Acceptability of Artificial Intelligence-enabled Digital Banking Among Customers: Insights from PLS-SEM Approach

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Abstract

AI has proved useful in almost every area, but its role in Indian banking is still something that needs to be examined. The study looks at how bank customers feel about tools that use AI. Making customers happy is the first step to getting them to accept and stick with less well-known banking technology and automated processes. The study utilizes the technological-acceptance model to figure out the level of acceptability of its parts and separate them into factors that are independent and those that are dependent. “Awareness level”, “efficiency”, “trust”, and “social influence” are the independent variables. “Customer satisfaction” is the dependent variable. So, the structural equation model was made from the answers of 239 retail bank users in northern India. According to the survey, trust is the most important thing for bank customers to enjoy AI-enabled services, followed by awareness. The least important part of customer satisfaction for AI-based banks is their protection. Age and gender are control factors that affect how people see things. In emerging markets like India, it is hard to find out how retail-banking customers feel about AI-based technology. The results shed light on compliance formation. At the end of this study, the paper discusses what it means for financial authorities and decision-makers to use AI in customer service.

Keywords: artificial intelligence, digital banking, customer acceptability, PLS-SEM

Introduction

Machine learning, cognitive computing, and natural language processing form the backbone of artificial intelligence (AI), which is revolutionizing our lives in ways we could never have imagined (Mangani, 2017). AI-enabled equipment can now reason, grasp, and carry out jobs formerly undertaken by humans. Complex cognitive tasks can be carried out by AI systems (Vieira & Sehgal, 2017). The development of AI is a major step forward in the process of digitizing and transforming contemporary business. The advent of AI in banking has sparked a worldwide upheaval that is altering the sector as a whole. Information systems and the application of AI have become increasingly important to banks as a means of handling financial transactions and providing consumers with individualized services and products (Abdulla, Ebrahim, & Kumaraswamy, 2020). With the help of AI, businesses are better able to anticipate their consumers' needs, provide individualized service, and create high-quality, persona-based goods (Payne, Dahl, & Peltier, 2021). As a result, AI has brought forth significant benefits for the banking industry. Reduced expenses, easier access, greater precision, and enhanced productivity are just some of the benefits.

Customers' openness to using AI in banking has a significant impact on banks' willingness to adopt digital technologies and their customers' level of happiness. Customer satisfaction rises as a result of AI's ability to make interactions more pleasant. Robotics and AI are helping financial institutions tailor their services to individual customers. Thus, this results in stronger customer relationships and higher levels of consumer engagement (Abdulla, Ebrahim, & Kumaraswamy, 2020). Since happy customers are a major factor in whether or not AI in banking will succeed, this is an issue that must be taken seriously.

Artificial intelligence (AI) has tremendous potential in the banking industry, especially in situations where a large number of customers must be managed effectively through a database system (Bharti, Prasad, Sudha, & Kumari, Customer acceptability towards AI-enabled digital banking: a PLS-SEM approach, 2023). The perceived utility and the simplicity of use of AI are two crucial criteria driving client acceptability. Therefore, "this study takes into account customer satisfaction as the dependent variable and incorporates awareness level, efficiency, trust, and social impact as independent variables in the conceptual construction of the model."

Previous AI research has provided only a partial picture of how widespread digitalization affects the financial sector. This study fills a need in the literature by analyzing the effects of using artificial intelligence-based technologies in banking. The research takes a Structural Equation Modelling (SEM) technique to answer questions concerning banking customers' satisfaction. Customers' familiarity and comfort with the banking system will be used to gauge the impact of these technological innovations**.**

Theoretical Background and Hypothesis Formulation

The construction of the model is driven by the Technology Acceptance Model (TAM) provided by (Davis, 1989). It primarily assesses whether a new information system will be accepted by its target audience. In the opinion of (Banna & Alam , 2021) **a**utomation is more accessible, less expensive, and more productive than the traditional banking system. It needs more understanding to grasp how AI-based technology will be accepted and maintained. Additionally, the post-adoption experience of users in banks will be determined by the measurement of consumer acceptability. Customer acceptance is thus closely related to the dimensions employed in this study since it will help clarify how the constructs are related to one another (Bharti, Prasad, Sudha, & Kumari, 2023)**.** As a result, a number of factors have a significant impact on how customers perceive AI in banks when the literature is critically analyzed. However, some key indications are exclusively chosen for use with theoretical models in order to ensure clear understanding. The degree of acceptance and customer preparedness are taken into consideration while choosing these indicators. The model of TAM constitutes constructs such as "attitude", "perceived usefulness", "perceived ease of use", and "behavioral intention to use"

Attitude

An individual's mental state of willingness to embrace a specific change is referred to as attitude (Belanche, Casaló, & Flavián , 2019). The perception is developed about a particular product or service through usage and usually with others who would develop similar perceptions (Kohnke, 2022), (Bhatia, Chandani, Atiq, Mehta, & Divekar , 2021). Likewise, trust and consumer social influence helps shape people's attitudes about the use of AI. Consequently, the following hypotheses were developed:

H1: Trust of customers in AI-based technology positively impacts customer satisfaction.

H2: The social influence of customers is positively linked with customer satisfaction.

Perceived Usefulness

Perceived usefulness (PU) is the extent to which an individual can see how technology improves a system's functionality (Davis, 1989). It is a crucial construct that determines how the user intends to behave (Robinson, 2020). Based on the level of awareness of AI-based technology, the user determines the significance of this technology in banks (Rahman, Ming, Baigh, & Sarker, 2021). The accuracy and volume of information an individual learns about unfamiliar technology serve as an indicator of their level of awareness (Shankar & Rishi, 2020). Therefore, the following hypothesis is generated:

H3: The level of customer awareness will positively impact customer satisfaction.

Perceived Ease of Use

The idea that using technology is basic and simple can be termed as perceived ease of use (PEOU) (Bawack, Wamba, & Carillo , 2021), (Gupta, Ghardallou, Pandey, & Sahu, 2022). Over time, it has a major impact on how often the service is to be used. The user is able to identify if they have a deeper fondness for the service (Fan, Han, & Gao, 2022), (Jakšiè & Marinè, 2019). The PEOU of AI in banks, as represented by efficiency, is thus another independent variable. Optimizing resource consumption for customers is how efficiency is defined (Przegalinska, Ciechanowski, Stroz, Gloor, & Mazurek, 2019), (Hasal, Nowaková, Saghair, Abdulla,, & Snášel, 2021). Hence the following hypothesis is formulated:

H4: Efficiency of AI-enabled technology is positively associated with customer satisfaction.

Customer satisfaction

The factor that contributes to the outcome is behavioral intention (BI) to use AI in banks, which is determined by how satisfied customers are i.e. customer satisfaction with the financial products and services (Gunawardane, 2023). Hence it serves as a dependent variable. Customer satisfaction ultimately determines whether a product will be used consistently in the future (Venkatesan, 2017), (Boustani, 2021).

Therefore, in order to clarify the positive aspects of deploying AI-based technology, this study delves more deeply into consumer TAM and its significance to digitalization.

Table 1: Description of constructs in brief Source authors

Concept	Description
Perceived usefulness	The extent to which users perceive the advantages of technology on system performance.
Awareness level of the customer	Quality and quantity of customer knowledge about unknown technology
Perceived ease of use	The illusion that using technology is simple
Efficiency	Customer-focused resource optimization
Attitude	mental preparedness for a change in the user
Trust	Consumers' confidence in a novel concept
Social influence	Influence of other people's opinions on the buyer
Customer satisfaction	When a customer's wants and needs are accurately perceived
Occupation	User's academic and occupational history

Research framework

This study concentrates on examining consumer satisfaction about the application of AI-based technology, which influences the demand for digital adoption among bank clients. This examination is conducted through the utilization of a theoretical model. The research framework provides a comprehensive overview of the investigation and succinctly presents the acquired results.

Materials and Methods

Data sources and sample composition

Three hundred customers of "private and public sector retail banks" in northern India were selected at random to fill out questionnaires as part of the research strategy. However, a grand total of 239 responses were considered fully complete. This yielded a response rate of 79.66%. Sixty-one out of the total number of responses (20.33%) were either missing information or were left blank on purpose. During the prototype stage, we calculated the total number of responses. The test's consistency and reliability were calculated using the Cronbach alpha coefficient. According to SmartPLS's analysis, the response rate of the primary data is satisfactory. The size of the sample was picked so that all viewpoints and points of view would be adequately represented in the allotted amount of time. The participants in this study range in age from 18 to 60, and they all know their way around a bank. They are a technologically savvy bunch, made up of clients of public and private retail banks in the north of India. Therefore, in order to select people for the study, the researchers used snowball and purposive sampling. The respondent has experience with the banking system, either formally or informally, and is familiar with basic banking concepts and products such savings and checking accounts. Students, working professionals, and retired persons were all represented among the attendees. In their responses to the questions, the participants showed a great deal of energy and interest. The participants' level of agreement or disagreement with the claims was used to determine the order in which the traits were ranked. Twenty statements in all make up the final questionnaire, which has been broken down into seven sections based on factors such as respondents' levels of awareness, efficiency, trust, social influence, and customers' overall satisfaction. The items included in the aforementioned surveys were taken directly from the Technology Acceptance Model (TAM). The TAM is a groundbreaking concept for gauging the satisfaction of customers (Ladhari et al., 2011). This tactic is frequently used when fully deploying cutting-edge company technology after initial trials. Compared to other theoretical frameworks, the items in the Technology Acceptance Model (TAM) had a far higher degree of coherence with the research objectives of the study. Previous studies' scales were different from those used here. In light of this, the authors crafted the questionnaire's scale to match the question's intended response and the items used in the study. The questions are written in clear, simple language that can be easily understood. Before beginning the response activity, participants were given a brief introduction to artificial intelligence (AI). In order to obtain the participants' written responses at the banking facilities, we gave them a self-administered questionnaire. Participants were given paper forms to fill out at local bank locations and were given the option to participate. The remaining statistics came from surveys and online forums, with an emphasis on northern India. To better reach the target audience and ensure they can understand the questions, they were translated into English and Hindi. The collected responses were imported into a comma-separated value Excel spreadsheet for further processing before being integrated into SmartPLS 4.0. Banking institutions have a lot to gain from, and their customers have a lot to learn from, asking questions about the effects of implementing AI-enabled technologies. The participants' demographic information is presented in Table 2. There was an age disparity between individuals who responded to the self-administered questionnaire and those who responded via email or other online platforms. Participants were informed that their privacy would be protected before they even filled out the survey. If there is a breach of confidentiality, it will be dealt with immediately. There was no requirement to reveal identifying information like name or occupation, and the questions asked raised no moral issues. There was no special effort made to ensure the participants felt at ease when providing information about their investments.

Table 2: Demographic profile of the respondents.

Characteristic	**Frequency**	**Percentage**
Age		
18-35 year	118	49.4
35-46 year	38	15.9
47-54 year	46	19.2
>55 year	37	15.5
Education level		
Others	6	2.5
Postgraduate	65	27.2
Graduate	141	59
High school	27	11.3

Gender		
Male	190	79.5
Female	49	20.5
Income		
>5 Lakhs	54	22.6
<5 Lakhs	102	42.7
Prefer not to answer	36	15.1
>10 Lakhs	47	19.7
Occupation		
Manufacturing/industrial sector	46	19.2
Service sector	75	31.4
Student	29	12.1
Retired	3	1.3
Commercial sector	87	36.4

Source: The authors

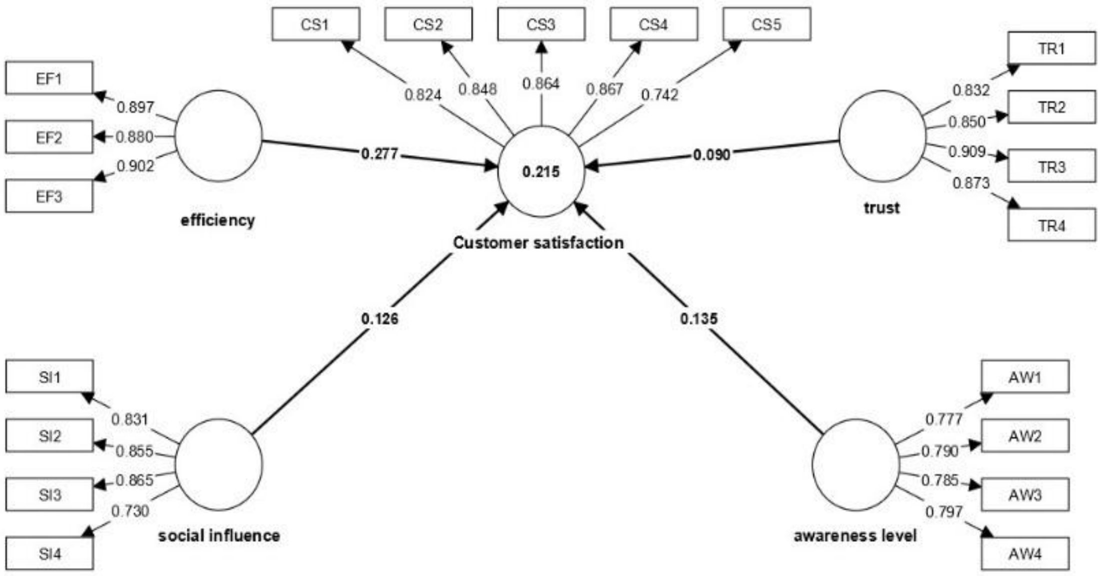
The survey data reveals a population predominantly within the 18-35 age bracket (49.4%), majorly graduates (59%), and predominantly male (79.5%). In terms of income, a significant portion earns below 5 Lakhs (42.7%), with the commercial sector (36.4%) being the largest employer. The education level shows a considerable number of postgraduates (27.2%), and the age distribution indicates a minor segment above 55 years (15.5%). This demographic profile highlights a young, educated, male-dominated population, with varied income levels and occupations, mainly concentrated in the commercial and service sectors.

Measurement Scale and Methodology

Each topic is broken down into multiple parts, and the participants' responses to each section are tallied using a Likert scale, where a rating of "1" indicates strong disagreement and a rating of "5" indicates strong agreement. The study participants were selected by a combination of snowball and purposive sampling by the researchers. This method guaranteed that the sample would be statistically representative of the whole. The responses were admirably well-rounded, providing both an insightful viewpoint on AI and a critical examination of its potential applications. According to the remarks made by the participants, there was a noticeable lean towards the perceived acceptance of AI-based technology in banks and the benefits associated with it. Using SmartPLS version 4.0, a structural equation modelling (SEM) analysis was performed on the data. To ensure the reliability of the instruments employed in the study, a pilot study was conducted using a convenience sample of 30 persons. It was determined, through preliminary research, whether or not the respondents could answer all the survey questions and understand their relevance. It was also crucial to determine the sample size and the results gained from the survey before undertaking the inspection on a larger scale. The results of the present study were similar to those of the pilot study, which also used SPSS version 26, with a few minor tweaks. Because of the potential for erroneous findings, the expected sample size was doubled. In addition, only fully completed responses were included in the analysis; the few partially completed surveys were from the pilot phase. Because of the possibility of missing data to introduce bias into the study, it was decided to throw out the questionnaire with the holes in it. According to (Hair, 2019), whose research supported the development of the theoretical framework, a larger sample size was associated with a smaller degree of bias in the results. In addition, structural equation modelling (SEM) methods can work with non-standard data sets, such as those with missing information, non-normally distributed variables, or autocorrelated error structures (as is commonly seen in time series research). Furthermore, SEM offers flexible strategies for handling longitudinal data (Oino, 2018; Abikari et al., 2022). The research results are separated into two sections. The measurement model is discussed in the first part, while the structural model is discussed in the second. The Maximum likelihood (ML) estimate is used in the context of structural models to increase the likelihood that the observed covariance matrix is drawn from the population in a way that is consistent with the proposed covariance matrix. One significant benefit of covariance-based SEM over competing models is that, during the iterative phase, the fitness function is continuously optimised through the use of maximum likelihood estimation (MLE) (Khan et al., 2017). Structural Equation Modelling (SEM) is a powerful tool for reducing the impact of multicollinearity. When using a reflecting scale or reliability test, it's crucial to pay attention to how statistically significant each independent variable is. There is a high degree of correlation between the independent variables, but this does not have a major impact on the overall measurement and structural models.

Because the approach employs questions that evaluate the same construct and measure the same unit of analysis, it is considered reflective. For this theory to hold, it's necessary to interpret the questions as evidence of a common worldview.

Figure 1: Structural equation model obtained from SmartPLS.



Source: The authors

Table 3: Summary of internal consistency, reliability, and convergent validity of the model.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Customer satisfaction	0.887	0.896	0.917	0.689
awareness level	0.798	0.803	0.867	0.620
efficiency	0.875	0.897	0.922	0.798
social influence	0.838	0.843	0.893	0.676
trust	0.889	0.897	0.923	0.751

Source: The authors

Table 4: "Outer loadings" and "collinearity statistics" of the measurement model

S. no.	Items	VIF	Outer loadings
1	*AW1*	1.472	0.777
2	*AW2*	1.576	0.790
3	*AW3*	1.813	0.785
4	*AW4*	1.611	0.797
5	*CS1*	2.322	0.824
6	*CS2*	2.702	0.848
7	*CS3*	2.612	0.864
8	*CS4*	2.402	0.867
9	*CS5*	1.568	0.742
10	*EF1*	2.224	0.897
11	*EF2*	2.551	0.880
12	*EF3*	2.368	0.902
13	*SI1*	1.943	0.831
14	*SI2*	2.223	0.855
15	*SI3*	2.193	0.865
16	*SI4*	1.462	0.730
17	*TR1*	2.108	0.832
18	*TR2*	2.254	0.850
19	*TR3*	3.052	0.909
20	*TR4*	2.451	0.873

Source: The authors

Findings

Reliability and validity

Since there were many things to test, measurement models were used to determine factors like optimism, overconfidence, and a willingness to take risks. Internal consistency is measured by Cronbach's alpha and composite dependability, both of which are presented in Table 3. The SEM model used in this investigation is also reflective in its approach. Therefore, Table 4 displays the results of the calculations made to determine the outer loading values. Outer loading levels are generally higher than 0.708 (Fornell and Larcker, 1981), as is well accepted. All measures in table-4 (Cronbach alpha, composite reliability, and Average Variance Extracted) are above the minimum threshold of

0.7 (Li et al., 2021) and much beyond the maximum threshold of 0.5 (Li et al., 2021). The composite reliability metric takes into account both the convergent validity and the average extracted variance. The results provide evidence for the convergent and robust validity of the model (Fornell and Larcker, 1981). According to Ahmadi Danyali (2018), outer loading values ranged from 0.73 to 0.90, with VIFs typically falling below 3. Discriminant validity is established by calculating the average variance of the retrieved data using the HTMT ratio and the Fornell-Larcker criterion. The Fornell-Larcker criteria provide support for establishing discriminant validity by contrasting the square root of the average variance extracted (AVE) with correlation values of latent variables (Chong et al., 2021). The Fornell-Larcker criteria are mentioned, so Table 6 satisfies this requirement. Table 7 provides a comprehensive breakdown of the HTMT values. The fact that the reported HTMT ratio values are all smaller than the cutoff value of 0.85 demonstrates that all components within the construct are statistically unique from one another and have individual significance. To evaluate discriminant validity, Hair et al. (2019) suggest the heterotrait-monotrait ratio of correlations (HTMT). This leads us to believe there is discriminant validity in this case.

Structural model

The current research endeavors to probe this concept from within an internal structural model with multiple branches. To test for a statistically significant link between the latent constructs, the bootstrapping method is used. Figure 1 depicts the value of the path coefficient, which indicates that the effect of trust on customer satisfaction in AI-based banks is quite small. All t-values obtained were more than the cutoff value of 1.96 (Bellini et al., 2017), as shown in Table 7. A 0.05 level of confidence is assumed; hence it is essential that the t-values coincide with the measured route coefficient. Table 8 shows that all of the hypotheses were supported by the data (p-values were less than 0.05, which is the threshold for statistical significance). Therefore, the internal model demonstrates the importance of efficiency in affecting customer satisfaction with AI-enabled solutions in the financial services industry.

Table 5: Fornell–Larcker criteria.

	Customer satisfaction	awareness level	efficiency	social influence	trust
Customer satisfaction	0.830				
awareness level	0.315	0.787			
efficiency	0.401	0.373	0.893		
social influence	0.285	0.351	0.313	0.822	
trust	0.279	0.364	0.379	0.278	0.866

Source: The authors

Multivariate research of customers' feelings towards AI-enabled financial institutions revealed an R2 of 0.215 in table-8. Thus, the remaining 21.5% of the observed variation in customers' levels of satisfaction can be attributed to the other four latent variables. Therefore, the study's hidden elements are the most important ones in determining consumer happiness. The adjusted R-squared value was remarkably close to the real coefficient of determination. R2 variation is quantified by the effect size f2, which can be thought of as a scale with three distinct levels. Values of R2 between 0.26 and 0.13 indicate a considerable association between the latent variables, while values between 0.02 and 0.06 indicate a weak relationship (Cohen, 1988).

Table 6: Heterotrait-monotrait ratio (HTMT) – List

	Heterotrait-monotrait ratio (HTMT)
awareness level <-> Customer satisfaction	0.358
efficiency <-> Customer satisfaction	0.436
efficiency <-> awareness level	0.438
social influence <-> Customer satisfaction	0.325
social influence <-> awareness level	0.419
social influence <-> efficiency	0.365
trust <-> Customer satisfaction	0.305
trust <-> awareness level	0.432
trust <-> efficiency	0.428
trust <-> social influence	0.323

Table 7: Sample mean, standard deviation, T-values, P-values.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
awareness level -> Customer satisfaction	0.135	0.140	0.064	2.118	0.034
efficiency -> Customer satisfaction	0.277	0.274	0.070	3.960	0.000
social influence -> Customer satisfaction	0.126	0.131	0.063	2.020	0.043
trust -> Customer satisfaction	0.090	0.092	0.066	1.356	0.175

Source: The authors

Table 8: R Square and Adjusted R Square Values

	R-square	R-square adjusted
Customer satisfaction	0.215	0.201

Table 9: F Square Matrix

	Customer satisfaction
Customer satisfaction	
awareness level	0.018
efficiency	0.075
social influence	0.017
trust	0.008

Table 9 presents a comprehensive overview and analysis of the impact sizes pertaining to the latent variables. The p-values were verified using the Kolmogorov-Smirnov test in SPSS version 26 software, revealing that all values were below the significance threshold of 0.05. The Kolmogorov-Smirnov test is a statistical method used to assess the empirical distribution function of a sample in order to detect significant variations in the position and shape of the distribution. In this study, the test is utilised to validate the findings derived from the Smart PLS software and to establish a comparative analysis using the SPSS software. Therefore, the variables of 'efficiency' and 'awareness level of the customer' exert a more substantial influence on the model, whereas the variable of 'trust' in banks has the least impact on the model.

The inclusion of control variables, such as age and gender, has a limited impact on the statistical significance of the association between the inner and outer models.

Discussions and Implications

The goals of this research are to (1) determine how digital penetration relates to AI adoption and (2) identify the major characteristics that significantly contribute to the application of AI in banks. The research looks at four factors to determine which ones matter most to customers. The model was able to extract the most important latent variables from the path modelling framework. When looking at the direct relationship between parameters that affect customer satisfaction, the study found that the adoption of security measures in AI-based banking systems exhibited the least significant path coefficient.

Awareness Level

The first factor identified is the 'level of awareness' with a weighting of 0.135. For banking entities, it's imperative to prioritize this area. Elevating the customers' understanding through insights about the bank's operations and the potential benefits can heighten their awareness.. As a result, Hypothesis H1, which postulates that heightened customer awareness directly correlates with increased satisfaction (with a coefficient of 0.135 and a t-value of 2.118), is accepted.

Efficiency

Next in line is the long-term 'effectiveness' of AI-integrated technologies, represented by a value of 0.277. Existing research indicates a relationship between the seamless integration of such technology and optimal resource utilization, a notion supported by findings. Given the positive association between the efficacy of AI solutions and customer gratification (with a coefficient of 0.277 and a t-value of 3.960), Hypothesis H2 is accepted.

Social Influence

The 'societal impact' factor, with a magnitude of 0.126, is predominantly molded by mainstream media and interpersonal endorsements. In regions that display apprehension toward new tech adoption, individuals often rely on counsel from their acquaintances. For this reason, banks need to establish robust bonds with pivotal customers who disseminate feedback. Therefore, Hypothesis H3, which posits a direct positive relation between societal influence and customer contentment (with a coefficient of 0.126 and a t-value of 2.020), is accepted.

Trust

Based on the internal assessment, 'trust' is highlighted as the most salient variable, albeit with a score of 0.090 concerning customer contentment. Retail banking sectors should craft strategies to engender trust, possibly through timely service provision and addressing grievances. However, the notion that the trust of customers plays a significant role in shaping their satisfaction, as proposed in Hypothesis H4 (with a coefficient of 0.090 and a t-value of 1.356), is rejected.

Conclusions

This study provides a comprehensive framework for understanding the factors influencing the acceptability of AI-enabled digital banking among customers in northern India. Utilizing the PLS-SEM approach, it reveals that trust, awareness, efficiency, and social influence significantly impact customer satisfaction. The findings underscore the critical role of trust in AI-enabled products, followed by customer awareness, indicating that banks must prioritize building trust and raising awareness to enhance customer satisfaction. Interestingly, the study also found that customer satisfaction is least influenced by the perceived security of AI-based banking services, challenging the common assumption that security is a primary concern for digital banking customers.

Limitations

While the study offers valuable insights, it acknowledges several limitations. The research is geographically limited to northern India, suggesting the need for caution when generalizing findings to other regions or countries with different economic conditions or digital penetration levels. Additionally, the cross-sectional nature of the data may not fully capture the dynamic nature of customer attitudes towards AI over time. The study also recognizes the potential for broader factors, such as education level, customer engagement, and income level, which were not extensively covered, to influence the acceptability of AI-enabled banking services.

Future Directions

The study opens several avenues for future research. Given the geographical limitation of the current research, subsequent studies could explore the acceptability of AI-enabled digital banking in different regions or countries to understand cultural and economic impacts on customer attitudes. Longitudinal studies are recommended to assess how customer perceptions of AI-enabled banking services evolve over time. Furthermore, future research could delve into additional factors such as personalization, data privacy concerns, and the role of digital literacy in shaping customer acceptability. Investigating the impact of specific AI applications within banking, such as chatbots for customer service or AI-driven personal financial management tools, could provide deeper insights into which aspects of AI technology are most valued by customers.

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