

Research Article

Linking FinTech Platform Service Quality and User Loyalty: The Mediating Roles of Perceived Switching Costs and User Trust via a SEM-ANN Approach

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Abstract

This study examines how FinTech platform service quality influences user loyalty in China, and focuses on two mediators: perceived switching costs and user trust. Data were collected from 290 Chinese commercial bank customers with active FinTech platform usage experience, using purposive sampling to ensure respondents had sufficient experience to evaluate the services. A hybrid Structural Equation Modeling-Artificial Neural Network (SEM-ANN) Approach is applied to test both linear and non-linear relationships. The findings from SEM show that service quality has positive effects on perceived switching costs, user trust, and user loyalty. User trust also positively affects loyalty. However, perceived switching costs do not show a significant direct effect on loyalty. This suggests that in mature markets, trust matters more than switching barriers. For mediation, user trust plays a significant partial mediating role. The indirect path through perceived switching costs is not significant. ANN sensitivity analysis confirms this: user trust has the highest predictive importance (100%), followed by service quality (78.29%). Perceived switching costs rank lowest (31.35%). This study makes contributions by verifying the dual-mediator model in China's mature FinTech context, providing a framework for customer retention. Bank managers should build trust via service quality instead of artificial switching barriers.

Keywords

FinTech Platform Service Quality, Perceived Switching Costs, User Trust, User Loyalty, PLS-SEM-ANN

1. Introduction

Banking has transformed from physical branches to intelligent platforms [1]. In China, this unfolded gradually with financial informatization marking the beginning, and open banking defining the present stage [2]. Customer-bank relationships have been fundamentally altered, as FinTech platforms now mediate every interaction. Demographics have

shifted too, with younger users now dominating [3].

However, competition in this mature digital financial ecosystem has created a paradox. Technological advancements have made platform switching easy, and they have lowered user switching barriers for customer retention. With the in-

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Received: 22 April 2026; Accepted: 1 June 2026; Published: 9 June 2026



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creasing reliance on FinTech platforms as the primary channels for banks' customer engagement [4], recent evidence shows that traditional switching costs mechanisms are becoming less robust. Users now prioritize trust and personalized experiences over mere transactional convenience [5]. This shift requires a re-examination of the psychological mechanisms that drive user loyalty in mature FinTech markets.

Despite extensive research on electronic service quality and customer loyalty, three gaps remain. First, existing studies usually examine switching costs and trust as separate mechanisms, and fail to capture their simultaneous, competing influences on loyalty formation. Second, most of the empirical data are from Western markets or early-stage emerging markets, and the characteristics of the FinTech ecosystem in China are not yet clear. Third, a single-technique structural equation model cannot provide enough explanations or prediction testing [5].

To address these gaps, this study combines the Stimulus-Organism-Response (S-O-R) paradigm with Social Exchange Theory (SET), Relationship Quality Theory (RQT) and Customer Retention Theory (CRT). It examines how FinTech platform service quality (SQ) influences user loyalty (UL) through parallel psychological pathways: perceived switching costs (PSC) and user trust (UT). This research uses a hybrid Partial Least Squares-Structural Equation Modeling-Artificial Neural Network (PLS-SEM-ANN) methodology, offering both theoretical integration and methodological robustness for understanding loyalty formation in mature digital banking contexts.

2. Theoretical Foundation and Hypotheses Development

To unpack how SQ builds user loyalty, a strict theoretical framework is needed that covers the rational and psychological aspects of technology-mediated service interactions [6].

Grounded on the S-O-R paradigm [7], this study takes this paradigm as the core analytical framework, with SET, RQT and CRT providing supplementary theoretical support. SET lays the foundation for analyzing cost-benefit trade-offs and mutual obligations in user-platform relationships [8]. From another perspective, RQT clarifies how trust drives the formation of long-term user-platform bonds [9]. Customer Retention Theory (CRT) distinguishes between coercive retention (switching costs) and voluntary retention (trust), and its contemporary extensions show that trust-driven retention dominates in mature FinTech markets [4], justifying our dual-mediator design.

Before proposing specific hypotheses, this study clarifies the operationalization of core constructs: SQ, PSC, UT and UL are all treated as unidimensional reflective measures of users' holistic evaluation, rather than multidimensional composites. This operationalization is inspired by Abbas [10], who confirmed that users' holistic perception of FinTech services dominates the formation of their attitudinal and behavioral intentions in digital banking contexts. However, differing from the single linear modeling framework used by Abbas [10], this study adopts the dual psychological mechanisms, where SQ affects UL, and the differential effects of PSC and UT are distinguished as parallel mediators. In addition, a hybrid SEM-ANN approach is adopted to verify both linear causal relationships and non-linear predictive validity.

Building on the above theoretical basis, this section puts forward a series of research hypotheses, explaining the direct effects of SQ on UL and its two mediators (PSC and UT), as well as the indirect effects of SQ on loyalty through these two parallel psychological paths. The framework is built on a multi-theoretical foundation including SET, RQT, CRT and the E-S-QUAL model [11], with the S-O-R paradigm as the core analytical framework, and is shown in Figure 1.

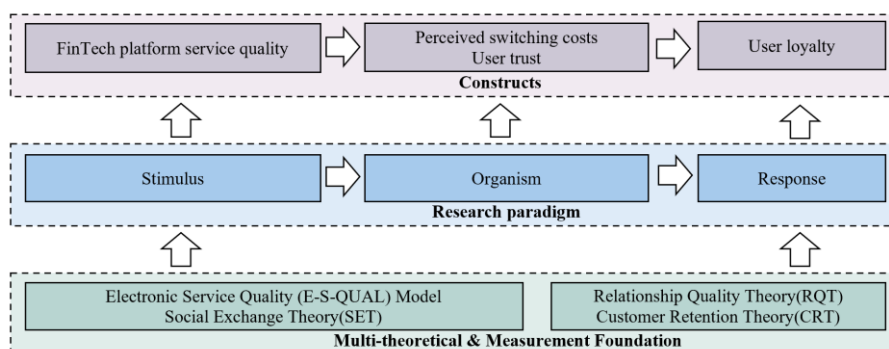


Figure 1. Theoretical foundation and research framework.

2.1. SQ and UL

In this study, SQ refers to users' overall perception of the

service performance of commercial banks' FinTech platforms, and covers four core dimensions: efficiency, system availability, fulfillment, and privacy security. These dimensions come

from the Electronic Service Quality (E-S-QUAL) model [11]. UL is the core outcome variable in this study, which refers to users' deep commitment to continuously use a preferred FinTech platform in the future, and comes with positive recommendation intention and resistance to alternative platforms [10]. SET points out that individuals engage in social interactions to pursue maximum rewards with minimum costs [12]. On commercial bank FinTech platforms, users view high-quality electronic services as valuable rewards, and they will return to the platform with high loyalty behaviors, and establish relatively stable relationships [2]. Thus, the following hypothesis is proposed:

H1: SQ exerts a direct positive effect on UL.

2.2. SQ and PSC

PSC in this study refers to users' overall perception of the time, cognitive effort, financial risk, and relational loss they will face when switching from the current commercial bank FinTech platform to an alternative provider [13].

Nguyen et al. [14] confirmed the positive effect of switching costs on customer loyalty in Vietnam's e-banking context, suggesting that accumulated platform-specific investments increase users' psychological barriers to switching. This mechanism is typically observed in emerging digital banking contexts, particularly the FinTech market of China's commercial banks. In this context, superior SQ can more effectively capture users' sunk costs and habituation effects, thereby enhancing users' perceived switching costs. Users' sunk costs and habituation benefits further strengthen perceived switching barriers. Thus, the following hypothesis is proposed:

H2: SQ exerts a direct positive effect on PSC.

2.3. SQ and UT

In the commercial bank FinTech context, UT refers to users' overall perception of a platform's ability to deliver on the service promises reliably, act with integrity, and protect their financial information and lawful rights and interests [15]. According to RQT, SQ is the core antecedent of trust formation in technology-mediated interactions [16]. FinTech platforms' consistent technical competence, operational transparency and security assurance help users form rational-cognitive trust based on performance credibility [5].

Recent studies emphasize that in the context of rapid FinTech development, UT is important for loyalty formation [5]. Thus, the following hypothesis is proposed:

H3: SQ exerts a direct positive effect on UT.

2.4. PSC and UL

PSC are retention barriers that bind users to their current service relationships regardless of their satisfaction. From the perspective of CRT, high switching costs make users rationally choose to stay with their current FinTech platform to maximize utility and minimize risks [13].

Recent research indicates that in the digital banking contexts, the relationship between switching costs and loyalty is more complex. In terms of exploring the boundary role, Mackay et al. [4] studied the boundary role of switching costs in digital banking loyalty formation, while traditional studies have shown that switching costs create user "stickiness" and enhance relationship maintenance. Thus, the following hypothesis is proposed:

H4: PSC exerts a direct positive effect on UL.

2.5. UT and UL

UT reduces the uncertainty and vulnerability in technology-mediated service relationships [15]. Within the framework of SET, UT forms emotional bonds beyond rational calculation and cultivates users' affective commitment to FinTech platforms [9]. UT within FinTech platforms enhances confidence in future service interactions, reduces perceived risks and increases willingness for continuous usage [17].

Consistent with other studies, Kim et al. [1] concluded that UT is an important psychological factor in customer loyalty. In addition, Sharma et al. [5] demonstrated that in Indian FinTech payment contexts, UT, alongside perceived security and ease of use constitutes the core catalyst for sustained digital engagement. Thus, the following hypothesis is proposed:

H5: UT exerts a direct positive effect on UL.

2.6. The Mediating Effect of PSC

In this study, SQ as a stimulus forms switching barriers through users' habit formation and asset specificity accumulation, and finally leads to UL.

Tuong et al. [13] investigated switching costs as antecedents of loyalty for Gen Z digital banking users, in which empirical support for this relationship was found. However, recent studies suggest that the mediating effect of switching costs may be context-dependent. While Nguyen et al. [14] showed that switching costs are significantly associated with loyalty in Vietnam's emerging e-banking market, their mediating role needs to be tested in China's mature FinTech market. Thus, the following hypothesis is proposed:

H6: PSC mediates the relationship between SQ and UL.

2.7. The Mediating Effect of UT

UT is the psychological path through which SQ affects UL—users need to have UT in the platforms' competence and benevolence before making a long-term usage commitment [15].

Alnaim et al. [18] confirmed that e-trust mediates the effect of e-service quality on e-loyalty, and this mediating effect is more prominent in financial services where trust is a necessary psychological buffer against risk perception [17]. This study demonstrates that excellent SQ alone cannot maintain users' UL without UT. Thus, the following hypothesis is proposed:

H7: UT mediates the relationship between SQ and UL.

Figure 2 shows the conceptual model and the hypotheses.

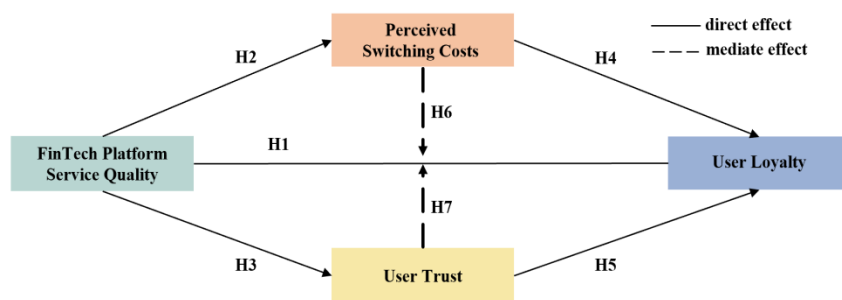


Figure 2. Conceptual Model.

3. Methodology

3.1. Methodology Design

This study adopts PLS-SEM and ANN to ensure both theoretical hypothesis testing and predictive validity verification. PLS-SEM is selected for its adaptability to predictive research models and relaxed data distribution assumptions [19]. The analysis follows two steps: (1) evaluating the measurement

model to verify construct reliability and validity; (2) evaluating the structural model to test hypothetical relationships, using SmartPLS 4.0.

To address PLS-SEM’s limitation in capturing non-linear relationships, this study uses ANN with the Multilayer Perceptron (MLP) algorithm to verify non-linear associations and predictive validity, following Albahri et al. [20] who demonstrate the effectiveness of hybrid SEM-ANN approaches. The MLP model uses dual hidden layers with a 70: 30 train-test split and Root Mean Square Error (RMSE) evaluation.

Table 1. Sample characteristics.

| Demographic | Categories | Frequency | Percent |
|-------------|------------------------------|-----------|---------|
| Gender | Male | 130 | 44.828% |
| | Female | 160 | 55.172% |
| Age groups | < 18 | 45 | 15.517% |
| | 18–30 | 106 | 36.551% |
| | 31–40 | 107 | 36.897% |
| | 41–50 | 23 | 7.931% |
| | 51–60 | 3 | 1.034% |
| | > 60 | 6 | 2.069% |
| Education | Junior high school or below | 29 | 10.000% |
| | High secondary school | 62 | 21.379% |
| | College | 73 | 25.172% |
| | Undergraduate | 100 | 34.483% |
| Profession | Postgraduate or above | 26 | 8.966% |
| | Student | 48 | 16.558% |
| | Enterprise employee | 171 | 59.966% |
| | Government institution staff | 44 | 15.172% |
| | Freelancer | 27 | 9.310% |

| Demographic | Categories | Frequency | Percent |
|------------------|-------------------|-----------|---------|
| Using time of | 1–3 years | 99 | 34.138% |
| FinTech platform | More than 3 years | 191 | 65.862% |

3.2. Construct Measurement and Control Variables

Consistent with the unidimensional operationalization in Section 2, all constructs are measured as reflective first-order factors for users' holistic evaluation instead of multidimensional composites.

All constructs are measured using validated multi-item scales adapted from existing literature to ensure content validity: SQ is measured by a modified 5-item E-S-QUAL scale [11]; PSC by 4 items [13, 21]; UT by 3 items [22]; and UL by 5 items measuring behavioral intention adapted from established scales in digital banking loyalty research [23, 24].

All items use a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). In line with technology adoption research practices [19], five control variables (gender, age, education, usage frequency, platform type) are included following Sharma et al. [5].

3.3. Survey and Data Collection

Data were collected via structured online questionnaires from Chinese commercial bank customers with active FinTech platform usage experience (including mobile banking, internet banking, and digital wallets). Purposive sampling ensured that respondents had sufficient experience to evaluate service interfaces. Exclusion criteria included straight-line answers and failed attention checks. 290 valid responses were obtained, meeting the minimum requirement of a 10: 1 ratio of sample size to independent variables [25]. Table 1 presents the characteristics of the sample.

3.4. Common Method Variance

Common Method Variance (CMV) needs be analyzed because data were collected from one source only. Following Kock [26], Variance Inflation Factor (VIF) values were checked. All values were below 3.3000, which meant common method bias was not present. Items with high VIF values were removed, following the solution for multicollinearity from [27]. Harman's single-factor test was also used. The first factor explained 32.99% of the total variance, which was below the 40.00% limit. Thus, serious common method bias was not a concern.

4. Results and Findings

4.1. Evaluating the Measurement Model

The measurement model was assessed using standard criteria: indicator reliability (outer loadings ≥ 0.70), internal consistency reliability (Cronbach's α and CR ≥ 0.70), and convergent validity (AVE ≥ 0.50) [19]. Discriminant validity was verified via the Fornell-Larcker criterion [28] and the Heterotrait-Monotrait Ratio (HTMT) with a threshold of < 0.85 [29].

Reliability was assessed using Composite Reliability (CR) and Cronbach's α , while convergent validity was evaluated through Average Variance Extracted (AVE) and standardized factor loadings. Consistent with the guidelines of Hair et al. [19], CR values above 0.7, Cronbach's α values exceeding 0.7, and AVE values no less than 0.5 indicate acceptable reliability and convergent validity. As shown in Table 2, the CR and Cronbach's α values for all constructs meet the 0.7 benchmark, demonstrating strong internal consistency. AVE values surpass the critical value of 0.5, confirming sufficient convergent validity.

Table 2. Measurement of construct.

| Constructs | α | CR | AVE |
|------------|----------|-------|-------|
| SQ | 0.888 | 0.888 | 0.614 |
| PSC | 0.875 | 0.875 | 0.637 |
| UT | 0.861 | 0.861 | 0.674 |
| UL | 0.894 | 0.894 | 0.628 |

Note: α = Cronbach's alpha, CR = Composite reliability, AVE = Average variance extracted.

Discriminant validity was verified using the Fornell-Larcker criterion and the HTMT analysis. The Fornell-Larcker criterion posits that the square root of the AVE for each construct should be greater than its correlation coefficients with all other constructs [28] — this criterion ensures that a construct is more strongly related to its own items than to items of other constructs. As presented in Table 3, the square root of the AVE for each construct (diagonal values) exceeds its correlation coefficients with other constructs. All HTMT values are below the 0.85 threshold, confirming that

the constructs are empirically distinct.

Table 3. Result of discriminant validity measures.

| Fornell-Larcker Criterion | | | | |
|---------------------------|--------------|--------------|--------------|--------------|
| | SQ | PSC | UT | UL |
| SQ | 0.784 | | | |
| PSC | 0.354 | 0.798 | | |
| UT | 0.378 | 0.356 | 0.821 | |
| UL | 0.363 | 0.287 | 0.432 | 0.793 |
| HTMT Criterion | | | | |
| | SQ | PSC | UT | UL |
| SQ | 0.402 | | | |
| PSC | 0.402 | 0.444 | | |
| UT | 0.459 | 0.444 | 0.525 | |
| UL | 0.406 | 0.338 | 0.525 | 0.525 |

Note: For Fornell-Larcker criterion, the bolded diagonal numbers are the square root of AVE. For HTMT criterion, the bolded numbers are the highest HTMT ratios.

4.2. Hypotheses Testing by PLS-SEM

Hypotheses regarding direct effects were tested using bootstrapping (5000 resamples) to obtain standard deviations (SD), standardized path coefficients (β), t-values, and p-values [19]—this method is the gold standard for significance testing in PLS-SEM, as bootstrapping accounts for non-normal data distributions common in social science research. The results are summarized in Table 4. As presented in Table 4, SQ has a significant positive direct impact on UL ($\beta = 0.363$, $p < 0.001$), supporting H1. SQ also significantly affects PSC ($\beta = 0.354$, $p < 0.001$) and UT ($\beta = 0.378$, $p < 0.001$), supporting H2 and H3. UT positively impacts UL ($\beta = 0.317$, $p < 0.001$), supporting H5, while the effect of PSC on UL is non-significant ($\beta = 0.100$, $p = 0.094$), rejecting H4. The indirect effect of SQ on

UL through UT is significant ($\beta = 0.120$, $p < 0.001$), supporting H7, while the indirect effect through PSC is non-significant ($\beta = 0.036$, $p = 0.116$), rejecting H6. The non-significance of Hypothesis 4 (PSC \rightarrow UL) and Hypothesis 6 (SQ \rightarrow PSC \rightarrow UL) can be attributed to two key contextual factors in the FinTech setting, which are consistent with recent related studies. First, while Nguyen et al. [14] identified a significant "lock-in" effect of PSC on UL in Vietnam's early-stage e-banking market, this effect is weakened in China's mature FinTech context due to seamless onboarding and platform interoperability. Second, users in this mature FinTech context prioritize UT and perceived reliability [5, 30], making the indirect path through UT the dominant mechanism, while the mediating role of PSC becomes secondary and statistically non-significant. These findings confirm that only UT plays a significant mediating role in the relationship between SQ and UL.

Table 4. Results of mediation analysis.

| Hypotheses | SD | β | t-value | p-value | Result | 95%CI |
|--------------------------|-------|---------|---------|---------|-----------|----------------|
| Direct Effects | | | | | | |
| H1: SQ \rightarrow UL | 0.066 | 0.363 | 6.518 | < 0.001 | Supported | [0.242,0.461] |
| H2: SQ \rightarrow PSC | 0.054 | 0.354 | 6.619 | < 0.001 | Supported | [0.235,0.446] |
| H3: SQ \rightarrow UT | 0.054 | 0.378 | 7.010 | < 0.001 | Supported | [0.263,0.475] |
| H4: PSC \rightarrow UL | 0.060 | 0.100 | 1.674 | 0.094 | Rejected | [-0.017,0.219] |

| Hypotheses | SD | β | t-value | p-value | Result | 95%CI |
|--------------------------|-------|---------|---------|---------|-----------|----------------|
| H5: UT →UL | 0.063 | 0.317 | 5.047 | < 0.001 | Supported | [0.190,0.437] |
| <i>Mediation Effects</i> | | | | | | |
| H6: SQ →PSC →UL | 0.023 | 0.036 | 1.573 | 0.116 | Rejected | [-0.006,0.085] |
| H7: SQ →UT →UL | 0.030 | 0.120 | 4.019 | < 0.001 | Supported | [0.067,0.183] |

Note: *** t-value > 3.2905 of significance at 0.1% level (two-tailed), β = path coefficients, SD = Standard deviation, CI = Confidence Interval.

As shown in Figure 3, the explanatory power of the structural model is evaluated using the coefficient of determination (R^2) and effect sizes (f^2).

Regarding R^2 values, PSC achieves an R^2 of 0.125, UT achieves 0.143, and UL achieves 0.241. Consistent with the criteria proposed by Hair et al. [19], the R^2 values for PSC and UT indicate weak explanatory power. UL reaches a moderate level of explanatory power. This result is reasonable in the FinTech context. UL is inherently influenced by multiple external factors (e.g., market competition, individual user traits) beyond the scope of the current research model.

For effect sizes (f^2), SQ exerts a medium effect on both PSC ($f^2 = 0.143$) and UT ($f^2 = 0.166$), which is in line with PLS-SEM guidelines [19, 31]. In contrast, SQ has a small direct effect on UL ($f^2 = 0.046$). UT demonstrates a small-to-medium effect on UL ($f^2 = 0.106$). These results align with the theoretical framework, and confirms that SQ primarily influences user loyalty indirectly through PSC and UT rather than through a strong direct path.

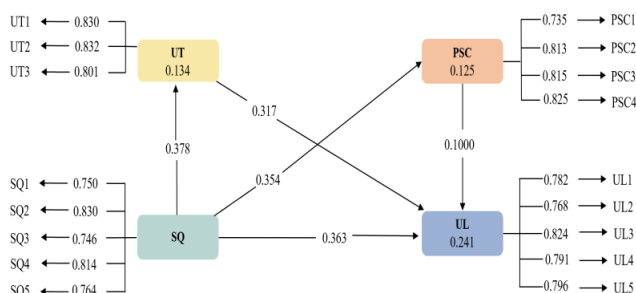


Figure 3. Mediation model.

4.3. Hypotheses Testing by ANN

The ANN analysis conducted in SPSS uses UL as the output neuron, with SQ, PSC and UT as the input neurons, with full details provided in Table 5. The ANN adopts a two-hidden-layer architecture, and uses hyperbolic tangent activation for both hidden and output neurons, as illustrated in Figure 4. All input and output data are normalized to the [0,1] range to improve training efficiency. To minimize overfitting, ten-fold cross-validation is utilized, with the dataset randomly divided into a 70: 30 ratio for training and testing.

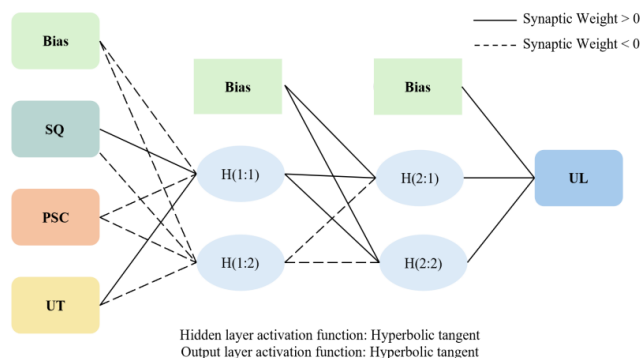


Figure 4. Structure of ANN model.

The RMSE metric evaluates predictive accuracy. The trained models generate a mean RMSE of 0.7864 for training and 0.7787 for testing, with standard deviations of 0.0362 and 0.0713, which confirm high precision. Sensitivity analysis results show that UT is the most critical predictor of UL, with normalized importance (NI) of 100%. SQ ranks second (NI = 78.29%), while PSC has the weakest predictive effect (NI = 31.35%), highlighting the dominant role of UT in shaping loyalty. The results are presented in Table 5.

5. Conclusion

5.1. Discussion

This study explores the mechanism through which SQ of commercial bank FinTech platforms influences UL, with PSC and UT as parallel mediators, using a hybrid PLS-SEM-ANN approach. The empirical results show that SQ has a significant positive direct effect on UL, supporting H1; SQ has significant positive effects on both PSC and UT, supporting H2 and H3; UT has a significant positive effect on UL, supporting H5, while the direct effect of PSC on UL is not significant, rejecting H4; UT plays a significant partial mediating role in the relationship between SQ and UL, supporting H7, while the mediating effect of PSC is not significant, rejecting H6. The ANN sensitivity analysis further confirms that UT has the highest predictive importance for UL, followed by SQ, while PSC has the weakest predictive power, and these findings are highly consistent with the PLS-SEM-ANN results.

Overall, in China's mature FinTech market, this study reveals that SQ mainly promotes UL through the trust path, rather than through the switching costs lock-in path, a finding that provides both theoretical evidence and practical guidance for commercial banks' user retention strategies in the digital era.

5.2. Theoretical and Practical Implications

This study makes three key theoretical contributions to FinTech user loyalty research.

Table 5. RMSE values of ANN models.

| Neural networks | RMSE (Training) | RMSE (Testing) | Total Sample | SQ | PSC | UT |
|-----------------|-----------------|----------------|--------------|--------|--------|-------|
| ANN1 | 0.758 | 0.831 | 290 | 0.337 | 0.156 | 0.507 |
| ANN2 | 0.767 | 0.825 | 290 | 0.257 | 0.169 | 0.574 |
| ANN3 | 0.770 | 0.784 | 290 | 0.303 | 0.127 | 0.570 |
| ANN4 | 0.745 | 0.821 | 290 | 0.378 | 0.177 | 0.445 |
| ANN5 | 0.871 | 0.664 | 290 | 0.400 | 0.139 | 0.462 |
| ANN6 | 0.794 | 0.898 | 290 | 0.526 | 0.018 | 0.457 |
| ANN7 | 0.795 | 0.738 | 290 | 0.376 | 0.176 | 0.449 |
| ANN8 | 0.786 | 0.769 | 290 | 0.455 | 0.211 | 0.334 |
| ANN9 | 0.815 | 0.679 | 290 | 0.369 | 0.137 | 0.496 |
| ANN10 | 0.763 | 0.778 | 290 | 0.335 | 0.186 | 0.479 |
| Mean | 0.786 | 0.778 | | 0.374 | 0.149 | 0.477 |
| SD | 0.036 | 0.071 | | | | |
| NI | | | | 78.290 | 31.349 | 100 |

First, this study integrates the S-O-R paradigm with SET and RQT, constructing and verifying a dual-mediator model of the effect of SQ on UL. This model fills the research gap of studies that fail to simultaneously examine the competing mechanisms of PSC and UT in mature FinTech markets. Second, the findings clarify the boundary effect of switching costs in digital banking. While high SQ significantly increases users' PSC, this indirect path could not effectively translate into UL in China's mature FinTech context, which supplements the contextual contingency conclusions of customer retention theory. Third, this study adopts a hybrid PLS-SEM-ANN approach, complements linear hypothesis testing with non-linear predictive validation, and confirms the dominant role of UT in loyalty formation through sensitivity analysis. This approach provides a robust methodological paradigm for subsequent FinTech user behavior research.

The findings provide targeted practical guidance for the FinTech platform operations of commercial banks. First, banks should prioritize the optimization of core SQ dimensions (efficiency, system availability, fulfillment, privacy security), taking UT as the core mediating factor. Second, banks should abandon the operation logic of building artificial switching barriers, and instead focus on shaping sustainable

user stickiness through transparent operation, reliable service fulfillment and strict data protection to enhance user trust. Third, banks should formulate differentiated operation strategies based on the core predictive factors identified by the ANN model, taking UT as the core starting point, to optimize the full-process user experience of FinTech platforms.

5.3. Limitations and Future Work

This study has four main limitations, which are detailed below. First, this study uses cross-sectional survey data. These data only show the links between variables at a single time point, and cannot fully show how the links change over time. UT and UL change as platform services and the market environment change. Cross-sectional data cannot reflect these dynamic changes. Second, the sample is restricted to users of commercial bank FinTech platforms in China, and this study does not investigate user heterogeneity across different regions. This limits the external validity of the research, and the findings may not be applicable to other regional markets. Third, the model only examines the mediating effects of UT and PSC, and does not include other factors that may affect

the relationships between core variables (e.g., market competition, user financial knowledge). Fourth, this study treats SQ as a single overall factor, and the separate effects of its four sub-dimensions: efficiency, system availability, fulfillment, and privacy security - are not tested. Thus, the specific service dimension that is most important for maintaining UL cannot be identified.

Building on the above limitations, this study proposes three future research directions: First, future research should optimize research designs for causal inference, adopting longitudinal tracking or scenario-based experiments to verify the causal links between SQ, UT and UL, and combining qualitative methods with the PLS-SEM-ANN framework to explore the psychological mechanisms of user loyalty formation. Second, future research should expand the sample scope to improve external validity, including cross-regional or cross-national samples to compare user loyalty drivers across markets, test the boundary of the switching costs effect, and enhance the generalizability of the findings. Third, future research should deepen the theoretical model and clarify boundary conditions, deconstructing the multi-dimensional structure of SQ to identify core drivers of UT and UL, and introducing moderating variables such as user financial literacy, market competition and regulation to refine the dual-mediator model.

Abbreviations

| | |
|----------|--|
| ANN | Artificial Neural Network |
| AVE | Average Variance Extracted |
| CMV | Common Method Variance |
| CR | Composite Reliability |
| CRT | Customer Retention Theory |
| E-S-QUAL | Electronic Service Quality |
| f^2 | Effect Size |
| HTMT | Heterotrait-Monotrait Ratio |
| MLP | Multilayer Perceptron |
| NI | Normalized Importance |
| PSC | Perceived Switching Costs |
| PLS-SEM | Partial Least Squares Structural Equation Modeling |
| R^2 | Coefficient of Determination |
| RMSE | Root Mean Square Error |
| RQT | Relationship Quality Theory |
| SD | Standard Deviation |
| SEM | Structural Equation Modeling |
| SET | Social Exchange Theory |
| S-O-R | Stimulus-Organism-Response |
| SQ | Service Quality |
| UL | User Loyalty |
| UT | User Trust |
| VIF | Variance Inflation Factor |

Author Contributions

Yuxin Wang: Conceptualization, Formal analysis, Investigation, Software, Writing – original draft

Tengyu Li: Project administration, Visualization, Writing – review & editing

Data Availability Statement

The data which support the findings of this study can be found at: <https://doi.org/10.6084/m9.figshare.31986672.v1>.

Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this article.

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