	Mean Signed SHAP	Interpretation
		Panel A: Strongest Positive Directional Tendencies		
7	T2	Trust	−0.000175	Weak net downward tendency

Table 16 contrasts mean absolute SHAP values with mean signed SHAP values to clarify the distinction between importance magnitude and directional tendency. Trust exhibits the largest absolute contribution (0.510), accounting for approximately 37.7% of total model-based predictive signal, yet its mean signed SHAP value is slightly negative. This does not imply that trust reduces retention intention. Rather, it suggests that trust-related variables contribute differently across observations, depending on their value range and interaction context. In contrast, security variables display both substantial absolute SHAP values (0.290) and slightly positive signed means, suggesting a more consistently positive directional pattern in the fitted model. Switching costs exhibit meaningful absolute importance (0.258) but mixed signed tendencies, indicating that their contribution may vary across users. Ease of payment contributes more modestly (0.171), while demographic variables show smaller but non-zero model-based influence.

Overall, the contrast between absolute and signed SHAP values provides useful diagnostic evidence that the fitted XGBoost model may be capturing heterogeneous and potentially nonlinear predictive patterns. This is broadly consistent with the predictive logic underlying H1, H3, H5, and H7. However, these results should not be interpreted as causal or confirmatory evidence of nonlinear retention dynamics, threshold effects, or trust-security complementarity. Instead, they provide exploratory model-based indications that are further examined through SHAP dependence plots, GAM robustness analysis, and construct-sensitivity checks.

Table 16. Absolute vs Signed SHAP Comparison.

Construct	Mean Absolute SHAP	Directional Signal (Signed Mean Pattern)	Interpretation
Trust	0.510	Slightly negative mean	Strong but nonlinear
Security	0.290	Slightly positive	Moderately monotonic
Switching	0.258	Mixed	Context-dependent
Ease	0.171	Slightly positive	Weak but consistent
Demographics	0.126	Age negative	Heterogeneity effect

5.6. Shap Dependence Analysis

The SHAP dependence analysis provides exploratory insight into how the fitted XGBoost model uses key predictors when generating retention-intention predictions. The patterns should be interpreted as model-based explanations rather than causal or confirmatory evidence.

Trust (T4) appears to be one of the most influential predictors and displays a nonlinear pattern (Figure 1). Lower trust values are associated with negative SHAP contributions, while higher trust values are associated with stronger positive contributions to predicted retention intention. This pattern is consistent with H3 in a predictive sense, suggesting that trust may contribute more strongly once it reaches higher levels. However, this should not be interpreted as confirmation of a causal threshold effect.

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Perceived Security (PS2) shows a generally positive and more stable pattern (Figure 2). Higher perceived security values tend to increase predicted retention intention, which is broadly consistent with H4. Compared with trust, the security pattern appears less asymmetric and more consistently positive across the observed range.

Switching Costs (SCTB5) also show evidence of nonlinear variation (Figure 3). The SHAP pattern suggests that switching costs may contribute differently across value ranges, with stronger positive contributions at higher levels. This is consistent with H5 in an exploratory predictive sense, although the evidence should be described as threshold-like rather than as confirmation of a clear threshold mechanism.

Ease of Payment (EP2) displays a generally positive relationship with predicted retention intention (Figure 4), although its contribution appears smaller than that of trust and perceived security. This suggests that payment convenience supports retention prediction but is not the dominant driver in the fitted model.

Finally, age shows possible nonlinear heterogeneity in the SHAP dependence plot (Figure 5). However, because the sample is concentrated among younger respondents, this pattern should be interpreted cautiously at this stage. Rather than treating the SHAP pattern as confirmation of a U-shaped age effect, it is more appropriate to view it as exploratory evidence of possible age-related variation in predicted retention intention. This pattern is therefore further examined through the GAM robustness analysis reported in the subsequent section.

Overall, the SHAP dependence plots suggest that the XGBoost model captures heterogeneous and potentially nonlinear predictive patterns across trust, perceived security, switching costs, ease of payment, and age. These findings are broadly consistent with H3, H4, H5, and H6 in a model-based predictive sense, but they should not be interpreted as causal or confirmatory evidence of nonlinear behavioural mechanisms.

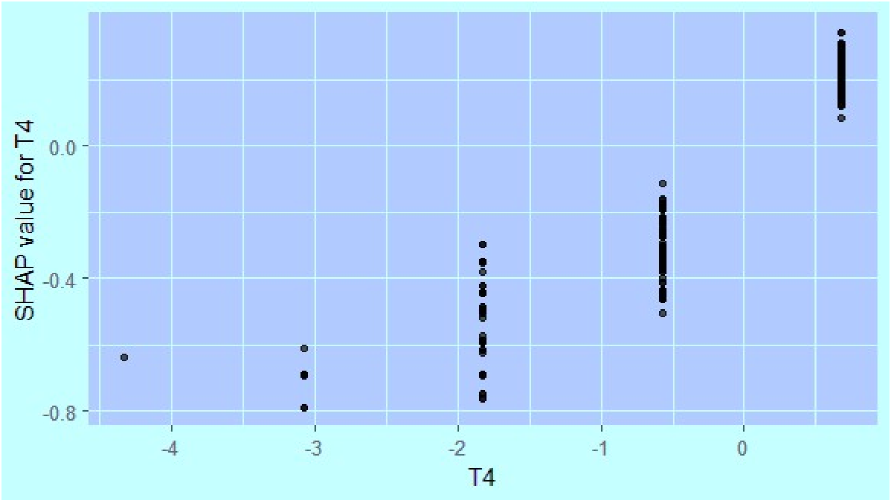

Figure 1. SHAP dependence plot for Trust (T4).

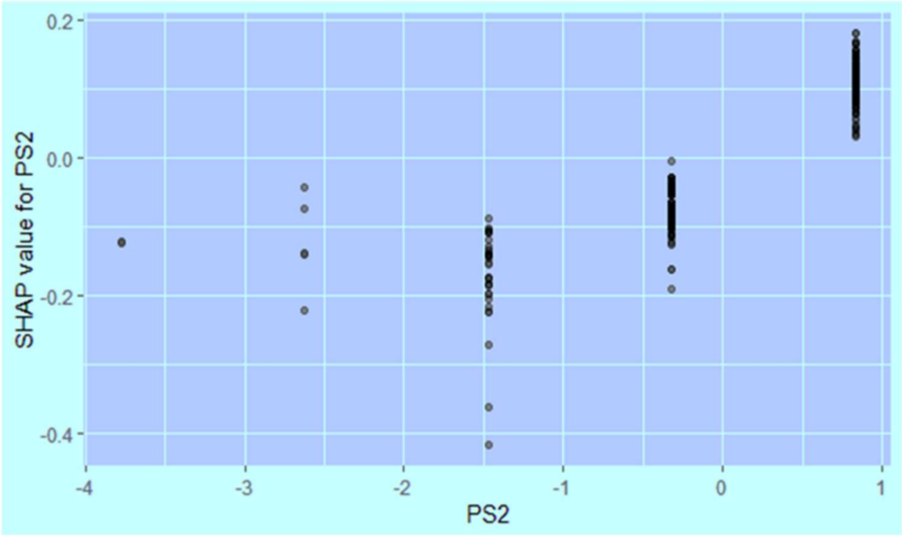

Figure 2. SHAP dependence plot for Perceived Security (PS2).

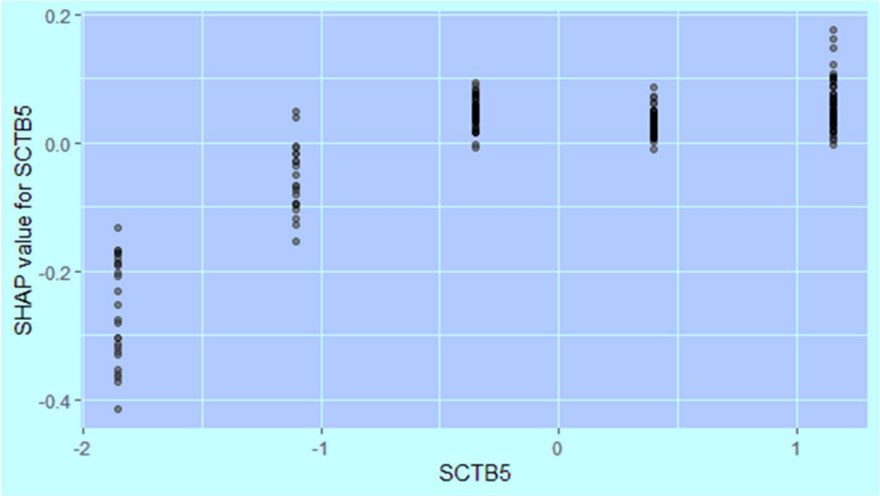

Figure 3. SHAP dependence plot for Switching Cost (SCTB5).

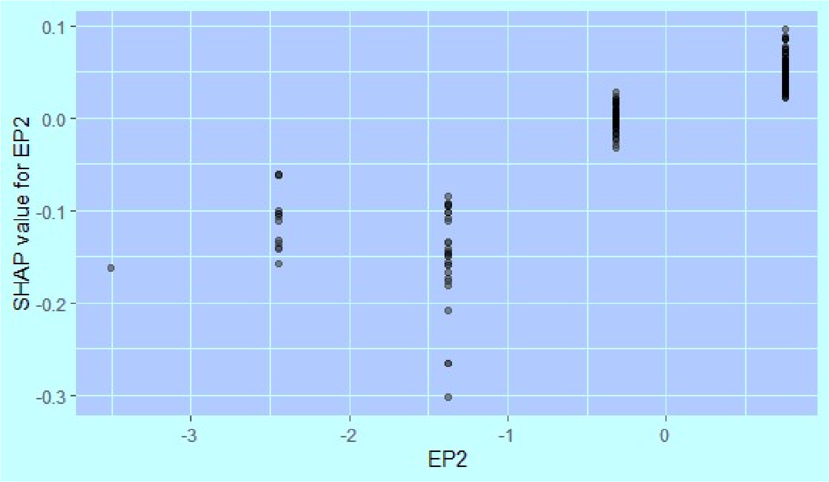

Figure 4. SHAP dependence plot for Ease of Payment (EP).

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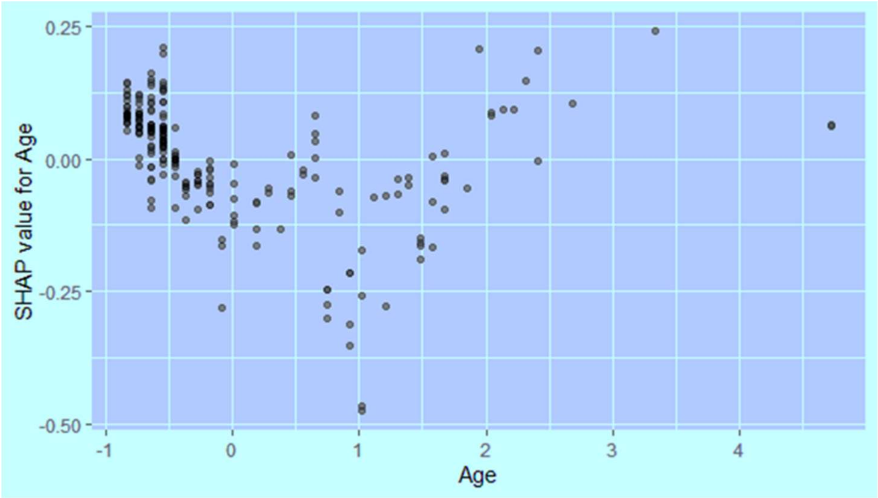

Figure 5. SHAP dependence plot for Age.

Table 17 provides an exploratory functional interpretation of the SHAP dependence plots by summarising how model-based contributions vary across low, medium, and high predictor ranges. The results suggest that several predictors contribute differently across the observed value spectrum. Trust (T4) shows a nonlinear pattern, with lower values associated with negative SHAP contributions and higher values associated with positive contributions. This pattern is broadly consistent with H3 in a predictive sense, although it should not be interpreted as confirmation of a causal threshold effect. Switching Costs (SCTB5) also show value-range heterogeneity, suggesting that their contribution to predicted retention intention may become more positive at higher levels. Perceived Security (PS2) and Ease of Payment (EP2) display more consistently positive patterns across their ranges. Age appears to show nonlinear variation, but this result should be treated as exploratory given the sample's concentration among younger respondents. Overall, the table suggests that the fitted XGBoost model captures heterogeneous predictor patterns that may not be fully represented by additive linear coefficients.

Table 17. Detailed Functional Interpretation.

Variable	Low Values	Medium Values	High Values	Overall Behaviour
Age	Slightly positive SHAP	Negative SHAP	Strong positive SHAP	Exploratory nonlinear variation
EP2	Strong negative SHAP	Mild negative	Positive SHAP	Generally increasing pattern
SCTB5	Large negative SHAP	Near zero	Positive SHAP	Value-range-dependent contribution
PS2	Strong negative SHAP	Neutral	Positive SHAP	Generally positive gradient
T4	Very large negative SHAP (~ -0.8)	Moderately negative	Strong positive (~ +0.3)	Nonlinear positive pattern

5.7. Binary Retention Classification Robustness

Following the methodology in section 4.3.5, the binary retention classification provided a sample that is well balanced (53.7% low vs. 46.3% high retention), eliminating the need for resampling

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techniques and enabling stable classification without class imbalance bias. Table 18 shows the result of the predictive robustness with strong hold-out performance, with an AUC of 0.886, indicating high discriminatory ability between high- and low-retention users. Precision (0.775) and recall (0.795) demonstrate accurate identification of high-retention customers, while the F1-score (0.785) confirms balanced and stable classification performance.

Table 18. Hold-Out Test Performance.

Metric	Value	Interpretation
AUC	0.886	Very strong discrimination
Precision	0.775	77.5% of predicted high-retention users are correctly classified
Recall	0.795	79.5% of actual high-retention users are identified
F1-score	0.785	Balanced classification performance

Figure 6 presents the ROC curve for the XGBoost classifier. The curve remains substantially above the random-classifier diagonal across thresholds, confirming robust predictive segmentation performance. The AUC of 0.886 reflects strong separability between high- and low-retention users in the hold-out test set. The binary classification robustness analysis primarily supports H1 by demonstrating that the nonlinear predictive structure remains stable under an alternative segmentation-based formulation, while also confirming the robustness and generalizability of the behavioural relationships underlying H2–H7.

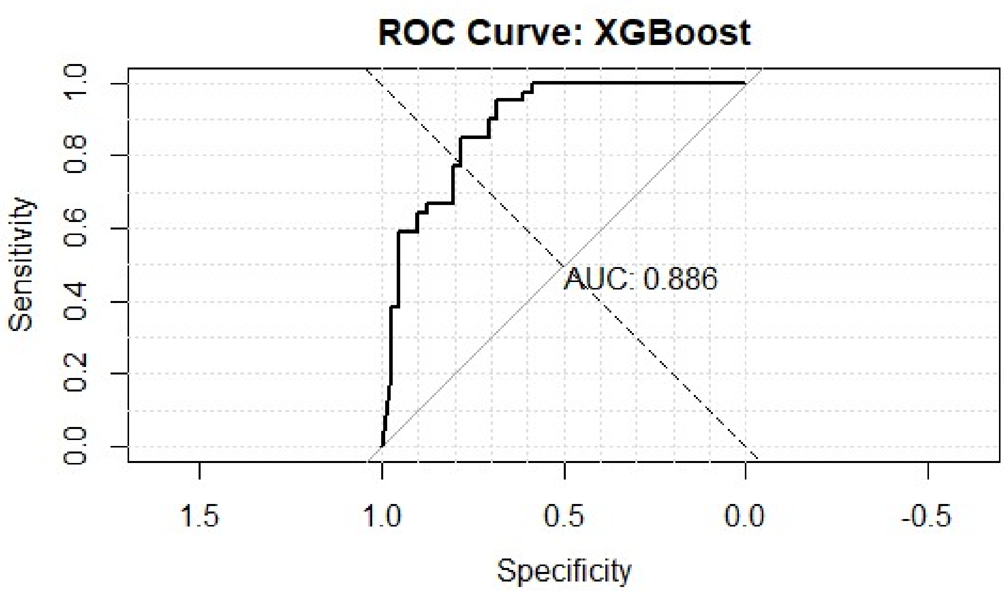

Figure 6. ROC-AUC Curve.

5.8. Shap Interaction Analysis:

To investigate non-additive effects, SHAP interaction values were computed from the trained gradient-boosted model. The resulting interaction tensor has dimensions 215 × 23 × 23, corresponding to 215 observations and 23 predictors. Table 19 reports the strongest Trust–Security interaction pairs ranked by mean absolute SHAP interaction values. These results indicate that interaction effects are

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concentrated in specific trust–security item combinations rather than being uniformly distributed across constructs. Several important patterns emerge. First, T4 appears in four of the top ten interaction pairs, including the two strongest interactions (T4 × PS2 and T4 × PS4). This indicates that the most influential trust dimension is also the one most strongly amplified by perceived security. Similarly, PS2 and PS4 repeatedly appear among the strongest interaction partners, suggesting that specific security dimensions act as enabling mechanisms that intensify the effect of trust on retention.

Table 19. Strongest Trust–Security Interaction Pairs.

Rank	Trust Item	Security Item	Mean ∣SHAP Interaction∣	Relative Strength
1	T4	PS2	0.01687	Very Strong
2	T4	PS4	0.01435	Very Strong
3	T1	PS2	0.01196	Strong
4	T1	PS1	0.01116	Strong
5	T4	PS3	0.00934	Moderate–Strong
6	T1	PS4	0.00933	Moderate–Strong
7	T2	PS2	0.00551	Moderate
8	T4	PS1	0.00530	Moderate
9	T3	PS2	0.00488	Moderate
10	T3	PS1	0.00405	Moderate

Second, the block-level mean Trust × Security interaction is 0.00575, which is the highest among all cross-construct interaction blocks (Table 20). Importantly, the strongest item-level interaction (T4 × PS2 = 0.01687) is approximately 2.93 times larger than this construct-level average. This indicates that interaction effects are not diffusely distributed but instead concentrated in specific trust–security dimensions that drive synergistic reinforcement.

Table 20. Cross-Construct SHAP Interaction Strength.

Construct Pair	Mean ∣SHAP Interaction∣	Relative Rank
Trust × Security	0.00575	1
Trust × Ease	0.00310	2
Security × Switching	0.00294	3

Importantly, the interpretation of Trust × Security interactions requires caution because the most influential trust indicator, T4 ("This company's application is safe to use"), conceptually overlaps with perceived security. The prominence of T4 in several leading interaction pairs may therefore partly reflect measurement proximity between safety-related trust perceptions and security evaluations, rather than a fully distinct cross-construct complementarity mechanism. For this reason, the Trust × Security interaction findings should be interpreted as preliminary model-based evidence.

The robustness of this interpretation is further examined in the construct-sensitivity analysis reported later, where T4 is excluded from trust and alternatively reclassified as a security-related item.

As shown in Table 21, the Trust–Security interaction is nearly twice as strong as other cross-construct interactions.

Table 21. Relative Dominance.

Comparison	Ratio
Trust × Security / Trust × Ease	1.85×
Trust × Security / Security × Switching	1.96×

These findings provide direct empirical support for H7, which posits that perceived security positively moderates the relationship between trust and customer retention. The dominance of Trust × Security interaction magnitudes indicates that the marginal effect of trust on retention increases when security perceptions are high. In other words, the joint contribution of trust and security exceeds the sum of their independent effects, a defining characteristic of positive complementarity.

If trust and security operated purely additively, interaction values would be negligible and uniformly small across constructs. Instead, the results reveal:

- Concentrated high-magnitude item-level interactions
- Dominant block-level Trust × Security synergy
- Amplification of trust effects under strong security conditions

Overall, the SHAP interaction results are broadly consistent with H7 in a predictive sense, suggesting that trust-related and security-related indicators may jointly contribute to retention-intention predictions. However, because T4 overlaps conceptually with perceived security, these findings should not be interpreted as definitive confirmation of trust-security complementarity. Instead, they provide exploratory evidence of possible non-additive predictive structure, which is evaluated more cautiously through the subsequent construct-sensitivity robustness checks.

5.9. Predicted Retention Surface Analysis

Figure 7 illustrates the fitted XGBoost model's predicted retention-intention surface across Trust (T4) and Perceived Security (PS2). The surface suggests that predicted retention intention is highest when both trust and perceived security are high. Conversely, predicted retention is lower when either trust or security is weak, with the lowest predictions occurring when both are low. This pattern is broadly consistent with H7 in a predictive sense, as it suggests that trust-related and security-related perceptions may jointly contribute to retention-intention predictions.

However, the surface should be interpreted cautiously. T4 refers to whether the application is safe to use, which overlaps conceptually with perceived security. Therefore, the apparent Trust × Security interaction may partly reflect shared safety-related measurement content rather than a fully distinct complementarity mechanism. Accordingly, Figure 7 is treated as exploratory visual evidence of possible non-additive predictive structure, rather than confirmatory evidence of synergistic reinforcement. This interpretation is further examined through the construct-sensitivity robustness analysis reported later.

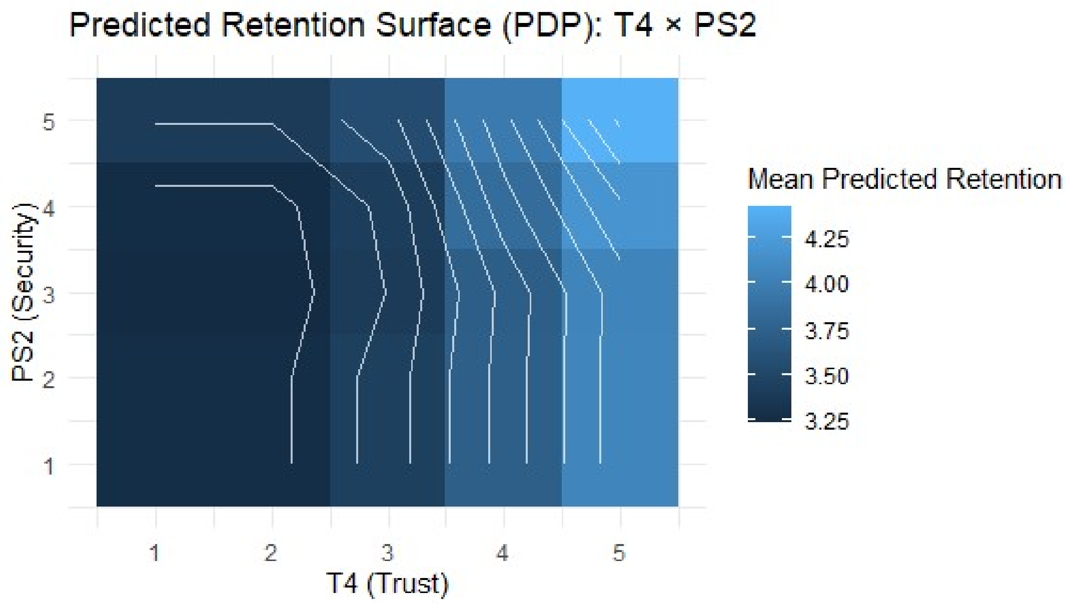

Figure 7. Retention Surface.

Table 22 provides a quadrant-based summary of the Trust × Security prediction surface. The table indicates that predicted retention intention is lowest when both trust and perceived security are low, while the highest predicted retention occurs when both are high. The intermediate quadrants suggest that high trust or high security alone may not produce the same level of predicted retention as their joint presence. This pattern is consistent with the possibility of complementarity between trust and security, but it should not be interpreted as causal evidence. Rather, it provides a model-based summary of how the fitted XGBoost model combines trust-related and security-related information when predicting retention intention.

Table 22. Quadrant Interpretation of Trust × Security Surface.

Trust Level	Security Level	Predicted Retention	Interpretation
Low	Low	Very Low	Severe churn risk; absence of both trust and security suppresses retention
Low	High	Low–Moderate	Security alone cannot compensate for lack of trust
High	Low	Moderate	Trust improves retention, but limited without security support
High	High	Very High	Maximum retention; strong complementarity between trust and security

5.10. Robustness Check

5.10.1. Generalized Additive Model (Gam) Robustness Analysis

To avoid relying exclusively on SHAP-based interpretation, a generalized additive model (GAM) was estimated using construct-level predictors. GAMs provide a transparent nonlinear modelling framework by estimating smooth functional relationships between predictors and retention intention. Specifically, smooth functions were estimated for ease of payment, perceived security, trust, switching costs, and age. This analysis serves as a robustness check to determine whether the nonlinear patterns identified by XGBoost and SHAP remain observable under a more interpretable nonlinear specification.

Table 23 reports the GAM estimation results. The model achieved a pseudo R^2 of 0.7256, indicating predictive performance comparable to the XGBoost model. Among the smooth terms, trust exhibited the strongest nonlinear effect and was highly statistically significant ($p < 0.001$). Perceived security also showed a statistically significant nonlinear relationship with retention intention ($p < 0.01$), while switching costs displayed weaker but still statistically meaningful nonlinear effects ($p < 0.05$). In contrast, the smooth terms for ease of payment and age were not statistically significant.

Overall, the GAM results provide additional support for the importance of trust and perceived security in explaining retention intention and offer qualified support for nonlinear switching-cost effects. Importantly, the absence of a significant nonlinear age effect suggests that the previously observed age-related SHAP pattern should be interpreted cautiously and treated as exploratory rather than confirmatory. Accordingly, nonlinear findings are interpreted as meaningful only when they appear consistently across multiple diagnostic approaches, including SHAP and GAM analysis.

Because smoothing parameters are estimated during GAM fitting, the associated p-values may be anti-conservative. Therefore, the GAM results are interpreted as robustness diagnostics rather than formal confirmatory hypothesis tests.

Table 23. Generalized additive model (GAM) robustness analysis.

Smooth Term	Effective DoF	p-value	Interpretation
s(EP)	11.8	0.106	No strong nonlinear effect detected
s(PS)	9.9	0.00797	Significant nonlinear relationship
s(Trust)	7.8	< 0.001	Strong nonlinear relationship
s(SCTB)	9.1	0.0482	Weak but significant nonlinear effect
s(Age)	6.7	0.310	No significant nonlinear effect
Intercept	—	< 0.001	Significant

Note: Pseudo R^2 = 0.7256; Effective Degrees of Freedom = 45.36; Generalized Cross-Validation = 0.3827; Number of observations = 305.

GAM smooth function for trust

Figure 8 presents the GAM smooth function for trust. The estimated smooth curve suggests a nonlinear positive relationship between trust and retention intention. At lower trust levels, the marginal effect on retention intention is weak or negative; however, the relationship becomes increasingly positive as trust increases, particularly beyond moderate trust levels. This pattern is broadly consistent with the SHAP dependence analysis and suggests that retention intention may respond more strongly once users develop relatively high levels of trust in the neobank platform. Importantly, the result should be interpreted as exploratory evidence of a model-learned nonlinear relationship rather than causal confirmation of a threshold mechanism.

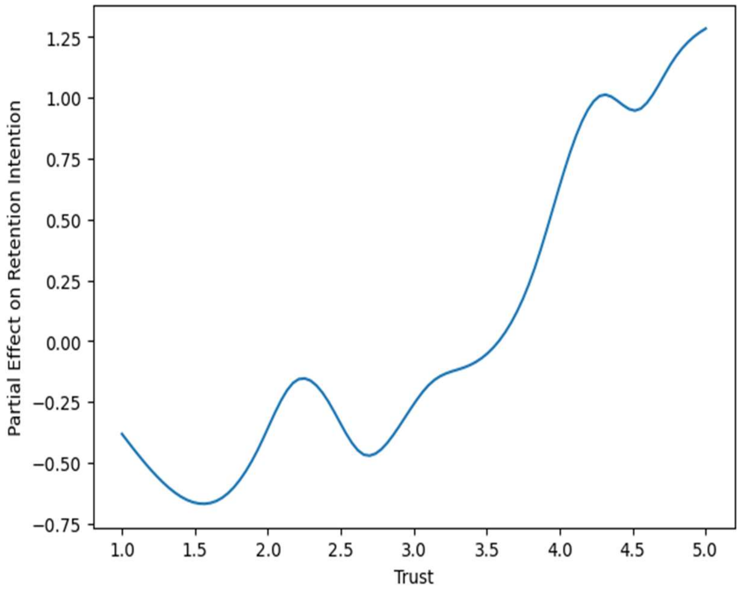

Figure 8. GAM smooth function for trust and retention intention.

GAM smooth function for switching costs

Figure 9 presents the GAM smooth function for switching costs. The estimated curve suggests a nonlinear and non-monotonic relationship between switching costs and retention intention. At lower switching-cost levels, the marginal effect appears weak or slightly negative, while moderate switching-cost levels are associated with stronger positive effects on retention intention. However, the relationship does not follow a simple monotonic pattern, as the marginal contribution weakens across some intermediate ranges before becoming positive again at higher switching-cost levels. This result is broadly consistent with the SHAP-based interpretation that switching costs may influence retention differently across user segments. Nevertheless, the pattern should be interpreted cautiously as exploratory evidence of heterogeneous nonlinear behaviour rather than confirmation of a single threshold mechanism.

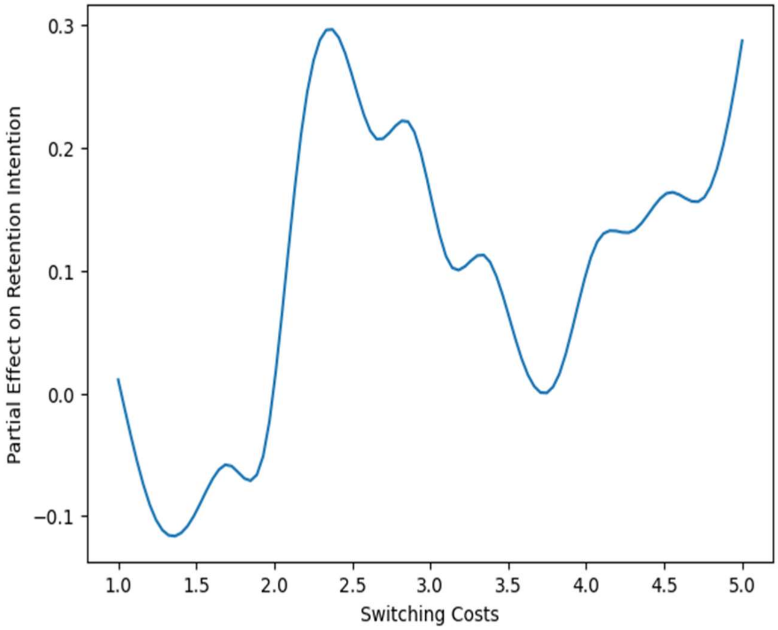

Figure 9. GAM smooth function for switching costs and retention intention.

GAM smooth function for age

Figure 10 presents the GAM smooth function for age. The estimated curve suggests some variation in the marginal contribution of age across different age ranges; however, the smooth term was not statistically significant. Although the pattern appears nonlinear, the evidence does not support a robust age-related nonlinear effect on retention intention within the present sample. This result contrasts with the more pronounced age pattern observed in the SHAP analysis and suggests that the apparent age-related nonlinearities may be sensitive to modelling approach and sample composition. Given the relatively young user profile of the dataset and the likely limited number of older respondents, the age-related findings should be interpreted as exploratory rather than conclusive.

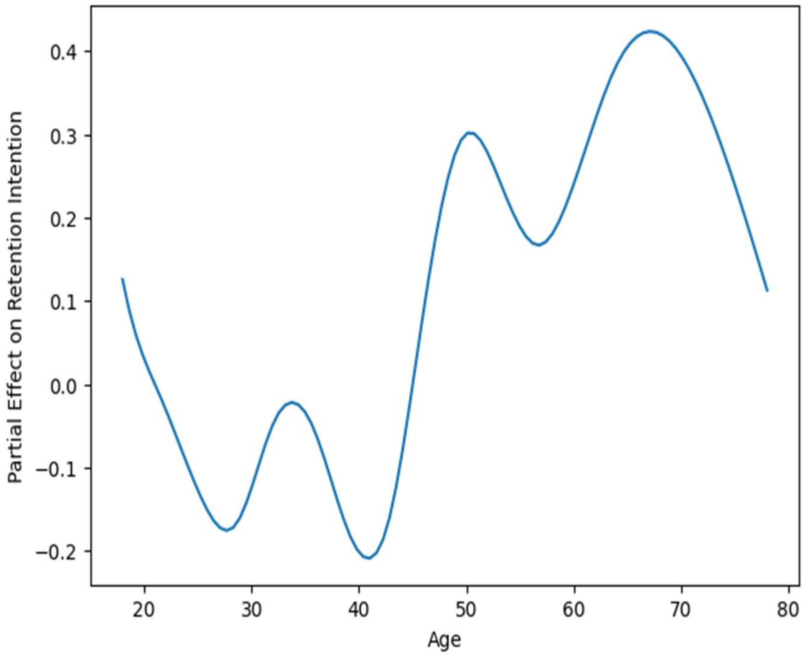

Figure 10. GAM smooth function for age.

5.10.2. Construct-Sensitivity Robustness Analysis

Because T4 (“This company’s application is safe to use”) conceptually overlaps with perceived security, additional construct-sensitivity analyses were conducted. Two alternative specifications were estimated. First, T4 was excluded from the trust construct, with trust measured only using T1–T3. Second, T4 was reclassified as a perceived-security item, with trust again measured using T1–T3 and perceived security measured using PS1–PS5 plus T4. XGBoost was then re-estimated using repeated nested cross-validation under both specifications.

The results (see Table 24 below) indicate that predictive performance remains strong under both alternative construct specifications. Excluding T4 from the trust construct reduces performance relative to the original XGBoost model, but the model still achieves a mean R^2 of 0.6677. Reclassifying T4 as a security item improves performance slightly compared with excluding it, producing a mean R^2 of 0.6826. These findings suggest that the original predictive results are not solely driven by the inclusion of T4 within the trust construct. However, the reduction in performance relative to the original specification also indicates that safety-related perceptions embedded in T4 contribute meaningfully to the prediction of retention intention. Therefore, the interpretation of trust dominance and trust-security complementarity should be made cautiously, acknowledging conceptual overlap between trust and perceived security in neobanking contexts.

 doi:10.20944/preprints202605.1452.v1

Table 24. Construct-sensitivity analysis: T4 exclusion and reclassification.

Model	N	RMSE Mean	RMSE SD	RMSE 95% CI	MAE Mean	R^2 Mean	R^2 95% CI
XGBoost: T4 excluded from Trust	100	0.5173	0.0760	[0.5022, 0.5324]	0.3843	0.6677	[0.6456, 0.6899]
XGBoost: T4 reclassified as Security	100	0.5045	0.0818	[0.4882, 0.5207]	0.3690	0.6826	[0.6595, 0.7057]

5.10.3. Construct-Level Composite Robustness Analysis

The preceding analyses already incorporate construct-level composite specifications through the PLS-SEM-inspired benchmark, the GAM robustness analysis, and the T4 construct-sensitivity tests. In these specifications, ease of payment, perceived security, trust, switching costs, and retention intention were operationalised as composite scores, reducing item-level noise and aligning the analysis more closely with the original S-O-R/PLS-SEM framework.

Overall, the construct-level evidence supports the stability of the main predictive conclusions. The PLS-SEM-inspired benchmark shows that the theory-driven linear structure explains a meaningful share of variation in retention intention, while the GAM and XGBoost construct-level robustness models indicate that nonlinear predictive structure remains present after aggregation to the construct level. At the same time, the T4 sensitivity results show that predictive performance is somewhat affected by how trust and perceived security are operationalised. Thus, the construct-level analyses suggest that the nonlinear findings are not merely driven by individual item-level noise, but they also reinforce the need to interpret trust-related effects cautiously because of conceptual overlap between trust and perceived security.

5.10.4. Age-Distribution Transparency Analysis

To provide transparency regarding the age-related nonlinear findings, Table 25 reports the age-group distribution of the sample. The distribution indicates that the sample is concentrated primarily among younger users, with approximately 61% of respondents aged between 18 and 24 years. In contrast, only 8.85% of respondents were aged 45 years or above. This imbalance is important when interpreting the exploratory age-related nonlinear patterns identified in the SHAP analysis. Consistent with the GAM results, the relatively limited representation of older respondents suggests that the apparent age-related nonlinearities should be interpreted cautiously and not treated as conclusive evidence of a stable age-based retention pattern.

Table 25. Age-group distribution of respondents.

Age Group	Frequency	Percentage
18–24	186	60.98
25–34	55	18.03
35–44	37	12.13
45+	27	8.85

5.11. Discussion of Empirical Findings

This study investigates customer retention in neobanking environments using a theory-informed explainable machine learning framework. Overall, the findings suggest that retention-intention prediction in digital financial services may involve heterogeneous and potentially nonlinear relationships that are not fully captured by conventional additive linear models.

First, the nonlinear XGBoost model consistently outperformed the regularized linear benchmarks under repeated nested cross-validation. The predictive improvement remained evident across multiple robustness checks, including construct-level composite specifications. These findings are broadly consistent with H1 and suggest that retention-intention prediction may involve nonlinear and interaction-based structure beyond standard linear specifications.

Second, trust-related indicators emerged as the most influential predictors within the fitted XGBoost model. SHAP aggregation results showed that trust-related variables contributed the largest share of model-based predictive importance. However, these findings should be interpreted cautiously because the most influential trust item, T4, refers to whether the application is safe to use and therefore overlaps conceptually with perceived security. The subsequent construct-sensitivity analyses were included to evaluate the robustness of this interpretation under alternative operationalisations of trust and security. Accordingly, the findings are interpreted as predictive rather than causal evidence regarding the importance of trust in retention-intention prediction.

Third, the SHAP dependence analysis suggested that trust may exhibit nonlinear predictive behaviour, with higher trust values associated with disproportionately stronger positive SHAP contributions. This pattern is broadly consistent with H3 in a predictive sense. However, rather than interpreting this result as confirmation of a behavioural threshold effect, the study treats it as exploratory evidence of possible nonlinear trust-related heterogeneity within the fitted model. The GAM robustness analysis provides additional transparency regarding this pattern.

Fourth, perceived security displayed a generally positive and more stable relationship with predicted retention intention. Compared with trust, the security-related SHAP patterns appeared less asymmetric and more consistently positive across the observed value range. These findings are broadly consistent with H4 and suggest that perceived security contributes meaningfully to the model's retention predictions.

Fifth, switching costs demonstrated heterogeneous predictive patterns across value ranges. The SHAP and GAM analyses suggested that switching costs may contribute more positively at higher levels, although the observed patterns were not uniformly monotonic. Consequently, the evidence is interpreted more cautiously as exploratory support for value-range-dependent switching-cost effects rather than definitive confirmation of a strict threshold mechanism. This interpretation is broadly consistent with H5 in a predictive sense.

Sixth, the SHAP analysis suggested possible age-related nonlinear variation in predicted retention intention. However, because the sample is heavily concentrated among younger respondents and the GAM robustness analysis did not detect a statistically significant age smooth effect, the evidence for a U-shaped age relationship is limited. Accordingly, the age-related findings are treated as exploratory rather than confirmatory, providing only qualified support for H6.

Finally, the interaction analyses suggested that trust-related and security-related variables may jointly contribute to retention-intention predictions. The strongest interaction effects were concentrated around T4 and several security items, particularly PS2 and PS4. However, because T4 overlaps conceptually with perceived security, the observed Trust × Security interaction patterns may partly reflect shared safety-related measurement content rather than a fully distinct behavioural complementarity mechanism. Therefore, the interaction results are interpreted cautiously as exploratory evidence of possible non-additive predictive structure rather than definitive confirmation of trust-security complementarity. In this sense, the findings provide only qualified and model-based support for H7.

Overall, the empirical findings suggest that customer retention in neobanking environments may be shaped by a combination of trust-related perceptions, security evaluations, switching barriers,

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and demographic heterogeneity. More broadly, the results indicate that explainable machine learning approaches can complement traditional theory-driven models by identifying potentially nonlinear and interaction-based predictive patterns that warrant further theoretical and empirical investigation.

6. Implications, Limitations, and Conclusion

6.1. Theoretical Implications

This study makes four distinctive contributions that differentiate it from existing research:

6.1.1. Extension of Relationship Marketing Theory

While relationship marketing theory (Morgan and Hunt, 1994) establishes trust as central to exchange continuity, it implicitly assumes linear, additive effects. Our findings extend this framework by demonstrating that trust operates through nonlinear acceleration in digital contexts. The convex trust-retention relationship (Figure 1) reveals that trust functions as a behavioural threshold mechanism: improvements at low trust levels yield minimal retention gains, whereas equivalent improvements at high trust levels produce disproportionately stronger loyalty responses. This aligns with prospect theory's loss aversion (Kahneman and Tversky, 2013) but extends it to positive domains, suggesting that trust-building investments exhibit increasing returns to scale beyond critical thresholds.

6.1.2. Refinement of Trust-Security Complementarity

Prior research models trust and security as sequential or parallel drivers (Stewart and Jürjens, 2018; Almaiah et al., 2023). Our SHAP interaction analysis reveals a more nuanced relationship: synergistic complementarity where the marginal effect of trust on retention increases by approximately 293% when moving from low to high security perceptions (based on T4 × PS2 interaction magnitude = 0.01687 versus main effect). This finding reframes security not merely as an antecedent to trust but as an enabling condition that amplifies trust's behavioural impact. Theoretically, this suggests that institutional assurances (security) and relational confidence (trust) are not substitutes but mutually reinforcing mechanisms requiring joint optimisation.

6.1.3. Switching Costs as Value-Range-Dependent Predictors

The findings also contribute to research on switching costs by suggesting that their predictive contribution may vary across value ranges. Rather than showing a simple linear effect, the SHAP and GAM results indicate that switching-cost perceptions may matter more under certain conditions or at higher levels. This is broadly consistent with behavioural arguments that switching barriers may not influence all users equally. However, the evidence does not conclusively establish a single threshold mechanism. Therefore, switching costs are interpreted as heterogeneous and value-range-dependent predictors of retention intention.

6.1.4. Demographic Nonlinearity in Digital Adoption

While technology adoption research acknowledges age differences (Morris & Venkatesh, 2000), the dominant practice of linear demographic controls obscures nonlinear patterns. The SHAP analysis suggests possible nonlinear age-related variation in predicted retention intention. However, the sample is concentrated among younger respondents, and the GAM robustness analysis does not provide strong support for a statistically meaningful nonlinear age effect. Therefore, this study does not claim to confirm a U-shaped age-retention relationship. Instead, it highlights age as a potentially heterogeneous demographic factor that requires further investigation using more age-balanced samples.

 doi:10.20944/preprints202605.1452.v1

6.1.5. Methodological Contribution to Information Systems and Fintech Research

Methodologically, this study demonstrates how explainable machine learning can complement theory-driven digital finance research. By combining repeated nested cross-validation, a PLS-SEM-inspired benchmark, SHAP interpretation, GAM diagnostics, and construct-sensitivity checks, the study shows how predictive modelling can be used to explore nonlinear and interaction-based patterns while retaining theoretical interpretability. This contribution is methodological and diagnostic rather than causal: explainable machine learning is used to identify patterns that may inform future confirmatory research.

6.2. Managerial Implications

6.2.1. Trust-Building Strategies

The findings suggest that trust-related perceptions are central to retention-intention prediction. Managers should therefore treat trust-building as a core retention priority. This may involve improving transparency, strengthening customer support, communicating reliability, and responding quickly to service failures. However, because trust effects are identified through predictive model explanations, managerial decisions should use these findings as diagnostic guidance rather than as causal evidence of guaranteed retention gains.

6.2.2. Security as A Visible Confidence Signal

Perceived security also emerges as an important predictor of retention intention. Neobanks should therefore ensure that security features are not only technically strong but also visible and understandable to users. Clear communication about fraud monitoring, authentication, data protection, and dispute-resolution procedures may help users interpret security as a signal of institutional reliability. Because trust and security overlap conceptually in this context, security communication should be integrated carefully with broader trust-building strategies.

6.2.3. Ecosystem Integration for Switching Costs

Perceived security also emerges as an important predictor of retention intention. Neobanks should therefore ensure that security features are not only technically strong but also visible and understandable to users. Clear communication about fraud monitoring, authentication, data protection, and dispute-resolution procedures may help users interpret security as a signal of institutional reliability. Because trust and security overlap conceptually in this context, security communication should be integrated carefully with broader trust-building strategies.

6.2.4. Age-Targeted Retention Strategies

Age-related results should be interpreted cautiously, as the sample is dominated by younger respondents. Nevertheless, managers may benefit from monitoring whether retention drivers differ across age groups. Younger users may respond more strongly to functionality, innovation, and user experience, while older users may place greater value on reliability, support, and security reassurance. These implications should be treated as tentative and should be validated with more balanced customer data.

6.2.5. Predictive Analytics Implementation

The repeated cross-validation results suggest that nonlinear models can improve retention-intention prediction relative to linear benchmarks. For neobanks, explainable predictive models may support customer segmentation, early warning systems, and targeted retention diagnostics. However, implementation should include model monitoring, fairness checks, construct validation, and human oversight. Explainability tools such as SHAP should be used to support managerial interpretation, not to replace substantive judgement or causal testing.

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6.3. Limitations and Future Research

Despite its contributions, this study has several limitations. First, the analysis relies on cross-sectional survey data, which limits the ability to infer causal relationships or examine changes in user behaviour over time. Future research could employ longitudinal data to investigate how trust, security perceptions, and retention evolve as users gain experience with digital financial platforms.

Second, the dataset represents neobank users in Mexico, which may limit the generalizability of the findings to other institutional or cultural contexts. Digital banking adoption patterns may differ across countries with varying financial infrastructures and regulatory environments.

Third, although explainable machine learning provides valuable insights into nonlinear relationships, the predictive models rely on self-reported perceptions rather than observed behavioural data. Future studies could combine survey data with transaction-level information to examine actual usage patterns.

Finally, future research may explore additional psychological or behavioural drivers of retention, such as perceived financial benefits, service personalization, or platform usability, to develop a more comprehensive understanding of customer loyalty in digital banking ecosystems.

6.4. Conclusions

This study examines customer retention in neobanking environments using a theory-informed explainable machine learning framework. The findings suggest that retention-intention prediction in digital financial services may involve heterogeneous and potentially nonlinear relationships that are not fully captured by traditional linear models. Across the analyses, trust-related indicators emerge as the strongest contributors to model-based retention predictions, while perceived security and switching costs also provide meaningful predictive influence.

By integrating behavioural theory with explainable predictive modelling, the study offers a more nuanced understanding of customer retention in digital banking contexts. At the same time, the findings are interpreted cautiously as predictive and exploratory rather than causal or confirmatory evidence. The results highlight the potential importance of trust-building practices, visible security assurance, and ecosystem integration strategies in supporting long-term user engagement with digital banking platforms. More broadly, the study demonstrates how explainable machine learning methods can complement theory-driven FinTech research by identifying potentially nonlinear and interaction-based predictive patterns that warrant further investigation.

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