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Research Article

Sustainable Digital: AI Applications in Modern Banking Services

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Abstract - *The banking sector in this tech era provides digital services enabled by Artificial Intelligence (AI) technology to gain a competitive advantage and offer customized and personalized banking services. Focusing on sustainable development and leveraging new technologies is essential to digitalize banking services. The study intends to demonstrate exactly how AI technology has a noteworthy influence on customer satisfaction and loyalty in digital banking for long-term growth and environmental sustainability. The desired outcome of the study is the development of a conceptual model by applying the Technology Acceptance Model (TAM) theory that connects these themes through a theoretical framework with the modified service quality dimensions (Reliability, Assurance, Customization, Empathy, and Responsiveness) and the altered AI technology acceptance elements (Perceived usefulness, Perceived ease of use, Perceived risk, Perceived trust, and Perceived benefit). The study gathered 278 valid responses from banking customers using a purposive sampling strategy and a structured questionnaire. Software tools SMARTPLS4 and SPSS29 are used to measure the model. The findings indicate that the altered AI technology factors and service quality aspects are fulfilling the threshold limits of respective statistical tests conducted in the study, resulting in improved user satisfaction and encouraging users to keep using AI-enabled digital banking. This research explores future directions, develops a model and theory, and offers helpful advice to researchers, practitioners, and environmentalists to enhance digital banking research and environmental sustainability.*

Keywords - *Artificial Intelligence, Sustainability, Technology Acceptance Model, Service Quality Dimensions, Customer Loyalty.*

1. Introduction

In today's rapidly evolving financial ecosystem, sustainable digital transformation has emerged as a strategic imperative for banks seeking to balance technological innovation with long-term environmental and social responsibility. Unlike traditional digitalization, which focuses primarily on speed and convenience, sustainable digital transformation emphasizes resilience, ethics, and environmental consciousness in technological progress. In the banking sector, this transformation translates to the development of intelligent, paperless, and customer-centric services that align with sustainability principles such as reduced energy consumption, responsible resource utilization, and ethical decision-making (Financial Stability Board, 2017).

Artificial Intelligence (AI) plays a central role in enabling this sustainable transformation. AI applications such as chatbots, Robotic Process Automation (RPA), fraud detection systems, and predictive analytics have redefined customer engagement and operational efficiency in financial services. By automating repetitive processes and providing data-driven insights, AI reduces resource wastage, paper dependency, and operational costs—thereby contributing to sustainable banking models (Wilson & Daugherty, 2018). Moreover, intelligent systems foster trust and transparency by ensuring accuracy and consistency in transactions, which are critical elements for ethical and sustainable finance (Yu et al., 2018).

The link between AI, customer satisfaction, and sustainability is increasingly vital in shaping digital banking experiences. AI-enabled services enhance customer satisfaction by offering reliability, personalization, and responsiveness—key service quality dimensions identified in the SERVQUAL model (Parasuraman et al., 1988; Zeithaml et al., 2009). Customers who perceive digital banking systems as useful, easy to use, and secure (Davis, 1989; Dwivedi et al., 2017) develop stronger trust and confidence in their banks, which reinforces their satisfaction and long-term loyalty. Simultaneously, these AI-driven services promote sustainable consumer behavior by encouraging paperless transactions, energy-efficient operations, and digital interactions that reduce environmental footprints (Vinuesa et al., 2020). Hence, AI enhances operational excellence and customer experience and accelerates the banking sector's transition toward sustainability and ESG-aligned goals.

Recognizing this synergy, the present study examines how AI-based digital banking services influence customer satisfaction and customer loyalty through a framework that integrates the Technology Acceptance Model (TAM) and Modified Service Quality Dimensions (RACER).

By incorporating key TAM factors—Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Risk (PR), Perceived Trust (PT), and Perceived Benefit (PB)—alongside modified SERVQUAL dimensions—Reliability (RE), Assurance (ASS), Customization (CUS), Empathy (EM), and Responsiveness (RE)—this research aims to establish a holistic model linking AI adoption, service quality, satisfaction, and sustainability.

Through this integrated approach, the study contributes to the rising knowledge base on sustainable digital transformation and offers practical insights for banking institutions, policymakers, and environmental strategists to leverage AI responsibly for long-term growth and sustainable customer relationships.

1.1. Artificial Intelligence and Sustainable Banking

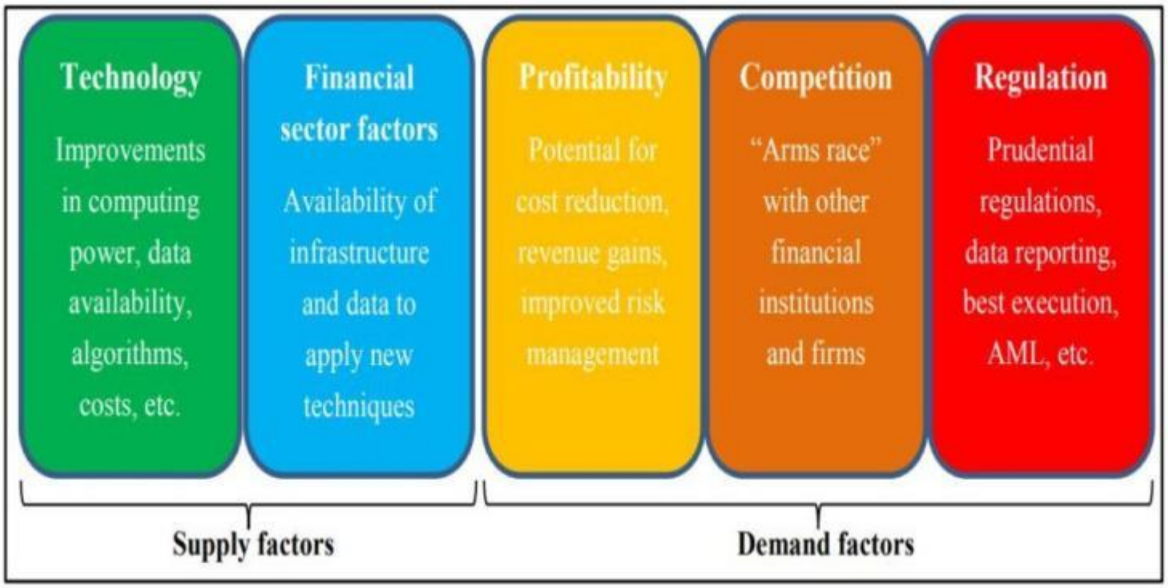

Fig. 1 The demand and supply aspects of AI and machine learning's financial adoption are given by the Financial Stability Board (FSB)

Financial institutions are undergoing a rapid digital shift in the era of the Fintech revolution. Lloyds Banking Group Inc. has made strategic investments of £3 billion to develop products for digital banking and update its workforce for the future of banking. Furthermore, according to JP Morgan lends sixteen percent of its total budget toward digital services, while Deutsche Bank, on the other hand, spends more than four billion dollars a year on technological advancements. Financial services, which deal with large amounts of data and demand organized problem-solving, are ideally suited for AI technology.

When financial institutions adopt AI, automation is undoubtedly the most noticeable aspect. To enhance customer interactions and assist staff in resolving complex issues, progressive banks actively create client-facing chatbots, also known as "virtual assistants." By utilizing more than 220 robotic devices for repetitive operations like error correction and data processing, BNY Mellon made significant advancements in artificial intelligence. An 88% improvement in overall processing time was made possible by this AI initiative at BNY Mellon ("Sustainable AI in Finance: Understanding the Promises & Perils").

Sustainability (ESG) factors are forecast to be significant trends in the digitalization of banking operations over the next ten years. The State Bank of Vietnam has also made decisions and directives to advance the nation's sustainable development goals and actively promote the National Green Growth Action Plan. Its goals include fighting climate change, directing credit flows toward environmentally friendly finance projects, and raising public awareness of the banking system and environmental protection.

A typical instance of how ESG was used to design the bank's digital transformation system is its M-Office electronic office system, which streamlines operations while cutting down on paper waste.

1.2. Problem Statement

Despite rapid advancements in AI-driven digital banking, there is a limited understanding of how Artificial Intelligence contributes to sustainable digital transformation and enhances customer satisfaction and loyalty. Existing studies focus mainly on the technical or efficiency aspects of AI, overlooking its sustainability implications and emotional factors such as trust, risk perception, and perceived benefits. Moreover, traditional models like TAM and SERVQUAL have not been sufficiently adapted to AI-enabled banking environments. There is also a scarcity of empirical evidence from emerging economies like India, where digital adoption is accelerating.

Hence, this study addresses these gaps by integrating modified TAM factors and service quality dimensions to examine how AI-based digital banking influences customer satisfaction, loyalty, and sustainable banking outcomes.

1.3. Research Objectives

Primarily, the research focuses on understanding the influence of AI technology on service quality. The study also assesses how characteristics of service quality affect bank Customer Satisfaction (CS) and Customer Loyalty (CL). Thirdly, how the TAM theory affects customers' satisfaction with the risks involved and, consequently, their intentions to remain loyal to banks in the long run.

2. Literature Review

Table 1. Systematic literature review and research gaps identification

Thematic Area	Existing Literature Insights	Identified Research Gaps	Relevance to the Present Study
AI Applications in Banking	Studies (Wilson & Daugherty, 2018) highlight AI's automation potential and financial efficiency.	Limited empirical evidence on sustainable AI adoption in digital banking and its impact on long-term customer loyalty.	Addresses how AI-enabled digital banking contributes to customer satisfaction and loyalty through sustainable practices.
Technology Acceptance Model (TAM)	TAM (Davis, 1989; Dwivedi et al., 2017) explains technology adoption via PU and PEU.	Past studies rarely integrate TAM with risk, trust, and benefit perceptions in the AI-banking context.	Extends TAM by incorporating perceived risk, trust, and benefit to explain customer satisfaction and loyalty.
Service Quality (SERVQUAL Model)	SERVQUAL (Parasuraman et al., 1988; 1991) is widely applied in conventional banking.	Few studies modify SERVQUAL for AI-based or digital banking environments.	Proposes a modified SERVQUAL model (RACER) tailored to AI-enabled banking service quality.
AI Technology Factors & Service Quality	Limited exploration of how AI acceptance variables influence service quality perceptions (Hoehle et al., 2012).	Lack of integrated models connecting AI factors (PU, PEU, PR, PT, PB) with service quality dimensions.	Establishes direct linkages between AI technology factors and service quality dimensions.
Customer Satisfaction (CS)	Studies (Oliver, 1999; Zeithaml et al., 2009) confirm satisfaction as a key outcome of service quality.	Insufficient empirical testing of satisfaction in AI-based sustainable banking scenarios.	Evaluates satisfaction as a mediator between AI technology factors, service quality, and loyalty.
Customer Loyalty (CL)	Prior research (Boulding et al., 1993; Bloemer et al., 1998) associates loyalty with service experience and satisfaction.	Limited understanding of how AI technology and sustainability jointly affect long-term customer loyalty.	Tests customer loyalty as a dependent variable influenced by AI-driven satisfaction and service quality.
AI and Sustainability Link	Studies (Gillham et al., 2020; Vinuesa et al., 2020) discuss AI's role in supporting sustainable development goals.	Few studies connect AI-enabled digital banking with environmental sustainability outcomes.	Integrates AI, sustainability, and digital transformation in a unified conceptual framework.
Geographical Scope	Existing works mostly focus on Western or developed economies.	There is a scarcity of studies focusing on *emerging economies* like India, where AI in banking is rapidly evolving.	Provides empirical evidence from Indian banking customers to fill this contextual gap.
Methodological Approach	Many studies rely on conceptual or qualitative approaches.	Lack of quantitative validation using advanced tools like SMARTPLS or SPSS in AI-banking studies.	Employs empirical modeling and hypothesis testing to validate conceptual relationships.

Demographic Moderation	Some works address gender and age in digital adoption.	Limited investigation of whether these factors influence AI acceptance or loyalty in digital banking.	Tests demographic effects (age, gender) through ANOVA for deeper insight into behavioral variations.

2.1. Development of Hypotheses of the Present Proposal

Theoretical Background

Digital Banking is a technology-driven banking service that has transformed conventional banking activities into a digital environment (Aarti Sarma, 2017). As a result, customers do not have to visit banks, and banks do not have to physically attend to their customers for any transaction, eventually making digital banking a service-oriented one as well (Van Looy et al., 1998).

While there is a considerable growth in the usage of Digital Banking, advanced research has yet to trace entirely the customer-relevant concerns that perhaps are inadequate due to partial results and research approaches (Hoehle et al., 2012).

AI-Technology Factors and Service Quality Dimensions Relationship

Artificial Intelligence

John McCarthy introduced the “artificial intelligence” (AI) concept in 1957 at a Dartmouth workshop. He described AI as being “the science and engineering of creating intelligent machines” (John McCarthy, 2007). The “General Problem Solver” computer-based program, which mimics human analytical skills and fundamentally resembles human thinking capacity, is where

Artificial Intelligence (AI) first emerged (Newell et al., 1958). In order to determine whether or not a computer could think and act like a human, Russell and Norvig proposed the four scopes of AI, which include thinking and acting like human brains, reasoning, and applying analytical thinking to complex problems (Russell and Norvig, 1995). AI in banking must “do the right thing.”

TAM Theory

Davis (1989) designed TAM to formulate the behavioral usage of computer technology. TAM indicators such as PU and PEU constitute user acceptance (Dwivedi Rana et al., 2017). Over the last 20 years, TAM has improved its understanding of the intention to use technology.

2.1.1. Factors of Modified TAM

PU is the individual’s degree of faith that digital technology could enhance the banking performance (Davis et al., 1989). As a result, if the customers perceive AI-based banking services as more valuable, then their usage has a positive impact on their satisfaction.

PEU is the CS and CL that are ultimately the outcome of an individual’s degree of certainty that a specific arrangement would increase attainment and positively affect users’ assertiveness toward technological strategies (Davis et al., 1989). PR refers to how uncertain and unfavorable they believe purchasing a good or service will be (Yang et al., 2015). Customers should be conscious of the risks involved, so strategies should be developed with that awareness.

It has been discovered that there is a discrepancy between the opinions of users and the technology’s actual functionality.

A customer’s likelihood of having a bad experience with banking services increases with the level of risk they perceive. Numerous studies have indicated that a significant psychological factor crucial to banking is customer emotional behavior.

The psychological variables related to individual-level experiences and cognitive processes, such as a person’s thoughts, feelings, and beliefs, are perceived trust and perceived benefit, which influence a customer’s satisfaction and loyalty (Junaid Khalid et al., 2015).

PT is used to determine the level of buoyancy associated with any financial operation that is proportionate to the individual’s satisfaction. Furthermore, it helps maintain the bank’s and customers’ transactional link (Jane Upton, 2013).

Thus, perceived trust has been considered one of the leading factors for valuing consumer loyalty in digital banking in the proposed study. PB is the privilege that consumers would become comfortable with digital banking.

Online consumers have observed many benefits like cost savings, time savings, increased convenience, and service variety in comparison with the conventional mode of banking (Peha and Khamitov, 2004). Therefore, the more consumers perceive benefits, the more they will perform more online transactions, leading to satisfaction and loyalty.

2.1.2. Modified Service Quality Dimensions

An intangible act or performance rendered to another party is known as a service without granting ownership of anything (Kotler and Keller, 2009). In contrast, *quality* assesses the integrality of a product or service’s features and characteristics and whether they can meet any stated needs.

The SERVQUAL model is a highly valuable tool for measuring customer service quality dimensions. The SERVQUAL model developed by Parasuraman et al. (1988) has proven five elements of service quality that together are referred to as RATER.

Although numerous efforts have been made to use the SERVQUAL model in conventional banking globally, limited attention has been given to assessing the service quality, satisfaction, and loyalty in the context of digital banking customers.

Hence, a five-dimensional Modified SERVQUAL model called RACER has been proposed using a conceptual framework in the present research through the following Hypotheses. RL has been suggested as the appropriate exercise of a self-service technology and accurate service delivery (Weijters et al., 2005).

Many reported studies have identified reliability as a significant dimension in determining service quality (Bagozzi, 1990). ASS is an assertion in an intangible service that indicates the consumable services conveyed to the related customers effectively, thus strengthening the constructive outcome of the service encounter.

Further, it appropriately increases the trust of the users and decreases risks while performing any transaction (Parasuraman et al., 1991). CUS has been defined as the build-to-order approach that offers a service that fits the requirements of the customer (Kaplan and Haenlein, 2007).

Firms could build an influential customer bond through customization, leading to higher customer retention (Lovelock & Wirtz, 2004). EM is the conveyance of the feelings that the customer is unique and special, which is the basic idea of empathy (Parasuraman et al., 2002). A SERVQUAL model describes the quantifiable studies that recognize service quality dimensions, which include access, security, and credibility to measure empathy that affects satisfaction.

The promptness with which banking operators respond to customers is called responsiveness (Sheng and Liu, 2010). Research indicates that responsiveness is critical in determining the eminence of digital banking services and their impact on CS and CL (Suleman et al., 2012).

H_1: AI Technology factors significantly impact Service Quality Dimensions.

CS - Oliver (1999) has defined satisfaction as the accomplished response of a consumer. It is a post-service activity that estimates the mindset of the customer's feelings about their past experiences (L.Margherio, 1998). Customers' decisions are greatly influenced by the experienced services that measure the degree of satisfaction.

CL - relates to the commitment that is deeply associated with re-patronize or repeat purchase of the preferred services consistently in the future, thus initiating a similar set of brands to purchase repeatedly regardless of the marketing efforts and situational impacts that have the ability to cause a shift in behavior (Oliver, R.L., 1997).

The dimensions on which customer loyalty is based are Purchase intentions (Oliver, R.L., 1999), Word of mouth (Boulding et al., 1993), and Commitment (Gremler et al., 2001).

Purchase intention is the propensity to make a future purchase of a good or service (Moorman et al., 1992). Non-commercial oral statements between people about a brand, product, or service are known as word-of-mouth (Ranaweera et al., 2003). Strong relationships and an intention to maintain them are components of customer commitment (Arndt, J., 1967).

Interrelationship among Service Quality, CS & CL

Today's competitive business environment, with the swift market entry of novel service innovations, requires a rigorous understanding of the relationship between service quality, CS, and CL, which has been considered as a significant factor for the basis of marketing strategy, success, and survival (Bansal et al., 2003).

Parasuraman et al. (1996) introduced a conceptual prototype on service quality, CS, and CL. The findings of service quality possess an indirect effect through satisfaction on loyalty, and eventually satisfaction possesses a direct effect on loyalty (Zeithaml et al., 2009).

H_2: Service Quality Dimensions significantly impact CS.
H_4: Service Quality Dimensions significantly impact CL.

Interrelationship between AI Technology Factors, Customer Satisfaction, and Customer Loyalty

According to Bloemer et al. (1998), the Technology Acceptance Model has two main dimensions: PU and PEU. The present study aims to add PR to basic TAM with the inclusion of PT and PB in order to examine how these factors influence the customers' satisfaction and loyalty in banking. Hence, the following hypotheses that could guide this research are:

H_3: AI Technology factors have no impact on CS.
H_5: AI Technology factors have no impact on CL.

Relationship between CS and CL

The studies conducted by Douglas et al. reveal a significant association between CS and CL (Davis, 1989).

Hence, it is recommended that banks achieve CL by influencing CS positively. Customers would exhibit less brand-swapping behavior and have high satisfaction (Douglas et al., 2017).

H_6: CS significantly impacts CL.

2.1.3 Conceptual Framework

Modified Service Quality Dimensions

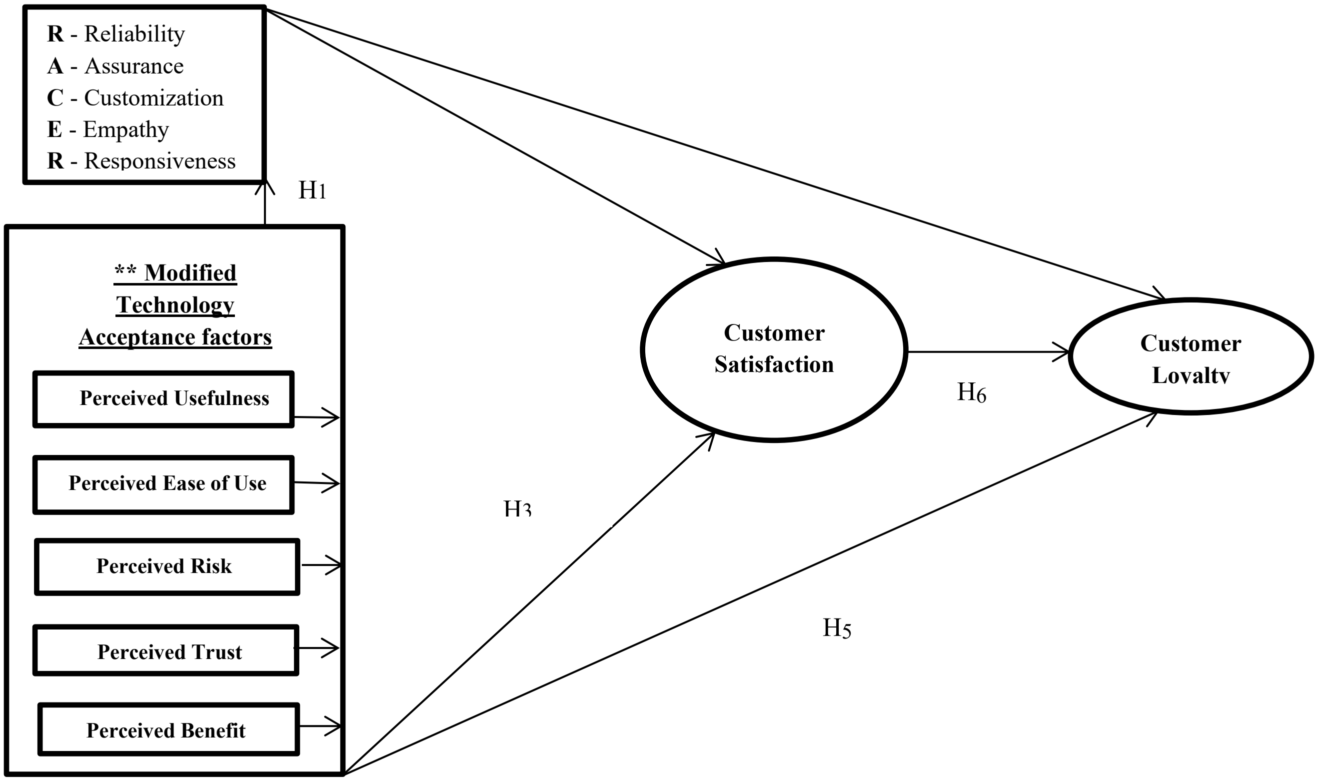

Fig. 2 Conceptual model

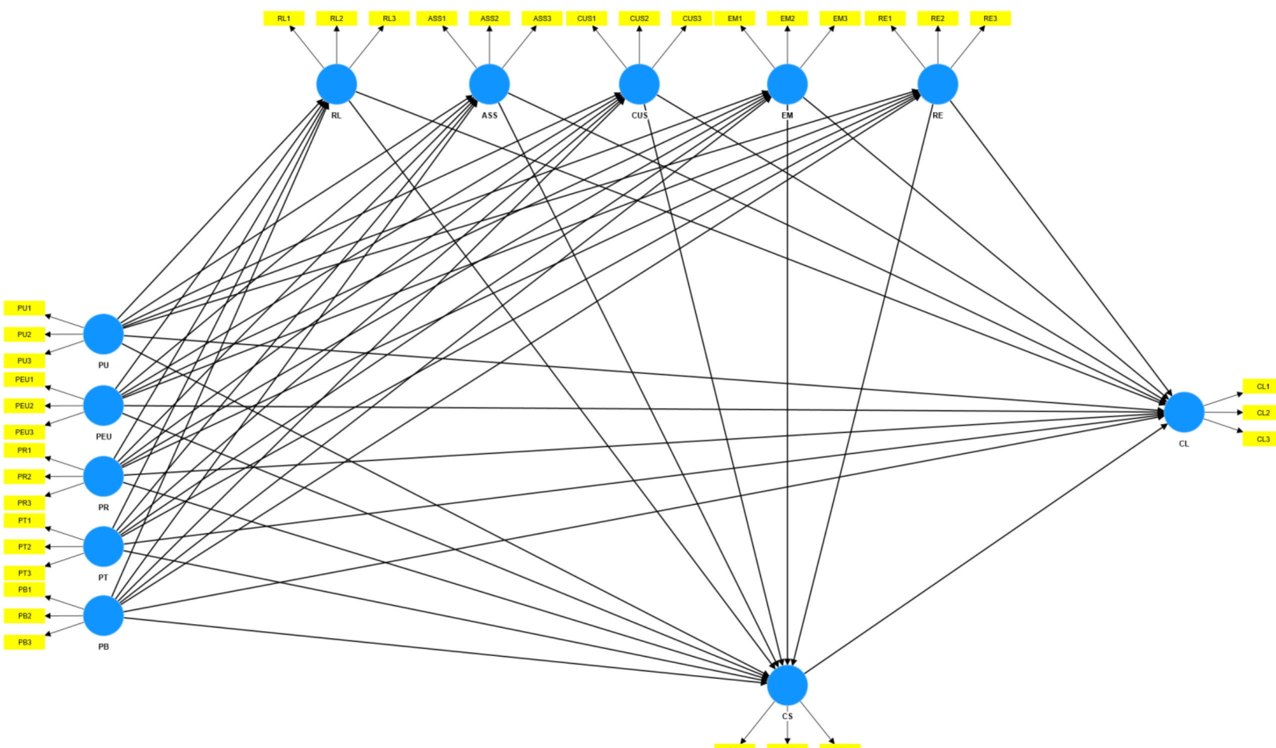

Fig. 3 Structural equation model-1

Source: SMARTPLS4

3. Research Methodology

3.1 Research Design

This study incorporated a quantitative, cross-sectional research design to examine the influence of AI on CS and CL in digital banking, framed within sustainable digital transformation. The research integrated constructs from the TAM—PU, PEU, PT, PR, and PB—and modified SERVQUAL (RACER) dimensions—RL, ASS, CUS, EM, and RE—to assess their combined impact on customer satisfaction and loyalty.

The target population comprises retail banking customers in Hyderabad and Secunderabad, Telangana, who actively use AI-enabled banking services such as mobile apps, chatbots, and automated transaction systems. These urban centers were selected due to their high levels of digital adoption and the availability of both public and private sector banks implementing AI technologies.A purposive sampling technique was used to identify respondents with relevant experience in AI-based digital banking.

3.2 Sample Size

Of 300 distributed questionnaires, 278 valid responses were retained for analysis. The sample size satisfied statistical adequacy for Structural Equation Modeling (SEM), exceeding the recommended minimum of 10–15 observations per indicator variable (Hair et al., 2010).

The survey instrument, structured on a five-point Likert scale, included demographic items and constructs measuring technology acceptance, service quality, CS, and CL. Questionnaire items were adapted from established scales (Davis, 1989; Parasuraman et al., 1988; Oliver, 1997) and refined through a pilot test with 30 respondents, achieving CA values above 0.70, confirming internal consistency and construct reliability.

3.3 Data Collection

Data collection was conducted between January and March 2024 using both online and in-person methods. The data were analyzed using SPSS 29 and SmartPLS4. Descriptive statistics were used to summarize demographic information, while inferential analyses—including correlation, regression, and SEM—tested hypothesized relationships among variables. Reliability and validity were confirmed through Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) following the criteria of Hair et al. (2013). Additionally, ANOVA tests examined demographic variations in customer loyalty.However, the non-probability nature of purposive sampling introduces certain limitations. First, participant selection was limited to urban customers already familiar with digital banking, potentially excluding rural or first-time users, which may affect generalizability. Second, the study's focus on two metropolitan regions—Hyderabad and Secunderabad—could introduce geographical bias, as customers in other regions might have differing perceptions of AI-based banking. Third, self-reporting bias may exist since responses are based on participants' subjective perceptions of satisfaction and trust. Despite these limitations, the sampling approach was suitable for exploratory analysis aimed at understanding the behavioral dynamics of experienced digital banking users in an emerging economy context.

4. Data Analysis & Empirical Results

4.1. An Analysis of Descriptive Statistics

As shown by Table 2, 65.4% of the samples are males, while 34.5% are females. Most respondents (35.6 %) are 40–59 years old, while 32% are between 20-39 years old. Besides, 30.5% of the respondents are Postgraduates. Finally, 96 respondents had 34.5 % income, while 84 respondents had 30.2% income.

Table 2. Respondents' demographic characteristics

		N	%
Gender	Female	96	34.5
	Male	182	65.4
	Total	278	100.0
Age	Below 20	73	26.2
	20 - 39	89	32.0
	40 - 59	99	35.6
	60 and above	17	6.1
	Total	278	100.0
Qualification	Under graduation	23	29.9
	Graduation	85	8.2
	Post-graduation	98	30.5
	Above Post-Graduation	72	25.8
	Total	278	100.0
Occupation	Student	65	22.3
	Service	84	28.7
	Business	25	8.9
	Professional	94	33.8

	Retired	12	4.3
	Home Maker	2	1.7
	Total	278	100.0
Income	Below 20000	64	23.0
	20000 - 39999	84	30.2
	40000 - 59999	96	34.5
	60000 and Above	34	12.2
	Total	278	100.0

4.1.1. Descriptive Analysis

Using descriptive statistics, value deviations from their mean scores are displayed. Table 3 lists each variable's descriptive statistics for both independent and dependent variables. A lower degree of variability and spread in the variables suggests that most results are near their means.

Table 3. Measurement scales & descriptive statistics

Construct	Mean	Std. Deviation	N
RL	3.97	1.118	278
	3.98	1.118	278
	3.96	1.077	278
ASS	3.92	1.123	278
	3.94	1.051	278
	3.96	1.101	278
CUS	3.97	1.092	278
	3.98	1.111	278
	3.92	1.045	278
EM	3.88	1.137	278
	3.79	1.139	278
	3.81	1.149	278
RE	3.8	1.142	278
	3.92	1.101	278
	3.94	1.086	278
PU	3.93	1.027	278
	3.93	1.03	278
	3.98	1.096	278
PEU	3.88	1.117	278
	3.88	1.123	278
	3.84	1.118	278
PR	3.68	1.139	278
	3.53	1.12	278
	3.6	1.12	278
PT	3.77	1.096	278
	3.88	1.115	278
	3.87	1.12	278
PB	3.96	1.058	278
	3.95	1.062	278
	3.91	1.081	278
CS	3.93	1.096	278
	3.91	1.104	278
	3.9	1.079	278
CL	3.93	1.089	278
	3.85	1.125	278
	3.92	1.071	278

4.2. Inferential Statistical Analysis

4.2.1. Correlation Study

The statistical technique known as correlation is used to determine the relationship between two variables. The range of values for the coefficient of correlation is -1 to +1.

The relationship directions are indicated by the coefficient sign; a variable has a negative correlation if its correlation coefficient is close to -1 and a positive correlation if it is close to +1. The present investigation demonstrates that CL has a moderately strong correlation with PEU, PR, PT, RL, RE, PU, and CS, but a weak correlation with ASS, CUS, and EM. It also possesses a strong correlation with PB and CS.

A positive correlation was found between all of the variables (Refer to Table 4).

Table 4. Correlation matrix

	RL	ASS	CUS	EM	RE	PU	PEU	PR	PT	PB	CS	CL
RL	1											
ASS	.774**	1										
CUS	.730**	.878**	1									
EM	.751**	.911**	.918**	1								
RE	.846**	.861**	.788**	.837**	1							
PU	.867**	.775**	.682**	.728**	.848**	1						
PEU	.873**	.802**	.723**	.762**	.893**	.924**	1					
PR	.860**	.677**	.645**	.648**	.759**	.836**	.829**	1				
PT	.859**	.666**	.640**	.650**	.752**	.836**	.818**	.964**	1			
PB	.896**	.727**	.658**	.672**	.812**	.874**	.886**	.926**	.926**	1		
CS	.903**	.703**	.663**	.668**	.786**	.868**	.857**	.929**	.932**	.959**	1	
CL	.899**	.753**	.694**	.721**	.807**	.870**	.878**	.875**	.878**	.924**	.929**	1

** A significant Pearson Correlation exists at the 0.01 level. (2-tailed)

4.2.2 Regression Analysis

Regression analysis is a crucial method for figuring out how various variables that are recognized as independent variables affect the dependent variable. A multivariate regression technique is used as this study has multiple independent variables and a single dependent variable. Table 5 shows the influence of PU, PEU, PR, PT, PB, RL, ASS, CUS, EM, and RE on the CS and CL's acceptance of AI in banking. At $p < 0.001$, the F-statistics show that the overall predictive model is significant.

In other words, if the model is valid, the outcomes produced by applying it are likewise trustworthy and broadly applicable. R^2 and adjusted R^2 convey the explanatory power of the independent variables, which shows the extent to which the independent variable explains the dependent variable.

a. Predictors: (Constant), Technology acceptance factors (PU, PEU, PR, PT, and PB), Service quality dimensions (RL, ASS CUS, EM, and RE)
b. Dependent Variable: CL.

Table 5 and 6 show that the chosen influencing factors result in R = 0.977 percent of the variations in customer loyalty. There is 0.955 percent Adjusted R^2. The coefficient of determination is 0.846; therefore, the selected variables explain about 84.60% of the variation in the satisfaction data. For making predictions, the regression equation is favorable since the value of R^2 is close to 1.

Table 5. Regression matrix

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	PB, PR, EM, PT, PEU, RL, PU, RE, CUS, ASS[b]	.	Enter
a. Dependent Variable: CL			
b. All requested variables entered.			

Table 6. Model summary

Model Summary[b]				
M Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.977[a]	0.955	0.953	0.6959
a. Predictors: (Constant), PB, PR, EM, PT, PEU, RL, PU, RE, CUS, ASS				
b. Dependent Variable: CL				

The chosen influencing variables account for R = 0.977 percent of the variations in customer loyalty. The table below shows us the F-test result, giving us an indication of the extent to which the model fits the data overall. The model does fit the data in this case, as indicated by the highly significant F-test result.

Table 7. ANOVA

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2450.74	10	245.07	506.06	<.001[b]
	Residual	114.774	237	0.484		
	Total	2565.51	247			
a. Dependent Variable: CL						
b. Predictors: (Constant), PB, PR, EM, PT, PEU, RL, PU, RE, CUS, ASS						

It is well known that the beta value quantifies the degree to which each predictor variable affects the criterion variable. In addition, standard deviation units are used to measure the beta. In the table below, perceived benefit has the highest beta value (0.635), meaning that a change in perceived benefit will shift customer loyalty to public and private banks in Hyderabad and Secunderabad by 0.635 standard deviations.Therefore, the higher the beta value, the more significant the predictor variable's influence on the criterion variable.

Table 8. Coefficients

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	Collinearity Statistics
		B	Std. Error	Beta			Tolerance	VIF
	(Constant)	0.006	0.182		0.034	0.973		
	RL	0.202	0.074	0.203	2.713	0.007	0.034	2.531
	ASS	-0.21	0.092	-0.202	-2.247	0.026	0.023	3.857
	CUS	-0.04	0.078	-0.035	-0.46	0.646	0.033	3.524
	EM	0.111	0.047	0.115	2.332	0.021	0.078	2.828
	RE	0.174	0.064	0.172	2.73	0.007	0.047	1.145
	PU	-0.15	0.062	-0.145	-2.436	0.016	0.053	1.781
	PEU	0.247	0.045	0.251	5.513	<.001	0.091	1.02
	PR	-0.07	0.026	-0.071	-2.656	0.008	0.268	3.733
	PT	0.076	0.046	0.076	1.66	0.098	0.091	1.028
	PB	0.647	0.06	0.635	10.722	<.001	0.054	1.562

Table 9. Regression analysis results are summarized for the hypothesis testing

Hypotheses	Remarks - Supported
Hypothesis 1	Yes
Hypothesis 2	Yes
Hypothesis 3	Yes
Hypothesis 4	Yes
Hypothesis 5	Yes
Hypothesis 6	Yes

4.2.3. An ANOVA Test

An ANOVA test was conducted to ascertain whether age and gender have an impact on a CL's use of banking services. Table 10 displays the F-statistics using customer loyalty in banking for the variables age and gender.

Table 10. ANOVA test CL in banking with respect to Age

Descriptives						
CL						
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Below 20	70	3.628	1.02939	0.139	3.3494	3.9059

20-39	89	4.079	0.84507	0.091	3.8978	4.2602
40-59	99	4.013	0.97832	0.103	3.8078	4.2176
60 and above	20	3.899	0.96429	0.234	3.4033	4.3949
Total	278	3.943	0.95552	0.061	3.823	4.062

Table 11. Tests of homogeneity of variances

Tests of Homogeneity of Variances			
	Levene Statistic	df1	df2
CL	1.206	11	267
	0.621	11	267
	0.621	11	266
	1.629	11	267

Table 12. ANOVA

ANOVA			
CL			
	df	F	Sig.
Between Groups	11	2.81	0.04
Within Groups	267		
Total	278		

The significant F-value in the table above suggests that there is no age difference in terms of banking CL.

Table 13. ANOVA analysis of CL in banking with respect to Gender

Descriptives						
CL						
	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Male	182	4.018	0.90743	0.071	3.877	4.1585
Female	96	3.801	1.0307	0.111	3.5798	4.0218
Total	278	3.943	0.95552	0.061	3.823	4.062

Table 14. Tests of homogeneity of variances

Tests of Homogeneity of Variances					
		Levene Statistic	df1	df2	Sig.
CL	Based on Mean	5.203	1	276	0.023
	Based on Median	3.009	1	276	0.084
	Based on Median and with adjusted df	3.009	1	272.368	0.084
	Based on the trimmed mean	5.672	1	276	0.018

Table 15. ANOVA

ANOVA					
CL					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.644	1	2.644	2.919	0.089
Within Groups	272.869	276	0.906		
Total	275.513	277			

The significant F-value in the table above suggests that there is no age difference in terms of banking customer loyalty.

4.3. Measurement Model

4.3.1. KMO and Bartlett's Test

Table 16. Measure of sampling adequacy

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.963

Bartlett's Test of Sphericity	Approx. Chi-Square	22203.455
	df	630
	Sig.	<.001

Table 16 presents the results of the Bartlett's test of factors and the Kaiser-Meyer-Olkin (KMO) test based on data collected on particular variables. When values are high (0.50-1.0), factor analysis is appropriate. Factor analysis might only be suitable if the value is at least 0.50. KMO is a tool used to assess the suitability of factor analysis by measuring the sphericity of sampling adequacy. KMO indicates that the sampling adequacy in this instance is (value of 0.50< KMO<1.0), meaning that 0.963 for a selected group of customers using bank facilities is appropriate. To assess the hypothesis that there is no correlation between the variables in the population, the statistical test known as Bartlett's Test of Sphericity is employed. Every variable in the population correlation matrix (r=1) has a perfect correlation with itself but not with any of the other variables (r=0). This matrix is known as an identity matrix. In the present study, as per Bartlett's Test of Sphericity, the approximated chi-square value for <0.001 significance levels is 22203.455 with 630 (df). Factor analysis is, therefore, a suitable method.

4.3.2. FL, CA, CR, and AVE

According to Hair et al. (2013), 0.7 is the acceptable level of CA and CR. Each construct's AVE threshold value must be higher than 0.5 (Hair et al., 2013). The output of CA, CR, and AVE for each construct that satisfies the reliability and validity criteria is also displayed in Table 17. For all constructs that meet convergent validity, the factor loading results are shown in Table 9, as each indicator has a loading factor value greater than 0.70. The study's findings in Smart PLS4 have passed the outer model test.

Table 17. Results related to Items, FL, CA, CR, and AVE

Items	FL	CA	CR	AVE
RL1	0.977	0.974	0.983	0.96
RL2	0.974			
RL3	0.974			
ASS1	0.953	0.962	0.976	0.93
ASS2	0.961			
ASS3	0.979			
CUS1	0.978	0.97	0.98	0.943
CUS2	0.969			
CUS3	0.967			
EM1	0.969	0.975	0.983	0.951
EM2	0.98			
EM3	0.976			
RE1	0.936	0.958	0.972	0.939
RE2	0.974			
RE3	0.968			
PU1	0.987	0.981	0.987	0.963
PU2	0.987			
PU3	0.97			
PEU1	0.985	0.974	0.983	0.951
PEU2	0.968			
PEU3	0.972			
PR1	0.963	0.967	0.977	0.935
PR2	0.962			
PR3	0.975			
PT1	0.947	0.962	0.974	0.925
PT2	0.962			
PT3	0.977			
PB1	0.984	0.987	0.992	0.975
PB2	0.991			
PB3	0.987			
CS1	0.985	0.988	0.992	0.977
CS2	0.99			
CS3	0.99			

CL1	0.991	0.981	0.987	0.97
CL2	0.964			
CL3	0.989			

4.3.3 Discriminant validity

Table 18 shows the result of all constructs that meet the Discriminant Validity using the Fornell and Larcker criterion. This method estimates factors' discriminant validity through the extracted square root of average variance (Hair et al., 2013).

Table 18. Discriminant validity-Fornell-Larcker Criterion

	ASS	CL	CS	CUS	EM	PB	PEU	PR	PT	PU	RE	RL
ASS	0.964											
CL	0.942	0.985										
CS	0.944	0.981	0.988									
CUS	0.953	0.939	0.939	0.971								
EM	0.921	0.894	0.899	0.876	0.975							
PB	0.937	0.956	0.949	0.952	0.846	0.988						
PEU	0.928	0.929	0.932	0.902	0.902	0.886	0.975					
PR	0.742	0.723	0.72	0.704	0.801	0.687	0.795	0.967				
PT	0.906	0.895	0.894	0.876	0.911	0.847	0.925	0.831	0.962			
PU	0.934	0.925	0.922	0.951	0.834	0.965	0.872	0.658	0.835	0.981		
RE	0.96	0.943	0.951	0.945	0.937	0.921	0.923	0.75	0.903	0.922	0.969	
RL	0.957	0.941	0.946	0.97	0.891	0.933	0.914	0.715	0.901	0.929	0.947	0.977

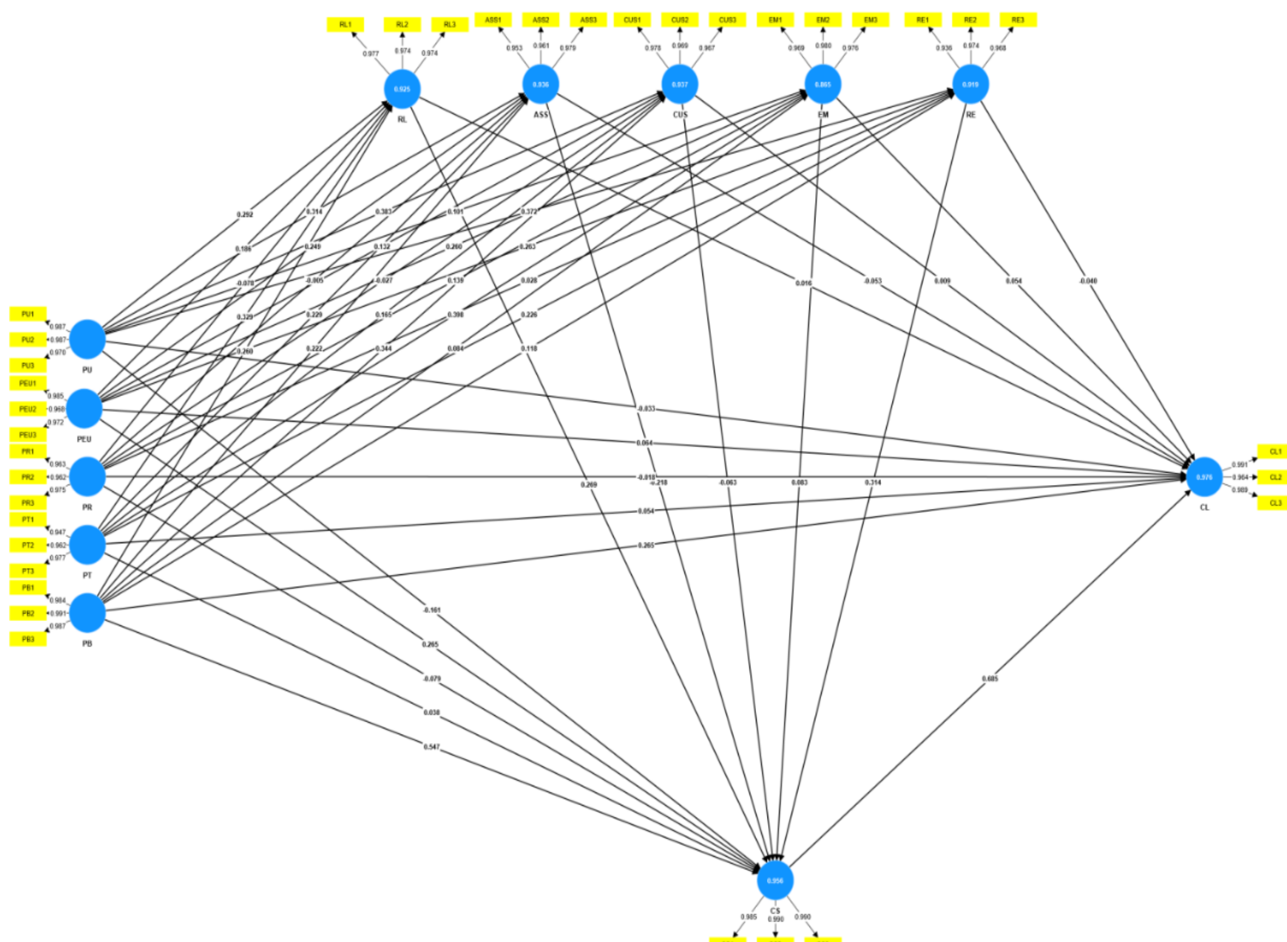

Fig. 4 Structural equation model-2

Source: SMARTPLS4

5. Discussion and Implications

5.1. Discussion

The modern world has made AI indispensable in all spheres of existence. Both industrialized and developing nations attempt to use AI in various fields. One of the most critical industries for any country is banking. Keskinbora (2019) argues that AI systems possess intelligence and problem-solving abilities that surpass those of humans, which may pose ethical and societal risks. Public values like autonomy, privacy, security, human dignity, and justice have all been pressed (Yu et al., 2018). Ethical governance has become essential as these technological systems become increasingly commonplace (Wallach & Allen, 2008).

Financial risks associated with climate change may immediately affect the counterparties and financial assets that central banks use to manage collateral and implement monetary policy. The United Nations' AI Summit, which was held in Geneva in 2017, recognized that artificial intelligence (AI) has the potential to accelerate humanity's transition towards a life of dignity, peace, and prosperity. It also recommended that AI—which powers self-driving cars and voice and facial detection in smartphones—be used more strategically to brace global efforts to end hunger and poverty, preserve the environment, and conserve natural resources. In particular, improved regulatory expectations and audit process facilitation between government agencies and organizations are critical to the broad adoption of sustainable AI.

As demonstrated by the study's findings, all AI technology acceptance elements and service quality dimensions certainly correlate with customer satisfaction and loyalty. This suggests that providing excellent banking services and advancing technology are necessary to win over satisfied and committed customers. It indicates that the bank should compel the establishment of personalized, attentive, and caring conditions for its users. It is also imperative for banks to devise tactics that increase CL.

The aforementioned research findings are statistically significant and meet all threshold limits. As a result, the findings thoroughly understand the implications of extended TAM dimensions and present a comprehensive image of how changed TAM dimensions might influence CS and CL.

Present research contributes to academia and the area professionals' valuable comprehension to become aware of sustainable AI applications. For beginners, greater use of AI technology in all its forms (RPA and Chatbots) eases the achievement of sophisticated tasks, thus reducing human manual capability. For area experts related to various organizations, AI would be beneficial in avoiding technical glitches and simultaneously stimulating favorable opportunities for their future growth.

5.2. Implications

5.2.1. Theoretical Implications

1. The study integrates the TAM and RACER framework, offering a holistic explanation of CS and CL in AI-enabled digital banking.
2. It extends TAM by including PT, PR, and PB, capturing emotional and psychological dimensions of AI acceptance.
3. The research links AI adoption with sustainability, advancing theory on how digital transformation supports ESG goals.
4. It reinforces CS as a key mediator between AI technology usage and loyalty.

5.2.2. Managerial Implications

1. Banks should use AI to enhance reliability, responsiveness, and customization, improving service quality and satisfaction.
2. Strengthening trust, transparency, and data security reduces perceived risk and fosters long-term loyalty.
3. Managers should position AI as a sustainability enabler, promoting paperless and energy-efficient operations.
4. Continuous usability improvements and customer feedback integration are essential for sustained satisfaction.
5. Employee training for effective human–AI collaboration enhances empathy and personalized service delivery.

5.2.3. Policy Implications

1. Regulators should establish ethical AI frameworks ensuring fairness, accountability, and data privacy.
2. Policies promoting AI-driven sustainable finance (e.g., green lending, ESG monitoring) can advance national sustainability goals.
3. Financial inclusion policies must ensure equal access to AI-enabled services across all demographics.

6. Conclusion, Limitations, and Future Scope

6.1. Conclusion

The banking sector plays an essential part in the contemporary economic domain, enhancing conventional banking services by making them more customer-centric, as they are the need of the hour. Thus, banks are exploring advanced technologies such as AI to provide convenient and user-friendly services.

It required time and effort to transform the banking industry completely. The banking sector underwent a dramatic transition from traditional banking (established in 1472) to AI-based banking (which began to emerge in 2017); this transition will become more noticeable in key banking domains like core banking, efficiency in operations, and customer support. This research attempts to understand sustainable finance by combining AI with banking customers' intentions to remain loyal. Consequently, the exploratory approach was taken to investigate the association between the dependent variables, or readiness for AI in the banking industry, and the independent variables/predictors, or RL, ASS, CUS, EM, RE, PU, PEU, PT, PR, and PB. The outcome demonstrates a positive correlation between CS and CL to accept AI in the banking sector for all predictors. Furthermore, the analysis showed that the acceptance of AI in the banking industry is not affected by the age or gender of the clientele. The results provide valuable insights for bank management as they develop future strategies, like algorithms powered by AI that collect and assess customer data, make relevant product recommendations that have already been approved, and offer customized financial advice.

The study's findings can assist banking management in improving and modifying their marketing strategies to win over customers' trust and help them reduce the risk of transacting through digital technology. Consequently, more investigation is needed to evaluate the differences in CL intentions between the banking industry's early and late adopters of AI. In this way, banks, practitioners, and environmentalists may find it easier to formulate their plans and future directions for development and sustainability with the present study's suggested conceptual framework.

6.2. Limitations and Future Scope

As this study was restricted to two cities, additional research on other Indian cities may be undertaken, and by examining consumers' perspectives on artificial intelligence, the results may be compared. Only the banking industry was the focus of this investigation. Future considerations will also extend to other financial sectors. This study uses a survey to collect self-reported data, which is a methodological necessity.

These kinds of data could be ambiguous. Future researchers should use different techniques for gathering data, like field experiments, and enlarge the sample size to improve accuracy. The survey sample size was limited to 300 banking respondents; in future research, even larger sample collections could be performed. The impact of AI technology stimuli is expected to be more widespread in this era of rapid technological advancement, urging more study. Future studies must investigate new aspects of AI technology stimuli and consider more extensive and varied case samples in addition to larger data sets. In this study, the EFA is completed, and a full CFA would be suggested for Model Fit to continue.

Author Contributions

MAH: Wrote the original draft, Data Collection, Data analysis, Visualization & Mapping.

SV: Conceptualisation and Methodology.

SK: Proofreading and revisions.

All the authors read and approved the final manuscript.

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