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AI-ENABLED FINTECH SERVICE FEATURES AND BEHAVIORAL INTENTION TO USE ONLINE PAYMENT SERVICES: THE MEDIATING ROLE OF CONSUMER TRUST AND THE MODERATING ROLE OF BLOCKCHAIN TRANSPARENCY

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A B S T R A C T

This study examines the relationships between AI-enabled FinTech service features and consumers' behavioral intention to use online payment services. It further investigates the mediating role of consumer trust and the moderating role of blockchain transparency in the first stage of the trust-formation process. Approach/Design/Methodology: A quantitative cross-sectional survey design was employed, and 500 valid responses were obtained through structured questionnaires. The proposed model included AI-enabled personalization, machine-learning risk assessment, AI-enabled customer service quality, online payment convenience, and payment protection security as independent variables. Consumer trust was positioned as the mediator, blockchain transparency as the moderator, and behavioral intention to use online payment services as the dependent variable. SPSS and AMOS were used to conduct descriptive analysis, data screening, reliability testing, confirmatory factor analysis, structural equation modeling, mediation analysis, first-stage moderation analysis, and moderated mediation analysis. The results confirmed acceptable reliability, convergent validity, and construct validity. The structural equation model demonstrated good model fit (CMIN/DF = 1.116; CFI = .991; RMSEA = .015). The findings indicate that AI-enabled FinTech service features were positively associated with consumer trust and behavioral intention to use online payment services, while the direct path from blockchain transparency to behavioral intention was not statistically significant. Consumer trust partially mediated the relationships between AI-enabled FinTech service features and behavioral intention. The study provides empirical evidence on how consumer trust explains the relationship between perceived AI-enabled service features and behavioral intention to use online payment services, and how blockchain transparency strengthens the trust-formation process.

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1. INTRODUCTION

1.1 Background of the Study

Digital financial services have increasingly incorporated data-driven personalization, automated decision support, secure transaction processing, AI-enabled customer service, and real-time interaction with users. These developments have positioned artificial intelligence as an important technological component in contemporary FinTech service delivery (Alt et al., 2018; Davenport et al., 2020). In the FinTech context, artificial intelligence is not limited to algorithms or technical infrastructure. It is also associated with how consumers perceive service convenience, reliability, security, confidence, and transparency when using online payment services (Dwivedi et al., 2021). As a result, online transactions are no longer viewed merely as simple automated data-transfer processes. They have become part of complex digital financial service ecosystems in which consumers evaluate whether they can trust the platform and whether they are willing to continue using online payment services for shopping, fund transfers, settlements, and other financial activities (Bawack et al., 2022).

FinTech services have become a major component of digital finance because they combine mobile technologies, platform-based services, artificial intelligence, data analytics, and cost-efficient transaction infrastructure (Lee & Shin, 2018). Previous studies have commonly examined these services in relation to perceived benefits, risk management, ease of use, reliability, security, and transparency. In this study, behavioral intention to use online payment services is therefore considered not only as a matter of technological acceptance, but also as a consumer decision that is closely associated with trust, perceived service capability, payment convenience, and perceived protection in digital financial transactions (Milian et al., 2019).

1.2 Research Gap and Rationale

Previous studies on FinTech and mobile payment adoption have commonly examined perceived usefulness, perceived risk, trust, consumer attitude, security, and ease of use as key determinants of technology acceptance and payment adoption (Ryu, 2018). However, limited attention has been given to the simultaneous integration of multiple AI-enabled FinTech service features, consumer trust, and blockchain transparency within a single moderated mediation framework. In particular, prior research has often examined AI-related service capabilities and blockchain-related mechanisms separately, rather than considering how blockchain transparency may strengthen the trust-formation process in AI-enabled online payment services.

Another important gap concerns the conceptual role of blockchain transparency. Previous studies have often treated blockchain as a technical architecture, security mechanism, or direct technological feature. In contrast, the present study positions blockchain transparency as a boundary condition that may strengthen the relationship between AI-enabled FinTech service features and consumer trust. This distinction is important because consumers may not evaluate online payment services only based on AI-enabled personalization, automated risk assessment, customer support, convenience, or payment protection. They may also rely on transparent and verifiable technological signals when forming trust in digital financial transactions (Belanche et al., 2019; Chawla & Joshi, 2019).

The rationale for this study is based on the assumption that AI-enabled personalization, machine-learning risk assessment, AI-enabled customer service quality, online payment convenience, and payment protection security are positively associated with consumers' behavioral intention to use online payment services. These relationships may also operate indirectly through consumer trust, as trust represents an important psychological mechanism in online financial service adoption (Oliveira et al., 2016). At the same time, blockchain transparency may strengthen the relationships between AI-enabled FinTech service features and consumer trust by providing perceived traceability, record verification, transaction visibility, and reduced uncertainty in online financial interactions (Patil et al., 2020).

Therefore, this study proposes a first-stage moderated mediation framework. In this framework, AI-enabled FinTech service features are associated with behavioral intention to use online payment services both directly and indirectly through consumer trust. Blockchain transparency is expected to moderate the first-stage relationships between AI-enabled FinTech service features and consumer trust. In other words, the trust-building role of AI-enabled FinTech service features may become stronger when consumers perceive a higher level of blockchain transparency in online payment services (Gao & Waechter, 2017).

1.3 Research Objectives

This study aims to examine the relationships between AI-enabled FinTech service features and consumers' behavioral intention to use online payment services, with consumer trust as a mediator and blockchain transparency as a first-stage moderator. Specifically, this study aims to:

1. Examine the relationships between AI-enabled FinTech service features and consumer trust.
2. Examine the relationships between AI-enabled FinTech service features and consumers' behavioral intention to use online payment services.
3. Assess the mediating role of consumer trust in the relationships between AI-enabled FinTech service features and consumers' behavioral intention to use online payment services.

4. Examine the relationship between consumer trust and consumers' behavioral intention to use online payment services.
5. Assess the moderating role of blockchain transparency in the relationships between AI-enabled FinTech service features and consumer trust.
6. Examine whether blockchain transparency moderates the indirect relationships between AI-enabled FinTech service features and consumers' behavioral intention to use online payment services through consumer trust.

2. LITERATURE REVIEW

2.1Theoretical Foundation

The theoretical foundation of this study draws on technology acceptance theory, trust theory, and conditional process analysis. Technology acceptance theory suggests that consumers are more likely to adopt digital services when they perceive those services as useful, easy to use, secure, reliable, and compatible with their needs (Venkatesh et al., 2016). In the context of online payment services, these perceptions are particularly important because consumers interact with platforms that process sensitive financial and personal information.

Trust theory further explains why consumers' confidence in digital financial platforms is central to online payment adoption. Since online payment services involve financial transactions, privacy concerns, platform reliability, and automated service processes, consumers may be more willing to use such services when they believe that the platform is competent, secure, transparent, and acting in their best interests (Dash & Paul, 2021). Therefore, consumer trust is positioned in this study as a psychological mechanism that helps explain how AI-enabled FinTech service features are associated with behavioral intention to use online payment services.

Conditional process analysis provides the basis for examining mediation, moderation, and moderated mediation within the same conceptual model. In the present study, AI-enabled FinTech service features are treated as perceived service capabilities, consumer trust is treated as the mediator, blockchain transparency is treated as the first-stage moderator, and behavioral intention to use online payment services is treated as the outcome variable. This means that AI-enabled FinTech service features may be associated with behavioral intention both directly and indirectly through consumer trust, while blockchain transparency may strengthen the relationship between AI-enabled FinTech service features and consumer trust (Hair et al., 2019).

In this model, consumer trust and blockchain transparency perform different conceptual roles. Consumer trust is positioned as a mediator because it explains the psychological pathway through which AI-enabled FinTech service features are associated with behavioral intention to use online payment services. In contrast, blockchain transparency is positioned as a moderator because it represents a boundary condition that may strengthen or weaken the relationship between AI-enabled FinTech service features and consumer trust. Therefore, this study proposes a first-stage moderated mediation framework.

2.2 AI-Enabled Personalization

AI-enabled personalization refers to the ability of FinTech services to provide payment advice, reminders, user-interface adjustments, fraud alerts, and financial messages based on individual users' needs and transaction patterns. Personalized services may help consumers feel that the platform understands their preferences, lifestyle, and financial behavior. As a result, consumers may perceive the service as more relevant, responsive, and reliable (Davenport et al., 2020).

In online payment services, personalization can also reduce search effort and decision complexity by offering relevant recommendations and timely payment-related information. When consumers receive personalized service experiences, they may develop stronger confidence in the platform because the service appears more adaptive and user-centered. Prior studies have suggested that personalized digital services can support stronger customer-platform relationships and improve users' willingness to continue using digital services (Belanche et al., 2019; Bawack et al., 2022). Therefore, AI-enabled personalization is expected to be positively associated with consumer trust and behavioral intention to use online payment services.

H1: AI-enabled personalization is positively associated with consumer trust.

H6: AI-enabled personalization is positively associated with consumers' behavioral intention to use online payment services.

H12: Consumer trust mediates the relationship between AI-enabled personalization and behavioral intention to use online payment services.

H17: Blockchain transparency moderated the relationship between AI-enabled personalization and consumer trust.

H22: Blockchain transparency moderated the indirect relationship between AI-enabled personalization and behavioral intention to use online payment services through consumer trust.

2.3 Machine-Learning Risk Assessment

Machine-learning risk assessment refers to the use of intelligent algorithms to identify transaction abnormalities, fraud signals, unusual account behavior, and potential risk patterns in online payment services (Liu, 2025). In digital financial transactions, consumers are often concerned about fraud, unauthorized access, payment errors, and misuse of financial information.

When users believe that the payment platform can detect suspicious activities and learn from transaction patterns, they may perceive the platform as more capable of protecting their financial assets (Xiong et al., 2022).

Machine-learning risk assessment may also be associated with behavioral intention to use online payment services because it can reduce uncertainty and increase confidence during transactions. Consumers may be more willing to use online payment services when they believe that risks are being monitored and managed by intelligent systems. Therefore, machine-learning risk assessment is expected to be positively associated with consumer trust and behavioral intention, with consumer trust serving as a mediating mechanism in this relationship (Shi et al., 2019).

H2: Machine-learning risk assessment is positively associated with consumer trust.

H7: Machine-learning risk assessment is positively associated with consumers' behavioral intention to use online payment services.

H13: Consumer trust mediates the relationship between machine-learning risk assessment and behavioral intention to use online payment services.

H18: Blockchain transparency moderated the relationship between machine-learning risk assessment and consumer trust.

H23: Blockchain transparency moderated the indirect relationship between machine-learning risk assessment and behavioral intention to use online payment services through consumer trust.

2.4 AI-Enabled Customer Service Quality

AI-enabled customer service quality refers to consumers' perceptions of the usefulness, responsiveness, reliability, and clarity of support provided by AI-based service tools such as chatbots, virtual assistants, automated dispute-handling systems, and transaction-status support. In online payment services, consumers may require immediate assistance when they face failed transactions, delayed payment confirmation, refund concerns, account issues, or security-related problems (Blut, 2016).

Responsive and reliable AI-enabled customer support may help reduce service uncertainty and strengthen consumers' confidence in the platform. When consumers perceive that the platform can provide timely and understandable assistance, they may view the service provider as more competent and dependable (Wirtz et al., 2018). In addition, convenient and accessible support may be associated with stronger behavioral intention because users may feel more comfortable continuing to use online payment services when assistance is readily available (Mofokeng, 2021). Therefore, AI-enabled customer service quality is expected to be positively associated with consumer trust and behavioral intention to use online payment services.

H3: AI-enabled customer service quality is positively associated with consumer trust.

H8: AI-enabled customer service quality is positively associated with consumers' behavioral intention to use online payment services.

H14: Consumer trust mediates the relationship between AI-enabled customer service quality and behavioral intention to use online payment services.

H19: Blockchain transparency moderated the relationship between AI-enabled customer service quality and consumer trust.

H24: Blockchain transparency moderated the indirect relationship between AI-enabled customer service quality and behavioral intention to use online payment services through consumer trust.

2.5 Online Payment Convenience

Online payment convenience refers to consumers' perceptions of speed, accessibility, ease of use, transaction simplicity, and compatibility with daily payment activities (Oliveira et al., 2016). In FinTech services, consumers often adopt online payment platforms because they reduce transaction time, lower physical transaction effort, and support faster completion of payment activities. Convenience is therefore an important service feature in the adoption of mobile and online payment systems (Patil et al., 2020).

When online payment services are convenient, consumers may perceive the provider as more capable, user-oriented, and reliable. This perception may support consumer trust because users are more likely to trust platforms that allow them to complete financial transactions smoothly and efficiently. Online payment convenience may also be directly associated with behavioral intention to use online payment services because low-effort transaction processes can make digital payment options more attractive than cash-based or traditional banking methods (Chawla & Joshi, 2019). Therefore, online payment convenience is expected to be positively associated with consumer trust and behavioral intention.

H4: Online payment convenience is positively associated with consumer trust.

H9: Online payment convenience is positively associated with consumers' behavioral intention to use online payment services.

H15: Consumer trust mediates the relationship between online payment convenience and behavioral intention to use online payment services.

H20: Blockchain transparency moderated the relationship between online payment convenience and consumer trust.

H25: Blockchain transparency moderated the indirect relationship between online payment convenience and behavioral intention to use online payment services through consumer trust.

2.6 Payment Protection Security

Payment protection security refers to consumers' perceived confidence that an online payment platform can protect personal data, payment information, transaction history, account access, and login credentials from misuse, fraud, unauthorized access, and system failure. Security is a key concern in online payment adoption because consumers may avoid digital financial services if they perceive that their financial information or transactions are not adequately protected (Gao & Waechter, 2017).

Perceived payment protection security may be positively associated with consumer trust because secure payment systems can reduce perceived risk and strengthen confidence in the service provider. Consumers may also be more willing to use online payment services when they believe that the platform has sufficient mechanisms to protect transactions and financial information. Therefore, payment protection security is expected to be positively associated with consumer trust and behavioral intention to use online payment services (Kock et al., 2021; Pearce et al., 2022).

H5: Payment protection security is positively associated with consumer trust.

H10: Payment protection security is positively associated with consumers' behavioral intention to use online payment services.

H16: Consumer trust mediates the relationship between payment protection security and behavioral intention to use online payment services.

H21: Blockchain transparency moderated the relationship between payment protection security and consumer trust.

H26: Blockchain transparency moderated the indirect relationship between payment protection security and behavioral intention to use online payment services through consumer trust.

2.7 Consumer Trust as Mediator

Consumer trust refers to consumers' belief that an online payment service is honest, competent, secure, reliable, and concerned with users' interests. In online payment services, trust is especially important because consumers must rely on digital platforms to process sensitive financial information, complete transactions accurately, protect personal data, and manage potential service failures. When consumers trust an online payment platform, they may be more willing to continue using the service and recommend it to others.

In the present study, consumer trust is positioned as a mediator between AI-enabled FinTech service features and behavioral intention to use online payment services. AI-enabled personalization, machine-learning risk assessment, AI-enabled customer service quality, online payment convenience, and payment protection security may each be associated with behavioral intention because they help consumers evaluate the service as useful, secure, responsive, and reliable. However, these service features may also operate through consumer trust. In other words, consumers may be more likely to form behavioral intention when these service features first strengthen their trust in the platform (Nguyen et al., 2020).

H11: Consumer trust is positively associated with consumers' behavioral intention to use online payment services.

2.8 Blockchain transparency as Moderator

Blockchain transparency refers to consumers' perceived ability to verify, trace, and confirm transaction records through transparent, tamper-resistant, and auditable blockchain-enabled mechanisms (Casino et al., 2019). In digital FinTech payment services, transparency may provide assurance because consumers may believe that transaction information can be recorded, verified, and protected from unauthorized alteration (Treiblmaier, 2018).

In the present study, blockchain transparency is positioned as a moderator rather than a mediator. This means that blockchain transparency is expected to strengthen the relationships between AI-enabled FinTech service features and consumer trust. When consumers perceive higher blockchain transparency, the positive association between AI-enabled service features and trust may become stronger because transparent transaction records, traceability, and verification mechanisms can reduce uncertainty in online financial interactions (Figure 1). Therefore, blockchain transparency is treated as a boundary condition in the first stage of the moderated mediation model (Kshetri, 2017).

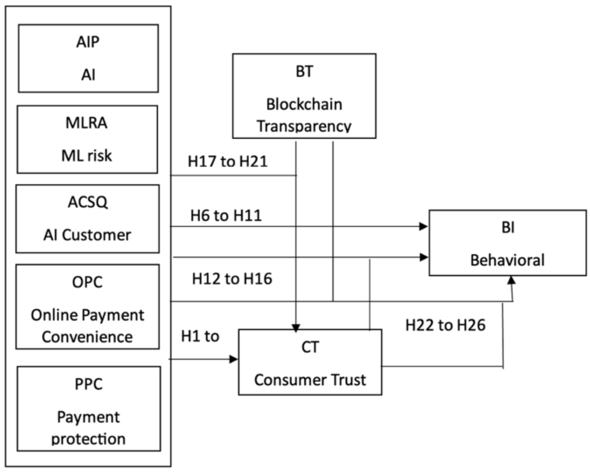

Figure 1. Conceptual Framework

Note. *AIP = AI-enabled personalization; MLRA = machine-learning risk assessment; ACSQ = AI-enabled customer service quality; OPC = online payment convenience; PPS = payment protection security.*

Specifically, this study proposes that AI-enabled FinTech service features are associated with behavioral intention to use online payment services both directly and indirectly through consumer trust. Blockchain transparency is expected to moderate the first-stage relationships between AI-enabled FinTech service features and consumer trust. As a result, the indirect relationships between AI-enabled FinTech service features and behavioral intention through consumer trust may become stronger when perceived blockchain transparency is higher.

Based on the reviewed literature and the proposed hypotheses, this study develops a first-stage moderated mediation framework. The framework shows that AI-enabled FinTech service features are directly associated with behavioral intention to use online payment services and indirectly associated with behavioral intention through consumer trust. Consumer trust is positioned as the mediator, while blockchain transparency is positioned as the first-stage moderator that strengthens the relationships between AI-enabled FinTech service features and consumer trust. The proposed conceptual framework is presented in Figure 1.

3. RESEARCH DESIGN AND METHODOLOGY

3.1 Research Design

This study used a quantitative cross-sectional survey research design to examine the direct relationships, mediating relationships, moderating relationships, and moderated mediation relationships proposed in the conceptual model. This design was appropriate because the study aimed to test latent constructs and their statistical relationships using survey data rather than establishing causal effects through an experimental design (Dash & Paul, 2021). Confirmatory factor analysis was conducted to assess the measurement model, and structural equation modeling was used to examine the direct paths and mediation relationships. Preliminary data screening, reliability analysis, descriptive analysis, correlation analysis, multicollinearity diagnosis using variance inflation factors (VIF), multivariate outlier assessment using Mahalanobis distance, moderation analysis, and moderated mediation analysis were performed using SPSS and AMOS (Hair et al., 2019; Sarstedt et al., 2020).

3.2 Sample and Measurement Instrument

After data screening, 500 valid responses remained for analysis. The study included eight reflective constructs: AI-enabled personalization, machine-learning risk assessment, AI-enabled customer service quality, online payment convenience, payment protection security, consumer trust, blockchain transparency, and behavioral intention to use online payment services. Each construct was measured using seven reflective items on a five-point Likert scale ranging from strongly disagree to strongly agree (Henseler et al., 2015). The measurement model was assessed using item reliability, Cronbach's alpha, standardized factor loadings, composite reliability, average variance extracted (AVE), the Fornell-Larcker criterion, and the heterotrait-monotrait (HTMT) ratio to establish reliability, convergent validity, and discriminant validity (Voorhees et al., 2016; Franke & Sarstedt, 2019).

3.3 Data Analysis Procedure

The data analysis followed several stages. First, the dataset was screened for missing values, normality, multivariate outliers, and multicollinearity (Kock et al., 2021). Second, internal consistency reliability was assessed using Cronbach's alpha and corrected item-total correlations. KMO and Bartlett's test of sphericity were also conducted to examine sampling adequacy and factorability (Shi et al., 2019). Third, CFA and SEM were performed in AMOS to evaluate the measurement model, model fit, direct paths, explained variance, and bootstrapped indirect relationships. Fourth, first-stage moderation was examined by estimating interaction terms between each AI-enabled FinTech service feature and blockchain transparency in predicting consumer trust. Finally, moderated mediation was assessed through the index of moderated mediation for each indirect relationship. Common method bias, multicollinearity, and model fit were interpreted using established methodological guidelines (Henseler et al., 2015).

4. RESULTS AND FINDINGS

4.1 Respondents' Demographic Profile

The descriptive results show that 500 respondents with online payment experience were included in the analysis (Table 1). The gender distribution was almost balanced, with males representing 49.80% and females representing 48.80% of the sample. In terms of age, the largest group was 25-34 years old (36.80%), followed by 18-24 years old (26.20%) and 35-44 years old (22.60%). Regarding education, nearly half of the respondents held a bachelor's degree (47.40%), while 20.60% held a master's degree. These results indicate that the sample included respondents with sufficient educational background to evaluate online payment services and related digital financial features.

Regarding income level, the largest group consisted of middle-income respondents (32.60%), followed by lower-middle-income respondents (20.20%) and upper-middle-income respondents (19.00%). For online payment experience, 35.00% of respondents had 1-3 years of experience, and 40.00% had 4 years or more of experience. The most frequently used payment methods were mobile banking (30.00%) and e-wallets (27.60%). Most respondents used online payment services several times per week (38.40%) or daily (30.60%). In terms of blockchain transparency familiarity, the largest group reported a moderate level of familiarity (38.40%). Overall, the sample provided a relevant basis for examining AI-enabled FinTech service features, consumer trust, blockchain transparency, and behavioral intention to use online payment services.

Table 1. Demographic Profile of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	249	49.80%
	Female	244	48.80%
	Prefer not to say	7	1.40%
Age	18-24	131	26.20%
	25-34	184	36.80%
	35-44	113	22.60%
	45-54	46	9.20%
	55 or above	26	5.20%
Education	High school or below	61	12.20%
	Diploma	86	17.20%
	Bachelor's degree	237	47.40%
	Master's degree	103	20.60%
	Doctoral degree	13	2.60%
Income level	Low income	92	18.40%
	Lower-middle income	101	20.20%
	Middle income	163	32.60%
	Upper-middle income	95	19.00%
	High income	27	5.40%
	Prefer not to say	22	4.40%
Online payment experience	Less than 6 months	45	9.00%
	6 months-1 year	80	16.00%
	1-3 years	175	35.00%
	4-5 years	104	20.80%
	More than 5 years	96	19.20%
Primary online payment method	Mobile banking	150	30.00%
	E-wallet	138	27.60%
	QR payment	92	18.40%
	PayPal	37	7.40%
	Apple Pay / Google Pay	37	7.40%
	Alipay / WeChat Pay	31	6.20%
	Other	15	3.00%
Online payment frequency	Daily	153	30.60%
	Several times per week	192	38.40%
	Once per week	73	14.60%
	Several times per month	60	12.00%
	Rarely	22	4.40%
Blockchain transparency familiarity	Not familiar at all	58	11.60%
	Slightly familiar	119	23.80%
	Moderately familiar	192	38.40%
	Familiar	103	20.60%
	Very familiar	28	5.60%

Source: Survey Data 2026

4.2 Descriptive Statistics and Normality

The descriptive statistics show that the mean scores of the constructs ranged from 3.432 to 3.513, indicating moderately favorable perceptions of AI-enabled FinTech service features, consumer trust, blockchain transparency, and behavioral intention to use online payment services (Table 2). AI-enabled personalization had the highest mean score, while AI-enabled customer service quality had the lowest mean score; however, the differences among construct means were relatively small. Standard deviations ranged from 0.883 to 1.008, suggesting acceptable dispersion in the responses.

Table 2. Descriptive Statistics and Normality

Construct	N	Minimum	Maximum	Mean	SD	Skewness	Kurtosis
AIP	500	1.143	5	3.513	0.924	-0.279	-0.653
MLRA	500	1.143	5	3.496	0.968	-0.22	-0.971
ACSQ	500	1	5	3.432	0.974	-0.199	-0.829
OPC	500	1.143	5	3.457	0.977	-0.264	-0.757
PPS	500	1	5	3.497	1.008	-0.394	-0.667
CT	500	1	5	3.449	0.883	-0.107	-0.584
BT	500	1.143	5	3.445	0.957	-0.276	-0.693
BI	500	1	5	3.475	0.929	-0.203	-0.585

The skewness values were mildly negative, indicating a slight tendency toward agreement, while the kurtosis values were below zero and did not indicate serious normality concerns. These results suggest that the data were suitable for subsequent multivariate analysis.

4.3 Reliability, Sampling Adequacy, Common Method Bias, and Multicollinearity

The reliability, sampling adequacy, and multicollinearity results indicate that the measurement data were statistically adequate for further multivariate analysis (Table 3). Cronbach's alpha values for all constructs were above the commonly accepted threshold of 0.70, ranging from 0.908 for consumer trust to 0.940 for payment protection security. These values indicate strong internal consistency reliability across all constructs.
The KMO value for all 56 observed items was 0.951, and the KMO value for the eight mean constructs was 0.865 (Table 4). Both values exceeded the recommended minimum threshold of 0.60, indicating adequate sampling adequacy. Bartlett's test of sphericity was also significant for both datasets ($p < .001$), confirming that the correlation matrix was suitable for factor analysis.
The multicollinearity results showed that all VIF values were below 5, ranging from 1.181 to 1.510, and all tolerance values were above 0.10, ranging from 0.662 to

0.847 (Table 5). Therefore, no serious multicollinearity concern was observed among the predictors. Taken together, the reliability, factorability, and multicollinearity results support the use of the dataset for CFA, SEM, mediation, moderation, and moderated mediation analysis.

Table 3. Reliability Summary

Construct	Number of items	Cronbach alpha	Decision
AIP	7	0.916	Excellent
MLRA	7	0.929	Excellent
ACSQ	7	0.927	Excellent
OPC	7	0.932	Excellent
PPS	7	0.94	Excellent
CT	7	0.908	Excellent
BT	7	0.925	Excellent
BI	7	0.925	Excellent

Table 4. KMO and Bartlett's Test

Dataset	KMO	Bartlett Chi-square	df	p-value	Decision
All 56 observed items	0.951	13249.08	1540	<.001	Suitable for factor analysis
Eight mean constructs	0.865	924.89	28	<.001	Suitable for factor analysis

Table 5. VIF and Tolerance

Predictor	Tolerance	VIF	Decision
AIP	0.775	1.29	Passed
MLRA	0.825	1.213	Passed
ACSQ	0.846	1.182	Passed
OPC	0.778	1.286	Passed
PPS	0.741	1.35	Passed
CT	0.662	1.51	Passed
BT	0.847	1.181	Passed

4.4 Correlation Analysis

The correlation results indicate positive associations among all constructs, suggesting theoretical coherence within the proposed model. Behavioral intention to use online payment services showed the strongest correlation with consumer trust (r = 0.632), highlighting trust as an important construct in online payment adoption (Table 6). Behavioral intention was also moderately associated with AI-enabled personalization, online payment convenience, and payment protection security, indicating that perceived personalization, convenience, and security are relevant to users' adoption intention. Correlations among predictors were low to moderate, and no coefficient approached the critical threshold of 0.80. Therefore, the results support theoretical consistency and indicate no serious multicollinearity concern.

Table 6. Correlations

Construct	AIP	MLRA	ACSQ	OPC	PPS	CT	BT	BI
AIP	1							
MLRA	0.292	1						
ACSQ	0.248	0.254	1					
OPC	0.226	0.261	0.238	1				
PPS	0.272	0.264	0.254	0.356	1			
CT	0.398	0.323	0.319	0.379	0.414	1		
BT	0.277	0.169	0.147	0.257	0.294	0.278	1	
BI	0.46	0.375	0.355	0.453	0.455	0.632	0.306	1

4.5 CFA Measurement Model

All constructs demonstrated acceptable item reliability, with standardized factor loadings ranging from 0.727 to 0.851 (Table 7).

Table 7. CFA Factor Loading Summary

Construct	Items	Standardized Loading Range	Decision
ACSQ	ACSQ1-ACSQ7	0.780-0.831	Accepted
AIP	AIP1-AIP7	0.769-0.793	Accepted
BI	BI1-BI7	0.785-0.816	Accepted
BT	BT1-BT7	0.778-0.812	Accepted
CT	CT1-CT7	0.727-0.796	Accepted
MLRA	MLRA1-MLRA7	0.768-0.824	Accepted
OPC	OPC1-OPC7	0.779-0.836	Accepted
PPS	PPS1-PPS7	0.804-0.851	Accepted

These values were above the commonly accepted threshold of 0.70, indicating that the observed items adequately reflected their corresponding latent constructs. Payment protection security showed the highest loading range, while consumer trust also remained above the minimum acceptable level. Therefore, the CFA results support the adequacy of the measurement model and provide a basis for subsequent validity assessment, SEM analysis, and hypothesis testing (Figure 2).

4.6 Convergent and Discriminant Validity

The measurement validity results indicate acceptable reliability, convergent validity, and discriminant validity across all constructs. Composite reliability values ranged from 0.908 to 0.940, exceeding the recommended threshold of 0.70. The AVE values ranged from 0.586 to 0.690, all above the recommended threshold of 0.50, indicating adequate convergent validity. These results suggest that each latent construct explained a sufficient proportion of variance in its observed indicators.

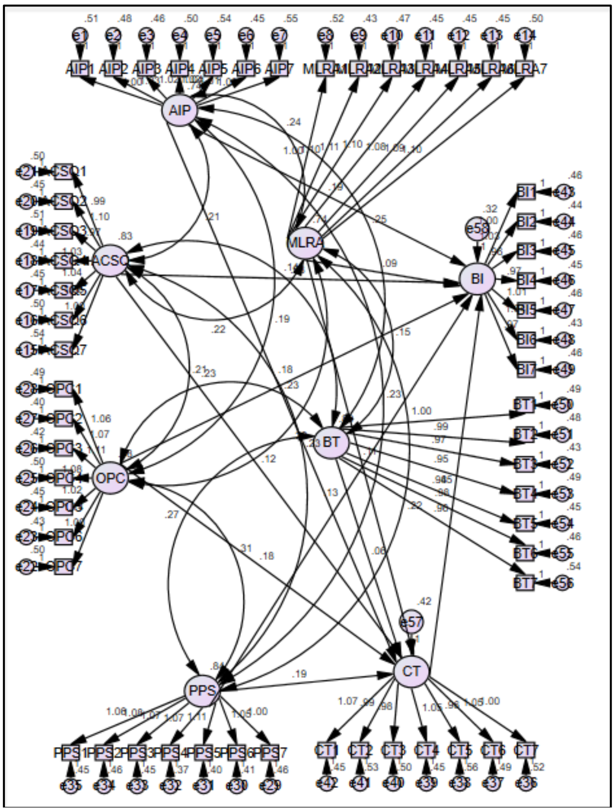

Figure 2. CFA Measurement Model

The Fornell-Larcker results also supported discriminant validity because the square root of AVE for each construct was higher than its correlations with other constructs in the model (Table 9). Although consumer trust and behavioral intention showed a relatively strong association, the square root of AVE for both constructs remained higher than their inter-construct correlation, indicating adequate discriminant separation (Table 8).

Table 8. Composite Reliability and Average Variance Extracted

Construct	Composite Reliability (CR)	Average Variance Extracted (AVE)	Square root of AVE	Decision
AIP	0.916	0.61	0.781	Passed
MLRA	0.929	0.651	0.807	Passed
ACSQ	0.927	0.645	0.803	Passed
OPC	0.932	0.661	0.813	Passed
PPS	0.94	0.69	0.831	Passed
CT	0.908	0.586	0.765	Passed
BT	0.925	0.64	0.8	Passed
BI	0.925	0.638	0.799	Passed

The HTMT results further supported discriminant validity. All HTMT values were below the accepted threshold of 0.85, with the highest value observed between consumer trust and behavioral intention (Table 10). This indicates that the constructs were conceptually and empirically distinct. Overall, the measurement model demonstrated sufficient reliability, convergent validity, and discriminant validity for structural equation modeling.

Table 9. Fornell-Larcker Criterion

Construct	AIP	MLRA	ACSQ	OPC	PPS	CT	BT	BI
AIP	0.781	0.292	0.248	0.226	0.272	0.398	0.277	0.46
MLRA	0.292	0.807	0.254	0.261	0.264	0.323	0.169	0.375
ACSQ	0.248	0.254	0.803	0.238	0.254	0.319	0.147	0.355
OPC	0.226	0.261	0.238	0.813	0.356	0.379	0.257	0.453
PPS	0.272	0.264	0.254	0.356	0.831	0.414	0.294	0.455
CT	0.398	0.323	0.319	0.379	0.414	0.765	0.278	0.632
BT	0.277	0.169	0.147	0.257	0.294	0.278	0.8	0.306
BI	0.46	0.375	0.355	0.453	0.455	0.632	0.306	0.799

Table 10. HTMT Ratio

Construct	AIP	MLRA	ACSQ	OPC	PPS	CT	BT	BI
AIP	1							
MLRA	0.317	1						
ACSQ	0.269	0.274	1					
OPC	0.244	0.281	0.256	1				
PPS	0.292	0.283	0.272	0.38	1			
CT	0.437	0.351	0.347	0.412	0.448	1		
BT	0.301	0.183	0.159	0.276	0.316	0.303	1	
BI	0.5	0.405	0.384	0.487	0.487	0.69	0.331	1

4.7 SEM Structural Model and Direct Path Results

The structural model demonstrated good model fit. Although the chi-square statistic was significant, this result is common in large samples and should be interpreted together with other fit indices (Table 11). The CMIN/DF value of 1.116 indicated excellent fit, while GFI, NFI, IFI, TLI, and CFI exceeded the recommended threshold values. RMSEA was 0.015 and PCLOSE was 1.000, indicating good to excellent model fit (Table 11.

The direct path results show that all five AI-enabled FinTech service features were positively and significantly associated with consumer trust. Among these features, AI-enabled personalization showed the strongest standardized path to consumer trust, followed by payment protection security, online payment convenience, AI-enabled customer service quality, and machine-learning risk assessment.

Table 11. Model Fit Indices for the Structural Equation Model

Fit index	Value	Criterion	Decision
CMIN	1625.61	Lower is better; use with df and sample size	Reported
DF	1457	Model degrees of freedom	Reported
p-value	0.001	Often significant in large samples	Reported
CMIN/DF	1.116	< 3 good; < 5 acceptable	Excellent
RMR	0.041	Lower values preferred	Accepted
GFI	0.902	> .90	Accepted
AGFI	0.893	~ .90 acceptable	Acceptable
NFI	0.922	> .90	Accepted
IFI	0.991	> .90	Excellent
TLI	0.991	> .90	Excellent
CFI	0.991	> .90	Excellent
RMSEA	0.015	< .08 acceptable; < .05 excellent	Excellent
PCLOSE	1	> .05	Accepted

Table 12. Explained Variance

Endogenous variable	Squared multiple correlation / R-square	Interpretation
CT	0.381	38.1% variance explained
BI	0.598	59.8% variance explained

The results also show that all five AI-enabled FinTech service features were positively and significantly associated with behavioral intention to use online payment services, with AI-enabled personalization and online payment convenience showing relatively stronger standardized paths (Table 12). Consumer trust was also positively and significantly associated with behavioral intention. In contrast, the direct path from blockchain transparency to behavioral intention was not statistically significant. Therefore, H1 to H11 were supported, except for the control path from blockchain transparency to behavioral intention, which was not hypothesized as a main direct relationship (Table 13).

Table 13. SEM Direct Path Results

Hypothesis	Path	Estimate	SE	CR/t	p-value	Standardized beta	Decision
H1	AIP → CT	0.241	0.045	5.389	<.001	0.251	Supported
H2	MLRA → CT	0.11	0.043	2.542	0.011	0.114	Supported
H3	ACSQ → CT	0.125	0.04	3.118	0.002	0.138	Supported
H4	OPC → CT	0.187	0.043	4.318	<.001	0.199	Supported
H5	PPS → CT	0.204	0.042	4.835	<.001	0.226	Supported
H6	AIP → BI	0.183	0.042	4.329	<.001	0.176	Supported
H7	MLRA → BI	0.093	0.039	2.381	0.017	0.09	Supported
H8	ACSQ → BI	0.08	0.036	2.191	0.028	0.081	Supported
H9	OPC → BI	0.171	0.04	4.227	<.001	0.168	Supported
H10	PPS → BI	0.124	0.039	3.174	0.002	0.127	Supported
H11	CT → BI	0.448	0.053	8.474	<.001	0.415	Supported
Control	BT → BI	0.038	0.035	1.1	0.271	0.04	Not significant

4.8 Predictive Relevance and Effect Size

The explanatory and predictive findings indicate that the proposed model has adequate explanatory relevance. The predictors explained 38.1% of the variance in consumer trust and 59.8% of the variance in behavioral intention to use online payment services (Table 14). The positive Q^2-style values for consumer trust and behavioral intention also suggest predictive relevance.

Table 14. R^2 and Supplementary Predictive Relevance

Endogenous variable	Metric	Value	Interpretation
CT	R^2 from AMOS	0.381	38.1% variance explained
BI	R^2 from AMOS	0.598	59.8% variance explained
CT	Cross-validated Q^2-style	0.315	Positive predictive relevance
BI	Cross-validated Q^2-style	0.516	Positive predictive relevance

Table 15. f^2 Effect Size Results

Endogenous variable	Predictor	R2 included	R2 excluded	f-square	Effect size
CT	AIP	0.333	0.288	0.067	Small
CT	MLRA	0.333	0.322	0.017	Small
CT	ACSQ	0.333	0.318	0.023	Small
CT	OPC	0.333	0.304	0.043	Small
CT	PPS	0.333	0.294	0.059	Small
BI	AIP	0.533	0.509	0.052	Small
BI	MLRA	0.533	0.526	0.016	Very weak
BI	ACSQ	0.533	0.526	0.014	Very weak
BI	OPC	0.533	0.511	0.047	Small

BI	PPS	0.533	0.52	0.028	Small
BI	CT	0.533	0.441	0.197	Medium
BI	BT	0.533	0.532	0.003	Very weak

Regarding f² effect sizes, the AI-enabled FinTech service features showed small effects on consumer trust and small or very weak effects on behavioral intention (Table 15). Consumer trust showed the largest effect size on behavioral intention, with a medium f² value. Blockchain transparency showed a very weak direct effect size on behavioral intention, which is consistent with the non-significant direct path from blockchain transparency to behavioral intention.

4.9 Mediation Analysis

The bootstrapped mediation results indicate that the indirect relationships between all AI-enabled FinTech service features and behavioral intention to use online payment services through consumer trust were positive and statistically significant. The confidence intervals for all indirect relationships did not include zero. AI-enabled personalization showed the strongest indirect relationship through consumer trust, followed by payment protection security, online payment convenience, AI-enabled customer service quality, and machine-learning risk assessment. Because the corresponding direct paths also remained significant, the results indicate partial mediation rather than full mediation. Therefore, H12 to H16 were supported (Table 16).

Table 16. Bootstrapped Mediation Results

Hypothesis	Indirect path	Indirect effect	Boot LLCI	Boot ULCI	p-value	Mediation type
H12	AIP → CT → BI	0.108	0.069	0.158	<.001	Partial mediation
H13	MLRA → CT → BI	0.049	0.009	0.093	0.012	Partial mediation
H14	ACSQ → CT → BI	0.056	0.019	0.097	0.003	Partial mediation
H15	OPC → CT → BI	0.084	0.046	0.132	<.001	Partial mediation
H16	PPS → CT → BI	0.091	0.055	0.134	<.001	Partial mediation

4.10 Moderation and Moderated Mediation

The first-stage moderation results show that blockchain transparency positively moderated the relationships between all five AI-enabled FinTech service features and consumer trust. The interaction terms for AI-enabled personalization, machine-learning risk assessment, AI-enabled customer service quality, online payment convenience, and payment protection security were all positive and statistically significant, with confidence intervals excluding zero. These findings indicate that the associations between AI-enabled FinTech service features and consumer trust become stronger when perceived blockchain transparency is higher. Therefore, H17 to H21 were supported (Table 17).

Table 17. First-Stage Moderation Results

Hypo-thesis	Interaction path	B	SE	t	p	LLCI	ULCI	Decision
H17	AIP × BT → CT	0.08	0.018	4.356	<.001	0.044	0.116	Supported
H18	MLRA × BT → CT	0.097	0.018	5.423	<.001	0.062	0.132	Supported
H19	ACSQ × BT → CT	0.092	0.018	5.153	<.001	0.057	0.127	Supported
H20	OPC × BT → CT	0.1	0.018	5.603	<.001	0.065	0.134	Supported
H21	PPS × BT → CT	0.102	0.017	5.979	<.001	0.068	0.135	Supported

The moderated mediation results further show that blockchain transparency moderated the indirect relationships between all five AI-enabled FinTech service features and behavioral intention to use online payment services through consumer trust. The five indices of moderated mediation were positive, and the bootstrap confidence intervals did not include zero. These results indicate that the trust-mediated relationships between AI-enabled FinTech service features and behavioral intention become stronger when perceived blockchain transparency is higher. Among the moderated mediation paths, payment protection security showed the largest index, followed by online payment convenience and machine-learning risk assessment. Therefore, H22 to H26 were supported (Table 18).

Table 18. First-Stage Moderated Mediation Results

Hypothesis	Moderated mediation path	Index	Boot LLCI	Boot ULCI	Decision
H22	AIP → CT → BI moderated by BT	0.033	0.018	0.049	Supported
H23	MLRA → CT → BI moderated by BT	0.041	0.026	0.056	Supported
H24	ACSQ → CT → BI moderated by BT	0.039	0.024	0.054	Supported
H25	OPC → CT → BI moderated by BT	0.042	0.027	0.057	Supported
H26	PPS → CT → BI moderated by BT	0.043	0.029	0.057	Supported

4.11 Final Hypothesis Decision

The final hypothesis decision indicates that the proposed relationships in the conceptual model were empirically supported. The SEM results show that AI-enabled personalization, machine-learning risk assessment, AI-enabled customer service quality, online payment convenience, and payment protection security were positively associated with consumer trust and behavioral intention to use online payment services. Consumer trust was also positively associated with behavioral intention, supporting its central role in the model. The bootstrapped mediation results confirm that consumer trust mediated the relationships between AI-enabled FinTech service features and behavioral intention. The moderation results also confirm that blockchain transparency strengthened the relationships between AI-enabled FinTech service features and consumer trust. In addition, the moderated mediation results support the proposed first-stage moderated mediation model, indicating that blockchain transparency strengthens the indirect relationships between AI-enabled FinTech service features and behavioral intention through consumer trust (Table 19).

Table 19. Final Hypothesis Decision Table

Hypothesis	Relationship / path	Decision
H1	AIP → CT	Supported
H2	MLRA → CT	Supported
H3	ACSQ → CT	Supported
H4	OPC → CT	Supported
H5	PPS → CT	Supported
H6	AIP → BI	Supported
H7	MLRA → BI	Supported
H8	ACSQ → BI	Supported
H9	OPC → BI	Supported
H10	PPS → BI	Supported
H11	CT → BI	Supported
H12	AIP → CT → BI	Supported
H13	MLRA → CT → BI	Supported
H14	ACSQ → CT → BI	Supported
H15	OPC → CT → BI	Supported
H16	PPS → CT → BI	Supported
H17	AIP × BT → CT	Supported
H18	MLRA × BT → CT	Supported
H19	ACSQ × BT → CT	Supported
H20	OPC × BT → CT	Supported
H21	PPS × BT → CT	Supported
H22	AIP → CT → BI moderated by BT	Supported
H23	MLRA → CT → BI moderated by BT	Supported
H24	ACSQ → CT → BI moderated by BT	Supported
H25	OPC → CT → BI moderated by BT	Supported
H26	PPS → CT → BI moderated by BT	Supported

5. DISCUSSION AND CONCLUSION

5.1 Discussion

Overall, the findings indicate that perceived AI-enabled FinTech service features are positively associated with consumer trust and behavioral intention to use online payment services. Among the five service features, AI-enabled personalization showed the strongest association with consumer trust, followed by payment protection security and online payment convenience. This suggests that consumers may develop stronger trust in online payment services when they perceive the platform as personalized, secure, convenient, responsive, and capable of assessing transaction risks.

The results also show that AI-enabled personalization and online payment convenience had relatively stronger direct associations with behavioral intention to use online payment services. Consumer trust showed the strongest association with behavioral intention, confirming its important role in online payment adoption. Blockchain transparency did not show a significant direct relationship with behavioral intention; however, it significantly strengthened the relationships between AI-enabled FinTech service features and consumer trust. This finding supports the view that blockchain transparency operates more as a trust-building boundary condition than as a direct predictor of intention.

The mediation and moderated mediation results provide further support for the proposed framework. AI-enabled FinTech service features were indirectly associated with behavioral intention through consumer trust, and these indirect relationships became stronger when perceived blockchain transparency was higher. Therefore, the findings highlight the importance of combining AI-enabled service capabilities with transparent and verifiable transaction mechanisms to strengthen consumer trust in online payment services.

5.2 Conclusion

This study examined the relationships between AI-enabled FinTech service features and behavioral intention to use online payment services, with consumer trust as a mediator and blockchain transparency as a first-stage moderator. The findings show that AI-enabled personalization, machine-learning risk assessment, AI-enabled customer service quality, online payment convenience, and payment protection security are positively associated with consumer trust and behavioral intention. Consumer trust partially mediates these relationships, indicating that trust is an important psychological mechanism through which perceived service features are linked to online payment adoption. Blockchain transparency strengthens the first-stage relationships between AI-enabled FinTech service features and consumer trust and also strengthens the indirect relationships between these service features and behavioral intention through consumer trust. Overall, the findings support the proposed first-stage moderated mediation model.

5.3 Theoretical and Practical Implications

Theoretically, this study contributes to the FinTech adoption literature by integrating AI-enabled service features, consumer trust, and blockchain transparency into a first-stage moderated mediation framework. The findings clarify that consumer trust functions as a mediating mechanism, while blockchain transparency functions as a boundary condition that strengthens the trust-formation process. Practically, the findings suggest that FinTech providers should not focus only on AI-enabled service functions, but should also strengthen transparent, traceable, and verifiable transaction mechanisms. Service providers may improve online payment adoption by offering personalized services, intelligent risk assessment, responsive AI-enabled support, convenient transaction processes, strong payment protection, and clear transparency signals that help consumers trust the platform.

5.4 Limitations

This study has several limitations. First, the cross-sectional survey design limits the ability to make strong causal claims. Therefore, the findings should be interpreted as statistical relationships rather than definitive causal effects. Second, the study relied on self-reported perceptions, which may be subject to common method bias despite the statistical checks conducted. Third, the study examined perceived blockchain transparency rather than the technical implementation of blockchain systems. Finally, the sample consisted of respondents with online payment experience, and the findings may not fully represent consumers with limited digital finance exposure.

5.5. Future Research

Future studies may extend this research by using longitudinal or experimental designs to examine changes in trust and behavioral intention over time. Further research may also compare different types of online payment platforms, such as mobile banking, e-wallets, QR payment systems, and international payment applications. In addition, future studies could examine other contextual factors, such as regulatory trust, digital literacy, perceived privacy risk, platform reputation, and user experience. Cross-country or multi-group comparisons may also provide deeper insights into how AI-enabled FinTech service features and blockchain transparency shape online payment adoption across different digital finance environments.

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