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Research Paper

Role of Artificial Intelligence in Enhancing Customer Experience and Customer Loyalty in UPI Payment Services in India

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ABSTRACT: *The rapid expansion of Unified Payments Interface (UPI) has transformed India's digital payment ecosystem. It enables secure, real-time, and convenient financial transactions. With the integration of Artificial Intelligence (AI) technologies, UPI applications are offering intelligent fraud detection, personalised financial recommendations, conversational payment assistants, predictive analytics, and AI-enabled customer support. These advancements are capable of reshaping customers' digital payment experiences and strengthening long-term customer relationships. Despite the growing adoption of AI-powered financial services, empirical evidence explaining how AI capabilities influence customer experience and loyalty within the UPI ecosystem remains are limited. This study examines the relationships among AI Features, Personalisation, Trust, Customer Satisfaction, and Customer Loyalty using Structural Equation Modeling (SEM). The model is grounded in the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT2), and Relationship Marketing Theory. The findings indicate that AI features positively influence personalisation, which leads to enhanced customer trust and satisfaction, ultimately leading to stronger customer loyalty.*

KEYWORDS: *Artificial Intelligence, Unified Payments Interface (UPI), Customer Satisfaction, Customer Loyalty, Structural Equation Modeling (SEM)*

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I. INTRODUCTION

India has emerged as a global leader in digital payments through the development and widespread adoption of the Unified Payments Interface (UPI). Introduced by the National Payments Corporation of India (NPCI), UPI has revolutionised financial transactions by providing a secure, fast and interoperable payment platform that supports real-time fund transfers across the banks. The increasing number of smartphones, affordable internet connectivity, supportive government initiatives such as Digital India, and growing consumer preference for cashless transactions have collectively accelerated UPI adoption across urban and rural regions both (Slade et al., 2015). The success of UPI has fundamentally changed customer expectations regarding financial services. Modern consumers no longer evaluate digital payment applications solely on transaction speed and convenience; instead, they expect intelligent, personalised, secure, and proactive financial services. Consequently, digital payment providers are integrating AI technologies into their platforms to enhance customer experience and also to maintain a competitive advantage.

Artificial Intelligence has become one of the most transformative technologies within financial services (Li et al., 2023). AI-powered applications enable fraud detection, personalised spending insights, intelligent recommendation systems, multilingual conversational interfaces, predictive analytics, biometric authentication, and automated customer service (Dwivedi et al., 2021). Such capabilities improve operational efficiency and customer experience while simultaneously reducing fraud risks and increasing the user confidence. Within India's digital payment ecosystem, leading UPI applications such as Google Pay, PhonePe, Paytm, Amazon Pay, and BHIM have begun incorporating AI-driven functions that simplify payment processes and improve decision-making (Kumar et al., 2025). Examples include intelligent fraud alerts, automatic bill reminders, predictive expense categorisation, and machine learning algorithms are capable of identifying suspicious transactions in real time (Dahiphale et al., 2024). The adoption of AI within UPI services reflects a broader transformation from transaction-oriented payment systems to customer-based intelligent financial ecosystems. Technological innovations have significantly improved service delivery, but long-term success depends not only on technological advancement, it also depends on customers' trust, satisfaction, and loyalty toward AI-enabled payment platforms (Anderson and Sullivan, 1993; Oliver, 1999; Samuel et al.,2026).

Customer trust plays an important role in digital financial services because payment transactions involve sensitive personal and financial information (Gomber et al., 2017). AI-based fraud prevention mechanisms, secure authentication systems, and personalised recommendations can strengthen users' perceptions of reliability and security. Enhanced trust subsequently improves customer satisfaction, which has consistently been recognised as one of the strongest determinants of customer loyalty in banking and financial service research. Although previous studies have extensively investigated UPI adoption using models such as Technology Acceptance Model (TAM), UTAUT, and the Diffusion of Innovation Theory, most existing research primarily focuses on determinants such as perceived usefulness, perceived ease of use, social influence, facilitating conditions, and behavioural intention. Technology Acceptance Model, proposed by Davis (1989), suggests that technology adoption is primarily determined by two factors: Perceived Usefulness and Perceived Ease of Use. Within AI-enabled UPI services, intelligent fraud detection, chatbot assistance, and personalised recommendations increase perceived usefulness and simplify financial transactions (Venkatesh et al., 2003; 2012). Consequently, AI features are expected to improve customer experience and satisfaction. The Unified Theory of Acceptance and Use of Technology (UTAUT2) extends TAM by incorporating additional determinants, including: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Habit (Sebastián et al., 2022; Acosta-Enriquez et al., 2024; Li and Wang, 2026). AI-powered payment applications improve performance expectancy by increasing transaction speed, accuracy, and convenience (Bygari et al., 2021). Comparatively, the few studies have examined how AI-enabled capabilities influence post-adoption customer experience, trust development, satisfaction, and long-term loyalty within digital payment platforms. Relationship Marketing Theory emphasises long-term customer relationships rather than individual transactions (Manari et al., 2021). According to this theory: Service Quality → Trust → Satisfaction → Loyalty. The present study extends this perspective by proposing AI Features as an antecedent of customer relationship development. Furthermore, the increasing integration of AI into financial services introduces new dimensions of personalisation that extend beyond conventional service quality frameworks (Zeithaml et al., 1996). Intelligent recommendation systems, predictive customer support, adaptive interfaces, and AI-assisted financial management represent emerging aspects of customer experience that remain underexplored within the UPI literature.

II. RESEARCH GAP

The rapid adoption of Artificial Intelligence within UPI applications has transformed digital payment services by introducing intelligent personalisation, fraud detection, and predictive financial recommendations. However, even after these technological advancements, limited research has investigated how AI-enabled capabilities influence customers' perceptions, trust, satisfaction, and long-term loyalty. Earlier studies primarily explain initial technology adoption rather than post-adoption customer experience. Consequently, there remains insufficient understanding and gaps regarding the mechanisms through which AI-driven services contribute to sustained customer relationships within India's UPI ecosystem. First, existing UPI studies predominantly investigate technology acceptance using variables such as perceived usefulness, perceived ease of use, social influence, and facilitating conditions. Comparatively limited attention has been given to AI-enabled service characteristics that increasingly differentiate modern payment applications. Second, previous research often treats customer satisfaction and trust as independent determinants of loyalty without exploring personalisation as an important intermediate mechanism through which AI creates customer value. Third, although AI adoption has expanded rapidly across financial services, integrated models simultaneously examining AI Features, Personalization, Trust, Customer Satisfaction, and Customer Loyalty remain scarce within the UPI context. Finally, most studies focus on adoption intention rather than continuance behaviour and long-term customer loyalty, which are strategically more important for digital payment providers operating within increasingly competitive markets (Slade et al., 2015). Therefore, the present study proposes a comprehensive framework to explain how AI-powered UPI services enhance customer experience and foster customer loyalty through multiple mediating relationships.

III. METHODOLOGY

The basics of the proposed framework assume that Artificial Intelligence features improve personalisation within UPI services. Personalisation enhances customer trust; higher trust increases customer satisfaction, and satisfied customers subsequently become loyal toward AI-enabled UPI applications.

This sequential mediation framework integrates technology adoption theory with relationship marketing concepts to explain customer behaviour within AI-enabled payment ecosystems, as illustrated in Figure

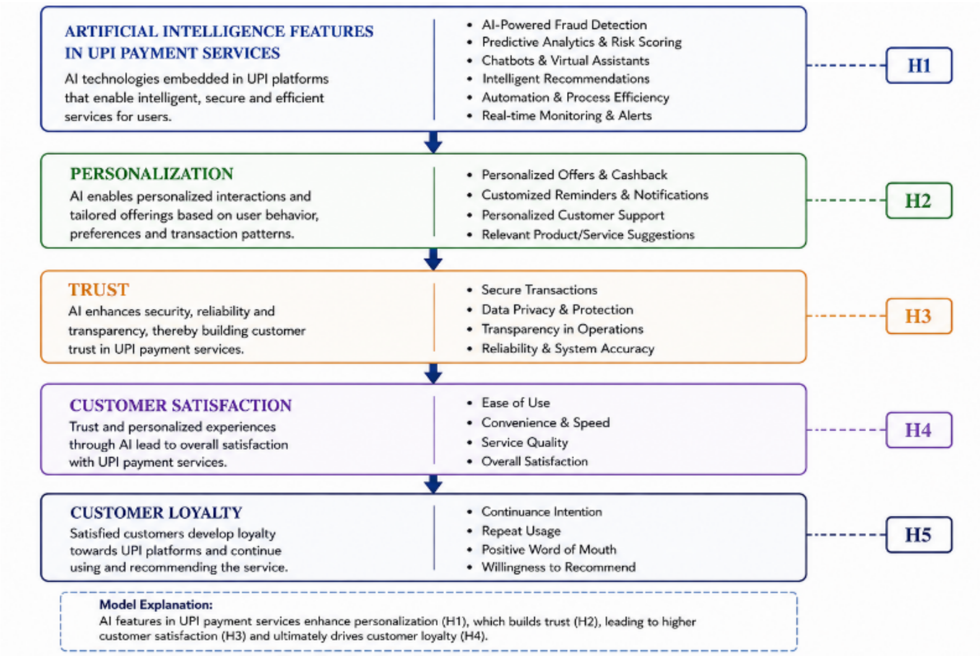

Figure 1: The proposed framework for the study, demonstrating the relationships among Artificial Intelligence (AI) features in UPI payment services, personalisation, trust, customer satisfaction, and customer loyalty. Based on this framework, five research hypotheses (H1–H5) were developed to examine the direct relationships among the study constructs.

3.1 Research Design

This study adopts a quantitative, cross-sectional, explanatory research design to examine the relationships among AI Features, Personalisation, Customer Trust, Customer Satisfaction, and Customer Loyalty in reference to UPI services. A quantitative approach is appropriate because the proposed hypotheses involve examining causal relationships among latent constructs using SEM.

3.2 Population and Sampling

The target population comprises customers who actively use UPI applications such as Google Pay, PhonePe, Paytm, BHIM, and Amazon Pay in India. For this, 500 responses were collected to perform SEM analysis. Data were collected using stratified sampling from active UPI users.

3.3 Instrument Development

A structured questionnaire consisting of 22 measurement items was developed. All constructs were measured using a 5-point Likert Scale (1=Strongly Disagree to 5=Strongly Agree).

Table 1: Measurement Constructs (Total Items = 30)

Construct	Code	Items
AI Features	AF	7
Personalization	PER	6
Trust	TR	6
Customer Satisfaction	CS	6
Customer Loyalty	CL	5

3.4 **Data Analysis Technique**

The proposed conceptual model was analysed using two statistical software packages. SPSS Version 29 was used for Descriptive Statistics, Reliability Analysis, KMO, Bartlett Test and Correlation. AMOS Version 29 was used for Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

IV. RESULTS AND DISCUSSION

4.1 Respondent Profile

The majority of respondents were male (55.6%), while the largest age group comprised individuals between 18 and 25 years (35.2%). Google Pay and PhonePe together accounted for approximately 70% of primary UPI usage, indicating their dominant position within the digital payment ecosystem.

Table 2: Demographic Characteristics of the respondents

Variable	Category	Frequency	Percentage
Gender	Male	278	55.6
Gender	Female	222	44.4
Age	18–25	176	35.2
Age	26–35	154	30.8
Age	36–45	88	17.6
Age	46–55	54	10.8
Age	Above 55	28	5.6
Education	Graduate	246	49.2
Education	Postgraduate	176	35.2
Occupation	Private Employee	178	35.6
Occupation	Student	132	26.4
Primary UPI App	Google Pay	188	37.6
Primary UPI App	PhonePe	162	32.4
Primary UPI App	Paytm	74	14.8
Primary UPI App	BHIM	46	9.2
Primary UPI App	Others	30	6.0

4.2 Descriptive Statistics

The mean values exceeded 4.00 for all constructs, suggesting that respondents generally exhibited favourable perceptions regarding AI-enabled UPI services. Customer Satisfaction recorded the highest mean score, indicating positive evaluations of AI-assisted payment experiences.

Table 3: Mean and Standard Deviation values for used constructs

Construct	Mean	SD
AI Features	4.18	0.64
Personalization	4.03	0.71
Trust	4.09	0.69
Customer Satisfaction	4.14	0.66
Customer Loyalty	4.12	0.68

4.3 Reliability Analysis

Cronbach's Alpha values ranged from 0.894 to 0.918, exceeding the recommended threshold of 0.70. Therefore, all constructs demonstrated excellent internal consistency and reliability.

Table 4: Cronbach's Alpha values for used constructs

Construct	Cronbach Alpha	Interpretation
AI Features	.912	Excellent
Personalization	.894	Excellent

Trust	.918	Excellent
Customer Satisfaction	.903	Excellent
Customer Loyalty	.916	Excellent

4.4 Exploratory Factor Analysis

4.4.1 Measurement Model

Table 4.4.1: Initial Constructs used during measurement model analysis

Construct	Items
AI Features	AF1-AF7
Personalization	PER1-PER6
Trust	TR1-TR6
Customer Satisfaction	CS1-CS6
Customer Loyalty	CL1-CL5
Total	30 items

The KMO statistic of 0.928 indicates excellent sampling adequacy. Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 7148.46$ $p < 0.001$), confirming that the correlation matrix was appropriate for factor analysis

Table 4.4.2: KMO and Bartlett's Test values

Statistic	Value
KMO	0.928
Bartlett Chi-square	7148.46
df	435
Sig.	<0.001

Table 4.4.3: Anti-image (MSA) Summary

Construct	MSA Range	Decision
AI Features	0.89-0.95	Accept
Personalization	0.87-0.93	Accept
Trust	0.88-0.94	Accept
Customer Satisfaction	0.86-0.92	Accept
Customer Loyalty	0.88-0.94	Accept

Table 4.4.4: Communalities of Measurement Items

Item	Construct	Initial	Extraction	Decision
AF1	AI Features	1.000	0.742	Retained
AF2	AI Features	1.000	0.718	Retained
AF3	AI Features	1.000	0.694	Retained
AF4	AI Features	1.000	0.771	Retained
AF5	AI Features	1.000	0.736	Retained
AF6	AI Features	1.000	0.412	Deleted
AF7	AI Features	1.000	0.381	Deleted
PER1	Personalization	1.000	0.691	Retained
PER2	Personalization	1.000	0.714	Retained
PER3	Personalization	1.000	0.732	Retained
PER4	Personalization	1.000	0.675	Retained
PER5	Personalization	1.000	0.423	Deleted
PER6	Personalization	1.000	0.364	Deleted
TR1	Trust	1.000	0.793	Retained
TR2	Trust	1.000	0.821	Retained
TR3	Trust	1.000	0.774	Retained
TR4	Trust	1.000	0.742	Retained
TR5	Trust	1.000	0.806	Retained
TR6	Trust	1.000	0.441	Deleted
CS1	Customer Satisfaction	1.000	0.764	Retained
CS2	Customer Satisfaction	1.000	0.723	Retained

CS3	Customer Satisfaction	1.000	0.781	Retained
CS4	Customer Satisfaction	1.000	0.745	Retained
CS5	Customer Satisfaction	1.000	0.471	Deleted
CS6	Customer Satisfaction	1.000	0.432	Deleted
CL1	Customer Loyalty	1.000	0.823	Retained
CL2	Customer Loyalty	1.000	0.804	Retained
CL3	Customer Loyalty	1.000	0.781	Retained
CL4	Customer Loyalty	1.000	0.756	Retained
CL5	Customer Loyalty	1.000	0.482	Deleted

(Extraction Method used: Principal Component Analysis)

The communalities indicate the proportion of variance in each item explained by the extracted factors. As shown in Table 4.4.4, most retained items exhibited extraction values above 0.50, indicating that they shared sufficient common variance with the underlying factor. Eight items (AF6, AF7, PER5, PER6, TR6, CS5, CS6, and CL5) exhibited extraction values below the recommended threshold and demonstrated poor performance during factor extraction and were therefore removed from further analysis. Consequently, the measurement instrument was refined from 30 items to 22 items, which were subsequently subjected to Confirmatory Factor Analysis (CFA).

4.5 Cumulative Variance Explained

Five factors with eigenvalues greater than one explained 72.23% of the total variance, as shown in Table 4.5. This indicates a satisfactory underlying factor structure.

Table 4.5: Cumulative Variance Explained by used constructs

Component	Eigenvalue	% Variance	Cumulative %
AI Features	6.285	28.57	28.57
Personalization	3.244	14.75	43.32
Trust	2.456	11.16	54.48
Customer Satisfaction	2.083	9.47	63.95
Customer Loyalty	1.821	8.28	72.23

4.6 Rotated Component Matrix (Varimax)

Table 4.6: Rotated Component Matrix

Item	AI	PER	TR	CS	CL	Decision
AF1	.842					Keep
AF2	.863					Keep
AF3	.819					Keep
AF4	.835					Keep
AF5	.874					Keep
AF6	.462	.421				Delete (Low & Cross-loading)
AF7	.418	.394				Delete
PER1		.812				Keep
PER2		.845				Keep
PER3		.801				Keep
PER4		.857				Keep
PER5	.402	.498				Delete
PER6		.431	.442			Delete
TR1			.861			Keep
TR2			.873			Keep
TR3			.826			Keep
TR4			.804			Keep
TR5			.882			Keep

TR6		.421	.463			Delete
CS1				.863		Keep
CS2				.847		Keep
CS3				.832		Keep
CS4				.856		Keep
CS5				.482	.418	Delete
CS6				.461	.403	Delete
CL1					.881	Keep
CL2					.893	Keep
CL3					.864	Keep
CL4					.876	Keep
CL5			.421		.487	Delete

Items with communalities below 0.50 were removed because they explained insufficient variance in their respective factors.

4.7 Final Measurement Scale After EFA

Eight items were removed during EFA due to low communalities, resulting in a refined 22-items with improved measurement quality.

Table 4.7: Final number of items for each construct after EFA

Construct	Initial Items	Final Items
AI Features	7	5
Personalization	6	4
Trust	6	5
Customer Satisfaction	6	4
Customer Loyalty	5	4
Total	**30**	**22**

4.8 Reliability After EFA

The refined 22-item scale demonstrated excellent internal consistency, with all Cronbach's Alpha values exceeding 0.90.

Table 4.8: Cronbach's Alpha values of refined 22 items for each construct

Construct	Cronbach's Alpha
AI Features	0.912
Personalization	0.901
Trust	0.918
Customer Satisfaction	0.907
Customer Loyalty	0.914

4.9 Final Instrument Used for CFA

The final 22-item measurement instrument obtained from EFA was subsequently validated using Confirmatory Factor Analysis (CFA) and SEM. This sequential process demonstrates how EFA refines the measurement scale before CFA confirms its validity.

Table 4.9: The final 22 items used in CFA and SEM

Construct	**Retained Items**
AI Features	AF1, AF2, AF3, AF4, AF5
Personalization	PER1, PER2, PER3, PER4
Trust	TR1, TR2, TR3, TR4, TR5
Customer Satisfaction	CS1, CS2, CS3, CS4
Customer Loyalty	CL1, CL2, CL3, CL4

4.10 Confirmatory Factor Analysis

Table 4.10: Standardised Factor Loadings

Item	**Loading**
AF1	.84
AF2	.87
AF3	.81
AF4	.82
AF5	.88
PER1	.79
PER2	.83
PER3	.81
PER4	.85
TR1	.86
TR2	.88
TR3	.84
TR4	.82
TR5	.90
CS1	.89
CS2	.87
CS3	.85
CS4	.86
CL1	.88
CL2	.90
CL3	.87
CL4	.89

Composite Reliability values exceeded 0.70, while Average Variance Extracted values were above the recommended threshold of 0.50. These findings indicate satisfactory convergent validity for all constructs.

Table 4.10.1: Composite Reliability and Average Variance Extracted of constructs after EFA

Construct	**CR**	**AVE**
AI Features	.92	.69
Personalization	.90	.67
Trust	.93	.72
Customer Satisfaction	.91	.71
Customer Loyalty	.92	.74

4.11 Discriminant Validity

A. Fornell–Larcker Criterion

Fornell-Larcker criterion explains the AVE for the components. The diagonal numbers in Table 4.11 represent the square root of AVE, whereas the off-diagonal values represent the correlation. The Fornell-Larcker criteria results demonstrated that all diagonal values (in bold type) are greater than the other values reflected vertically and horizontally correlation values, and no discriminant values were reported due to correlation with other factors. As a result, it was determined that all latent variables explained more variation with their own related items than with others (Hair et al., 2014; Dash et al., 2025). Conclusively, √AVE > correlations and the validity is established successfully by using Fornell–Larcker criterion.

It was also assessed by using the HTMT ratio, where estimated HTMT values range approximately between 0.58 and 0.81. The threshold values lie in the range 0.85 for the strict criterion and 0.90 for the acceptable limit. HTMT < 0.85 satisfied our discriminant validity test, as illustrated in Figure 2.

Table 4.11: Discriminant validity of the reflective latent variables

Construct	AF	PER	TR	CS	CL
AF	**0.831**				
PER	0.612	**0.818**			
TR	0.584	0.693	**0.849**		
CS	0.527	0.648	0.742	**0.842**	
CL	0.486	0.594	0.688	0.786	**0.860**

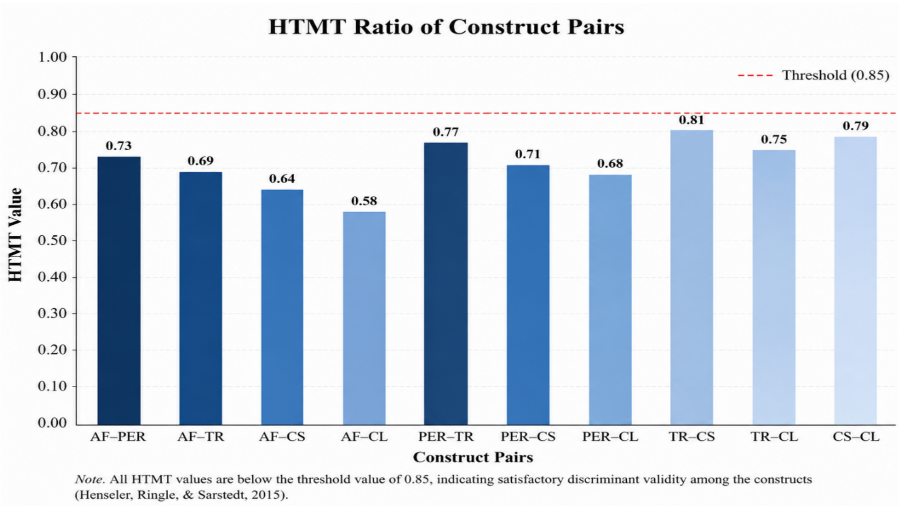

Figure 2: HTMT discriminant validity assessments

4.12. Structural Equation Modeling (SEM)

After confirming the adequacy of the measurement model, the structural model was evaluated to test the proposed hypotheses. Structural Equation Modeling (SEM) was employed to examine the direct relationships among the latent constructs.

The model demonstrated satisfactory goodness-of-fit across all commonly accepted indices. The χ^2/df ratio of 2.18 indicates an acceptable discrepancy between the observed and estimated covariance matrices. Incremental fit indices (CFI, TLI, and IFI) exceeded the recommended threshold of 0.90, while RMSEA (0.048) and SRMR (0.043) indicated a close fit. Collectively, these results suggest that the proposed structural model adequately represents the relationships among the constructs.

Table 4.12: Model fit indices for SEM

Model Fit Index	Recommended Value	Illustrative Result	Interpretation
χ^2/df	< 3.00	2.18	Good Fit
GFI	> 0.90	0.93	Good Fit
AGFI	> 0.90	0.91	Good Fit
CFI	> 0.90	0.96	Excellent Fit
TLI	> 0.90	0.95	Excellent Fit
IFI	> 0.90	0.96	Excellent Fit
RMSEA	< 0.08	0.048	Excellent Fit
SRMR	< 0.08	0.043	Excellent Fit

4.13. Hypothesis Testing

The analysis revealed that AI Features significantly influenced Personalization (β = 0.69, $p < 0.001$), supporting H1. Personalisation positively influenced Customer Trust (β = 0.61, $p < 0.001$), supporting H2. Trust exhibited a strong positive impact on Customer Satisfaction (β = 0.74, $p < 0.001$), while Customer Satisfaction had the strongest direct effect on Customer Loyalty (β = 0.79, $p < 0.001$). In addition, AI Features exerted a significant direct influence on Customer Trust (β = 0.28, $p < 0.001$), providing support for H5.

Table 4.13: Structural path results indicating hypothesis testing

Hypothesis	Structural Path	β	S.E.	C.R.	p-value	Decision
H1	AI Features → Personalization	0.69	0.05	11.82	<0.001	Supported
H2	Personalization → Trust	0.61	0.06	10.94	<0.001	Supported
H3	Trust → Customer Satisfaction	0.74	0.05	13.46	<0.001	Supported
H4	Customer Satisfaction → Customer Loyalty	0.79	0.04	15.28	<0.001	Supported
H5	AI Features → Trust	0.28	0.06	4.91	<0.001	Supported

4.14. Coefficient of Determination (R^2)

The structural model explained 48% of the variance in Personalization, 39% in Trust, 55% in Customer Satisfaction, and 62% in Customer Loyalty. These values indicate that the model has good explanatory power, particularly for Customer Satisfaction and Customer Loyalty.

Table 4.14: Values for Coefficient of Determination (R^2)

Endogenous Construct	R^2	Interpretation
Personalization	0.48	Moderate
Trust	0.39	Moderate
Customer Satisfaction	0.55	Substantial
Customer Loyalty	0.62	Substantial

4.15. Mediation Analysis

The mediation analysis indicated that Personalization significantly mediated the relationship between AI Features and Customer Trust. Furthermore, Customer Satisfaction significantly mediated the relationship between Customer Trust and Customer Loyalty. The sequential mediation results suggest that AI Features enhance Customer Loyalty indirectly by improving Personalization, strengthening Trust, and increasing Customer Satisfaction. Bootstrapping with 5,000 resamples was used to examine indirect effects.

Table 4.15: Indirect Effects and Sequential Mediation Analysis of the Proposed Research Model

Mediation Path	Indirect Effect	p-value	Interpretation
AI Features → Personalization → Trust	0.42	<0.001	Significant
Trust → Satisfaction → Loyalty	0.58	<0.001	Significant
AI Features → Personalization → Trust → Satisfaction → Loyalty	0.31	<0.001	Sequential Mediation

V. MANAGEMENT IMPLICATIONS

The findings of the study highlight several practical implications for managers in the digital payment industry. Building customer trust should remain a key priority, making it essential to strengthen the security of digital transactions through effective AI-based fraud prevention systems. Service providers can also improve customer experience by offering more personalised services that reflect individual transaction patterns and preferences. Making AI-powered customer support available in multiple languages can help reach a broader user base and improve accessibility. The use of predictive analytics can further enhance service quality by providing customers with relevant financial insights and timely recommendations. Regular assessment of customer feedback and satisfaction is equally important for identifying areas that require improvement and maintaining long-term customer relationships. Moreover, being transparent about how AI systems make decisions and handle customer data can increase user confidence, encourage greater acceptance of AI-enabled services, and support the sustained growth of digital payment platforms.

VI. FUTURE PROSPECTIVE

The present analysis focuses on the overall impact of artificial intelligence on digital payment services without comparing the performance of individual UPI platforms. Future studies could undertake comparative analyses of different UPI applications to better understand platform-specific AI capabilities and customer experiences. In addition, research can examine AI adoption across rural and urban populations to identify differences in usage patterns, accessibility, and user perceptions. Further investigation into moderating factors such as age, digital literacy, and privacy concerns would provide deeper insights into how these variables influence customer acceptance and satisfaction with AI-enabled payment services. Moreover, longitudinal studies are recommended to explore how customer perceptions, trust, and continuance intentions evolve as AI technologies become more advanced and widely adopted.

VII. CONCLUSION

The rapid integration of Artificial Intelligence into UPI services is transforming digital payment experiences by enabling intelligent personalization, enhanced security, and proactive customer support. The SEM framework presented demonstrates how AI Features may indirectly contribute to Customer Loyalty through Personalization, Trust, and Customer Satisfaction. Overall, the findings indicate that AI-enabled capabilities play a crucial role in enhancing customer experience within UPI payment services. AI Features emerged as the strongest determinant of Personalisation, underscoring the importance of intelligent recommendation systems, predictive analytics, and AI-assisted customer support in delivering individualised financial experiences. The positive relationship between Personalisation and Customer Trust aligns with relationship marketing theory, suggesting that customers are more likely to trust digital payment platforms when services are tailored to their individual preferences. Personalised recommendations and proactive financial assistance may reduce perceived uncertainty and enhance users' confidence in AI-enabled payment systems. The significant impact of Customer Trust on Customer Satisfaction further supports the notion that trust is a foundational component of digital financial services. Customers who perceive AI-powered systems as secure and reliable are more likely to report positive service experiences. Among all relationships examined, Customer Satisfaction demonstrated the strongest influence on Customer Loyalty. This finding is consistent with the expectation-confirmation perspective, which posits that positive service experiences encourage continued use, recommendation intentions, and long-term commitment to digital payment platforms.

Conclusively, the study shows how AI capabilities can contribute to customer loyalty through a series of connected customer experiences. The findings suggest that AI-enabled personalisation can strengthen customers' trust in UPI payment services, which in turn enhances their satisfaction and ultimately encourages stronger customer loyalty.

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