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Impact of Artificial Intelligence on Customer Satisfaction in Nepalese Banks: A Study of Karnali, Nepal

Dilip Jung Shahi[1]

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Abstract

Purpose: *Artificial Intelligence is transforming financial services by enabling automation, personalization, and intelligent decision-making; however, its impact on customer satisfaction in backward regions of Nepal, such as Karnali Province, remains largely unexplored. This study examines how Artificial Intelligence influences customer satisfaction, with Technology-Driven Customer Experience (TDC) serving as a mediating variable.*

Methods: *A descriptive and causal research design is adopted to both describe the current adoption and use of Artificial Intelligence (AI)-enabled financial services and to examine the causal relationships between AI and customer satisfaction. Survey data were collected from 150 respondents who use internet banking, mobile banking, and digital payment services through a structured questionnaire. Construct reliability and validity, as well as the hypothesized relationships, were tested using Partial Least Squares Structural Equation Modeling (PLS-SEM).*

Results: *TDC is significantly positively influenced by digitalization, as shown by the path coefficients (β = 0.749, t = 12.306; β = 0.686, t = 8.487). The findings also reveal a weak but significant direct effect of digitalization on customer satisfaction (β = 0.219, t = 2.891). Furthermore, the model explains 56.1% of the variance in TDC and 74.5% of the variance in customer satisfaction, confirming the mediating role of TDC.*

Conclusion: *Financial institutions should focus on digital skills education, user-centered innovation, and secure platforms to support service adoption and customer satisfaction in semi-urban and rural areas.*

Keywords: Customer satisfaction, Digitalization, Financial institution, Province, Technology-driven customer experience

JEL Classification: J21, O33, M31

I. Introduction

Artificial Intelligence (AI) is rapidly transforming the global banking industry by enhancing operational efficiency, decision-making processes, and customer service delivery. Recent studies indicate that AI technologies such as machine learning, natural language processing, and predictive analytics are increasingly integrated into banking functions, thereby reshaping

[1]*MetLife, Surkhet, Nepal*

traditional financial service models and improving customer experience (Noreen et al., 2023; Rahman & Sarkar, 2025; Vukovic et al., 2025). Banks that invest in AI-enabled applications such as automatic decision systems, virtual assistants, risk detection tools, and personalized financial recommendations will be able to build a strong competitive position both locally and internationally (Al-naser et al., 2023). Research shows that integrating Artificial Intelligence (AI) enables banks to enhance service quality, responsiveness, and customer satisfaction by meeting the growing demand for efficient, personalized, and user-centric financial services (Eneizan, 2022; Kumar & Patel, 2021).

Digital banking in Nepal has grown quite fast in the last few years. This is mainly due to the increased acceptance of mobile internet facilities and the availability of mobile banking services in more locations. By mid-2024, mobile banking adoption in Nepal had expanded rapidly, with approximately 24.7 million users engaging in digital financial services such as transactions, payments, and account management, reflecting a strong national shift toward digital financial inclusion. This trend is supported by official regulatory data indicating continuous growth in digital payment systems and mobile banking penetration in Nepal (Nepal Rastra Bank, 2024; Nepal Rastra Bank, 2025).Also, mobile internet penetration went beyond 72% as of 2025, providing the financial sector with the right conditions for digital innovation (New Business Age, 2025). At the same time, commercial banks and fintech companies are partnering to introduce AI features. These AI pilots include chatbot customer support, smart risk scoring, and fraud monitoring. These efforts are aimed at optimizing service delivery and enhancing operational efficiency.¶

However, there is limited empirical evidence on how specific Artificial Intelligence (AI) technologies such as chatbots, predictive analytics, and automated service systems affect distinct dimensions of customer satisfaction (e.g., service responsiveness, personalization, and trust) in the Nepalese banking sector, particularly in rural and semi-urban contexts. Existing studies on digital banking in Nepal largely follow global patterns and emphasize general convenience factors, such as increased use of mobile banking, without isolating the effects of AI-driven service features on customer satisfaction outcomes. This represents a significant research gap, especially considering that studies from other contexts, such as Arab and Indian banking sectors, have reported positive relationships between AI adoption and customer satisfaction (Alotaibi, 2024; Eneizan, 2022).

This study aims to examine the impact of AI-enabled banking services on customer satisfaction in Karnali Province, Nepal, a region characterized by socioeconomic diversity and varying levels of digital adoption. Specifically, the study focuses on the role of AI technologies such as chatbots, automated customer support, customer profiling, fraud detection systems, and AI-driven credit scoring in shaping customer satisfaction within banking services.

The specific objectives of the study are as follows:

- To examine the effect of AI chatbots on customer satisfaction in banking services.
- To analyze the impact of automated customer support systems on customer satisfaction.
- To assess the influence of AI-based customer profiling on customer satisfaction.
- To evaluate the role of AI-driven fraud detection systems in enhancing customer satisfaction.
- To investigate the effect of AI-based credit scoring on customer satisfaction.
- To explore the overall contribution of AI-enabled banking services to customer satisfaction in the context of Karnali Province, Nepal.

The study attempts to answer the following research questions:

- To what extent do AI chatbots and virtual assistants enhance the satisfaction of

customers of banks in Nepal?

- What is the effect of automated customer service on customer satisfaction?
- Is there any contribution of AI on Banking Customer Satisfaction through fraud detection AI solution?
- What is the significance of AI based credit scoring in customer satisfaction?
- What is the effect of personalised recommend systems on customers' satisfaction?
- In the context of Nepali banks, how do AI-based business services influence the satisfaction of their customers?

This study contributes to filling the existing gap in understanding how advanced AI technologies influence customer satisfaction in financially emerging and under-researched regions, while also providing practical insights for Nepalese banks seeking to enhance competitiveness and customer experience through digital transformation.

II. Reviews

Artificial Intelligence (AI) has become a transformative technology in the banking industry, enabling banks to improve service quality, enhance operational efficiency, and strengthen customer experience through automation and data-driven decision-making (Davenport & Ronanki, 2018; Huang & Rust, 2021; Wamba-Taguimdje et al., 2020). Artificial Intelligence (AI) technologies such as machine learning, natural language processing, and smart chatbots are increasingly used in banking to automate routine processes, analyze large volumes of customer data, and deliver more targeted financial products. These capabilities enable banks to better understand customer needs, respond more efficiently, and improve service personalization, which ultimately enhances customer satisfaction and loyalty (Rocha & Segovia-Vargas, 2025).

However, existing studies present both consistent and differing findings regarding the specific mechanisms through which AI influences customer satisfaction. For instance, research on AI voice chatbots shows that customer satisfaction largely depends on perceived chatbot performance, communication quality, and problem-solving ability, while also highlighting that AI-based interactions improve service responsiveness and operational efficiency, thereby strengthening trust in digital banking systems (Kondybayeva et al., 2024). This finding aligns with studies emphasizing the efficiency gains of AI chatbots, particularly their ability to provide instant responses, reduce waiting times, and offer 24/7 service, which collectively enhance service quality and customer satisfaction (El-Shihy et al., 2024).

In contrast, other studies extend the discussion by emphasizing that customer satisfaction is not only shaped by chatbot performance but also by broader system attributes such as system quality, information quality, and service quality. For example, research on AI-enabled banking applications indicates that these system-related factors significantly determine both user satisfaction and continued usage intention, suggesting that technological performance alone is insufficient without reliable service design (Pramana et al., 2024). Similarly, Kaakandikar et al. (2025) argue that customer perceptions of convenience, trust, and transparency play a critical role in shaping adoption and satisfaction with AI-based banking services.

Taken together, these studies suggest that while AI improves efficiency and responsiveness across banking services, customer satisfaction is a multidimensional outcome influenced by both technological performance and user-perceived service quality. This highlights the need for the current study to examine AI not only as a technological tool but also in terms of its service experience dimensions within the Nepalese banking context.

AI-powered conversational agents and virtual assistants have been widely recognized for improving service efficiency by reducing response time and enabling more personalized customer interactions, thereby enhancing customer service effectiveness and satisfaction

(Gnewuch et al., 2017; Huang & Rust, 2021). However, while Todupunuri (2024) highlights the disruptive potential of fintech and mobile banking in reshaping customer–bank interactions, other studies suggest that such technological advancement does not automatically lead to higher customer satisfaction, as outcomes depend on factors such as system reliability, perceived usefulness, and user trust in AI systems (de Keyser et al., 2019; Prakash et al., 2023). This indicates that although AI improves efficiency and accessibility in banking services, its impact on customer satisfaction is context-dependent and multidimensional.

A critical review of the literature further reveals a clear geographical and contextual imbalance in AI banking research. Most empirical studies have been conducted in technologically advanced or large emerging economies where digital infrastructure is well developed and customer readiness for AI adoption is relatively high (Wamba-Taguimdje et al., 2020; Huang & Rust, 2021). In contrast, limited attention has been given to developing countries with weaker digital ecosystems, where barriers such as low digital literacy, infrastructural constraints, and trust issues may significantly shape customer experiences. In particular, there is a notable lack of empirical evidence on the impact of AI-enabled banking services on customer satisfaction in the Nepalese context.

This gap is particularly significant for regions such as Karnali Province, where digital banking is still in an emerging stage and socioeconomic disparities may influence the effectiveness of AI-based service delivery. Addressing this gap is therefore essential to generate context-specific insights into how AI-based banking services operate in low-digital-adoption environments and to contribute to a more nuanced understanding of the role of AI in enhancing banking service quality and customer satisfaction in emerging financial markets.

The present study is grounded in the Technology Acceptance Model (TAM) and Service Quality Theory, which together provide a strong theoretical basis for explaining how Artificial Intelligence (AI) influences customer satisfaction through user perceptions and service experience.

TAM, developed by Davis (1989), posits that an individual's acceptance and use of technology is primarily determined by perceived usefulness and perceived ease of use. In the context of this study, AI-enabled banking technologies such as chatbots, automated customer support systems, fraud detection tools, and AI-based credit scoring are expected to influence customer satisfaction indirectly by shaping users' perceptions of usefulness (e.g., faster services, accurate transactions, and improved decision-making) and ease of use (e.g., convenience, accessibility, and reduced effort). Accordingly, it is theorized that when customers perceive AI-based banking services as useful and easy to use, their satisfaction with digital banking services increases, thereby supporting the proposed relationships in the study model.

Similarly, Service Quality Theory, operationalized through the SERVQUAL model by Parasuraman et al. (1988), explains customer satisfaction as a function of perceived service quality across five dimensions: reliability, responsiveness, assurance, empathy, and tangibles. In this study, AI technologies are expected to enhance these dimensions by providing more reliable and consistent service delivery, faster response times through automated systems, improved accuracy in financial processing, and more personalized customer interactions. For example, AI-driven chatbots improve responsiveness, while predictive analytics and fraud detection systems strengthen reliability and assurance. These improvements in service quality are theorized to positively influence customer satisfaction, thereby supporting the hypothesized relationship between AI-enabled service quality and satisfaction.

Recent literature further strengthens this theoretical linkage by showing that AI applications in banking improve personalization, real-time decision-making, and customer engagement, which enhance both perceived usefulness (TAM) and service quality dimensions (SERVQUAL) (Davenport & Ronanki, 2018; Huang & Rust, 2021; Verma et al., 2021). AI-based systems such as recommendation engines and intelligent chatbots enable banks to analyze customer behavior and deliver tailored services, thereby reinforcing both technology acceptance and

perceived service quality.

Taken together, TAM explains the cognitive acceptance process of AI in banking, while SERVQUAL explains how AI-driven service improvements translate into satisfaction outcomes. These two theories jointly support the hypothesized framework of the study, where AI influences customer satisfaction both directly and indirectly through perceived usefulness, ease of use, and enhanced service quality.

Based on theories and literature, the hypotheses are:

In the banking industry, AI chatbots and virtual assistants are now commonly employed to deliver immediate answers to customer questions, process transactions, and provide financial data. These AI applications improve the accessibility and responsiveness of services which are principal factors of customer satisfaction. According to the Technology Acceptance Model (TAM), proposed by Fred D. Davis, the perceived usefulness and perceived ease of use influence customer adoption and satisfaction towards the technologies (Davis, 1989). AI chatbots are able to offer customer support round the clock and reduce wait time, hence, perceived usefulness and convenience has been enhanced. Empirical studies reveal that AI-based conversational agents are proven to increase customer engagement and satisfaction as a result of providing fast and tailored services (Huang & Rust, 2021; Verma et al., 2021). Thus, the application of AI chatbots and virtual assistants for banking services is anticipated to have a positive impact on customer satisfaction.

H_1: AI chatbots and virtual assistants positively influence the customer experience.

Automated customer service systems are powered by AI technologies that enable customers to perform a variety of routine banking transactions including balance inquiries, transaction verification, and service requests. These are also the systems that enhance the day-to-day operations and reduce the delays in serving which then ultimately improves the quality of service. Service Quality Theory prescribes service responsiveness and reliability as predictors of customer satisfaction (Parasuraman et al., 1988). With AI-powered automation, banks have the potential to deliver services more quickly and accurately increasing customer perceptions of service dependability. Studies also suggest that automated service technologies can lead to a better customer experience by minimizing human errors and improving efficiency in delivering service (Davenport & Ronanki, 2018). Therefore, it can be inferred that automated customer service to a large extent has an impact on banking service customer satisfaction.

H_2: The impact of automated customer service on customer satisfaction is largely positive.

Security and trust are the key determinants of customers' satisfaction in digital banking system. AI-based fraud detection solutions process massive amounts of data and transactional patterns to detect anomalies and suspicious activities on the fly. These technologies provide greater financial protection and mitigate the chances of fraud, which builds confidence of customers in banking services. Based on models derived from trust, relating to the adoption of technology, customers are more satisfied when financial institutions deliver secure and dependable environments for transactions (Gefen et al., 2003). Research has also established that AI led fraud detection enhances banking security and trust on customers over digital financial services (Huang & Rust, 2021). Therefore, the enhanced security features through AI-based fraud detection might result in higher customer satisfaction.

H_3: The effect of AI-based fraud detection on customer satisfaction is positive and strong.

The AI-powered credit scoring models may use machine learning algorithm to evaluate customer financial behavior, credit records, and risk trends. These systems enable banks to reach lending decisions more rapidly and accurately than the traditional means of credit evaluation. According to the Information Processing Theory, the enhanced ability to analyze data would result in more efficient decision-making, thereby leading to better outcomes in terms of service. AI-based credit scoring allows banks to offer customers fairer and faster loan approvals, improving the perception of transparency and efficiency (Davenport & Ronanki,

2018). Research shows that advanced analytics and AI-based financial decision engines contribute largely to improving customer experience and satisfaction in financial services (Verma et al., 2021). Hence, AI-based credit scoring models will bring positive impact on customer satisfaction.

H_4: The effects of AI-enabled credit scoring on customer satisfaction is positive and significant.

AI-based personalized recommendation system processes customer information and recommends financial products and services that are more likely to be preferred by the customer based on his or her individual preferences and behavior. Personalization allows banks to provide a more relevant financial service offering, leading to better engagement and satisfaction. Application of the Relationship Marketing Paradigm to Interpersonal Service Encounters predicts that customers who receive personalized treatment during interaction with service providers feel more satisfied and loyal to those providers (Berry, 1983). With AI-powered recommendation systems, banks can analyze the customers' financial needs and propose tailored banking solutions, thus improving the customer experience. Prior work suggests a positive effect of AI based personalization on customer satisfaction for digital financial services (Huang & Rust, 2021). Therefore, personalized recommendation systems would be expected to have a positive influence on customer satisfaction.

H_5: The personalized recommendation systems exert balancing positive effects on the customer satisfaction.

AI-based banking services are a result of large enterprises of intelligent technologies including chatbots, predictive analytics, fraud detection, and auto decision systems within other and banking performances. These processes enhance service efficiency, precision, and availability, all of them being premises to influence the satisfaction of clients. The utilization of sophisticated technology to deliver services enhances service effectiveness and customers' service quality perceptions, as predicted in the technology acceptance model (TAM) (Davis, 1989). In addition, studies prove that the integration of artificial intelligence (AI) in banking leads to enhanced operational performance and customer experience by means of delivering faster, smarter, and more dependable financial services (Davenport & Ronanki, 2018; Huang & Rust, 2021). Hence, it is anticipated that AI based banking services will positively affect the satisfaction of the customer.

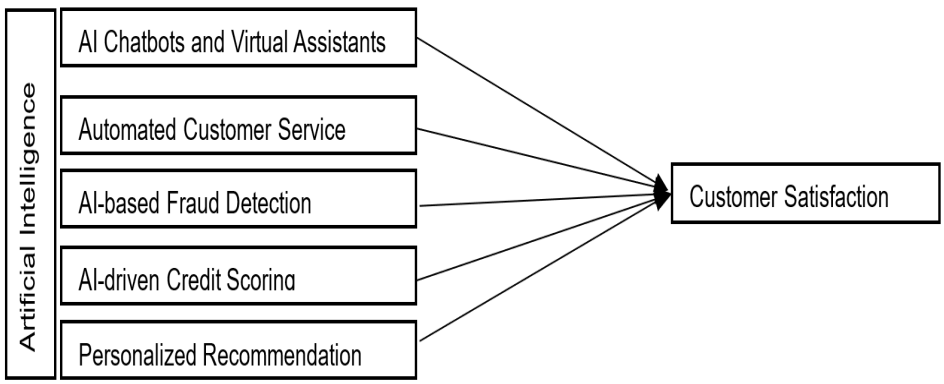
H_6: There is a significant positive effect of AI based banking services on the customer satisfaction.

Following these theoretical insights, our investigation supports a conceptual model in which AI-enabled banking technologies (predictors) have an effect on customer satisfaction (criterion). Specifically, AI chatbots and virtual assistants, automated customer service, AI-based fraud detection, AI-powered credit scoring and personal recommendation systems are the major technological elements that influence the customer satisfaction in Nepalese banks.

Figure 1 describes the conceptual framework of the study that depicts the effect of AI enabled banking technology on customer satisfaction. The model suggests that different types of AI tools applied in banking services can shape a customer's satisfaction. It breaks down into five areas of AI technology: AI chatbots and virtual assistants, automated customer service, AI-based fraud detection, AI-driven credit scoring and personalized recommendation systems. These are the independent constructs or variables which affect the dependent variable, customer satisfaction.

Figure 1

Conceptual Framework



Note. Adapted from Davis (1989); Davenport and Ronanki (2018); and Huang and Rust (2021).

III. Methodology

This research was cross-sectional survey research to explore the effect of artificial intelligence (AI)-based banking services on satisfaction of customers in Nepalese banks based in Karnali Province. The research was concentrated on AI-based banking tools including AI chatbots, automated customer services, fraud detection systems, AI-powered credit scoring and personalized recommendation systems and their impact on customer satisfaction.

The research was done in urban and semi-urban area of the Karnali Province, Nepal from January to March 2025. The study population is customers of commercial, development, and government banks which are the most dominant banks in the country and who have been users of the digital banking service. A sample of 150 respondents was used in the investigation to find correlation between AI-powered banking services and customer satisfaction in the current research.

The sample size was determined according to the best practice methodological standards in quantitative research. Sekaran and Bougie (2016) recommended that a sample size of 30 to 500 is suitable for most social science study. Likewise, Hair. et al. (2019), analyses involving multivariate statistics are more reliable and the results more stable if the sample size is no fewer than 100 to 200 observations. In view of these hints and the limitations on time, availability of respondents, and geographical coverage in Karnali Province a sample of 150 respondents was deemed sufficient to the purpose of conducting the analysis. Purposive sampling was employed to identify and banking and financial institutions customers are respondents who were judged to have relevant experience with AI-driven banking services, ensuring that only informed users of digital banking platforms were included in the study.

The data were collected using a structured questionnaire adapted from previous validated studies and modified to fit the context of the Nepalese banking industry. The survey instrument comprised six constructs: AI Chatbots and Virtual Assistants, AI-based Fraud Detection, AI-enabled Credit Scoring, Automated Customer Service, Personalized Recommendation Systems, and Customer Satisfaction. Five measurement items for each construct were adapted from established and widely cited (seminal and empirical) studies in the fields of AI-enabled services, digital banking, and customer satisfaction to ensure content validity and theoretical consistency (e.g., Huang & Rust, 2021; Davenport & Ronanki, 2018).

Each construct was measured using a five-point Likert scale ranging from 1 (strongly

disagree) to 5 (strongly agree). The adapted items were carefully reviewed and refined to ensure relevance to the Nepali banking context. Prior to the main survey, the questionnaire was pretested with a small group of respondents to assess clarity, reliability, and contextual appropriateness, and necessary modifications were made based on the feedback received.

Data were analyzed using SmartPLS. Descriptive statistics were used to describe the demographic characteristics of the respondents and their use of digital banking services. The measurement model was assessed by examining outer loadings, Cronbach's alpha, composite reliability, and average variance extracted (AVE) to determine reliability and convergent validity. Discriminant validity was evaluated using the Fornell–Larcker criterion, while Variance Inflation Factor (VIF) values were analyzed to detect multicollinearity among the constructs.

The structural model was tested based on path coefficients, T-statistics, P-values, R^2 values, and f^2 effect sizes to ascertain the strength and significance of the relationships between AI-driven banking services and customer satisfaction. In addition, model fit indices, namely SRMR, d_ULS, d_G, Chi-square, and NFI, were tested to evaluate the goodness of fit of the suggested model.

IV. Results and Discussion

The demographic profile of the 150 sample suggests an almost equal gender distribution (female = 50.7%, male = 49.3%), allowing for representation of views from both groups in the research to be considered. Most of the respondents were young and are engaged in economic activities, 50.7% of them were aged between 21-30 years, 48% between 31-40 years, and 1.3% only were in the age group of 41-50 years. This means that the results are heavily driven by young, digitally savvy individuals. The respondents were highly educated: 45.3% of them had attained a Bachelor's degree, 36% had a Master's degree, and 18.7% were MPhil or PhD level, which means that the sample was knowledgeable enough to comprehend and evaluate the services of digital banking effectively.

In terms of profession, 40% respondents were students, 32% worked in private sector, 25.3% were doing business and 2.7% were government employees. The percentage distribution also depicts the predominance of young and private-sector workers who are generally more acquainted with digital technologies. With respect to monthly earnings, the largest subset (46.7%) made NRs. 40,001-60,000; followed by 37.3% making less than NRs. 20,000 with not as much of many as those two in the higher income class. This suggests that the study mainly focuses on the low- and middle-income sectors, who constitute a major part of digital banking users.

With regard to the banking system, 89.3% of the respondents considered commercial banks as the major banking institution for them in terms of banking conduct, 5.3% for development banks and another 5.3% for government banks, that indicates the superiority of commercial banks in provision of DFIs. A majority of the respondents (52%) had a relationship with their current financial institution for 4-6 years, and 30.7% for 7-10 years, suggesting a fairly steady and loyal customer population. Digital banking use was particularly high (84% reported daily use, and 6.7% reported very frequent use), but there is also a number of users so infrequent (rare or occasional) of digital services. Mobile banking was the most popular among digital services (93.3%), followed by QR/digital wallet payments (5.3%) and ATM services (1.3%).

Taken as a whole, the results indicate that the respondents tend to be young, educated, frequent users of digital banking, who use mobile banking as the primary channel for conducting their financial transactions, highlighting the closely knit nature of digital financial services and daily living for these users.

The measurement model was evaluated by the value of outer loadings of each indicator on its construct. Outer loadings tell us how well the observed variable represents the latent

variable. Factor loadings larger than 0.70 are considered high according to standard SEM literature and those values larger than 0.80 indicate high indicator reliability.

Table 1

Outer Loadings

	AI Chatbots and Virtual Assistants	AI-based Fraud Detection	AI-driven Credit Scoring	Automated Customer Service	Customer Satisfaction	Personalized Recommendation Systems
ACS1				0.702		
ACS2				0.823		
ACS3				0.791		
ACS4				0.789		
ACS5				0.838		
ACV1	0.737					
ACV2	0.858					
ACV3	0.83					
ACV4	0.752					
ACV5	0.834					
AFD1		0.83				
AFD2		0.804				
AFD3		0.88				
AFD4		0.915				
AFD5		0.75				
AS1			0.862			
AS2			0.856			
AS3			0.809			
AS4			0.891			
AS5			0.81			
CS1					0.878	
CS2					0.84	
CS3					0.859	
CS4					0.839	
CS5					0.814	
PRS1						0.84
PRS2						0.848
PRS3						0.874
PRS4						0.849
PRS5						0.819

Table 1 reports the outer loadings of all the measurement items, and it can be seen that all the indicators load strongly on their corresponding constructs. All the values are above the suggested cut-off value of 0.70 and varies between 0.702 and 0.915, which suggests a good indicator reliability as well as convergent validity. Therefore, the constructs AI Chatbots & Virtual Assistants, AI-based Fraud Detection, AI-driven Credit Scoring, Automated Customer Service, Personalized Recommendation Systems and Customer satisfaction are adequately measured and the results reveals a satisfactory level of internal consistency.

The findings suggest that the measurement model is trustworthy and that the structural model can be analyzed further and the hypotheses tested.

Table 2

Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AI Chatbots and Virtual Assistants	0.863	0.874	0.901	0.646
AI-based Fraud Detection	0.893	0.905	0.921	0.702
AI-driven Credit Scoring	0.9	0.902	0.926	0.716
Automated Customer Service	0.849	0.857	0.892	0.624
Customer Satisfaction	0.901	0.904	0.926	0.716
Personalized Recommendation Systems	0.901	0.904	0.926	0.716

Table 2 presents the results for the assessment of construct reliability and convergent validity using Cronbach's Alpha, rho_A, Composite Reliability and Average Variance Extracted. Hence, it can be seen that the reliability of each construct is high for the constructs under study as the Cronbach's Alpha values were in the range of 0.849 and 0.901 which is well above the acceptable value of 0.70.

In addition, rho_A values (0.857 to 0.905) and Composite Reliability (0.892 to 0.926) suggested the reliability of the construct as the values exceed 0.7. As for convergent validity, we can easily see that all AVE values lie between 0.624 and 0.716 which are above 0.50, which means that all the constructs under consideration account for more than 50% of the variance of their measures.

Thus, it is concluded that the constructs are sufficiently reliable and valid in terms of convergent validity implying that the measurement model is statistically appropriate and the model could be tested with path analysis for further investigation in structural model.

Table 3

Fornell-Larcker Criterion

	AI Chatbots and Virtual Assistants	AI-based Fraud Detection	AI-driven Credit Scoring	Automated Customer Service	Customer Satisfaction	Personalized Recommendation Systems
AI Chatbots and Virtual Assistants	0.804					
AI-based Fraud Detection	0.788	0.838				
AI-driven Credit Scoring	0.789	0.82	0.846			
Automated Customer Service	0.789	0.721	0.696	0.79		
Customer Satisfaction	0.76	0.749	0.849	0.711	0.846	
Personalized Recommendation Systems	0.801	0.714	0.864	0.689	0.822	0.846

Table 3 indicates that the analysis of the discriminant validity using the Fornell–Larcker has-value for which the square root of the AVE of each construct should be greater than its correlation with other constructs. The square roots of AVEs are all in the diagonal line and are higher than the corresponding inter-correlation.

The square root of AVEs (off-diagonal) for AI Chatbots and Virtual Assistants is 0.804, for AU-based Fraud Detection is 0.838, for AI-driven Credit Scoring is 0.846, for Automated Customer Service is 0.790, for Customer Satisfaction is 0.846, and for Personalized Recommendation Systems is 0.846. Although some correlations are quite high, most notably between AI-DC and PRS (0.864), as well as between AI-DC and CS (0.849), all corresponding diagonal elements are still greater than or equal to these values, thus indicating good discriminant validity.

The results indicate that each construct is empirically unique and the utilized measures adequately represent an individual theoretical dimension in the model, suggesting that the measurement model was satisfactory for the subsequent structural analysis.

Table 4

Collinearity Statistics (VIF)

Statements	VIF
ACS1	1.598
ACS2	1.927
ACS3	1.864
ACS4	1.77
ACS5	2.197
ACV1	1.939
ACV2	2.512

ACV3	2.251
ACV4	1.771
ACV5	2.238
AFD1	2.089
AFD2	2.284
AFD3	3.021
AFD4	4.024
AFD5	1.714
AS1	3.39
AS2	3.348
AS3	2.081
AS4	3.508
AS5	2.471
CS1	3.417
CS2	2.542
CS3	2.756
CS4	2.522
CS5	2.236
PRS1	2.689
PRS2	2.494
PRS3	2.776
PRS4	2.409
PRS5	2.368

Table 4 with the collinearity statistics of all indicators based on VIF values is as follows. The VIFs vary from 1.598 to 4.024, which are less than the cut off of 5.0 and hence, there is no concern for multicollinearity. Most indicators are between 1.7 and 3.0, except a few which exceed this range, for example, AFD4 (4.024), AC4 (3.508), AS1 (3.390), AS2 (3.348), and CS1 (3.417). These findings imply that indicators are unique and they make unique contributions to their constructs, indicating that the measurement model fulfils the collinearity presumption and can be quantitatively further assessed by structural analysis.

Table 5

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
AI Chatbots and Virtual Assistants -> Customer Satisfaction	0.027	0.018	0.087	0.312	0.755
AI-based Fraud Detection -> Customer Satisfaction	0.074	0.082	0.091	0.805	0.421
AI-driven Credit Scoring -> Customer Satisfaction	0.419	0.415	0.114	3.667	0
Automated Customer Service -> Customer Satisfaction	0.151	0.15	0.073	2.057	0.04
Personalized Recommendation Systems_ -> Customer Satisfaction_	0.281	0.288	0.11	2.55	0.011

The path coefficient, T-statistic, and P value for the effect of AI-enabled banking services on customer satisfaction are shown in Table 5. The findings show that AI-enabled Credit Scoring has a positive and significant effect on consumer satisfaction ($\beta = 0.419$, $T = 3.667$, $P < 0.001$), indicating that customers regard AI-based credit evaluation as a major contributor to their overall satisfaction. Automated Customer Service also has a meaningful positive effect ($\beta = 0.151$, $T = 2.057$, $p = 0.04$), implying that quick, automated service improves customer experience. Personalized Recommendation Systems also have a positive and significant effect on customer satisfaction ($\beta = 0.281$, $T = 2.55$, $P = 0.011$), which confirms the relevance of a customized financial advice in increasing customer perception. However, AI Chatbots and Virtual Assistants ($\beta = 0.027$, $T = 0.312$, $P = 0.755$) and AI-enabled Fraud Detection ($\beta = 0.074$, $T = 0.805$, $P = 0.421$) fail to demonstrate statistically significant impact, indicating that although such offerings might be valued, they are not the most pivotal element of consumer satisfaction. The results suggest that the most important ones that make customers satisfied are credit scoring, automated customer service and personalized recommendations among AI based banking services.

Table 6

R Square

	R Square	R Square Adjusted
Customer Satisfaction	0.77	0.762

Table 6 shows the value of R Square for customer satisfaction, that shows what portion of variance in customer satisfaction is explained by the constructs related to AI driven banking in the model. The findings reveal an R Square of 0.77, this means that 77% of variance in customer satisfaction is explained by AI Chatbots and Virtual Assistants, AI-based Fraud Detection, AI-driven Credit Scoring, Automated Customer Service and

Personalized Recommendation System. A further adjusted R square of 0.762 also attests to the robustness of the model in terms of the number of the predictors. These results reveal that the AI-based banking services are the most significant factors influencing overall satisfaction, which suggest the prominence of AI technologies in improving the total customer experience in banking experience.

Table 7

f Square

	AI Chatbots and Virtual Assistants	AI-based Fraud Detection	AI-driven Credit Scoring	Automated Customer Service	Customer Satisfaction
AI Chatbots and Virtual Assistants					0.001
AI-based Fraud Detection					0.006
AI-driven Credit Scoring					0.129
Automated Customer Service					0.035
Personalized Recommendation Systems					0.072

Table 7 shows the effect sizes (f^2) of AI-enabled banking services on customer satisfaction. AI-driven Credit Scoring shows a noticeable effect ($f^2 = 0.129$), while Personalized Recommendation Systems ($f^2 = 0.072$) and Automated Customer Service ($f^2 = 0.035$) show weak effects. In contrast, AI Chatbots and Virtual Assistants ($f^2 = 0.001$) and AI-based Fraud Detection ($f^2 = 0.006$) have negligible effects. Overall, only credit scoring demonstrates a relatively meaningful impact, whereas other AI services show weak to minimal influence on customer satisfaction.

Table 8

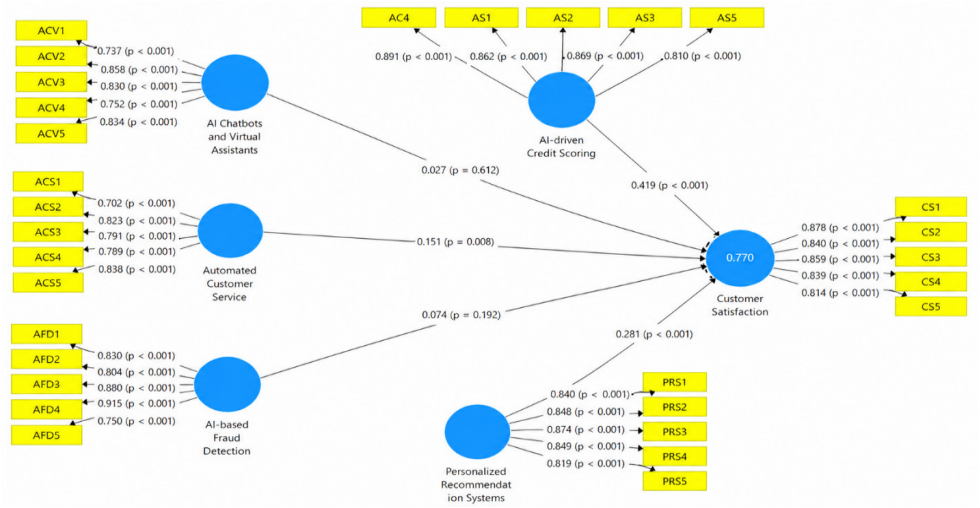
Model_Fit

	Saturated Model	Estimated Model
SRMR	0.087	0.087
d_ULS	3.488	3.488
d_G	4.113	4.113
Chi-Square	2333.721	2333.721
NFI	0.574	0.574

Table 8 presents the model fit indices for both the saturated and estimated models. The SRMR value (0.087) slightly exceeds the recommended threshold (≤ 0.08), indicating a marginal model fit. The d_ULS (3.488) and d_G (4.113) values suggest minor discrepancies between the observed and model-implied covariance matrices. The Chi-square value (2333.721) is relatively high, which is expected given the complexity of the model and number of indicators. However, the NFI value (0.574) is below the acceptable threshold (≥ 0.90), indicating poor overall fit. Overall, the model shows an acceptable but weak fit to the data for examining the impact of AI-based banking services on customer satisfaction.

Figure 1

Measurement Model



The path analysis shows that AI-driven Credit Scoring (β = 0.419, p < 0.001), Automated Customer Service (β = 0.151, p = 0.008), and Personalized Recommendation Systems (β = 0.281, p < 0.001) have statistically significant positive effects on customer satisfaction. In contrast, AI Chatbots and Virtual Assistants (β = 0.027, p = 0.612) and AI-based Fraud Detection (β = 0.074, p = 0.192) do not show significant influence on customer satisfaction.

The model explains 77% of the variance in customer satisfaction (R^2 = 0.770), indicating substantial explanatory power. Overall, the findings suggest that AI applications related to decision-making accuracy and personalized service delivery are the most influential drivers of customer satisfaction in the banking sector.

Discussion

The current study pertained to the effect of AI-enabled banking services on the satisfaction level of customers in Nepal with special reference to AI Chatbots and Virtual Assistants, AI-based Fraud Detection, AI-driven Credit Scoring, Automated Customer Service, and Personalized Recommendation Systems. Results indicate that AI-driven Credit Scoring, Automated Customer Service, and Personalized Recommendation System have a significant positive effect on customer satisfaction; whereas, AI Chatbots and Virtual Assistants, and AI-based Fraud Detection reveals no/small direct effect. The structural model accounts for 77% of the variance in customer satisfaction, which signifies the important impact of AI services on making customer experiences in banks. The demographic profile also showed that the research is the most representative of young, educated, and digitally active individuals who are also heavy users of mobile banking, which is consistent with the high adoption of AI-enabled services.

The observed strong effect of AI-enabled Credit Scoring on customer satisfaction is consistent with prior research emphasizing that accurate, data-driven credit evaluation systems enhance transparency, trust, and perceived value among customers (Huang & Rust, 2021; Loonam et al., 2020). These findings suggest that when AI directly supports financial decision-making, customers are more likely to perceive the service as reliable and beneficial, thereby increasing overall satisfaction.

Similarly, the positive influence of Automated Customer Service and Personalized

Recommendation Systems aligns with established literature indicating that responsiveness, convenience, and individualized service are key determinants of customer satisfaction and loyalty in digital financial environments (Garg & Jain, 2022; Ashrafuzzaman et al., 2025; Verhoef et al., 2021). These AI applications enhance user experience by reducing waiting time and providing tailored financial guidance, which strengthens customer engagement and perceived service quality.

In contrast, the relatively weaker impact of AI Chatbots and Fraud Detection systems reflects mixed findings in previous studies. While these technologies are essential for improving operational efficiency, service continuity, and security, they do not always translate directly into higher customer satisfaction because users may perceive them as background or technical support functions rather than value-generating services (Jiang et al., 2020; Davenport & Ronanki, 2018). This indicates that the customer-perceived value of AI depends not only on technological sophistication but also on the extent to which the service visibly improves personal financial decision-making and interaction quality. Overall, these results extend existing literature by reinforcing the argument that AI applications which are customer-facing and decision-supportive generate stronger satisfaction outcomes compared to those primarily focused on backend operations or security enhancement.

V. Conclusion and Implications

This study concludes that AI-enabled banking services have a significant positive influence on customer satisfaction in Nepalese banking institutions. In particular, AI-based credit scoring, automated customer service, and personalized recommendation systems are the most influential tools, as they directly support customers in financial decision-making and service personalization. These customer-facing AI applications enhance perceived value, trust, and overall satisfaction.

In contrast, AI chatbots, virtual assistants, and fraud detection systems show comparatively weaker direct effects on customer satisfaction. Although these tools are important for improving operational efficiency, communication support, and security, their impact is more indirect and less visible to customers in terms of satisfaction outcomes.

The findings also indicate that customer characteristics play an important role in AI adoption and perceived value. Younger, more educated, and digitally active users are more likely to adopt and benefit from AI-based banking services. Digital literacy and frequent use of mobile banking significantly strengthen customers' acceptance and evaluation of AI-enabled financial services.

Overall, the study highlights that AI in banking contributes most effectively to customer satisfaction when it enhances personalization and decision support rather than focusing solely on backend efficiency and security.

Banks in Nepal should prioritize investment in AI applications that directly improve customer decision-making and personalization, such as credit scoring systems and recommendation engines. These tools have the strongest impact on satisfaction and should be central to digital banking strategies. While chatbots and fraud detection systems remain essential for operational efficiency and security, they should be integrated in ways that also improve user experience to enhance their perceived value.

Policymakers should focus on promoting digital literacy and inclusive access to digital banking services. Since AI adoption and satisfaction are strongly influenced by education and digital skills, national strategies should support training programs that improve customer capability to effectively use AI-based financial services.

The findings contribute to the growing literature on AI in financial services by highlighting the role of customer perception and digital readiness in shaping satisfaction outcomes. Future research should further explore how trust, perceived risk, and user experience influence the relationship between AI adoption and customer satisfaction.

Banks should design AI systems that are transparent, user-friendly, and tailored to customer needs. Enhancing personalization and providing actionable financial insights can strengthen customer loyalty and long-term engagement, especially in emerging digital markets like Nepal.

Limitations and Future Research Directions

This study is subject to several limitations. First, the use of purposive sampling and a relatively small sample size limits the generalizability of the findings, particularly for less digitally literate populations. Second, the cross-sectional design captures perceptions at a single point in time, preventing analysis of long-term effects or causal relationships. Third, the study focuses only on selected AI-enabled banking services and does not include broader digital banking factors such as trust, privacy concerns, or cultural influences.

Future research should employ larger and more diverse samples, including different age groups, income levels, and geographic regions. Longitudinal studies are recommended to examine how customer satisfaction evolves with the continued development of AI technologies. Comparative studies across countries and banking systems would also help identify contextual differences in AI adoption and effectiveness.

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