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Role of AI-Driven Banking Technologies in Strengthening Fraud Prevention Mechanisms in Digital Banking

Prof. (Dr.) Pallavi Mehta[1], Tamanna Sharma[2]

[1]Professor, Faculty of Commerce and Management, Pacific Academy of Higher Education and Research University, Udaipur

[2]Research Scholar, Faculty of Commerce and Management, Pacific Academy of Higher Education and Research University, Udaipur

Abstract:
Digital banking has expanded the speed, convenience and reach of financial services, but it has also increased the need for stronger fraud prevention systems and customer security mechanisms. The present study examines the role of AI-driven banking technologies in strengthening fraud prevention mechanisms in digital banking. The study adopted a quantitative approach with a descriptive and causal research design. Data were collected from 336 digital banking users through a structured questionnaire based on five-point Likert-scale statements. The study considered AI-driven banking technologies as the independent variable and fraud prevention mechanisms in digital banking as the dependent variable, while type of bank was used as a grouping variable. Reliability analysis, descriptive statistics, simple linear regression and one-way ANOVA were applied for data analysis. The findings indicated that respondents perceived AI-enabled monitoring, authentication, alerts and transaction analysis favourably in relation to digital fraud prevention. Regression results showed a significant positive influence of AI-driven banking technologies on fraud prevention mechanisms. The ANOVA results also indicated significant differences in respondents' perceptions across different types of banks. The study highlights the relevance of AI-based banking systems in improving perceived fraud prevention and strengthening customer security in digital banking.

Keywords: AI-driven banking technologies, Fraud prevention, Digital banking, Banking fraud detection, Customer security.

AI-DRIVEN BANKING TECHNOLOGIES AND FRAUD PREVENTION IN DIGITAL BANKING

The rapid expansion of digital banking has changed the way customers access, manage and secure financial services. Online banking, mobile applications, digital wallets and automated transaction platforms have made banking more convenient, but they have also increased exposure to new forms of digital fraud. As financial transactions become faster and more technology-dependent, banks are expected to strengthen their fraud prevention systems without reducing customer convenience. In this context, artificial intelligence has become an important technological support for improving the security and reliability of digital banking services.

AI-driven banking technologies broadly refer to systems that use automated data processing, pattern recognition, transaction monitoring, customer authentication, fraud alerts and risk detection tools to support safer banking operations. These technologies can help banks identify unusual transaction behaviour, detect suspicious account activity and alert customers or banking institutions before major financial loss occurs. Their relevance is particularly important in digital banking, where fraudulent activities may occur quickly and may be difficult to identify through traditional monitoring methods alone.

Fraud prevention mechanisms in digital banking are not limited to technical controls. They also influence customer confidence, perceived safety and willingness to continue using digital banking services. When customers believe that banks are capable of detecting and preventing unauthorised transactions, they may feel more secure while using digital channels. However, perceptions of fraud prevention may not be uniform across all banking categories. Customers associated with public sector banks, private sector banks, cooperative banks and small finance banks may differ in their experiences and expectations regarding digital security practices.

The present study is positioned within this practical and academic context. It focuses on the relationship between AI-driven banking technologies and fraud prevention mechanisms in digital banking. The study also considers whether perceptions of fraud prevention differ with respect to type of bank. By examining these constructs, the study seeks to contribute to the understanding of how AI-enabled banking systems are perceived in relation to fraud prevention and customer security. The present study therefore examines the impact of AI-driven banking technologies on fraud prevention in digital banking.

REVIEW OF LITERATURE

(Chen et al., 2025) presented a systematic review of deep learning applications in financial fraud detection by examining 108 peer-reviewed publications published between 2019 and 2024. The review focused on model architectures such as convolutional neural networks, long short-term memory networks, transformers and ensemble methods across financial fraud domains. The authors highlighted data imbalance, explainability, privacy compliance and automation as key challenges in fraud analytics. This study is relevant to the present research because it supports the role of AI-driven and deep learning-based systems in strengthening fraud detection and prevention within digital financial environments.

(AbouGrad & Sankuru, 2025) examined an online banking fraud detection model using a decentralised machine learning framework. The study applied deep autoencoders and anomaly detection methods on real-world financial datasets, including a credit card fraud dataset and the NeurIPS 2022 Bank Account Fraud dataset. The findings indicated that privacy-conscious and decentralised detection systems can support fraud identification while reducing the need to expose sensitive institutional data. The study is directly relevant to digital banking because it links fraud detection effectiveness with data privacy, compliance and customer security.

(Compagnino et al., 2025) conducted a comprehensive review of machine learning methods for fraud detection, with attention to practical banking applications and operational challenges. The study discussed supervised, unsupervised and hybrid learning approaches, commonly used datasets, performance metrics and two case studies based on real-world banking data. The review noted persistent issues such as data imbalance, concept drift and privacy concerns. Its relevance to the present study lies in showing that AI and machine learning tools can support fraud prevention, but their success depends on adaptability, interpretability and practical implementation in banking systems.

(Uddin, 2025) reviewed the role of artificial intelligence in preventing financial crime through a broad analytical perspective. The study examined AI methods for handling dynamic fraud patterns, with specific attention to real-time analytics, explainable AI, federated learning and hybrid AI models. The review suggested that AI can strengthen fraud detection by improving accuracy, transparency and scalability, although deployment challenges remain. This work is relevant to the present study because it connects AI-driven financial systems with fraud prevention and highlights the need for secure, transparent and customer-sensitive fraud control mechanisms.

(Odufisan et al., 2025) investigated the potential of artificial intelligence and machine learning for fraud detection and prevention in Nigeria's digital economy. The paper reviewed AI methods, including supervised, unsupervised and deep learning approaches, and discussed their application in anomaly detection, behavioural analysis, risk scoring and network analysis. The authors observed that AI-powered systems can improve efficiency, accuracy and proactive risk mitigation, while also noting regulatory and technical challenges. The study is useful for the present research because it aligns AI-enabled fraud detection with digital transaction safety and institutional fraud prevention.

(Laxman et al., 2025) carried out a bibliometric review of emerging threats in digital payment fraud and financial crime using Scopus-based data, co-occurrence analysis, author collaboration mapping and theme identification. The review identified major themes such as fraud risk in e-commerce, learning systems for fraud detection and prevention, behavioural intention, digital banking fraud risk management, information security and fraud prevention. The study is relevant because it situates digital banking fraud within the broader digital payment ecosystem and shows that artificial intelligence and information security have become important research directions for fraud prevention and customer protection.

(Lee et al., 2025) evaluated machine learning algorithms for financial fraud detection in the Indonesian context. The study used multiple linear regression and classification algorithms, including logistic regression, K-nearest neighbours, support vector machine, decision tree and random forest. The results indicated that random forest performed strongly compared with other models, while some models faced overfitting limitations. The study is relevant to the present research because it demonstrates how AI-supported classification techniques can identify fraud patterns and improve the design of fraud prevention frameworks in financial institutions.

(Hernandez Aros et al., 2024) reviewed financial fraud detection through machine learning techniques by applying PRISMA and Kitchenham-based review procedures. The study examined 104 articles published between 2012 and 2023 from academic databases such as Scopus, IEEE Xplore, Taylor & Francis, SAGE and ScienceDirect. The review found that machine learning models are widely used for detecting different types of financial fraud, with credit card fraud detection receiving notable attention. The study is important for the present research because it confirms the growing academic relevance of machine learning-based fraud prevention in financial and digital transaction contexts.

(Khalid et al., 2024) examined credit card fraud detection through an ensemble machine learning approach. The study proposed a model combining support vector machine, K-nearest neighbour, random forest, bagging and boosting classifiers, while also addressing data imbalance through under-sampling and synthetic minority oversampling techniques. The ensemble model outperformed several traditional classifiers across accuracy, precision, recall and F1-score measures. This review is relevant because it shows that AI-enabled fraud detection can become more reliable when multiple models are integrated, which supports the present study's focus on AI-driven banking technologies and fraud prevention.

(Cherif et al., 2023) conducted a systematic review of credit card fraud detection in the context of disruptive technologies. The review covered 40 relevant studies published between 2015 and 2021 and classified them according to themes such as class imbalance, feature engineering, machine learning and deep learning. The authors observed that research on deep learning in fraud detection remained limited and that further work was required to address large-scale machine learning, big data analytics and cloud-based fraud detection challenges. This study is relevant because it highlights the continuing need for stronger digital fraud prevention systems in banking and card-based transactions.

Research Gap

The reviewed literature shows that recent studies have strongly emphasised the role of artificial intelligence, machine learning, deep learning and ensemble models in detecting and preventing financial fraud. However, much of the available research focuses on technical model performance, datasets, algorithm comparison and system-level fraud detection. Comparatively fewer studies examine how digital banking users perceive AI-driven banking technologies in relation to fraud prevention and customer security, particularly with reference to differences across types of banks. The present study addresses this gap by examining the impact of AI-driven banking technologies on fraud prevention mechanisms in digital banking and by assessing whether perceptions differ with respect to bank type.

RESEARCH OBJECTIVE

To examine the impact of AI-driven banking technologies on fraud prevention in digital banking.

RESEARCH METHODOLOG

Research design

The study adopted a descriptive and causal research design. The descriptive component was appropriate for examining respondents' perceptions of AI-driven banking technologies and fraud prevention mechanisms in digital banking. The causal component was suitable because the study also examined the impact of AI-driven banking technologies on fraud prevention mechanisms through statistical testing.

Research Approach

The study followed a quantitative research approach. This approach was appropriate because the variables were measured through structured Likert-scale statements and analysed using numerical techniques. The quantitative approach enabled the study to examine construct-level mean scores, test relationships between variables and compare perceptions across different types of banks.

Population and Sample

The target population of the study consisted of digital banking users who had experience with banking services offered by public sector banks, private sector banks, cooperative banks and small finance banks. The study used a non-probability convenience sampling technique, as respondents were selected on the basis of accessibility, availability and willingness to participate. A total of 336 respondents were included in the study. The sample was considered suitable for descriptive analysis, reliability testing, regression analysis and one-way ANOVA.

Research Variables

The study included AI-driven banking technologies as the independent variable and fraud prevention mechanisms in digital banking as the dependent variable. AI-driven banking technologies refer to the use of artificial intelligence-based tools, automated monitoring systems, customer authentication methods, alerts and transaction analysis systems in digital banking. Fraud prevention mechanisms refer to the systems and practices used by banks to reduce unauthorised transactions, detect suspicious activities, protect customers from financial loss and strengthen customer security.

For construct-level analysis, mean scores were calculated by averaging the relevant Likert-scale items under each variable. The mean score for AI-driven banking technologies was calculated from six items, while the mean score for fraud prevention mechanisms was calculated from six items. These construct mean scores were used for descriptive analysis, reliability testing and hypothesis testing.

Instrument Development and Measurement

Data were collected through a structured questionnaire. The instrument contained 12 Likert-scale statements, with six statements measuring AI-driven banking technologies and six statements measuring fraud prevention mechanisms. Responses were measured on a five-point Likert scale, where 1 represented Strongly Disagree, 2 represented Disagree, 3 represented Neutral, 4 represented Agree and 5 represented Strongly Agree. Higher mean scores indicated stronger agreement with the respective statements.

Data Collection Procedure

The data were collected from digital banking users through a structured questionnaire. Respondents were classified according to the type of bank used by them, namely public sector bank, private sector bank, cooperative bank and small finance bank.

Reliability of the Instrument

Reliability of the instrument was examined using Cronbach's alpha. The Cronbach's alpha value for AI-driven banking technologies was 0.901, based on six items. The value for fraud prevention mechanisms was 0.877, based on six items. The overall reliability value for the 12-item instrument was 0.921. These values indicate acceptable internal consistency, as all reliability coefficients exceeded the commonly accepted threshold of 0.70. Therefore, the instrument was considered reliable for further statistical analysis.

Statistical Tools and Techniques

The data were analysed using descriptive and inferential statistical techniques. Descriptive statistics, including frequency, percentage, mean and standard deviation, were used to summarise respondents' opinions on each Likert-scale statement. Reliability analysis was applied to assess the internal consistency of the questionnaire items.

Simple linear regression was used to test the hypothesis relating to the impact of AI-driven banking technologies on fraud prevention mechanisms in digital banking. This technique was appropriate because the study examined the predictive effect of one independent construct on one dependent construct. One-way ANOVA was used to test whether respondents' perceptions of fraud prevention mechanisms differed significantly with respect to type of bank. This technique was suitable because the grouping variable consisted of more than two categories. Hypothesis testing was conducted at the 5 per cent level of significance.

LIKERT SCALE STATEMENT ANALYSIS

Table 1: Likert Statements on AI-Driven Banking Technologies

S. No.	Likert Statement	SD	D	N	A	SA	$\overline{X}$	σ
1	AI-driven banking technologies help banks identify unusual digital banking transactions in real time.	4	49	143	114	26	3.32	0.86
2	AI-enabled monitoring systems improve the speed of detecting suspicious banking activities.	1	42	121	137	35	3.49	0.85
3	AI-based customer authentication methods strengthen the security of digital banking transactions.	4	42	133	129	28	3.40	0.86
4	AI-driven alerts and notifications make digital banking users more aware of possible fraud risks.	1	32	141	128	34	3.48	0.81
5	AI-supported transaction analysis helps banks respond more effectively to emerging fraud patterns.	5	44	127	119	41	3.44	0.92
6	AI-driven banking technologies improve the overall reliability of digital banking services.	2	32	128	144	30	3.50	0.81

The Likert-scale results indicate a generally favourable perception of AI-driven banking technologies in digital banking. Respondents showed moderate to high agreement that AI-enabled monitoring, authentication, alerts and transaction analysis help in identifying suspicious activities, improving fraud awareness and strengthening digital banking reliability. The mean scores, ranging from 3.32 to 3.50, suggest a positive but not extreme level of agreement.

Table 2: Likert Statements on Fraud Prevention Mechanisms

S. No.	Likert Statement	SD	D	N	A	SA	$\overline{X}$	σ
7	Fraud prevention mechanisms in digital banking reduce the chances of unauthorised transactions.	1	26	108	158	43	3.64	0.81
8	Digital banking fraud prevention systems help protect customers from financial loss.	1	26	114	139	56	3.66	0.86

S. No.	Likert Statement	SD	D	N	A	SA	$\overline{X}$	σ
9	Fraud alerts and verification checks improve customer confidence in digital banking.	4	31	126	132	43	3.53	0.87
10	Banks’ fraud prevention mechanisms are effective in detecting suspicious account activities.	0	39	122	133	42	3.53	0.86
11	Fraud prevention mechanisms encourage customers to use digital banking services safely.	3	28	130	130	45	3.55	0.86
12	Existing digital banking fraud prevention practices strengthen customer security.	0	30	139	129	38	3.52	0.81

The findings for fraud prevention mechanisms also reflect a positive response pattern. Respondents generally agreed that fraud prevention systems reduce unauthorised transactions, protect customers from financial loss, improve confidence and encourage safer use of digital banking. The mean scores, ranging from 3.52 to 3.66, indicate that fraud prevention mechanisms are perceived as useful and relevant for strengthening customer security.

HYPOTHESIS TESTING

H_{01}: There is no significant impact of AI-driven banking technologies on fraud prevention mechanisms in digital banking.

Simple linear regression was applied to examine the impact of AI-driven banking technologies on fraud prevention mechanisms in digital banking.

Table 3: Variables Used for Hypothesis Testing (H_{01})

Independent Variable	Dependent Variable
AI-driven banking technologies	Fraud prevention mechanisms in digital banking

The above table presents the variables used for testing H01. AI-driven banking technologies were considered as the independent variable, while fraud prevention mechanisms in digital banking were considered as the dependent variable. This classification indicates that the hypothesis examines whether AI-driven banking technologies influence the effectiveness of fraud prevention mechanisms in digital banking.

Table 4: Model Summary

R	R^2	Adjusted R^2	Standard error of the estimate
0.67	0.44	0.44	0.50

The model produced a strong positive association between AI-driven banking technologies and fraud prevention mechanisms, R = 0.67. The R^2 value was 0.44, with an adjusted R^2 of 0.44, indicating that AI-driven banking technologies explained 44 per cent of the variance in fraud prevention mechanisms.

Table 5: ANOVA

Model	df	F	p
Regression	1	264.98	<.001

The regression model was statistically significant, $F(1, 334) = 264.98$, $p < .001$.

Table 6: Summary of Regression Coefficient

Model	Unstandard. Coef. B	Standard. Coef. Beta	Std. Error	t	p
Constant	1.40		0.14	10.22	<.001
AI-driven banking technologies Mean Score	0.63	0.67	0.04	16.28	<.001

The coefficient result further showed that AI-driven banking technologies had a positive and significant effect on fraud prevention mechanisms, B = 0.63, SE = 0.04, $\beta = 0.67$, t = 16.28, $p < .001$. This indicates that for every one-unit increase in the mean score of AI-driven banking technologies, the mean score of fraud prevention mechanisms increased by 0.63 units.
The regression equation may be written as:
Fraud Prevention Mechanisms = 1.40 + 0.63(AI-driven Banking Technologies).
These results show that respondents who perceived AI-driven banking technologies more positively also reported stronger perceptions of fraud prevention mechanisms in digital banking.

Decision

For H_{01}, simple linear regression was applied to test whether AI-driven banking technologies significantly influence fraud prevention mechanisms in digital banking. Since the regression model was statistically significant at the 5 per cent level of significance, the null hypothesis is rejected.

Finding

The findings indicate that AI-driven banking technologies are positively associated with fraud prevention mechanisms in digital banking. This suggests that AI-enabled monitoring, authentication, alerts and transaction analysis may contribute to stronger perceived fraud prevention among digital banking users.

Hypothesis Conclusion

Since the null hypothesis is rejected, the researcher concludes that there is a significant influence of AI-driven banking technologies on fraud prevention mechanisms in digital banking.

H_{02}: There is no significant difference in respondents' perceptions of fraud prevention mechanisms in digital banking with respect to type of bank.

One-way ANOVA was used to examine whether respondents' perceptions of fraud prevention mechanisms in digital banking differed significantly with respect to type of bank.

Table 7: Variables Used for Hypothesis Testing (H_{02})

Independent Variable	Dependent Variable
Type of bank	Respondents' perceptions of fraud prevention mechanisms in digital banking

The above table presents the variables used for testing H02. Type of bank was considered as the independent variable, while respondents' perceptions of fraud prevention mechanisms in digital banking were considered as the dependent variable. This classification indicates that the hypothesis examines whether perceptions of fraud prevention mechanisms differ significantly across different types of banks.

Table 8: Descriptive Statistics

	n	Mean	Std. Deviation
Cooperative bank	57	3.24	0.61
Private sector bank	104	3.81	0.62
Small finance bank	49	3.60	0.56
Public sector bank	126	3.52	0.69
Total	336	3.57	0.66

The descriptive results showed variation across bank categories. Respondents from private sector banks reported the highest mean score for fraud prevention mechanisms (M = 3.81, SD = 0.62), followed by small finance banks (M = 3.60, SD = 0.56), public sector banks (M = 3.52, SD = 0.69) and cooperative banks (M = 3.24, SD = 0.61).

Table 9: ANOVA

	Sum of Squares	df	Mean Square	F	p
Type of Bank	12.44	3	4.15	10.16	<.001
Residual	135.47	332	0.41		
Total	147.90	335			

The ANOVA result showed a statistically significant difference among bank types, $F(3, 332) = 10.16$, $p < .001$. This indicates that respondents' perceptions of fraud prevention mechanisms were not uniform across different types of banks. The group pattern suggests that private sector bank respondents perceived fraud prevention mechanisms more favourably, while cooperative bank respondents reported comparatively lower perceptions.

Decision

For H02, one-way ANOVA was applied to test whether respondents' perceptions of fraud prevention mechanisms in digital banking differed significantly with respect to type of bank. Since the ANOVA result was statistically significant at the 5 per cent level of significance, the null hypothesis is rejected.

Finding

The findings show that perceptions of fraud prevention mechanisms differ across bank types. This suggests that customers of different banking categories may experience or perceive digital fraud prevention practices differently within the digital banking environment.

Hypothesis Conclusion

Since the null hypothesis is rejected, the researcher concludes that there is a significant difference in respondents' perceptions of fraud prevention mechanisms in digital banking with respect to type of bank.

OVERALL CONCLUSION

The study examined the role of AI-driven banking technologies in strengthening fraud prevention mechanisms in digital banking. The findings show that respondents perceived AI-enabled banking tools positively, particularly in relation to transaction monitoring, customer authentication, fraud alerts and overall service reliability. Similarly, fraud prevention mechanisms were viewed favourably, as respondents associated them with reduced chances of unauthorised transactions, protection from financial loss and improved customer confidence in digital banking.

The hypothesis results further support the empirical direction of the study. The regression analysis showed that AI-driven banking technologies had a significant positive influence on fraud prevention mechanisms, leading to the rejection of H_{01}. The one-way ANOVA result also indicated a significant difference in respondents' perceptions of fraud prevention mechanisms with respect to type of bank, leading to the rejection of H_{02}. Overall, the study suggests that AI-driven banking technologies play an important role in improving perceived fraud prevention in digital banking, although perceptions may vary across different banking categories.

SUGGESTIONS BASED ON FINDINGS

1. Banks should strengthen AI-enabled transaction monitoring systems to identify unusual digital banking activities more effectively and in real time.
2. AI-based fraud alerts should be made more precise, timely and user-friendly so that customers can respond quickly to suspicious transactions.
3. Banks should improve customer authentication methods by using secure AI-supported verification tools without making the process unnecessarily complex.
4. Digital banking platforms should integrate AI-driven risk detection systems that can identify emerging fraud patterns and support faster institutional response.
5. Banks should conduct regular customer awareness campaigns explaining how AI-based fraud prevention tools protect digital banking users.
6. Public sector, private sector, cooperative and small finance banks should review differences in customer perception and strengthen fraud prevention practices accordingly.
7. Cooperative banks may require additional attention in improving digital fraud prevention systems, as their respondents reported comparatively lower perception scores.
8. Private sector banks should continue strengthening AI-enabled fraud prevention practices, as their customers reported comparatively higher confidence in such mechanisms.
9. Banks should improve transparency by informing customers when AI-based systems are used for fraud detection, alerts and transaction security.
10. Customer support teams should be trained to respond efficiently when AI systems flag suspicious digital banking activities.
11. Banks should ensure that AI-driven fraud prevention systems are regularly updated to address new forms of digital banking fraud.
12. Digital banking users should be educated about safe banking behaviour, including verification checks, fraud alerts and responsible use of online banking platforms.
13. Banks should combine AI-driven monitoring with human review in sensitive fraud cases to reduce errors and improve customer trust.
14. Fraud prevention mechanisms should be designed to protect customers from financial loss while maintaining ease of access to digital banking services.
15. Banks should regularly evaluate customer perceptions of digital banking security so that fraud prevention systems can be improved according to user experience and expectations.

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