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Untertaking Ai-Enhanced Internet Banking: A Study Of Customer Perception

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Abstract: Th The banking environment is transforming from standard online banking to feature-rich mobile applications for fund transfers, bill payments, cross-border remittances, robo-advice, wealth management, etc. The allure of artificial intelligence-based financial innovations to reduce transaction costs has seen banking services undergo rapid transformation. Financial institutions are now deploying artificial intelligence (AI) and machine learning (ML) tools to meet growing customer demand for better, safer and more convenient ways to manage their money. The prime objective of this research is to analyse the customer perception towards AI enhanced features internet banking. The sample for this study were the general public from various districts in Tamil Nadu and it was selected using convenience sampling method. Mediation analysis is used to prove the two hypotheses.

***Index Terms* -** Artificial Intelligence, Customer experience, Customer perception, Internet Banking.

I. Introduction

The banking industry has made significant paces from its traditional roots in Banking 1.0 to the landscape of Banking 4.0. This transformation involves a towards utilizing advanced technology, AI, on a large-scale Banks are leveraging cutting innovations to maintain their competitiveness in market. In this of technological advancement, traditional practices seem increasingly challenging handle. Given the vast data and analysis requirements in the banking sector, incorporation of AI tools chatbots has had an impact. Throughout history, beginning with financial intermediation, banking has played a crucial role in the economics of progressive societies. It often serves as an indicator of strength, social progress and cultural development. While methods have evolved significantly over time, economists and finance experts typically attribute its origins to addressing imperfections within capital markets and trade mechanisms. (Dewatripont & Tirole, 1994); (Freixas & Rochet, 2008). Market inefficiencies often stem from higher transaction expenses and unequal distribution of information, concepts that hold significant importance in financial literature and are present in almost all economic dealings. These factors have played a crucial role in the emergence growing significance of financial institutions (Bhattacharya & Thakor, 1993); (Santomero, 1984). The realm of Artificial Intelligence (AI) is currently reshaping various sectors such as manufacturing, retail, and services. This technological advancement poses a threat to conventional economic and labor principles, as the integration of automated technology is expanding at a rapid annual rate of 20 percent, potentially displacing nearly half of the current workforce within the next two decades (Belanche et al., 2019). Artificial intelligence (AI) is a revolutionary advancement in service innovation that holds the potential to revolutionize the banking sector by providing tailor-made, customer-focused procedures. There is a growing consumer demand for more robust self-service technologies. Recent progress in generative AI (GenAI) utilizes advanced language models to replicate conversational responses to intricate inquiries. In contrast to earlier self-service technologies, AI can decode intricate data, engage in conversations, cater to consumer requirements, and conceivably supplant traditional human-to-human service interactions (Huang & Rust, 2018). The financial and banking industry is one of the economic domains that has reaped the benefits of adopting AI. The profound influence of AI in banking enables enhanced operational efficiency, resource optimization, and firm profitability growth by employing methodologies founded on the fusion of information and technology. AI enables faster and more precise appraisal of potential customers with reduced resource usage, facilitating an impartial identification of high-risk customers through the application of personalized learning models. AI algorithms scrutinize customer actions, user locations, and spending patterns to institute security mechanisms and safeguards for all transactions. Financial crimes can be prevented by identifying suspicious financial activities and unusual money movements, recognizing patterns.

The banking industry benefits from AI tools like bot technology and virtual/mobile apps, which interact with clients through pre-programmed queries to provide solutions. In various fields as education, business, ecommerce, health, and entertainment, chatbots play a significant role along with new products like intelligence messaging robots that offer personalized financial advice for faster decision-making and transactions (Shawar & Atwell, 2004). Productivity stands out as the primary driving force for chatbot, with additional motivations including entertainment, social aspects, and new experiences. In the business realm, chatbots have rapidly gained popularity due to their ability to cut service expenses and manage multiple clients simultaneously. Compared to static FAQ lists, chatbots offer a more engaging and personable experience for users. They efficiently assist users by delivering tailored responses to their queries, making interactions more pleasant and effective (Brandtzaeg & Følstad, 2017); (Ranoliya et al., 2017). Artificial Intelligence (AI) presents a significant opportunity for revolutionizing the finance industry by enhancing user value and boosting company revenues (Park et al., 2016).

Review of Literature - AI enhanced features

The integration of artificial intelligence (AI) has impacted daily interactions by creating and assessing sophisticated applications and tools, known as intelligent agents, that are capable of executing various. AI encompasses a broad scientific field comprising disciplines such as psychology, computer science, linguistics, and philosophy. It brings to the global economy, especially in service-oriented economic sectors, offering the potential for improved product and service quality. Notably, the implementation of AI in the worldwide banking sector could potentially generate around USD 1 trillion annually (Noreen et al., 2023). A chatbot represents an artificial intelligence software and a model of Human-Computer Interaction (HCI) (Bansal & Khan, 2018). According to the dictionary, a chatbot is ‘‘A computer program designed to simulate conversation with human users, especially over the Internet’’ (Lexico Dictionaires, 2019).

Natural Language Processing (NLP) and sentiment analysis are utilized to enable communication in human language through text or speech with individuals or other chatbots (Khanna et al., 2015). Chatbots, also referred as artificial conversation entities, interactive agents, smart bots, and digital assistants, have enhanced banking operations by incorporating features like innovation, attractiveness, and problem-solving capabilities. According to (Chung et al., 2020), customers now find trendy services more preferable over traditional ones. Additionally, a notable shift in the business landscape is the diminishing significance of salespeople, with customers increasingly relying on online systems to enhance their lifestyle (Godey et al., 2016). Earlier research has shown that digital banking built on artificial intelligence effectively caters to customers' needs and modern lifestyles, consequently boosting user satisfaction (Chung et al., 2020); (Godey et al., 2016); (Zolkepli & Kamarulzaman , 2015). Aside of trendiness digital banking services should be attractive and appealing (Bhandari et al., 2019). The concept of visual appeal refers to the personal perception that an online platform is colorful, vibrant, neat, transparent, imaginative, communicative, and engaging for users. Another crucial of technology is its ability to solve issues (Kim et al., 2016). Consequently, the integration of artificial intelligence in digital banking services enables providers to address customer concerns at all times, leading to increased customer satisfaction (Chung et al., 2020); (Kim et al., 2016). The term customization pertains to the extent to which an electronic service can be adjusted, personalized, and adaptable to meet customer requirements and preferences. Customization in electronic services fosters a strong connection between service providers and customers, resulting in increased satisfaction and loyalty towards the product (Perna et al., 2017).

Previous studies have confirmed that AI-based applications can help customers receive personalized services through chatbots to fulfil their needs (Andrade & Tumelero, 2022). Similarly, in the digital banking scenario, it was found that AI-based banking services include personalization features that assist bank users and improve the satisfaction of digital banking users. Communication quality is also a key feature of AI-based banking services. Communication quality refers to the extent to which service agents provide customers with accurate, reliable, efficient, and useful information to solve their problems and save time (Yuan et al., 2022). According to (Chakrabarty et al., 2014) rich contents and relevant information reduces uncertainty and enhance customer satisfaction. e-service agents provide efficient information about product/service, build positive relationship and boost customer satisfaction towards digital banking service (Mogaji et al., 2021); (Fares & Bitar, 2022). It is also found that if consumers perceive adequate quality communication through e-service agent, they will enjoy artificial intelligence based digital banking (Fares & Bitar, 2022).

Customer experience

Customer service is described as a complex concept that centers on a customer's thoughts, feelings, actions, sensory perceptions, and social reactions to a company's products throughout the entire purchasing process (Følstad & Brandtzæg, 2017). In the banking sector, customer experience denotes the integration and approval of digital banking services. Even as consumer preferences evolve across generations, there is a continued expectation for prompt responses coupled with personalized care and content. The current technology landscape, including the utilization of AI, can assist the banking industry in managing valuable customer data. Through the analysis of customer surveys, emails, and social media interactions, it becomes feasible to assess customer sentiments, predict their emotions and preferences (likes and dislikes), and understand their engagements with the brand (Oh et al., 2012) .

AI tools encompass machine learning and natural language processing, offering valuable insights into customer sentiments, allowing retailers to enhance the customer experience by highlighting the company's competitive strengths (Saponaro et al., 2018). This enhancement will lead to an improved customer experience and the fulfilment of their expectations (Lin & Lee, 2023). An increasing number of financial institutions are integrating chatbots into their services (Ng et al., 2020). For instance, Bank of America introduced a chatbot named Erica in 2017, enabling customers to receive alerts, check their account balances, obtain money-saving tips, and receive support with bill payments and transactions (Jang et al., 2021). As chatbots are well-suited for handling repetitive service inquiries, firms must comprehend the implications of chatbot usage on customer experience, particularly from the customer's viewpoint (Kushwaha et al., 2021); (Brandtzaeg & Følstad, 2018). The ease of use is a crucial indicator for the acceptance of any technology (Davis, 1989). Studies have indicated that customers usually have preconceived notions about the ease or difficulty of using specific technologies (King & He, 2006); (Jan & Contreras , 2011). Ease of use has been recognized as a significant factor influencing the willingness to adopt chatbots (Nordheim et al., 2019); (Zarouali et al., 2018). Customers engaging with banking chatbots should perceive them as user-friendly, thereby eliminating potential obstacles to their adoption. If customers find chatbot usage challenging, it could negatively impact their overall experience (Trivedi, 2019). The interpersonal trust between individuals and conversational agents plays a pivotal role in influencing users' acceptance and adoption of technology. As highlighted by (Lee & Choi, 2017), users may hesitate to embrace and utilize technology if they lack trust in the system. As suggested by (Lee & See, 2004), individuals are more inclined to trust technology when it aligns with their goals or requirements. Hence, trust emerges as a fundamental aspect of technology acceptance in this context. Numerous prior studies have underscored the significance of trust in the context of conversational agents.

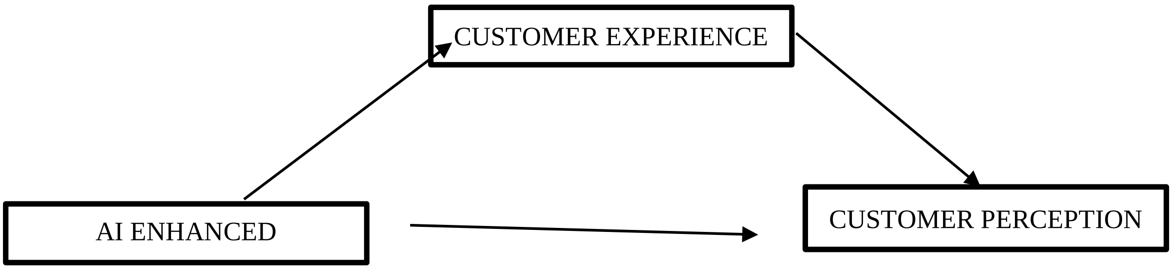
Customer perception

Customer perception factors encompass customers' thoughts and impressions regarding the financial institution. Satisfied customers are likely to continue their business dealings with a particular bank, leading to reduced costs for the bank, value creation (Tulcanaza-Prieto et al., 2022), integration of innovative AI strategies across all operations, and a sustainable competitive edge. Banks provide similar financial products and services, making client perception factors crucial in determining the primary competitive choice between parties, encouraging the adoption and advancement of digital banking products and AI-powered services (Tulcanaza-Prieto et al., 2023). Convenience also includes the time and effort savings perceived by customers during the purchase and usage of services (Berry et al., 2002). Customers demonstrate interest in products and services when they find convenience in using the purchased item or service. Additionally, a convenient product or service is viewed as a solution to a requirement, saving time and effort while satisfying clients who seek an enduring association with the vendor. Specifically, the ease of using AI-driven services will be classified into three aspects (Roy et al., 2016); (Doorn et al., 2010): availability of services, offering round-the-clock support and easy access to service/self-service; provision of real-time information and support; and proactive interactions between AI bots and clients, delivering relevant information and aid to customers.

These AI-driven elements can enhance time management, customer satisfaction, and interaction with the brand. Furthermore, convenience in use increases the sustainable competitive advantage, particularly in sectors where the primary offerings are perceived as homogeneous, like services provided by banks (Roy et al., 2016); (Bilgihan et al., 2016). Convenience in use fosters trust in the product, service, brand, and company. Hence, the perceived convenience in use positively influences customers' perception when evaluating service usefulness, leading to high ratings due to the minimized gap between product expectations and reality. The ease of use lessens customers' efforts, as AI-driven services are accessible at any time and any place (Kim et al., 2014). Personalization is facilitated by AI techniques such as visual analytics, data mining, automation, machine learning, and robotics, which analyze patterns in customer consumption data. Consequently, personalization is linked to AI-enabled services as resources are optimized through algorithms and predictive models to aid decision-making.

In particular, the personalization of online services can be gauged by the user interface's flexibility and functionality, content personalization based on individual user profiles to offer tailored product or service suggestions, and AI-supported interactions to engage users (Zanker et al., 2019). Artificial Intelligence (AI) entails establishing trust, which plays a crucial role in ensuring the acceptance of products or services, enhancing productivity through continuous advancements, fostering innovation within a firm, and driving technological development (Siau & Wang, 2018). The concept of trust in AI-enabled customer service encompasses various novel dimensions such as technology and its understanding, brand image, and the underlying purpose (confidence in intentions) (Lee & See, 2004); (Henseler et al., 2015). Consequently, trust in AI heavily relies on the transparency of functional logic, algorithms, and codes (syntaxis) as well as the integration of innovative technologies into the firm's operations. This integration necessitates proactive communication to positively influence the social acceptance of these new technologies. The enduring bond between a brand and its customers is contingent upon the customers' experiences and the level of trust, which exhibits a positive correlation across current and subsequent interactions (Keiningham et al., 2017); (Hengstler et al., 2016).
Customer satisfaction is gauged by the variance between performance/realization/inequity and expectation/confirmation of the product or service (Xu et al., 2007). Companies that incorporate AI into their workflows can offer the proactive and tailored services that customers desire. For example, banking institutions have embraced applications and new interfaces to deliver customer service, incorporating social and user-friendly payment systems that merge technology with existing governance structures. Consequently, leveraging AI-enabled customer experiences creates a virtuous cycle that enhances a business's value proposition by delivering superior service. By employing AI techniques, customer engagement can be enhanced, leading to increased opportunities for upselling and cross-selling with reduced cost-to-serve. Previous research has demonstrated a positive link between customer satisfaction and AI-driven customer experiences, which also positively impacts firm performance (Javed & Cheema, 2017); (Sayani, 2015).

Research Model



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Direct Effect Hypothesis:

H_1: AI-enhanced internet banking features will have a positive impact on customer perception.

Mediation Hypothesis:

H_2: The relationship between AI-enhanced internet banking features and customer perception will be mediated by Customer Experience.

Materials and Methods

The prime objective of this study to analyse the customer perception towards AI enhanced features in Internet banking and customer experience. The study was conducted in Tamil Nadu. The sample for this study were the general public from various districts in Tamil Nadu and it was selected using convenience sampling method. AI enhanced features was measured using 8 statements and it was adopted from the studies of (Lee & Chen , 2022); (Lee & Choi, 2017); (Chung et al., 2020); (Joosten et al., 2016). Customer perception was measured using 7 statements and it was adopted from various studies (Saniuk et al., 2020); (Spence, 1974); (Esterik-Plasmeijer & Raaij, 2017); (Chung et al., 2020); (Cheriyan et al., 2021); (Colwell et al., 2008). Customer experience was measured using 9 statements and it was adopted from the studies of various authors namely (Ameen et al., 2021); (Puntoni et al., 2020); (Longoni & Cian, 2020); (Ameen et al., 2021); (Zhen et al., 2017); (Chung et al., 2020). Exploratory factor analysis (EFA) using SPSS version 26, Confirmatory factor analysis (CFA), Structural Equation Modeling (SEM), Mediation analysis using AMOS 23 was undertaken to evaluate the proposed hypotheses.

Table 1 Demographic profile

Demographic variables	Categories	Frequency	Percent
Gender	Male	330	60.0
	Female	220	40.0
Age (in years)	20-30 years	103	18.7
	31-40 years	248	45.1
	41-50 years	136	24.7
	Above 50 years	63	11.5
Marital status	Single	290	52.7
	Married	260	47.3
Educational qualification	School level	62	11.3
	UG	243	44.2
	PG	195	35.5
	Professional degree	50	9.1
Occupation	Private employee	189	34.4
	Public employee	177	32.2
	Business	184	33.5
Monthly income	Below Rs. 20000	154	28.0
	Rs.20001-Rs.	279	50.7
	Above Rs. 40001	117	21.3
Nature of bank	Public bank	264	48.0
	Private bank	286	52.0

Table 1 shows the frequency distribution of the respondents. 60% of the respondents were male and remaining 40% of them were female. Maximum 45.1% of the respondents belongs to the age group between 31-40 years, 24.1% of them belongs to the age group between 41-50 years. 52.7% of them were single and 47.3% of them were married. 44.2% of the respondents were Undergraduates, 35.5% of the respondents were postgraduates. 34.4% of the respondents were private employees, 33.5% of them were businessman and remaining 32.2% of them were public employees. Majority 50.7% of the respondents' monthly income were between Rs. 20001-Rs.40000, and 52% of them were using private bank internet banking and 48% of them using public bank internet banking.

Table 2 Measure items and confirmatory factor analysis results

Items	Factor Loading	CR	AVE	Cronbach's Alpha
AI enhanced features		0.974	0.824	0.970
AIE1	0.958			
AIE2	0.943			
AIE3	0.943			
AIE4	0.933			
AIE5	0.922			
AIE7	0.916			
AIE6	0.910			
AIE8	0.713			
Customer Experience		0.964	0.794	0.940
CE5	0.936			
CE6	0.932			
CE1	0.924			
CE2	0.916			
CE4	0.894			
CE3	0.824			
CE7	0.803			
Customer Perception		0.951	0.734	0.958
CP4	0.902			
CP5	0.896			
CP6	0.896			
CP7	0.884			
CP3	0.827			
CP2	0.816			
CP1	0.768			

CR, composite reliability; AVE, average variance extracted.

Principal Component Factor Analysis

Predominantly, factor analysis was conducted on the samples, and the method of principal component analysis was used. The KMO value of the sample data is 0.892, and the Bartlett sphericity test P value is 0.000, which is lower than 0.05, which meets the two conditions of factor analysis. Factor analysis is carried out on the sample, factor rotation is carried out, and the first three principal components are extracted. The results show that three common factors are extracted from the scale. The cumulative explanation of the three common factors to the total variance is 79.295%, which is more than 50%. Thus, the validity of the above scale is good. Table 2 shows the factor loading matrix after varimax rotation.

Construct's Reliability and Validity

The measurement model was utilized for evaluating the internal consistency reliability and validity. Consequently, in order to ascertain the internal consistency reliability, the researchers utilized composite reliability. Moreover, the researchers employed AVE (Average Variance Extracted) for evaluating convergent validity. Accordingly, the factor loadings, construct reliability and validity results are shown in Table 2.

Internal Consistency Reliability and Convergent Validity

The Cronbach's Alpha for the construct AI enhanced features (AIE) was 0.970, Customer experience (CE) was 0.940, and customer perception was 0.958. Accordingly, all three constructs satisfy the accepted threshold value for Cronbach's Alpha in terms of reliability, as the accepted value for Cronbach's Alpha is 0.7 (Hair J. et al., 2010). Convergent validity evaluates the degree to which a particular indicator positively relates with other indicators of the same construct (Hair et al., 2016). This is measured through the AVE and factor loadings. Accordingly, the AVE value should be 0.50 or higher. Moreover, the factor loading values equal to 0.4 or higher are also acceptable if AVE scores are greater than 0.5 (Hulland, 1999). Accordingly, the AVEs of the constructs and factor loadings of the present research study's indicators satisfied the needed condition recommended by (Hair et al., 2016).

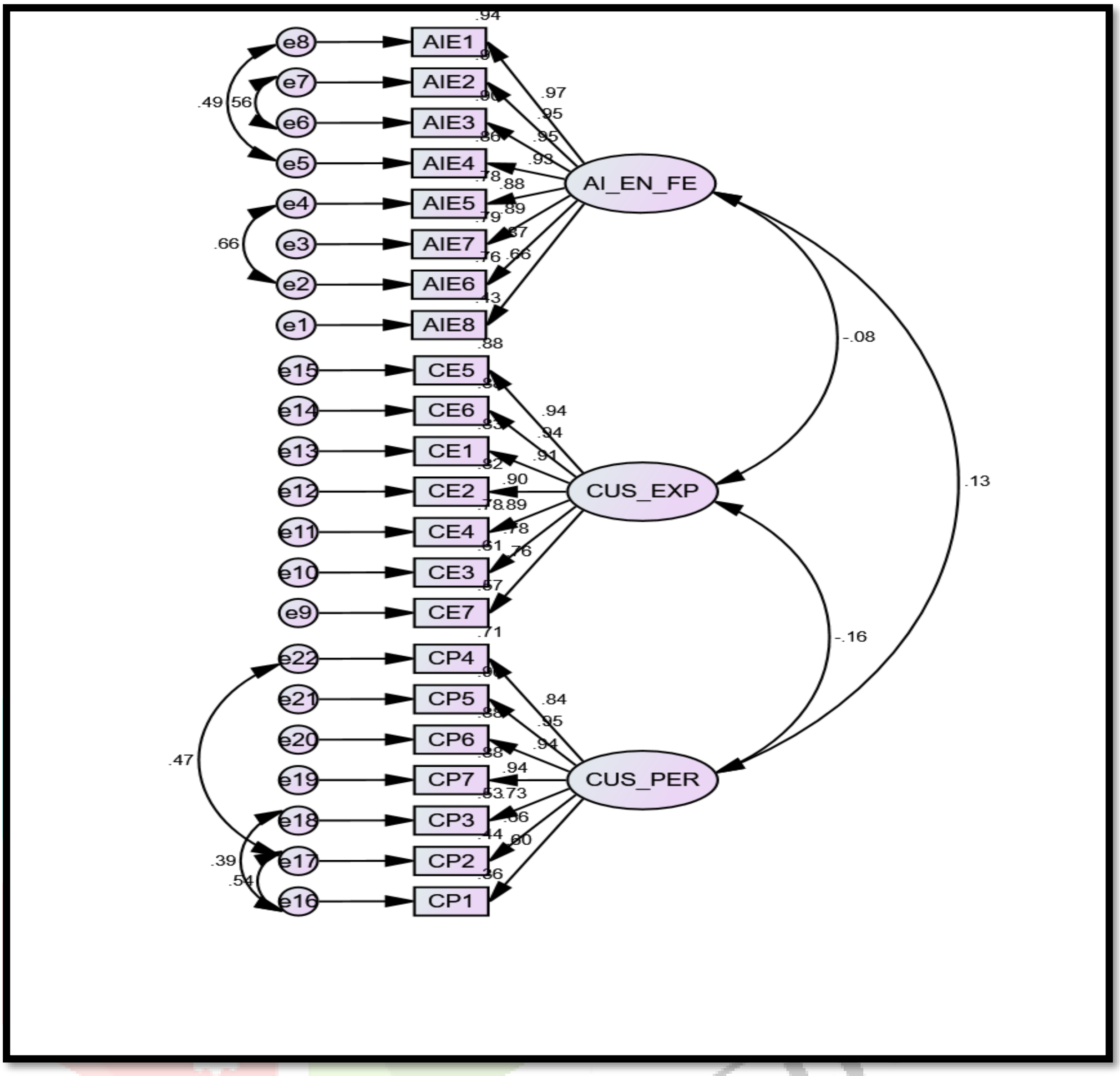

Fig 1: **Measurement model**

Table 3 CFA model fit indices

Table 3 Fit indicators of confirmatory factor analysis model			
Statistical inspection quantity	**Threshold Value**	**Inspection result**	**References**
X^2/df	<5.00	3.831	(Marsh & Hocevar , 1985)
GFI	>0.80	0.888	(Baumgartner & Homburg, 1996) and (Doll et al., 1994)
AGFI	>0.80	0.858	
NFI	>0.90	0.951	(Bentler & Bonett, 1980)
IFI	>0.90	0.963	(Bollen, 1989)
TLI	>0.90	0.957	(Tucker & Lewis, 1973)
CFI	>0.90	0.963	(Bentler P. , 1990)
RMSEA	<0.08	0.072	(Steiger, 1990)

Table 3 shows the goodness of fit indices for CFA obtained an acceptable level of fit (X^2/DF= 3.831; GFI= 0.888; AGFI= 0.858; NFI= 0.951; IFI= 0.963; TLI= 0.957; CFI= 0.963; RMSEA= 0.072). This goodness of fit index for the three-factor model shows the confirmation of construct in the study area namely AI enhance features of internet banking, customer experience and customer perception.

Structural Equation Modelling

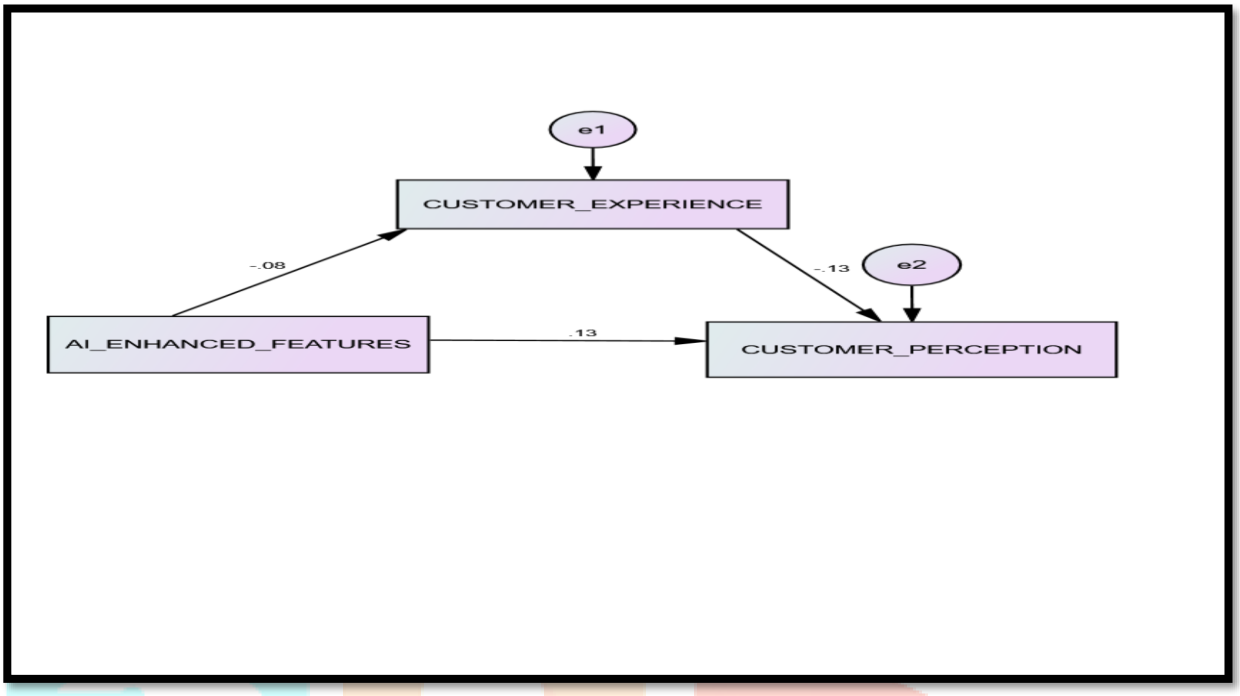

Fig 2: Structural model

Table 4 Path Coefficients

	Hypotheses	Estimate	S.E.	C.R.	P.
H_1	AI enhanced features ---> Customer Perception	0.126	0.039	3.009	0.003

***P<0.001

The H_1 hypothesis is AI-enhanced internet banking features will have a positive impact on customer perception. The table 4 shows that that AI enhanced internet banking features positively impact customer perception and the p value is less than 0.05, it is significant (0.003). Thus, the first hypothesis is supported.

Table 5 Standardized coefficients of direct, indirect, and total effects

	Standardized Estimation	p-value	Result
Total Effect	0.136	0.003	Significant
Direct Effect	0.126	0.003	Significant
Indirect Effect	0.010	0.042	Significant

Discussion

The table presents the results of a mediation analysis, which decomposes the total effect of an independent variable on a dependent variable into direct and indirect effects. A pathway analysis was done to analyse the direct relationship of independent variable AI enhanced features of internet banking and the dependent variable customer perception. Bootstrapping with 500 samples enabled the computation of the non-standardized estimates of the direct effects with 95% bias-corrected confidence intervals and significant p values. The total effect of the independent variable on the dependent variable is 0.136 which is positive, and this effect is statistically significant (p = 0.003). This means that the overall relationship between the independent and dependent variables is strong and statistically supported. The direct effect of the independent variable on the dependent variable, excluding any mediation has a positive impact which is 0.126. This effect is statistically significant (p = 0.003), indicating that the independent variable has a significant positive impact on the dependent variable. The indirect effect, representing the portion of the relationship that is mediated by another variable, is 0.010 which is also positive. This effect is statistically significant (p = 0.042), suggesting that there is a strong mediation between the independent and dependent variables. Thus, the mediation analysis proves that the relationship between AI-enhanced internet banking features and customer perception is strongly mediated by Customer Experience.

Conclusion

Disruptive technology such as artificial intelligence is increasingly vital in the banking sector to meet customer expectations and satisfaction. Within the realm of internet banking, artificial intelligence is widely utilized, encompassing areas like facial recognition, conversational bots, voice recognition, machine learning for fraud detection, cyber security, biometrics authentication, and humanoid robots. Despite the efficiency brought by artificial intelligence in banking operations and its capacity to address customer inquiries and complex issues, the adoption of AI-enhanced internet banking is still in its nascent phase. The integration of AI features in internet banking significantly enhances task performance, offering various advantages like operational efficiency, utility, simplicity, and prompt transactions, thereby increasing user inclination towards its utilization. Security and privacy stand out as the most critical concerns in online transactions and internet banking due to cyber threats such as data breaches from malware and phishing attacks (Kesharwani & Bisht , 2012). Incidents of data breaches result in financial losses for both users and financial institutions, leading to a decline in trust within the banking sector (Kang, 2018). Compromised customer data can pave the way for financial fraud, identity theft, and other illicit activities, eroding trust in financial institutions' ability to safeguard information. The lack of trust and dissatisfaction are key drivers for clients switching financial service providers (Maier, 2016). Financial institutions must invest in robust security mechanisms like firewalls, authentication protocols, multilayer inspection gateways, and enhanced customer service to ensure customer protection (Kaur & Arora, 2021). These security technologies collaborate to defend against cyber threats and unauthorized access attempts. The incorporation of AI features in internet banking enables the efficient management of vast data volumes from clients, transactions, and diverse sources with unparalleled accuracy, facilitating the delivery of highly personalized financial services. Apart from reducing operational costs, AI-based tools and algorithms enhance protection against fraudulent activities and other risks. Moreover, these technologies are expected to enhance compliance and operational efficiency. The insights from this research can guide banking executives in refining their marketing strategies to cultivate client trust, thus mitigating the risks associated with digital transactions. Furthermore, the study recommends that bank managements and technology regulatory bodies implement necessary security measures to enhance customer service and satisfaction, making AI in internet banking more dependable and appealing. This study concludes that managers should focus on refining AI-driven features in internet banking, such as chatbots, fraud detection, user expectation confirmation, performance improvement, visual aesthetics, communication effectiveness, corporate reputation, customer experiences, trust, satisfaction, ease of use, and customer perception, to bolster user confidence in embracing AI-powered internet banking.

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