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A Comparative Analytical Approach for Predicting Continuance Intention in Mutual-Fund Investment Apps

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ABSTRACT

Global economic challenges have spurred a rise in household investments worldwide, including in Indonesia. By 2023, retail investors in Indonesia's capital market have quadrupled, reaching over 12 million, with mutual fund investors driving this surge. Many new investors use mutual fund investment applications to purchase and manage their portfolios. Despite this growth, providers face challenges in maintaining user loyalty and increasing average investments due to Indonesia's low financial literacy rate of 38.03%. **This study investigates** the factors influencing users' adoption and continuous use of mutual fund investment apps. It examines the relationships between perceived service quality, perceived security and privacy, trust, familiarity, user satisfaction, and continuance intention. **The research uses** a comparative approach, combining Structural Equation Modeling (SEM) with machine learning regression models, including linear regression, support vector regression, and multilayer perceptron, to create a robust and comprehensive model. **The findings** reveal that trust significantly impacts both user satisfaction ($\beta = 0.463, p < 0.001$) and continuance intention ($\beta = 0.194, p < 0.05$). Perceived service quality strongly influences user satisfaction ($\beta = 0.523, p < 0.001$), while familiarity plays a key role in fostering trust ($\beta = 0.224, p < 0.001$) and encouraging continued use ($\beta = 0.206, p < 0.001$). **Based on these results**, strategies to enhance user loyalty, such as improving security, services, and providing transparent recommendations, are proposed. This study contributes to understanding digital investment behavior in emerging markets and offers insights for expanding financial inclusion.

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1. INTRODUCTION

The COVID-19 pandemic caused a 3.9% decline in global GDP and a 5.3% drop in global trade in 2020 [1], prompting households to adopt strategic financial approaches. In Indonesia, retail investors grew from 2.5 million in 2019 to over 12 million in 2023 [2], driven by affordable and secure mutual fund apps supervised by OJK. By 2022, over 80 licensed fintech apps were available, creating both opportunities and challenges [3]. However, retaining users is difficult due to price sensitivity [4], low financial literacy at 38.03% [5], and trust issues. Consumers tend to switch platforms for short-term benefits, while lack of knowledge causes hesitation to invest.

User satisfaction strongly influences continuance usage, shaped by system quality, trust, and security [6, 7]. Familiarity with brands also helps reduce uncertainty [8, 9]. This study examines how service quality, security, privacy, trust, familiarity, and satisfaction affect adoption and continued use of mutual fund apps in Indonesia using PLS-SEM and machine learning to provide insights for enhancing digital investment services.

1.1. Conceptual Framework and Hypotheses Development

Investigating the determinants of user behavior and continuance intention remains central to information systems research [10]. Perceived service quality (PSQ) plays a vital role in shaping users' behavior, influencing their impressions, usage patterns, and long-term engagement. In mutual fund investment apps, PSQ includes factors such as system design, fulfillment efficiency, and customer service responsiveness, all of which impact user satisfaction and continuance intention [11, 12].

Key dimensions of PSQ include:

- System Design: Usability, accessibility, and ease of navigation [13, 14].
- Fulfillment Efficiency: Performance in executing tasks like order placement and transfers [10].
- Customer Service Responsiveness: Speed and quality of support [15].

The fulfillment of users' expected benefits affects their satisfaction and intention to continue using the app [16, 17]. Based on these factors, the following hypotheses are proposed:

- H1: PSQ is positively associated with user satisfaction.
- H2: PSQ is positively associated with continuance intention.

Trust in mutual fund apps is crucial for adoption and continued use [18]. When users experience secure investments and real-time portfolio management, trust in the app strengthens, encouraging continued use. Thus, hypothesize:

- H3: PSQ is positively associated with trust.

Perceived security and privacy play a critical role in adoption decisions, shaping overall perceptions of financial safety. When security expectations are met, user satisfaction increases and the likelihood of continued platform usage becomes higher [19, 20]. Hence:

- H4: Perceived security and privacy is positively associated with trust.
- H5: Perceived security and privacy is positively associated with user satisfaction.

Trust is a key factor in online financial transactions, affecting adoption, satisfaction, and continued use [21]. Therefore, propose:

- H6: Trust is positively associated with user satisfaction.
- H7: Trust is positively associated with continuance intention.
- H8: User satisfaction is positively associated with continuance intention.

Familiarity with the app enhances trust and encourages continued use [22]. As users become familiar with the app, their confidence grows, leading to increased satisfaction and trust. Thus, hypothesize:

- H9: Familiarity is positively associated with trust.
- H10: Familiarity is positively associated with continuance intention.

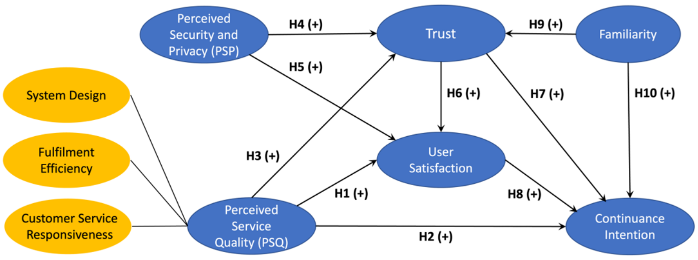

Figure 1. Presents the Research Model and Proposed Hypotheses.

The figure shows how key service factors shape Perceived Service Quality, which then builds Trust and User Satisfaction, ultimately leading to Continuance Intention, while figure 2 outlines the hypotheses supporting these relationships.

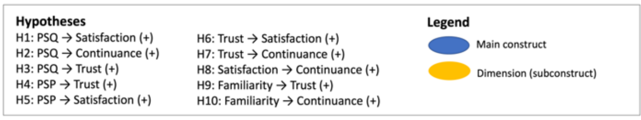

Figure 2. The Conceptual Model

2. RESEARCH METHODS

2.1. Questionnaire Design

This study used a questionnaire based on the Expectation Confirmation Model, perceived service quality, security, trust, and familiarity, adapted to the study's context [23]. The survey included demographic questions, app usage behavior, and 27 items on a 6-point Likert scale (1 = strongly disagree, 6 = strongly agree) to encourage decisive responses. The questionnaire, available in English and Indonesian, was distributed online via digital and social media platforms, with professional translation ensuring accuracy [24]. The questionnaire's validity and reliability were examined through expert reviews and the Content Validity Index (CVI). Four experts assessed item relevance using a four-point scale, and the instrument achieved an S-CVI/AVE of 0.90, surpassing the 0.83 threshold, indicating strong content validity [25]. A pilot test with 30 participants further evaluated readability and item clarity, producing a Cronbach's alpha of 0.954, which confirms high reliability. Minor revisions were made based on expert and participant feedback before the final data collection [26].

2.2. Data Collection and Analysis

This study recruited participants aged 18 years or older who had used at least one mutual fund investment app in Indonesia, such as Bareksa, Bibit, Ajaib, or IPOT, to actively invest in mutual funds [27]. The survey invitation was widely distributed through various mutual fund investment community groups on popular social media platforms and messaging apps (WhatsApp and Telegram), and several additional participants were also recruited through targeted email campaigns and direct messaging apps. The comprehensive online survey was conducted using a secure web-based survey system between July and August 2023, as well as October to November 2023, and all participants were explicitly requested to carefully review and acknowledge a consent form before proceeding to complete the questionnaire in full [17, 28, 29].

Table 1. Constructs, Indicators, and Questionnaire Items

Construct	Indicator	Questionnaire Item	Adapted From
System Design (SDE)	SDE1	The structure and contents of the mutual fund investment app is clear and understandable.	[10–12]
	SDE2	I can easily complete my investment tasks, including searching for mutual funds, placing an order (buy/sell), and confirming the transaction.	[10–12]
	SDE3	It is easy to navigate the interface of the mutual fund investment app and locate the features I am looking for.	[10–12]

Construct	Indicator	Questionnaire Item	Adapted From
Fulfillment Efficiency (FEF)	FEF1	The mutual fund investment app completes investment orders (buy and sell) within a reasonable timeframe and provides sufficient information about the order status.	[10–12]
	FEF2	The mutual fund investment app provides a guarantee for transaction fulfillment.	[10–12]
Customer Service Responsiveness (CSR)	CSR1	The mutual fund investment app provides dedicated customer support to address any questions or issues I may have related to the use of the app and investment transactions.	[11, 12]
	CSR2	The customer service of the mutual fund investment app promptly addresses my issues and offers effective solutions.	[11, 12]
Perceived Security and Privacy (PSP)	PSP1	I believe that my transactions in mutual fund investment apps are secure and protected.	[12, 28]
	PSP2	The mutual fund investment app protects my personal and financial information.	[12, 28]
	PSP3	The mutual fund investment app has rigorous security features.	[12, 28]
Trust (TRU)	TRU1	I trust the mutual fund investment app will perform well and thus process my transaction correctly.	[26, 30]
	TRU2	Mutual fund investment app offers access to reliable investment services.	[26, 30]
	TRU3	I feel assured that the mutual fund investment service provider has the legal and technological structures to protect my transactions.	[26, 30]
	TRU4	The network of the mutual fund investment app is trustworthy.	[26, 30]
	TRU5	The mutual fund investment app provides transparency of information to its users.	[26, 30]
User Satisfaction (US)	US1	The features on the mutual fund investment app meet my needs.	[17, 24, 26]
	US2	My experience of using the mutual fund investment app is satisfactory.	[17, 24, 26]
	US3	Overall, I am satisfied with the mutual fund investment app.	[17, 24, 26]
Familiarity (FAM)	FAM1	I have experiences in using mutual fund investment apps.	[15, 16, 31]
	FAM2	I feel familiar with terms and features in a mutual fund investment app.	[15, 16, 31]
	FAM3	Generally, I am familiar with how to use a mutual fund investment app.	[15, 16, 31]
Continuance Intention (CIN)	CIN1	I plan to continue to use the mutual fund investment app frequently in the future (repeat transactions).	[10, 24, 26]
	CIN2	I would rather continue using the app than discontinue its usage.	[10, 24, 26]
	CIN3	Using a mutual fund investment app for handling my investments is something I will fond.	[10, 24, 26]

Based on Table 1, this study uses eight key constructs: SDE, PFP, CSR, PSP, TRU, US, FAM, and CIN. These constructs help analyze factors influencing mutual fund app use, such as system design, security, and continuance intention, while ensuring valid and reliable measurements.

The participants' responses were analyzed using descriptive statistics, and the proposed model was tested with hierarchical partial least squares Structural Equation Modeling (PLS-SEM) and machine learning algorithms. PLS-SEM was chosen due to its suitability for non-normally distributed data [31]. A Shapiro-Wilk test confirmed non-normality for all constructs ($p < 0.001$). A hierarchical component model type II was applied, combining formative and reflective relationships (Figure 3). The extended repeated indicators approach was used [32]. Measurement model assessment included indicator reliability (outer loadings > 0.708), internal consistency (CR between 0.70–0.90), convergent validity (outer loadings > 0.70 and AVE ≥ 0.50), and discriminant validity using HTMT (> 0.90) [33].

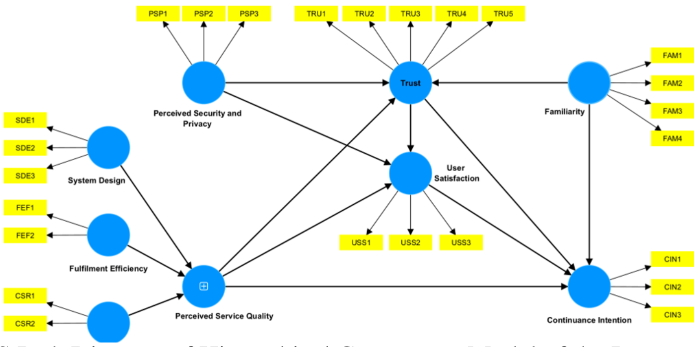

Figure 3. The PLS Path Diagram of Hierarchical Component Model of the Proposed Research Model Perceived Service Quality is the Second Order Construct.

The second stage evaluated the measurement model of HOCs using the extended repeated indicators approach, where latent variable scores of perceived service quality dimensions were treated as manifest variables for the construct. Evaluation was done at both dimension and construct levels. At the dimension level, multicollinearity was checked via Variance Inflation Factor (VIF) and cross-loadings. A VIF above five indicates collinearity issues [34], while acceptable values allow testing of outer weights and loadings. The structural model evaluation assessed R^2 and path coefficients of HOCs, excluding LOCs from the model. R^2 reflects explained variance in endogenous constructs, and lower values can still be acceptable in emerging research. Significance testing of path coefficients identified the strength of hypothesized relationships.

To enhance the model, machine learning regression models were applied [35]. Linear regression was the baseline for interpretability, SVR handled non-linear and high-dimensional data, and MLP captured complex hierarchical interactions. These models provided deeper insights and guided recommendations for improving user experience in mutual fund apps [36].

3. RESULTS AND DISCUSSION

Following the PLS methodology, this section reports the participants' descriptive profiles, measurement model assessment, and hypothesis testing using the structural model assessment and machine learning algorithms [37].

3.1. The Profile of the Participants

A total of 763 participants from Indonesia participated in the data collection via email, messaging apps, and social media, with 561 completing the questionnaire (73.53% response rate). After excluding 47 invalid responses, the final sample consisted of 514 valid responses. The majority were young, with over 86% aged 40 or younger, which aligns with recent findings that Generation Z and millennials make up the majority of active investment app users [38, 39].

Regarding usage duration, more than 90% had used the app for three years or less, supporting the Indonesian Central Securities Depository's report on the rise of retail investors during the COVID-19 pandemic [40]. Furthermore, 342 participants (66.24%) allocated 20% or less of their monthly income to investments, consistent with a recent survey by the Center for Economics and Law Studies and Pluang, which reported that

61% of respondents spent less than 20% of their income on various investments [41]. Table 2 presents the participants' profiles.

Table 2. Demographics Characteristics of the Participants.

Category	**n (%) N=514**
Gender	
Man	288 (56.03%)
Woman	226 (43.97%)
Age group (in years old)	
18 – 20	27 (5.25%)
21 – 30	232 (45.14%%)
31 – 40	185 (35.99%)
41 – 50	185 (35.99%)
$\geq$ 51	12 (2.33%)
Job	
University student	97 (18.78%)
Civil servant	85 (16.54%)
Private employee	138 (26.85%)
Professionals and self-employed	126 (24.51%)
Others	66 (12.84%)
Duration of usage	
<6 months	95 (18.48%)
6 months – 1 year	137 (26.65%)
1 year – 2 years	152 (29.57%)
2 years – 3 years	94 (18.29%)
3 years – 5 years	32 (6.25%)
>5 years	29 (5.75%)
Percentage of monthly income for investment	
10% – 20%	118 (24.96%)
>20%	12 (2.41%)
Depending on the remaining cash	100 (19.46%)
1%	61 (12.70%)
Top-up frequency per month	
4 – 6	28 (5.45%)
7 – 10	55 (10.74%)
>10	29 (5.67%)
Anytime as necessary	268 (52.14%)

Based on Table 2, most participants were man (56.03%) and aged 31–50 years (35.99%). The largest occupational group was professionals and self-employed (24.51%), followed by private employees (26.85%). Most had used the investment app for 1–2 years (29.57%) and allocated 10%–20% of their monthly income for investments (24.9%). Additionally, the majority preferred to top up anytime as necessary (52.14%), indicating flexible investment behavior.

3.2. Measurement Model First-order Constructs with Reflective Indicators

This study employed SmartPLS4 for partial least squares path analysis to test reliability and validity [42]. As shown in Table 3, outer loadings were above 0.7, AVE ranged from 0.595 to 0.826, and CR between 0.70 and 0.90, confirming indicator reliability, internal consistency, and convergent validity [43], thereby supporting the robustness and overall strength of the proposed measurement model.

Table 3. Outer Loadings, Internal Consistency, Convergent Validity (System Design Only)

Construct	Indicator	Outer Loadings (>0.7)	Cronbach's α (0.70 – 0.90)	CR[a]	AVE[b] (>0.5)
System Design (SDE)	SDE1	0.887	0.832	0.834	0.749
	SDE2	0.868			
	SDE3	0.840			
Fulfillment Efficiency (FEF)	FEF1	0.905	0.776	0.776	0.817
	FEF2	0.740			
Customer Service Responsiveness (CSR)	CSR1	0.805	0.790	0.792	0.826
	CSR2	0.927			
Perceived Security and Privacy (PSP)	PSP1	0.815	0.770	0.770	0.685
	PSP2	0.807			
	PSP3	0.829			
Trust (TRU)	TRU1	0.820	0.873	0.873	0.663
	TRU2	0.814			
	TRU3	0.804			
	TRU4	0.830			
	TRU5	0.822			
Familiarity (FAM)	FAM1	0.762	0.773	0.776	0.595
	FAM2	0.776			
	FAM3	0.803			
Satisfaction (USS)	USS1	0.828	0.838	0.842	0.756
	USS2	0.880			
	USS3	0.898			
Continuance Intention (CIN)	CIN1	0.863	0.760	0.771	0.675
	CIN2	0.805			
	CIN3	0.796			

Note: [a] Composite Reliability; [b] Average Variance Extracted.

Based on Table 3, all constructs demonstrate acceptable reliability and validity, as indicated by outer loadings above 0.70, Cronbach's alpha values between 0.70 and 0.90, and AVE values above 0.50. This suggests that the measurement model has good internal consistency and convergent validity, confirming that the indicators used effectively represent each construct [44].

Table 4. Discriminant Validity Test: Heterotrait-Monotrait (HTMT) Ratio of Correlations Criterion

Construct	CIN	CSR	FAM	FEF	PSP	SDE	TRU	USS
CIN	-	-	-	-	-	-	-	-
CSR	0.655	-	-	-	-	-	-	-
FAM	0.704	0.570	-	-	-	-	-	-
FEF	0.606	0.803	0.524	-	-	-	-	-
PSP	0.682	0.726	0.506	0.535	-	-	-	-
SDE	0.712	0.710	0.590	0.604	0.732	-	-	-
TRU	0.755	0.729	0.672	0.617	0.896	0.724	-	-
USS	0.792	0.777	0.644	0.702	0.657	0.799	0.834	-

Based on Table 4, all HTMT values are below the threshold of 0.90, indicating good discriminant validity among the constructs. This suggests that each construct is distinct and measures a unique concept, supporting the reliability and validity of the measurement model.

3.3. Measurement Model: Second-order Constructs with Formative Indicators

In the HOC measurement model, the latent variable scores of perceived service quality dimensions served as manifest variables for the perceived service quality construct (see Figure 3). All VIF values of perceived service quality dimensions were below the conservative threshold of 3 [45], suggesting that there was no indication of collinearity among perceived service quality dimensions. The results of the significance test in Table 5 show that all the dimensions were statistically significant $p < 0.05$. Hence, examined the outer weights and outer loadings of all formative indicators. The results in Table 6 show that all the formative indicators were significant $p < 0.05$. Likewise, all outer loading values of all indicators surpassed the threshold of 0.5, justifying the retention of all proposed perceived service quality dimensions. Following these results, this formative construct was deemed suitable for testing the structural model.

Table 5. Content Validity of the Formative Measurement Construct: VIFs, Weight Significances, and Bootstrap Tests.

Construct	**VIF**	**Weights**	***t-Stat***	***p-Value***
LV System Design → Perceived Service Quality	1.559	0.567	11.060	0.000
LV Fulfillment Efficiency → Perceived Service Quality	1.719	0.239	3.961	0.000
LV Customer Service Responsiveness → Perceived Service Quality	1.970	0.369	5.664	0.000

Based on Table 5, all constructs show VIF values below 5, indicating no multicollinearity issues. Additionally, the weights are significant with p-values of 0.000, demonstrating that System Design, Fulfillment Efficiency, and Customer Service Responsiveness have a significant impact on Perceived Service Quality in the formative measurement model.

Table 6. The Outer Loadings of Perceived Service Quality Dimensions

Construct	**Original sample (O)**	**Sample mean (M)**	***t-Stat***	***p-Value***
LV System Design → Perceived Service Quality	0.897	0.894	36.760	0.000
LV Fulfillment Efficiency → Perceived Service Quality	0.747	0.746	19.448	0.000
LV Customer Service Responsiveness → Perceived Service Quality	0.847	0.844	28.646	0.000

Based on Table 6, all constructs have high outer loading values, with System Design (0.897), Fulfillment Efficiency (0.747), and Customer Service Responsiveness (0.847), all showing p-values of 0.000. These results indicate that each construct significantly contributes to Perceived Service Quality, confirming the strong relationship and validity of the measurement model.

3.4. Structural Model and Hypothesis Test

The R^2 values for trust, user satisfaction, and continuance intention were 0.669, 0.643, and 0.511, respectively, demonstrating moderately strong explanatory power. Trust and user satisfaction showed a slightly greater influence on user behavior than continuance intention. Key factors perceived service quality, security, privacy, trust, familiarity, and user satisfaction significantly contributed to explaining variations in user behavior within mutual fund investment apps.

Statistical results revealed that hypotheses H5 and H7 were significant at the 0.05 level, H2 and H8 at the 0.01 level, and H1, H3, H4, H6, H9, and H10 at the 0.001 level, confirming strong overall support for all hypotheses.

As presented in Table 7 and Figure 4, perceived service quality, security, privacy, trust, and familiarity play crucial roles in shaping user satisfaction and continued app use. Trust emerged as a primary driver of satisfaction, suggesting that improving service quality and security can enhance user loyalty. These insights provide fintech providers with valuable guidance to optimize user experience and foster sustained engagement and growth.

Table 7. Structural Relationship Test Results (Part 1)

Hypothesis Statement	**Path coefficient^a (Sig. value)**	**T-value**	**Remark**
H1: Perceived Service Quality → User Satisfaction	0.523^{***} (0.000)	9.141	Supported
H2: Perceived Service Quality → Continuance Intention	0.189^{**} (0.002)	3.029	Supported
H3: Perceived Service Quality → Trust	0.264^{***} (0.000)	5.096	Supported
H4: Perceived Security and Privacy → Trust	0.486^{***} (0.000)	11.390	Supported
H5: Perceived Security and Privacy → User Satisfaction	0.150^{*} (0.017)	2.381	Supported

H6: Trust → User Satisfaction	0.463^{***} (0.000)	7.085	Supported
H7: Trust → Continuance Intention	0.194^{*} (0.023)	2.280	Supported
H8: User Satisfaction → Continuance Intention	0.251^{**} (0.003)	3.012	Supported
H9: Familiarity → Trust	0.224^{***} (0.000)	5.459	Supported
H10: Familiarity → Continuance Intention	0.206^{***} (0.000)	3.944	Supported

Based on Table 7, all hypotheses are supported, showing significant relationships. The strongest is between Perceived Security and Privacy and Trust (H4, $\beta = 0.486$, $p < 0.001$, $t = 11.390$). Perceived Service Quality also strongly impacts User Satisfaction (H1, $\beta = 0.523$, $p < 0.001$, $t = 9.141$). These findings confirm the importance of service quality, trust, and familiarity in enhancing user satisfaction and continuance intention.

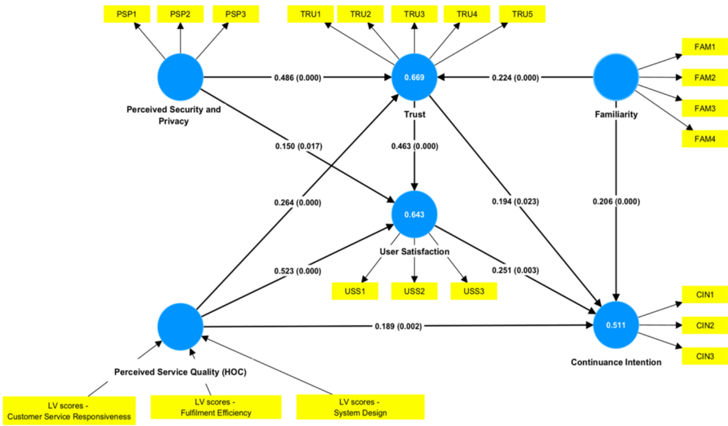

Figure 4. The HOC's Structural Model.

Figure 4 presents the HOC model linking Service Quality, Security, Trust, Familiarity, Satisfaction, and Continuance Intention, confirming strong relationships consistent with Table 7.

3.5. Hypothesis Testing Results Validation using Machine Learning Regression Models

Prior studies have used machine learning regression to test predictive models [46]. This study applied linear regression, SVR, and MLP with Latent Variable (LV) scores for predictors and targets, using 10-fold cross-validation in Python 15. Three regression models were developed, as shown in Figure 1.

- Estimating the effect of perceived service quality, perceived security and privacy, and familiarity on trust.
- Estimating the effect of perceived service quality, perceived security and privacy, and trust on satisfaction.
- Estimating the effect of perceived service quality, trust, satisfaction, and familiarity on continuance intention.

The regression models were evaluated using key metrics: R^2, MSE, RMSE, MAE, and MAPE [47]. Using multiple metrics ensures a comprehensive assessment of model performance.

As shown in Table 8, the linear regression model performed best in predicting trust, supporting H3, H4, and H9. For user satisfaction, Table 9 shows that the MLP model achieved the highest R^2 and lowest error values, confirming H1, H5, and H6. These findings indicate that trust-related variables exhibit more linear behavioral patterns, while satisfaction-related variables demonstrate more complex, nonlinear interactions. The results also highlight the importance of selecting appropriate machine-learning models based on the structural nature of each construct, ensuring more accurate predictions and deeper theoretical understanding across diverse user behavior contexts.

Table 8. Estimating the Effect of Perceived Service Quality, Perceived Security and Privacy, and Familiarity on Trust

Model	R^2	**MSE**[a]	**RMSE**[b]	**MAE**[c]	**MAPE**[d]
Linear	0.985052833	0.012566701	0.112101298	0.092617013	0.27348858%
Model	R^2	**MSE**[a]	**RMSE**[b]	**MAE**[c]	**MAPE**[d]
SVR[e]	0.887546789	0.094544061	0.307480179	0.149744177	0.32704395%
MLP[f]	0.976767819	0.019532254	0.139757842	0.109150712	0.32568691%

Note: MSE[a]: mean-squared error, RMSE[b]: root mean squared-error, MAE[c]: mean absolute error, MAPE[d]: mean absolute percentage error, SVR[e]: support vector regression, MLP[f]: multilayer perceptron.

Based on Table 8, the Linear model achieved the highest R^2 (0.985) and the lowest error rates, indicating strong predictive accuracy. In contrast, SVR and MLP had lower R^2 and higher error rates, making the Linear model the most effective for estimating the effects of service quality, security, privacy, and familiarity on trust.

Table 9. Estimating the Effect of Perceived Service Quality, Perceived Security and Privacy, and Trust on Satisfaction

Model	R^2	**MSE**[a]	**RMSE**[b]	**MAE**[c]	**MAPE**[d]
Linear	0.974009019	0.020401540	0.142833960	0.117441651	0.24746264%
SVR[e]	0.967597629	0.025434140	0.159480846	0.113872152	0.25320136%
MLP[f]	0.976569325	0.018391835	0.135616501	0.105297876	0.23830741%

Note: MSE[a]: mean-squared error, RMSE[b]: root mean squared-error, MAE[c]: mean absolute error, MAPE[d]: mean absolute percentage error, SVR[e]: support vector regression, MLP[f]: multilayer perceptron.

Based on Table 9, the Linear model achieved the highest R^2 (0.974) and lowest error values, indicating superior accuracy in predicting satisfaction. In contrast, SVR and MLP showed slightly lower performance, making the Linear model the most reliable.

Finally, Table 10 shows the MLP model has the best performance with high R^2 and low error values. However, the MAPE of 21.072% suggests some proportional errors. Overall, it reliably predicts continuance intention, supporting H2, H7, H8, and H10.

Table 10. Estimating the Effect of Perceived Service Quality, Trust, Satisfaction, and Familiarity on Continuance Intention

Model	R^2	**MSE**[a]	**RMSE**[b]	**MAE**[c]	**MAPE**[d]
Linear	0.732815265	0.129024263	0.359199475	0.296718404	37.3401929%
SVR[e]	0.552162916	0.381546172	0.617694239	0.376013598	42.9524135%
MLP[f]	0.926166053	0.062904706	0.250808105	0.185570382	21.0719675%

Note: MSE[a]: mean-squared error, RMSE[b]: root mean squared-error, MAE[c]: mean absolute error, MAPE[d]: mean absolute percentage error, SVR[e]: support vector regression, MLP[f]: multilayer perceptron.

Based on Table 10, the MLP model shows the best performance with the highest $R^2 = 0.926$ and the lowest error rates (MSE = 0.0629, RMSE = 0.2508, MAE = 0.1855, MAPE = 21.07%), making it the most reliable. In contrast, the Linear model and SVR perform worse, with SVR having the weakest $R^2 = 0.5521$ and the highest error rates.

Although mutual fund app users are growing rapidly, maintaining user loyalty and increasing investment levels remain difficult because many investors are price-sensitive, have limited purchasing power, and lack awareness of long-term financial planning. This study explores factors influencing continuance intention, discussed in three themes:

- Determinants influencing continuance intention.
- Implications.
- Limitations and future studies.

3.6. Determinants Influencing Users' Continuance Intention to Use Mutual Fund Investment Apps

H3, H4, and H9 confirm that service quality, privacy, security, and familiarity significantly influence trust in mutual fund apps. Trust is built through successful transactions and goal achievement. Providers must meet expectations and educate users about risks [48]. Privacy and security enhance trust, while familiarity reduces anxiety and increases reliability [49]. H1 shows service quality drives satisfaction, while H6 and H10 show security and trust boost satisfaction. H2, H7, H8, and H10 confirm that service quality, trust, satisfaction, and familiarity predict continuance intention [50].

3.7. Cross-Regional Comparative Analysis

While this study primarily focuses on the Indonesian context, it has been enhanced by comparing findings to similar studies conducted in other regions, particularly those from developed markets like the U.S. and the Netherlands. This comparison demonstrates how the adoption of mutual fund apps in Indonesia differs from more advanced markets, highlighting key challenges such as financial literacy, trust-building, and service reliability that are more prevalent in emerging markets. This addition strengthens the unique contribution of the study, emphasizing the global relevance of the findings and their implications for other developing regions like India and Vietnam.

4. MANAGERIAL IMPLICATIONS

4.1. Research Implications

This study highlights the role of trust, driven by service quality, security, and familiarity, in digital investment adoption in developing countries. Strengthening these factors boosts user loyalty and contributes to financial technology theory. The model, validated through PLS-SEM and machine learning, predicts trust, satisfaction, and continuance intention, with machine learning revealing satisfaction growth and complex continuance patterns. The findings are relevant to regions like Southeast Asia, South Asia, and Latin America, emphasizing the universal importance of these factors. The study also supports SDGs 8 and 1 by promoting financial inclusion for lower-income groups.

4.2. Practical Implications

This study offers insights for digital investment stakeholders. Service providers should build trust through integrity, competency, and benevolence, ensuring safety, delivering features, and enhancing investment literacy. Key technical considerations include diverse payment options and Shariah-compliant investments. Robo-advisory features should ensure unbiased decision-making. Policymakers must balance financial inclusion with stability, offering incentives for underserved populations. Consumer protection requires standardized security, transparent fees, and regular audits.

4.3. Limitations and Direction for Future Studies

This study offers insights into digital investment behavior but has limitations. Its findings are specific to Indonesian mutual fund apps and may not apply to other markets. The model may not fully capture the impact of perceived security on continued use. Future research should explore the relationship between trust, satisfaction, and continuance intention, and consider longitudinal studies. Integrating theories like UTAUT2 or Innovation Diffusion Theory and exploring behavioral factors such as risk, market conditions, and social networks would be valuable.

5. CONCLUSION

This study analyzed user behavior in mutual fund investment apps using Structural Equation Modeling and machine learning regression. The results show that perceived service quality, security, privacy, and trust significantly affect user satisfaction, while service quality, trust, satisfaction, and familiarity influence continuance intention. The study contributes to fintech adoption literature by confirming that trust mechanisms in technology adoption transcend cultures while revealing Indonesia-specific user patterns. Combining PLS-SEM and machine learning provides a broader understanding of behavior.

Practically, service providers should enhance trust through strong security, privacy protection, and continuous system improvements. Policymakers should balance financial inclusion with market stability via effective regulations. Ensuring transparency, reliability, and fairness in app functions is crucial to maintain user confidence and prevent churn.

6. DECLARATIONS

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Conceptualization: IP; Methodology: IP and NI; Software: IP and FR; Validation: FR and NI; Formal Analysis: IP and AY; Investigation: IP, NI, and FR; Resources: IP; Data Curation: IP; Writing Original Draft Preparation: IP; Writing Review and Editing: FR, NI, and AY; Visualization: FR; All authors, IP, FR, NI, and AY, have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon request.

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6.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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