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Customer loyalty in the age of AI: A comprehensive study on the mediating effect of satisfaction in digital banking

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Abstract

In this digital environment, Artificial Intelligence describes the technology that is considered to have changed the global economy the most. It is estimated that by 2030, AI will contribute approximately $15.7 trillion to the global economy due to its steady expansion in scope, application, and environmental protection. Achieving sustainable development goals depends on sustainable customer loyalty, as it significantly impacts the circular economy and social responsibility. The research aims to examine satisfaction as a mediator to understand how the modified Artificial Intelligence (AI) technology acceptance dimensions relate to customer loyalty in digital banking services. This study collected valid responses from 380 respondents through a cross-sectional survey in Hyderabad, India. A measurement model, developed using a survey questionnaire and partial least squares path modeling, was used to verify the measured items, test hypotheses, and evaluate the correlations among various constructs. Regarding digital banking services, satisfaction fully mediates the relationship between the modified AI Technology Acceptance Model (TAM) factors, perceived usefulness, perceived ease of use, perceived risk, perceived trust, and perceived benefit and customer loyalty. However, the results indicate that AI acceptance factors and customer loyalty are partly mediated by satisfaction. The relationship between AI acceptance factors, customer loyalty, and satisfaction is not moderated by gender. Conversely, age acts as a mediating factor in the relationship between satisfaction, loyalty, and AI acceptance factors. According to the study's findings, deploying AI technology in sustainable financial services is essential for providing clients with positive experiences, which influence customer satisfaction and loyalty, thereby attracting customers to use these services. The study demonstrates how marketing managers can leverage modified AI acceptance factors to promote digital banking services and foster favorable customer loyalty.

Keywords: AI acceptance factors, Artificial Intelligence, Digital Banking, Partial Least Square Path Modeling method, Satisfaction and Customer Loyalty, Sustainability.

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1. Introduction

With gadgets like smartphone apps, platforms, and QR codes, Asian consumers are adopting digital technology more quickly. Certain Asian nations are more advanced than others in this regard, even though Western nations have moved from branch banking to digital technologies, card payments, and automated teller machines (ATMs). The four primary trends in digital banking in Asian nations are digital sales, multi-channel customer journeys, digital usage, and channel preferences. More and more, it is becoming evident that marketers need to prioritize brand experience as the banking sector digitizes. Online banking platforms can create engaging activities that enhance the user experience of their brand. Loyalty and increased word-of-mouth are anticipated outcomes of a more satisfied customer [1]. Financial services companies aim to enhance customer loyalty by implementing self-directed solutions, artificial intelligence, real-time transactions, rich content management, and straight-through processing. Many modern industries are adopting AI for various applications as the era becomes more advanced and intelligent daily.

One of the first industries implementing AI is banking. Although AI cannot retain customers, it can improve processes and personalize their experiences, providing long-term services. For this reason, it is crucial to monitor how banks use AI. With the development of technology over the last few decades, industries have begun integrating cutting-edge technologies, such as artificial intelligence, to provide clients with higher-quality services [2]. Increasing bank customer loyalty requires the use of digital banking. According to a survey, if their current bank does not offer online banking, nearly 20% of clients are open to switching to another financial institution [3].

Companies must prioritize technology management to remain competitive, and technological innovation is essential to sustainability [4]. Since 1987, the World Commission on Sustainability and Development has held discussions regarding the impact of business operations on society and the environment. Corporate sustainability has drawn the interest of academia, policymakers, and businesses alike, resulting in a rise in interest in the concept.

Artificial intelligence (AI) is a decisive tool for effective risk management and forecasting techniques in the banking and financial industries. Primary data processing techniques can become more professional and effective with substantial data research. By automating the customer support system, banks and customers can communicate around the clock. In addition to technology, it provides clients with 24/7 account access. AI has a significant role that could influence banking in the future. Additionally, this system will sustain the company's profitability by extending credit and advising numerous clients on the best ways to invest their money immediately in the banking industry.

Considering the increasing number of people using online banking, assessing the level of service, customer satisfaction, and loyalty of AI-enabled digital banking services that banks consistently provide in India is critical. Customers frequently lament numerous persistent shortcomings in digital banking, even with its advantages. These include coverage of wireless networks, security concerns, technical difficulties, user incapacity, lack of banking technological advancements, etc.

The issue with the antiquated banking system currently in place is that decisions are made using massive amounts of data. It is very costly, and between twenty and thirty percent of decisions are erroneous because of inaccurate or insufficient information in the organizational plan. To process the reports, the AI system will intelligently handle these problems and monitor all stakeholder-related data. Additionally, it will use real-time data to guide and coordinate the customer's decision-making process to ensure compliance with laws and regulations.

A wave of digitization is transforming digital into a valuable offering in the financial services industry, as described by Roy and Balaji [5], Herington and Weaven [6] and Pikkarainen et al. [7]. It is, therefore, imperative that marketers reconsider their approach to customer experience.

AI acceptance factors are becoming increasingly important in marketing strategies in the current competitive landscape. Besides the rising significance of digital banking, financial services are now characterized by digital interfaces, intangibility, and trust, making it imperative to investigate the phenomenon of customer experience in the age of digitization, Zeithaml et al. [8] and Khan et al. [9]. Klein et al. [10] cite Nielsen's 2015 study as evidence that mass media marketing was less important (50%) than customer loyalty (87%) in driving business. Since customers rely so heavily on referrals and advice from one another, customer loyalty, a non-commercial, interpersonal preference, is crucial to providing services [11]. Customer loyalty marketing significantly impacts consumer behavior [12]. A breakdown in service could lead to negative loyalty [13]. Because of how consumers interact with service providers in the current digital era, loyalty has evolved and grown in importance [14]. Gender differences in consumer behavior and information processing have been studied in the past. Gender disparities in banks' convenience, service delivery strategies, and service scape concerning service marketing were discovered by Garg et al. [15]. Gender differences in self-awareness, materialism, aversion to risk, power, and societal contrast were examined by Keech et al. [16]. The study considers age, in addition to gender, as a moderating variable. Previous studies have found that age affects how technology is embraced and accepted [17]. Furthermore, past studies, Stafford et al. [18] discovered a relationship between the age of the customer base and their online purchasing behaviors. Khan et al. [19] found that affective commitment and customer experience were moderated by age.

The association between AI acceptance factors and other brand-related constructs, such as affective engagement, personality, trustworthiness, attitudes, satisfaction, loyalty, and consumer-based brand equity, has been examined in earlier research [20-24]. Studies that examine the effects of specific *AI acceptance factors* are scarce in any case. Analyzing TAM in a digital context is pertinent, considering how digital banking has transformed the banking sector.

Digital banking now includes more services than just online and mobile banking. Third, emerging countries are also starting to embrace digital banking, even in developed countries where it is a significant factor. A direct shift toward digital technologies is occurring among consumers in many developing nations. The research will be beneficial and insightful for brand managers working with developing countries. Finally, the moderating variables in this study include gender and age.

Concerning digital banking services, the study examines age and gender as moderating factors against demographic variations in banking service user loyalty. The primary objective of this study is to investigate the relationship between tailored *AI acceptance factors* and digital banking customer loyalty. As technology acceptance factors become increasingly important, managers in digital banking will be interested in understanding the connection between TAM and customer loyalty.

2. Literature Review and Hypotheses Development

According to Sharma and Piplani [25] digital banking converts all conventional banking services and activities into a digital setting. The technological demands of digital banking are very high. These demands include financial services innovation for consumer and business clients, encompassing regtech, data, blockchain, API, distribution channels, and mobile digital AI payment strategies [25]. Digital banking, as a whole, refers to an information-sharing and transaction-based operating model that banks use to communicate with their customers through technology platforms. Digital gadgets linked to internet-connected computer software carry out this process. To transact, customers do not need to visit a bank's physical branch, and vice versa. Banks can complete transactions (such as tracking records and signing documents) without meeting with customers. Service marketing theories play a significant role in conceptualizing database management systems despite their technological connection [26]. As a result, Hoehle et al. [27] observe that although the use of database channels has increased significantly, a previous study may have been limited because of its fragmented findings and study methods and has yet to identify all customer-related issues.

The Technology Acceptance Model (TAM) theory is commonly acknowledged within information technology. Davis [28] created TAM to theorize computer technology usage behavior. According to Ajzen and Fishbein [29], the theory of reasoned action (TRA) is another well-known theory that explains the connection between users' beliefs, attitudes, and intentions. This theory was the source of inspiration for the Theory of Accepted Model. As per Chuttur [30] and Dwivedi et al. [31], factors such as perceived ease of use and perceived utility can account for user acceptance. The TAM has been tested, improved, and expanded over the last 20 years to better understand the intent to use technology. Therefore, the TAM has been primarily used by researchers to comprehend digital banking practices [7, 32-35]. This study employed modified versions of the AI acceptance factors: Perceived Usefulness, Perceived Ease of Use, Perceived Risk, Perceived Trust, and Perceived Benefit.

2.1. Perceived Usefulness

The amount a person thinks information system technology could increase efficiency and save costs is perceived usefulness [28]. The benefit of using chatbots and other AI-enabled devices could be best described as "perceived usefulness". As per Herrero and San Martín [36] it is the point at which a person considers that utilizing a specific system will enhance their ability to complete a task. Customers' perceptions of AI devices, like chatbots, are greatly influenced by their perceived usefulness. It demonstrates that people are more likely to embrace technology if they believe it is functional. In order to gain their trust, banks that want their clients to use chatbots and other devices should speak convincingly and highlight the advantages of doing so, such as quicker and easier procedures, priority customer service, etc. User satisfaction should increase if users believe digital banking payments using AI technology are more beneficial than other payment methods.

2.2. Perceived Ease of Use

According to Davis [28], a system's ease of use is measured by the manner in which a user perceives its usability. A system can enhance work performance if it is easy to operate. Studies reveal a direct and indirect relationship between intention and perceived usefulness, which influences perceived ease of use. The perceived ease of use of technological devices shapes users' attitudes toward and intention to use them. To reach a broad audience, developers of AI devices should focus on making these devices simple to operate. Customer loyalty and satisfaction are affected by perceived ease of use.

2.3. Perceived Risk

Customers' perception of probable adverse outcomes and reluctance to purchase a good or service is known as perceived risk. Five categories of risks are present for customers: time, money, social, psychological, and performance. Every transaction entails some degree of risk. Clients should be aware of these risks and adjust their plans and strategies accordingly. Consumers using AI-enabled devices for transactions may encounter privacy violations. For instance, their address, phone number, or other personal information might be misused or disclosed to uninvited parties. Users' perceptions and the technology's actual performance are only partially consistent. Users often need to be aware of the risks associated with that inconsistency. Customers who perceive a higher risk in a banking transaction are more likely to have a negative experience. The role of risk should be examined in technology research.

2.4. Perceived Trust

The degree of risk associated with financial transactions is assessed using trust, which is closely linked to user satisfaction. Users' perceptions of digital banking will naturally improve when trust increases. The transactional relationship between banks and customers is maintained by trust [37]. Prior research has revealed that perceived trust plays a beneficial role in banking services. Digital banking has shown that the effective integration of new technologies into services depends heavily on trust. It has been established that there is a positive correlation between perceived usefulness (PU), perceived ease of use (PEoU), and consumers' trust in online technologies. In light of these considerations, the current study suggests that perceived trust is the primary criterion for measuring customer loyalty across different banking perspectives.

2.5. Perceived Benefit

The perceived benefit is the extent to which customers believe they will gain more from an online transaction. Compared to traditional banking methods, internet users report numerous advantages, such as greater convenience, cost and time savings, and a more comprehensive selection of products [38]. Consumers may find using a specific system enjoyable and believe that utilizing new technology is entertaining. Users are more likely to return to a system they find enjoyable. Customers who think that using a specific technology will benefit them are more likely to engage in online transactions that lead to satisfaction and loyalty.

2.6. Customer Satisfaction

The post-activity measuring indicator, also known as satisfaction, evaluates customer sentiment about past purchases or services and their shopping or service-using experiences. Customer satisfaction levels are essential to gauge because they affect whether or not a customer decides to stick with a particular channel after experiencing a certain level of satisfaction with the distribution service. Oliver [39] defined fulfillment as the customer's reaction to a product. In accordance to some researchers, a comprehensive post-purchase assessment constitutes customer satisfaction Mano and Oliver [40], Fornell [41] and Westbrook [42]. Shankar et al. [43] distinguish between two categories of customer satisfaction: satisfaction with service interactions and overall customer satisfaction. While overall customer satisfaction results from accumulated time, satisfaction with service encounters is transaction-specific [39, 44]. Customers' relationships with banks via the Internet constitute the primary construct, so this psychological viewpoint is appropriate for the research setting. Based on this interpretation, a customer's attitude toward the bank throughout their relationship leads to satisfaction [45, 46].

2.7. Customer Loyalty

Oliver [47] defines customer loyalty as the unwavering determination to consistently purchase the same brand or assortment of goods or services in the future, despite outside influences and promotional efforts that might persuade them to shop elsewhere. According to Ranaweera and Prabhu [48], loyalty comprises behavioral and attitudinal aspects. Purchase intentions were the inclination to buy a good or service later [48]. According to Arndt [11], word-of-mouth refers to oral, interpersonal communication between a communicator and a recipient that the recipient understands to be non-commercial and relates to a company, product, or service. The strength of a relationship and the aspiration to maintain it are referred to as customer commitment [49].

2.8. Artificial Intelligence and Customer Loyalty

While many studies have examined marketing management and artificial intelligence, very few have concentrated primarily on customer loyalty. In a recent study that investigated the effect of AI service quality on customer loyalty, Chen et al. [50] examined the possible advantages of artificial intelligence (AI) chatbots for customer retention. It was discovered that, through affective trust, perceived value, cognitive trust, and satisfaction, AI chatbots have a positive impact on customer loyalty and service quality.

Prentice et al. [51] in another study the connection between customer satisfaction and loyalty, artificial intelligence, and employee service quality was examined. The survey was conducted in various Portuguese hotels, with particular emphasis on departing guests who had interacted with AI and employee services related to the hotels under investigation. Customer satisfaction and loyalty were found to be positively influenced by AI and employee service quality. However, AI's impact became negligible and negative when both AI and employee services declined within the same scenario.

Hanifin [52] explored the implications of artificial intelligence for customer loyalty marketing in a Forbes leadership report. The CEO of Hanifin Loyalty LLC, Bill Hanifin, said that his company's research revealed that in 2017, 80% of businesses had incorporated augmented reality (AR), machine learning, or deep learning into their production systems. Another 30% were planning to increase their investment in AI. The same survey also discovered that 62% of businesses choose to invest in AI because they want to improve customer experiences.

As a result, management agrees that AI positively affects customer loyalty since it improves service delivery and overall customer satisfaction [52].

2.9. Interrelationship between AI acceptance factors, Customer Satisfaction and Customer Loyalty

This study relies on the following hypotheses, supported by the modified AI acceptance factors: perceived usefulness, perceived ease of use, perceived risk, perceived trust, and perceived benefits. According to Davis [28] perceived usefulness and ease of use are the two main elements affecting a technology user's acceptance. Ease of use is the capacity to persuade someone that information system technology is straightforward. A person's perception of the cost-effectiveness and performance-enhancing potential of information system technology is known as perceived usefulness. In addition to the basic TAM model, five dimensions of website design and content, delivery speed, security and transparency, accessibility, and convenience may be used to evaluate e-banking practices [71-74]. Considering what was previously discussed, this study aims to find out how additional technological factors, such as perceived risk, perceived trust, and perceived benefits, affect customers' satisfaction and loyalty when using AI-enabled digital banking services. Therefore, we propose the following hypotheses:

H_1: Modified AI Technology Acceptance factors *and customer satisfaction have a positive relationship*

2.10. Relationship among Customer Satisfaction and Customer Loyalty

According to research by Douglas et al. [75], customer loyalty and satisfaction are positively correlated. To gain client loyalty, banks are advised to positively impact customer satisfaction. Prus and Brandt [76] thought that satisfied customers would likely be more loyal, make repeat purchases, and recommend businesses to others. Customers rarely switch brands when they are more satisfied; in other words, they will stick with the brand's original goods or services [77]. Additionally, Kim [78] established that customer satisfaction positively impacts consumer loyalty. We propose the following hypotheses:

H_2: Customer satisfaction and customer loyalty have a positive relationship.

H_3: Modified AI Technology Acceptance factors *and customer loyalty are mediated by satisfaction.*

2.11. Gender being a Moderating Variable

Previous studies examining gender differences have looked at perceived risk [79], processing of information [80] and making decisions [81]. While women emphasize emotional value, men process information more analytically and selectively [82, 83]. Researchers contend that the relationship between word-of-mouth, satisfaction, and brand experience dimensions will be moderated by gender. Gender modifies the association between customer experience, loyalty, and emotional attachment, as revealed by Khan and Rahman [84]. There is likely to be a gender difference in the degree of association between word-of-mouth, satisfaction, and brand experience dimensions. Consequently, the following hypotheses are proposed:

H_4: The influence of modified AI Technology Acceptance factors *on customer satisfaction is moderated by gender*

2.12. Age as a Moderating Variable

According to Ye et al. [85], age is a significant demographic variable in marketing research. It has been observed that younger consumers make greater use of digital products. Age may moderate the adoption and acceptance of technology, according to previous research [17, 55]. According to Khan et al. [19], age moderates the relationship between affective commitment and the experience of customers. Thus, the relationship among customer experience dimensions, satisfaction, and word-of-mouth will be moderated by the age of the customer. Variations exist in the correlations among various consumer age groups and customer experience, satisfaction, and word-of-mouth. It is, therefore, assumed that:

H_5: The influence of modified AI Technology Acceptance factors *on customer satisfaction is moderated by age.*

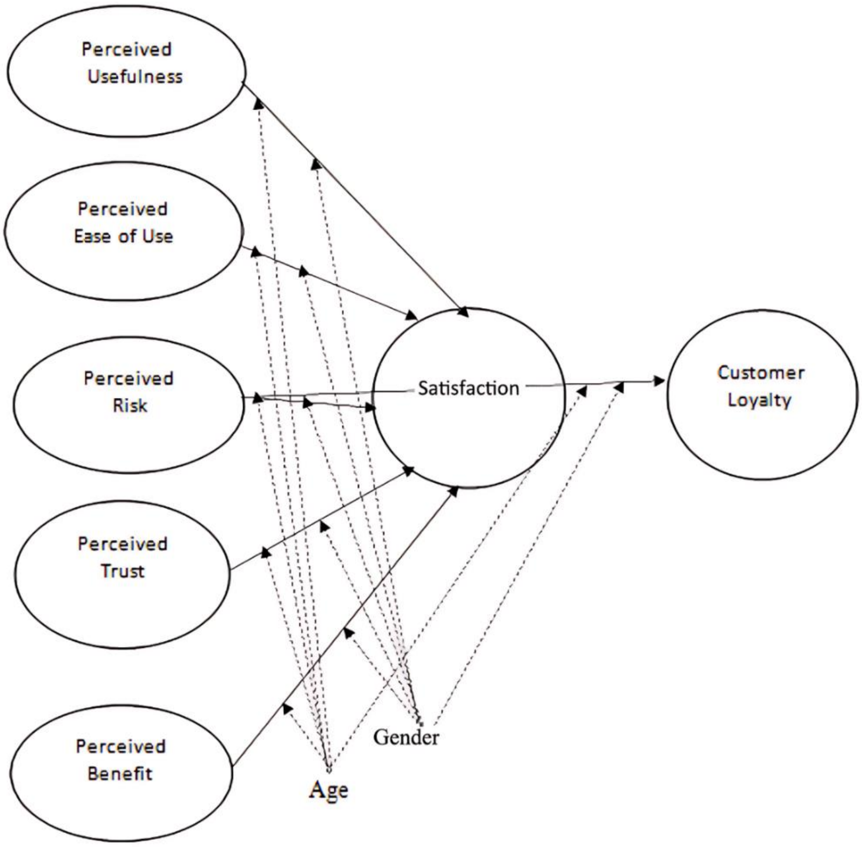

Figure 1.
The above proposed model illustrates the relationships among customer satisfaction, customer loyalty, and AI acceptance factors.
Note: The moderating effect is shown by the dotted line.

Depicts the suggested model that illustrates how AI technology influences customer satisfaction and impacts customer loyalty. The model for digital banking services considers modified AI acceptance factors, which are acknowledged as a critical component in the financial services context.

3. Methodology

3.1. Sample Profile

The study included 380 participants, of whom 200 were female and 180 were male. By age, there were 90 respondents under 21 years, 196 between 21 and 39 years, 75 between 40 and 59 years, and 19 over 60 years old.

3.2. Data Collection

With a structured questionnaire, a single cross-sectional survey design was employed in the study. Through an online survey, information was gathered from Indian digital banking clients. Practitioners with relevant expertise determined the content validity prior to the pilot study starting, and then they carried out the pilot study. Data from 402 clients were gathered using a purposive sampling technique. The study excluded 22 incomplete responses from a total of 402 responses. For the additional analysis, 380 responses in total were used.

3.3. Measurement of Variables

Customer satisfaction, loyalty, and AI acceptance factors were the three variables used in the study. The Davis [28] scale was used as a model for the modified AI acceptance factors, which include perceived usefulness, perceived ease of use, perceived risk, perceived trust, and perceived benefits. Alonso-Dos-Santos et al. [86] and Oliver [47] developed the customer loyalty scale, while Fornell [41] and Oliver [65] developed the satisfaction scale. provides specific dimensions and descriptive statistics. The reliability and construct validity values are displayed in Table 1. According to Nunnally [87] all calculated values exceed the minimum threshold level. In addition, the item factor loadings are higher than the significance level of 0.50 [88].

Convergent and discriminant validity need to be confirmed next. To assess convergent validity, the 'Average Variance Extracted (AVE)' value was calculated. According to Hair et al. [89], the AVE value, or the number of related variances between the indicators for a construct, ought to be greater than 0.50. Each construct meets the convergent validity requirements. Fornell and Larcker [90] examined the constructs' discriminant validity. There is a larger intercorrelation between the construct and the other variable than the squared root of the AVE. Each construct's strong discriminant validity is shown in Table 3. Therefore, the variables in the research model are appropriate for assessing the hypotheses.

4. Results

4.1. Structural Model Assessment

According to Chin [91], Partial Least Squares (PLS) is a variance-based method for concurrently analyzing the associations between variables in structural equation modeling. Without mediation, all constructs had a statistically significant positive relationship with customer loyalty (see Table 3 and Figure 3). 73.40 percent of customer loyalty constructs explained the variation. The study used the integrated assessments for the mediation effect, as suggested by Iacobucci and Duhachek [92].

Table 1.
The details of the items, source, mean, standard deviation, and AI acceptance factors are listed below.

	Factors	Source	Items	Mean	Standard Deviation
1	Perceived Usefulness (PU)	Davis [28]	PU1	3.48	0.94
2			PU2		
3			PU3		
4	Perceived Ease of Use (PEU)	Davis [28]	PEOU1	3.35	0.90
5			PEOU2		
6			PEOU3		
7	Perceived Risk (PR)	Yang et al. [93]	PR1	3.04	0.92
8			PR2		
9			PR3		
10	Perceived Trust (PT)	Owusu Kwateng et al. [94]	PT1	3.16	0.94
11			PT2		
12			PT3		
13	Perceived Benefit (PB)	Owusu et al. [95]	PB1	3.18	0.93
14			PB2		
15	Customer Satisfaction (CS)	Sikdar and Makkad [96]	CS1	3.54	0.89
16			CS2		
17	Customer Loyalty (CL)	Alonso-Dos-Santos et al. [86]	CL1	3.49	0.95
18			CL2		

Table 2.
Construct reliability and validity.

Construct	No. of items	Cronbach'sAlpha	CompositeReliability	AverageVarianceExtracted (AVE)
PU	3	0.88	0.94	0.83
PEU	3	0.89	0.93	0.81
PR	3	0.82	0.88	0.74
PT	3	0.83	0.92	0.78
PB	2	0.87	0.91	0.79
CS	2	0.84	0.92	0.76
CL	2	0.86	0.93	0.74

Table 1 shows the result of Cronbach's alpha, composite reliability, and AVE of all constructs that meet the construct reliability and validity. According to Hair et al. [97], each construct's average variance extracted (AVE) threshold value needs to be greater than 0.5. Cronbach's α and composite reliability are acceptable at 0.7 [97].

Table 3.
Regression Analysis.

	R-square	R-square adjusted
CS	0.625	0.612
CL	0.605	0.591

According to Hair et al. [97] and Lee et al. [98], the model's explanatory power can be indicated by the R^2 value. In Table 2, the R^2 values of exogenous variables such as customer satisfaction and customer loyalty are 0.625 and 0.605, respectively, drawn from SmartPLS4-PM, thus indicating the model's significance and substantive explanatory power.

Table 4.
Discriminant Validity-HTMT.

Construct	PU	PEU	PR	PT	PB	CS	CL
PU	0.83						
PEU	0.65	0.82					
PR	0.58	0.55	0.75				
PT	0.59	0.48	0.67	0.78			
PB	0.33	0.54	0.48	0.33	0.80		
CS	0.62	0.80	0.56	0.75	0.49	0.82	
CL	0.81	0.64	0.59	0.53	0.63	0.80	0.84

Table 4 shows the result of all constructs that meet the Discriminant Validity. Hair et al. [99] state that the Heterotrait-Monotrait (HTMT) ratio of correlations ought to be lower than the 0.85 threshold.

Table 5.
Multicollinearity statistics

	VIF
PU1	1.754
PU2	2.038
PU3	2.894
PEU1	1.732
PEU2	1.677
PEU3	1.633
PR1	2.506
PR2	2.777
PR3	2.79
PT1	2.357
PT2	1.859
PT3	2.854
PB1	1.799
PB2	1.99
CUS1	1.776
CUS2	1.889
CL1	1.812
CL2	1.812

According to Hair et al. [99], a VIF value of 5 or higher in the PLS-PM context indicates a possible collinearity issue. The present study model has no collinearity issue, as shown by all of the VIF values in Table 5 that are less than 5.

Table 6.
Measuring model without a mediator.

Relationship	Coefficients	Standard Error	T Statistics	Results
PU ->CL	0.08	0.02	2.14	Significant
PEU ->CL	0.23	0.05	3.00	Significant
PR -> CL	0.19	0.07	2.42	Significant
PT ->CL	0.07	0.04	2.32	Significant
PB ->CL	0.22	0.05	3.53	Significant

Table 6 indicates the measurement model without mediator customer satisfaction, and the results were significant as the path coefficients fulfilled the threshold value between 0 and 1.

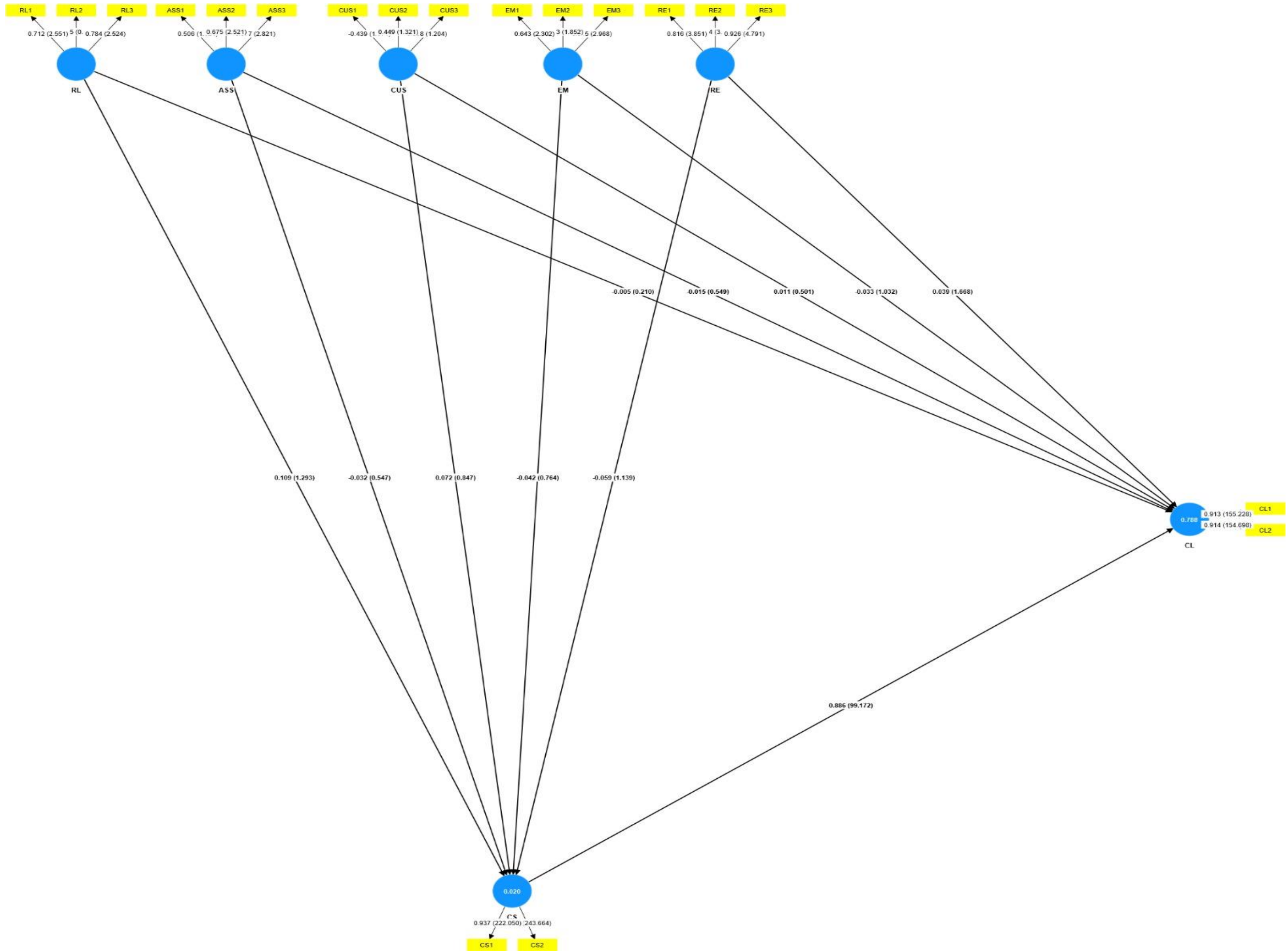

Figure 2.
SmartPLS4-PM demonstrating the relation between customer loyalty, customer satisfaction, and *AI acceptance factors.*

Table 7.
Outer Loadings.

	PU	PEU	PR	PT	PB	CS	CL
PU1	0.792						
PU2	0.92						
PU3	0.882						
PEU1		0.833					
PEU2		0.807					
PEU3		0.792					
PR1			0.916				
PR2			0.895				
PR3			0.935				
PT1				0.909			
PT2				0.837			
PT3				0.9			
PB1					0.886		
PB2					0.928		
CS1						0.938	
CS2						0.937	
CL1							0.915
CL2							0.912

Table 7 indicates that all constructs' factor loading results meet convergent validity requirements as all indicators have loading factor values greater than 0.70. The study's outcomes satisfied the Smart PLS outer model test.

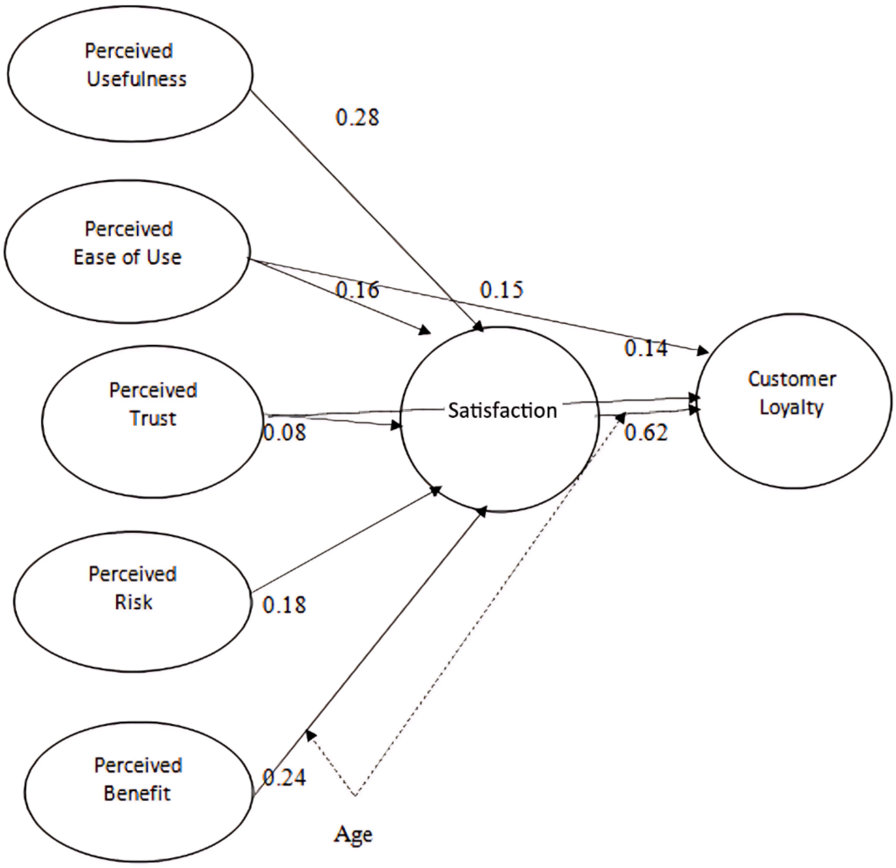

Figure 3.
The below figure illustrates the Path coefficients for *AI acceptance factors*, customer satisfaction, and customer loyalty.
Note: The moderating effect is shown by the dotted line.

To test for mediation, the study ensured that predictors and the mediator significantly affected the outcome variable (Table 8). Using Sobel's Z-test [100], an indirect effect was confirmed at the 1% significance level ($Z = 2.98$; $p < 0.01$). Results showed that Perceived Risk and Ease of Use had indirect effects on Customer Loyalty. Full mediation was observed for Perceived Benefit, Usefulness, and Trust (Tables 8 & 9). Among the predictors, Perceived Usefulness ($\beta = 0.28$) and

Benefit (β = 0.24) had strong effects on Satisfaction, which in turn strongly influenced Loyalty (β = 0.62).

Table 8.
A mediator-based measurement model.

Constructs	Coefficients	Standard Error	T Statistics	Results	Hypotheses
PU ->CS	0.28	0.07	3.98	Significant	H1a supported
PU ->CL	0.10	0.05	1.76	Insignificant	
PEU ->CS	0.16	0.07	2.15	Significant	H1b supported
PEU ->CL	0.15	0.06	2.24	Significant	
PR->CS	0.08	0.04	1.99	Significant	H1c supported
PR ->CL	0.14	0.06	2.06	Significant	
PT->CS	0.18	0.07	2.35	Significant	H1d supported
PT ->CL	-0.03	0.05	-0.70	Insignificant	
PB ->CS	0.24	0.06	3.76	Significant	H1e supported
PB ->CL	0.07	0.04	1.56	Insignificant	
CS -> CL	0.62	0.06	10.10	Significant	H2 supported

Table 9.
Customer loyalty and AI acceptance factors are mediated by satisfaction.

Constructs	Hypotheses Support	Mediation	Hypotheses
PU -> CS -> CL	Yes	Full	$H3_a$
PEU -> CS-> CL	Yes	Partial	$H3_b$
PR ->CS - > CL	Yes	Partial	$H3_c$
PT -> CS -> CL	Yes	Full	$H3_d$
PB ->CS -> CL	Yes	Full	$H3_e$

Table 10.
Gender as a moderator in multigroup analysis.

	Female		Male		Difference	Hypotheses
	β	p- value	β	p- value	p-value	Support
PU ->CS	0.373	0.000	0.175	0.100	0.154	$H4_a$ not supported
PEU-> CS	0.106	0.332	0.203	0.06	0.547	$H4_b$ not supported
PR-> CS	0.164	0.100	0.175	0.054	0.960	$H4_c$ not supported
PT-> CS	0.023	0.803	0.241	0.02	0.062	$H4_d$ not supported
PB-> CS	0.215	0.041	0.212	0.010	0.987	$H4_e$ not supported
CS-> CL	0.796	0.000	0.865	0.000	0.156	$H4_f$ not supported

This study links AI acceptance factors with technology adoption in digital banking, a key area for competitive advantage. Table 10 shows no significant gender moderation. For females, Satisfaction was influenced by Perceived Usefulness (β = 0.373) and Benefit (β = 0.215), with Loyalty strongly driven by Satisfaction (β = 0.796). Table 11 reveals that age moderates the relationships between AI factors, Satisfaction, and Loyalty. For younger users, Satisfaction was affected by Perceived Usefulness (β = 0.332), Benefit (β = 0.426), and Loyalty (β = 0.678). For older users, Satisfaction was shaped by Benefit (β = 0.146), Risk (β = 0.197), Ease of Use (β = 0.228), and Usefulness (β = 0.228), while Loyalty was strongly influenced by Satisfaction (β = 0.881). Figure 3 illustrates these effects and path coefficients.

Table 11.
Age as a moderator in multigroup analysis.

	Low age		High age		Difference	Hypotheses
	β	p-value	β	p- value	p-value	Support
PU-> CS	0.332	0.015	0.228	0.013	0.467	$H5_a$ not supported
PEU-> CS	0.003	0.506	0.254	0.003	0.056	$H5_b$ not supported
PR-> CS	0.074	0.575	0.197	0.015	0.309	$H5_c$ not supported
PT-> CS	0.002	0.93	0.152	0.072	0.297	$H5_d$ not supported
PB-> CS	0.426	0.003	0.146	0.028	0.038	$H5_e$ supported
CS-> CL	0.678	0	0.881	0	0	$H5_f$ supported

5. Findings

5.1. Construct Reliability and Validity

- All constructs demonstrated high internal consistency, with Cronbach's alpha values ranging from .82 to .89 and composite reliability values between .88 and .94.
- Average Variance Extracted (AVE) values ranged from .74 to .83, indicating acceptable convergent validity [90].
- Indicator loadings exceeded the recommended threshold of .70, confirming item reliability.

- Discriminant validity was established using the Fornell-Larcker criterion, where the square root of AVE for each construct exceeded inter-construct correlations.
- Variance Inflation Factor (VIF) values were below the acceptable limit of 3.0, indicating no multicollinearity issues [101].
- Explained Variance (R^2 values):
- Customer Satisfaction (CS) was explained by PU, PEU, PR, PT, and PB with an $R^2 = .625$.
- Customer Loyalty (CL) was predicted by CS and other constructs with an $R^2 = .605$.
- Direct Effects on Customer Satisfaction (CS):
- Perceived Usefulness (PU) had a significant positive effect on CS ($\beta = .28$, $t = 3.98$, $p < .05$). → *H1a supported*
- Perceived Ease of Use (PEU) had a significant positive effect on CS ($\beta = .16$, $t = 2.15$, $p < .05$). → *H1b supported*
- Perceived Risk (PR) had a significant positive effect on CS ($\beta = .08$, $t = 1.99$, $p < .05$). → *H1c supported*
- Perceived Trust (PT) had a significant positive effect on CS ($\beta = .18$, $t = 2.35$, $p < .05$). → *H1d supported*
- Perceived Benefit (PB) had a significant positive effect on CS ($\beta = .24$, $t = 3.76$, $p < .05$). → *H1e supported*
- Direct Effects on Customer Loyalty (CL):
- PU did not have a significant direct effect on CL ($\beta = .10$, $t = 1.76$, $p > .05$).
- PEU had a significant positive effect on CL ($\beta = .15$, $t = 2.24$, $p < .05$).
- PR had a significant positive effect on CL ($\beta = .14$, $t = 2.06$, $p < .05$).
- PT had a non-significant negative effect on CL ($\beta = -.03$, $t = -0.70$, $p > .05$).
- PB had a non-significant positive effect on CL ($\beta = .07$, $t = 1.56$, $p > .05$).

Customer Satisfaction (CS) had a strong, significant effect on CL ($\beta = .62$, $t = 10.10$, $p < .001$) → *H2 supported.*

6. Discussions and Implications

The present study investigates the impact of key AI-related constructs on customer satisfaction and loyalty in the context of digital banking, drawing upon the TAM framework. The findings offer several valuable insights.

First, Perceived Usefulness (PU) was found to significantly influence Customer Satisfaction (CS) ($\beta = 0.28$, T = 3.98), aligning with the foundational work of Davis [28] and subsequent studies such as Bhattacherjee [102]. This suggests that when customers perceive AI tools as helpful and capable of enhancing their banking experience, their satisfaction increases. The practical implication is that banks should design AI functionalities that clearly demonstrate practical utility, such as faster service, accurate recommendations, and streamlined processes, to positively impact satisfaction.

Second, Perceived Ease of Use (PEU) demonstrated a significant positive effect on both CS ($\beta = 0.16$) and Customer Loyalty (CL) ($\beta = 0.15$). This result supports the technology acceptance literature [28, 53], confirming that ease of interaction with AI systems fosters a more positive user experience. The justification lies in the reduced cognitive load and enhanced confidence that come with intuitive interfaces. Banks should therefore prioritize user-centric AI design and minimize complexity to improve both satisfaction and long-term loyalty.

Third, Perceived Risk (PR) had a significant negative impact on CS ($\beta = 0.08$) and a notable positive association with CL ($\beta = 0.14$), emphasizing customer concern over data privacy, system reliability, and potential fraud in AI systems. This finding echoes prior research by Yang et al. [93], who indicated that perceived digital risk undermines trust and satisfaction. The implication for banks is to focus on enhancing transparency in AI-driven decision-making and to provide visible security assurances to mitigate risk perceptions.

Fourth, Customer Satisfaction (CS) was the strongest predictor of Customer Loyalty (CL) ($\beta = 0.62$, T = 10.10), reinforcing classical theories by Oliver [47] and more recent empirical studies such as those by Sikdar and Makkad [96]. This strong relationship suggests that delivering consistently satisfying AI-based experiences significantly strengthens customer loyalty. It underscores the need for ongoing customer engagement, feedback integration, and performance enhancement of AI systems in banking environments.

Finally, the study found that age significantly moderates the relationship between Perceived Benefit (PB) and CS ($\beta = 0.24$), indicating that different age groups interpret and value the benefits of AI in distinct ways. This finding aligns with the extended UTAUT2 model [103] and research by Chen and Chan [104], both of which assert that age plays a crucial role in technology adoption and user satisfaction. Older users may prioritize clarity, simplicity, and security, while younger users might value speed and personalization. Banks should tailor AI experiences according to user demographics, ensuring that communications, interfaces, and services are relevant and accessible to all age groups.

7. Conclusion

The present study concludes that artificial intelligence positively and significantly impacts customer satisfaction and loyalty. The influence of artificial intelligence is partially mediated in a positive way by satisfaction. Consequently, banks that wish to enhance customer loyalty and satisfaction must employ artificial intelligence to customize their offerings of products and services. Thus, integrating the bank's products and services according to the customer's needs and convenience increases customer satisfaction and loyalty.

Prioritizing sustainable development requires balancing innovation, security, competition, and customer satisfaction. With this strategy, optimum customer satisfaction can be attained and maintained, fostering increased customer loyalty.

8. Limitations and Future Research Scope

This study offers valuable insights for practitioners but has limitations that affect its generalizability. It focused on one industry and country (India), so future research should explore different industries and cross-cultural contexts to enhance applicability. Additional TAM dimensions should be included to deepen understanding. Expanding sample sizes and industry types will also strengthen findings. Moreover, future studies should examine negative technology acceptance factors alongside positive ones to guide managers more comprehensively. Since this study relied on self-reported data, incorporating objective measures like transaction records and customer demographics (e.g., occupation, education) is recommended. These variables could also serve as moderators in future research.

Future research should focus on the specific variables used to measure customer satisfaction and loyalty to better understand how artificial intelligence affects these variables. This recommendation arises from the mentioned limitations. Such research should also be specific about the products or services under investigation, as this will limit the applicability of the results to particular product or service categories.

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