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[AI to Enhance the Transactional Security in Digital Banking]

Sohaib uz Zaman
Assistant Professor, Karachi University Business School, University of Karachi, ORCID: https://orcid.org/0000-0002-0135-3292, sohaibuzzaman@uok.edu.pk
Erum Parveen
Karachi University Business School, University of Karachi, Erum.perveen@outlook.com
Syed Hasnain Alam
Karachi University Business School, University of Karachi, ORCID: https://orcid.org/0000-0002-5008-7365, hasnainalam@gmail.com

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ABSTRACT

The integration of artificial intelligence (AI) has enhanced banking operations by providing improved customer service, security, and efficiency. For data privacy and security, Banks must implement robust data security measures to gain customer trust as well as comply with regulatory requirements. Therefore, this study examined whether AI-based security systems can augment transactional safety, secure pay systems, and strengthen customer trust in digital banks. Quantitative research design and stratified random sampling technique is used for data collection. Questionnaire is filled up with digital banking customers and professionals. Descriptive statistic is used to understand the demographics of respondent, Cronbach's alpha test for reliability e and regression analysis is applied to analyze how AI can enhance the transactional security in digital banking. The findings point out that AI techniques are most influential on transaction security and customer trust, and powered security systems play an auxiliary role in securing payment systems. The digital banking platforms are also significant mediators that make both AI techniques and powered security systems more effective. AI-based security solutions, such solutions provide extensive protection against cyber threats and improve the user experience to bring about easy and hassle-free transactions with the help of different features like AI chatbots, real-time fraud alerts, and automated dispute resolution add up to make the banking environment secure and customer-friendly.

Keywords: AI techniques, transactional security, payment system security, digital banking platforms, customer trust and powered security systems.

Introduction

In the banking sector, the integration of artificial intelligence (AI) has caused a revolution in the banking operations that existed traditionally. This has offered various new opportunities regarding improvement in the customer service, enhancement in security, and efficiency in the operations. Machine learning and natural language processing, two of the AI technologies, have been widely adopted so far in order to streamline the processes, analyze customer data, and provide various personalized services. Solutions provided by AI can play a role in enhancing efficiency by involving automation of routine tasks and reduction of costs, which enables the banks to offer customized services on the basis of data-driven insights (Smith and Jones, 2018; Biswas & Carson, 2020). Furthermore, involving the use of AI in the banking sector has led to the expansion, which is beyond the chatbots for the detection of frauds, management of risks, and compliance, which makes it a critical component for the transformation of strategies digitally for the financial institutions (Mughal & Karim, 2021; Haralayya, 2023).

Digital technologies, which have been advancing rapidly, have led to a crucial shift in the banking sectors, which has pushed banks to adopt AI-driven solutions for remaining in the healthy competition with other banks. Banks have been using AI over the past few years for the improvement of customer experiences, strengthening security measures, and streamlining operations. For example, in many of the banking apps, AI-powered chatbots and virtual assistants have become common for the handling of various customer inquiries with efficiency while also offering real-time assistance (Indriasari & Zaki, 2019; Nuthalapati, 2024). The adoption of artificial intelligence has also

proven to be significant for banks, additionally, in order to stay forward in this competitive landscape through enhancement in capabilities related to data analytics, which has led to an increase in informed decision-making (Apoga & Rahman, 2021). The ability that artificial intelligence possesses related to the analysis and interpretation of significant amounts of data on a rapid basis assists the banks in the detection of trends, forecasting of risks, and identification of potential opportunities, which in turn improves the operational efficiency and the overall levels of profitability.

Digital Banking and AI Integration

The banking industry has been undergoing a major transformation over the last decade, driven by technological advancements and the rise of digital platforms. With the introduction of online and mobile banking, customers now expect seamless, efficient, and secure services that can be accessed from anywhere at any time. According to recent research, the global digital banking market is projected to grow significantly over the next few years, driven by the increasing adoption of mobile devices and internet penetration (Yalamati, 2023; Haralayya, 2023). Financial institutions are investing in AI technologies to meet these demands and to differentiate themselves in a competitive market (Apoga et al., 2021). As the demand for digital services grows, banks are looking to AI to help manage increased transaction volumes and to improve the overall customer experience.

The integration of AI in banking has been instrumental in transforming traditional banking practices. Banks now use AI to analyze vast amounts of data, identify trends, and make predictions, which has significantly improved the quality of services they offer. For example, AI-powered systems can assess creditworthiness more accurately than traditional methods, reducing the risk of loan defaults (Nuthalapati, 2024; Indriasari & Zaki, 2019). Moreover, AI is being used to enhance customer relationship management (CRM) by providing personalized recommendations and solutions based on individual customer profiles (Chowdhury & Biswas, 2022). This shift towards personalized banking experiences is one of the key trends shaping the future of digital banking, as customers increasingly expect tailored solutions that meet their specific financial needs.

Problem Statement and Purpose of Study

Despite the numerous benefits AI offers to the banking industry, there are still challenges that need to be addressed. One of the primary concerns is the issue of data privacy and security. With AI systems relying on vast amounts of customer data to function effectively, ensuring that this data is protected from breaches is critical. Banks must implement robust data security measures to gain customer trust and comply with regulatory requirements (Yalamati, 2023; Smith & Jones, 2018). Furthermore, the rise of sophisticated cyberattacks calls for the development of more advanced AI-powered security frameworks to safeguard sensitive financial data (Nuthalapati, 2024). Failure to address these concerns could undermine the trust that is essential for the widespread adoption of digital banking solutions.

Literature Review

More especially, the adoption of the internet and advanced technology in the banking industry has enhanced the growth of online transactions which in turn has raised significant fears with regard to transaction security. Today, cyber threats including identity theft, fraud, and unauthorized access to personal and organizational accounts

are common, and there is increasing pressure for better security systems (Smith et al., 2023). Research also estimates that the cost of cybercrime across the world will touch $10.5 trillion by 2025 which in fact underlines the importance of improving the security measures regarding digital banking (Kumar et al., 2021). This need has led to increased interest in the use of sophisticated technologies such as Artificial Intelligence (AI) for security boost, especially through techniques such as Machine learning and Natural language processing, which provide real-time and proactive analysis and detection of anomalous behavior (Johnson & Lee, 2022). From a conventional risk management perspective, AI allows banks to identify a threat before it happens; this gives added value in protecting both the banks and the customers, to their financial transfers (Williams et al., 2022).

Theoretical Framework

Technology Acceptance Model (TAM)

Some theoretical frameworks used to understand the application of AI to Digital banking security are the Technology Acceptance Model TAM, Artificial Neural Networks ANN and Machine learning ML frameworks. Each model is useful in understanding AI in establishing safe and secure digital transactions in the market (Davis, 1989; Venkatesh & Bala, 2008). For instance, TAM shows that perceived ease of use and perceived usefulness are key determinants of the use of AI in security solutions, mainly where the customers are receptive to the change in experience due to the access of the security solutions (Hussain & Shah, 2023).

Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are allowed to recognize pattern between two large sets of data hence proving useful when it comes to identifying fraudulent transactions. ANNs update their efficiency from old data and the new ones rising; moreover, the performance in terms of fraud detection is much higher than rule-based systems (Smith et al., 2021). The latest studies give confidence to deep learning in ANN which achieved higher accuracy of fraud detection a breakthrough in digital banking security (Johnson & Lee, 2022).

Mediating Effects

User Behavior Analysis (UBA) plays a crucial role of a mediator with fraud detection behavior-analysis that allows for the setting of the individual fraud detection parameters depending on the user's transaction history (Ahmed et al., 2020). Thus, rising accuracy and relevancy of such approach can contribute in strengthening fraud identification that provides users with a helpful instrument in protecting clients (Patel & Sinah, 2023). In the same way, AI integrated authentication like biometric or multi-factor authentication (MFA), offers more security than the normal ones.

Mediating Effects

This paper establishes customer trust as a critical determinant of AI-driven security both in the realization of digital banking and the overall effectiveness of the solutions offered. The high-level implementation of AI technologies in the banks makes the customers feel safe due to these protective tools of fraud detection. This perception of security results in increased customer satisfaction, and customer loyalty whereby, customers are most likely to work with a bank that has increased security measures in place (Li et al., 2021). Notably, those systems that employ artificial intelligence for detecting fraud actions and

reporting in real-time enhance this trust as most clients feel that the bank is addressing security early enough (Prasad & Verma, 2021).In other words, the trust element acts like a moderator in the relationships between AI's implementation and the customers' satisfaction level. For example, customers who have trust their transactions are secured exhibit higher satisfaction because of these perceived securities (Zhao et al., 2023). In this capacity, trust helps link AI security to general user satisfaction, making it possible for security to feed and create satisfaction while satisfaction feeds and maintains security.

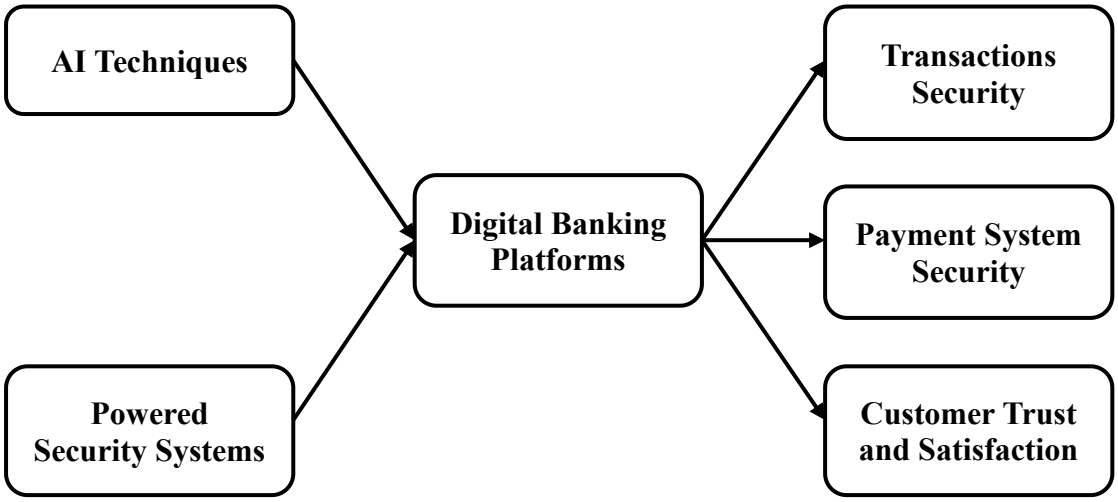

Figure 1: Conceptual Framework

Hypothesis Development

AI Techniques and Digital Banking Platforms

Artificial Intelligence (AI) techniques have significantly reshaped digital banking platforms (DBPs), enabling intelligent interfaces, automated services, and personalized customer journeys. Recent studies highlight that AI tools such as chatbots, real-time fraud detection systems, and biometric verification have led to more robust and user-friendly platforms (Chowdhury & Biswas, 2022; Nuthalapati, 2024; Kim et al., 2022). These platforms are no longer just transactional portals but dynamic ecosystems influenced by AI-driven customization. From a foundational perspective, Mughal and Karim (2021) noted that early AI adoption improved backend automation in digital banking, increasing scalability and reducing errors. Thus, AI techniques are a critical enabler for advancing the structure, interactivity, and operational intelligence of digital banking platforms.

H1: Implementation of AI techniques positively impacts digital banking platforms.

AI Techniques and Transactions Security

AI techniques contribute directly to enhancing transaction security by enabling proactive threat detection, anomaly recognition, and behavioral analytics. Tools such as machine learning and deep learning allow systems to identify suspicious patterns before a breach occurs, safeguarding users' digital transactions (Zhao et al., 2023; Johnson & Lee, 2022; Yalamati, 2023). Additionally, AI ensures secure identity verification via facial and fingerprint recognition, which minimizes unauthorized access. Earlier research by Williams and Barnett (2022) confirms that AI-powered fraud detection systems reduce transaction fraud more effectively than traditional rule-based systems. These

contributions establish AI techniques as a powerful force in securing financial transactions in digital environments.

H2: Implementation of AI techniques positively impacts transaction security.

AI Techniques and Payment Security System

In digital banking, AI-driven solutions like dynamic risk scoring, adaptive authentication, and biometric tokenization enhance payment system security by ensuring the validity and safety of payment flows. These techniques enable banks to assess risk in real time and trigger verification layers based on transaction behavior (Indriasari & Zaki, 2019; Haralayya, 2023; Apoga et al., 2021). The integration of AI into payment systems also allows for continuous fraud monitoring, reducing vulnerabilities in payment gateways. Supporting this view, Green (2020) emphasized the role of intelligent algorithms in real-time anomaly detection in payment networks. Thus, AI creates a secure payment ecosystem through intelligent processing and predictive safeguards.

H3: Implementation of AI techniques positively impacts payment system security.

AI Techniques and Customer Trust & Satisfaction

AI techniques improve customer trust and satisfaction by providing real-time security, seamless experiences, and personalized services. AI-driven tools like fraud alerts, smart chatbots, and instant verification processes increase user confidence in the system (Chowdhury & Biswas, 2022; Kim et al., 2022; Nuthalapati, 2024). These tools foster a sense of reliability and responsiveness, which are essential to building trust. Earlier findings by Apoga and Rahman (2021) showed that AI integration improved digital banking satisfaction levels by enhancing responsiveness and transaction clarity. Customers who perceive higher protection and convenience through AI systems are more likely to develop loyalty toward the platform.

H4: Implementation of AI techniques positively impacts customer trust and satisfaction.

Powered Security Systems and Digital Banking Platforms

Powered security systems such as firewalls, biometric logins, and secure encryption protocols significantly influence the functionality and reliability of digital banking platforms. These tools create a foundational layer of trust and technical robustness that platforms depend on (Yalamati, 2023; Patel & Sinha, 2023; Haralayya, 2023). Inadequate security protocols can compromise user engagement with the platform, while enhanced systems promote consistent usage and trust. As emphasized by Kumar et al. (2021), the security architecture of digital portals greatly affects their long-term adoption. Therefore, powered security mechanisms are vital in shaping dependable digital banking infrastructures.

H5: Powered security systems positively influence digital banking platforms.

Powered Security Systems and Transactions Security

Powered security systems are instrumental in reducing risks in digital transactions by using encryption layers, intrusion detection, and access control. These systems support secure transmission protocols, protecting transaction data from interception and manipulation (Wang et al., 2022; Patel & Sinha, 2023; Kim et al., 2022). Such tools improve user perception regarding the safety of each financial interaction. Supporting this, Green (2020) found that banks implementing multilayered security protocols reported up to 30% fewer transaction-related fraud incidents. These findings suggest that powered security systems create structural defenses essential for transaction integrity.

H6: Powered security systems positively influence transaction security.

Powered Security Systems and Payment System Security

The integration of strong powered security mechanisms significantly strengthens payment system security by providing real-time encryption, tokenized payments, and secure verification protocols. This leads to reduced vulnerability in peer-to-peer and gateway-based payments (Zhao et al., 2023; Haralayya, 2023; Johnson & Lee, 2022). These mechanisms prevent phishing, data tampering, and unauthorized transactions. Kumar et al. (2021) earlier argued that robust security frameworks in payment systems correlate positively with customer retention. Thus, such mechanisms are vital for protecting financial flows in modern digital banking.

H7: Powered security systems positively influence payment system security.

Powered Security Systems and Customer Trust & Satisfactions

When customers perceive that a platform employs robust powered security systems, they feel safer conducting financial transactions, which enhances their trust and satisfaction. Systems such as OTP authentication, firewalls, and biometrics convey an institution's commitment to user safety (Li et al., 2021; Wang et al., 2022; Zhao et al., 2023). These mechanisms reduce anxiety around cyber threats and identity theft. Green (2020) noted that user trust is directly linked to visible and consistent security protocols. Consequently, security assurances increase both usage frequency and satisfaction with digital banking services.

H8: Powered security systems positively influence customer trust and satisfaction.

Digital Banking Platforms and Transactions Security

Digital banking platforms with well-integrated AI and security tools contribute to higher transaction security by enabling users to interact securely and intuitively. Secure logins, real-time feedback on suspicious activities, and account notifications empower users to detect and report irregularities (Apoga et al., 2021; Patel & Sinha, 2023; Chowdhury & Biswas, 2022). These platform features create a feedback loop where digital interfaces act as security enablers. Earlier studies by Mughal & Karim (2021) highlight how platforms with enhanced user interfaces reduced fraud reports due to user awareness and usability. Therefore, digital platforms are not just mediums they actively ensure transaction safety.

H9: Digital banking platforms positively impact transaction security.

Digital Banking Platforms and Payment System Security

Digital banking platforms contribute to payment system security by integrating layers of secure APIs, payment authorization protocols, and user-friendly dashboards that flag anomalies. When a platform is secure by design, its embedded payment workflows are inherently more trustworthy and less vulnerable to breaches (Haralayya, 2023; Yalamati, 2023; Chowdhury & Biswas, 2022). Additionally, seamless interface design and secured backend APIs ensure safe, quick, and error-free payments. According to Green (2020), payment errors and fraud cases decrease significantly when platforms feature high levels of integration between frontend and backend security elements. This proves the instrumental role platforms play in maintaining secure payments.

H10: Digital banking platforms positively impact payment system security.

Digital Banking Platforms and Customer Trust & Satisfaction

The interface, responsiveness, and security of digital banking platforms directly influence customer trust and satisfaction. Well-designed platforms foster ease of navigation and

provide real-time updates, fraud alerts, and transaction confirmations (Zhao et al., 2023; Patel & Sinha, 2023; Wang et al., 2022). These features reduce user uncertainty and boost confidence in the bank's technological capacity. Apoga and Rahman (2021) emphasized that ease of use and system reliability were top predictors of user satisfaction in digital banking platforms. Hence, optimized platforms foster lasting trust and usage loyalty.

H11: Digital banking platforms positively influence customer trust and satisfaction.

AI Techniques, Digital Banking Platforms and Customer Trust & Satisfactions

AI techniques indirectly influence customer trust and satisfaction by enhancing the capabilities of digital banking platforms that deliver secure, responsive, and personalized experiences. Through tools like fraud alerts, sentiment analysis, and chatbots, AI elevates the functionality of platforms, which in turn foster user trust (Chowdhury & Biswas, 2022; Nuthalapati, 2024; Kim et al., 2022). Venkatesh & Bala (2008) earlier highlighted that user perception of ease and usefulness are critical in trust-building. Hence, the effect of AI on customer satisfaction is significantly mediated by how well it is embedded within digital banking platforms.

H12: Digital banking platforms mediate the relationship between AI techniques and customer trust and satisfaction.

Powered Security Systems, Digital Banking Platforms and Customer Trust & Satisfactions

Powered security systems impact customer trust and satisfaction through their influence on digital banking platforms, which serve as the delivery channel for these protections. Secure login interfaces, two-step verifications, and encrypted transaction displays increase user confidence when accessed via intuitive platforms (Wang et al., 2022; Patel & Sinha, 2023; Li et al., 2021). Earlier literature (Green, 2020) confirms that platforms designed around security functions yield greater customer satisfaction due to improved perceived control. This shows that powered security's trust-enhancing potential is maximized when channeled through secure, user-friendly platforms.

H13: Digital banking platforms mediate the relationship between powered security systems and customer trust and satisfaction.

Conceptualization

This includes the Technology Acceptance Model (TAM) as well as the Trust Theory which have theoretical background knowledge on how the use of AI improves security and trust in the digital banking of customers. Prior research has found that TAM measures have received a consistent level of support for digital banking: perceived usefulness/ ease of use are significantly related to perceived customer confidence/ adoption rates (Venkatesh & Bala, 2008; Hussain & Shah, 2023). Trust Theory enhances security and reliability in building a relationship of trust between the customer and digital banking empowered with Artificial Intelligence (AI) (Zhao et al., 2023). But even more important than its technical and operational advantage embellished through models such ML and ANNs there is still some literature gap in terms of the ethical, privacy, and regulatory implications of applying the banking security frameworks through the AI lens (McKinney et al., 2021; Smith et al., 2021; Shah & Lee, 2020). These are areas that future research should investigate through studies that specifically examine how regulatory systems and privacy issues may mediate customer satisfaction and trust of AI in banking which would further expand the premise of AI to increase security while not infringing on a user's

rights (Poddar et al., 2022; Rana & Barve, 2023).

Methodology

The methodology of this study, "Unleashing the Power of AI to Enhance Transactional Security in Digital Banking," includes a structured quantitative approach to appraise the impact of AI techniques and AI-driven security solutions on strengthening transactional security and customer trust in digital banking. This chapter describes the research design, data collection methods, and sampling strategy as well as the various data analysis approaches applied to dissect how AI can enhance the security of digital banking.

Research Approach

This research uses a method of quantitative research to examine the relations of the AI-driven techniques with various aspects of transactional security in digital banking. The methods used were best suited for the capture of quantitative data regarding the effects that the AI-powered tools had on objectively evaluating hypotheses regarding the relationships that existed between specific variables. It will determine how much applications of AI, namely, Machine Learning and Natural Language Processing, impact the key security outcome such as fraud detection, the security of the payment, or trust of customers. The paper will be survey based to collect the right data. A sample of digital banking customers and professionals will be handed structured questionnaires to conduct an empirical study of the impact that AI security tools have on perception and experience. In this regard, survey data are sure to provide insights statistically strong enough to affirm whether AI-driven techniques really enhance transactional security and robust trust-building.

Sampling

The research adopts the deductive research approach, starting from an established theory on the application of AI in digital security toward establishing and testing specific hypotheses derived from that theory. In view of the previous literature which showed that AI can help improve security in financial transactions, this direction is appropriate since it will eventually facilitate hypothesis testing with real-life data based on respondents' survey. It would use a deductive approach to establish whether AI methods, like Machine Learning and fraud detection algorithms, can indeed be expected to reduce transactional fraud, authenticate better, and build customer confidence in digital banking services.

The research philosophy will be based on positivism, which deals with objective measurement as well as evidence drawn from observation. This is because it will involve quantifiable data-gathering through structured instruments to test predefined hypotheses. Grounding in facts minimizes bias. This philosophy ensures that all findings of the research are based on facts. In this technology-based research, where AI-driven security outputs can be seen and measured, positivism provides a rich basis to journey further into cause-and-effect relations. With the philosophy being applied, the research will remain objective mainly and focus on observable impacts of AI technologies on digital banking security.

Data Analysis Techniques

The study examines the relations of several variables with a strong grounding in statistics. It will use both descriptive and inferential statistics from SPSS and SMART PLS software for processing data. The research will first start with descriptive about the demographics

of the respondents' variable means and other metrics deemed pertinent for the study. This summary will thus provide the initial insight into how respondents view AI-driven security in digital banking. Cronbach's alpha test for reliability ensures that the measurement scales applied to variables such as AI Techniques and Transaction Security are reliable and consistent in measuring the same aspect. The reliability of the measurement instrument for Cronbach's alpha is thus confirmation that it fits the experiences and perceptions of respondents. Regression analysis will be used to understand the independent variables, specifically AI Techniques and AI-powered Security Solutions, while the dependent variables are transaction security, security in a payment system, and customer trust. Path analysis further makes it possible to establish that mediation works through Digital Banking Platforms so that the impact of AI techniques and security solutions might be indirect in nature, working their way through digital devices like mobile applications and web portals.

Results and Discussion

Descriptive Statistics

The descriptive statistics reveal important aspects of the variables in relation to digital banking security and user perception. All variables have a sample size of 200. All the means for the different variables are over 3.5 on the 5-point scale, signifying generally positive perceptions. AI Techniques has a mean of 3.81 (SD = 0.74), which means that the respondents have a moderate high perception about the role of AI in strengthening the security of digital banking. The negative skewness is -1.137, which implies that most respondents rated AI techniques favorably and fewer lower ratings were received for Powered Security Systems, with the highest mean at 3.99, SD = 0.63. The mediating variable, Digital Banking Platforms, has a mean of 3.61 (SD = 0.51) with high negative skewness (-1.658) and kurtosis (4.279), suggesting that responses are concentrated at the higher end and do not exhibit much variability. Among dependent variables, Transaction Security was reported to be 3.86 (SD = 0.67), and *Payment System Security was reported at 3.85 (SD = 0.68) with slight variations. Customer Trust and Satisfaction was also reported at 3.85 (SD = 0.74), implying that users do trust digital banking services. All the variables are negatively skewed, implying that respondents rated them significantly higher overall. Kurtosis values indicate a peaked distribution with Digital Banking Platforms, which attests to consistency in response. These results present a rosy picture about AI-driven security in digital banking, further emphasizing the role of AI techniques and powered security systems in terms of trust and satisfaction.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AI Techniques	200	1.00	5.00	3.8100	.74098	-1.137	.172	2.187	.342
Powered Security Systems	200	1.20	5.00	3.9930	.63575	-1.009	.172	2.394	.342

Digital Banking Platforms	200	1.00	4.60	3.6130	.50964	-1.658	.172	4.279	.342
Transaction Security	200	1.00	5.00	3.8590	.67035	-.778	.172	1.521	.342
Payment System Security	200	1.00	5.00	3.8530	.68096	-.884	.172	2.042	.342
Customer Trust and Satisfaction	200	1.00	5.00	3.8526	.73992	-.957	.175	1.804	.347
Valid N (list wise)	200								

Table 2: Descriptive Statistics

Correlation Analysis

The correlation analysis shows important associations among the key variables in digital banking security. All of the correlations are found to be statistically significant at the 0.01 level, revealing strong associations among AI techniques, powered security systems, digital banking platforms, transaction security, payment system security, and customer trust and satisfaction. AI Techniques is significantly positively correlated with Transaction Security (r = .683) and Customer Trust and Satisfaction (r = .715). This indicates that AI-driven security integration has a positive impact on the safety of transactions and impacts customer confidence in internet banking. High-powered Security Systems also have a highly significant relation with Transaction Safety (r = .579) and Customer Confidence and Satisfaction (r = .562), thereby again revealing the impact of advanced security infrastructure on trust. The mediating variable, Digital Banking Platforms, was positively related with both Transaction Security, r = .507, and Customer Trust and Satisfaction, r = .530, supporting the variable's role in bridging between AI-driven security measures and user perceptions. This suggests that well-developed digital banking platforms enhance security, an ultimate influence on customer satisfaction. The strongest correlation emerges between Transaction Security and Payment System Security, at r =.803. Then, it shows a significant positive correlation between Payment System Security and Customer Trust and Satisfaction at r =.821. Such findings suggest that customer trust and loyalty are built from a safe payment system. These results are consistent with the theme of research, and it reinforces that AI techniques and powered security systems are important in enhancing the digital security of banking, leading to heightened customer confidence and satisfaction.

Correlation Matrix

	AIT	PSS	DBP	TS	PSSEC	CTS
AIT	1					
PSS	.624**	1				
DBP	.504**	.381**	1			
TS	.683**	.579**	.507**	1		
PSSEC	.638**	.531**	.504**	.803**	1	
CTS	.715**	.562**	.530**	.810**	.821**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3: Correlation Matrix Results

Reliability Analysis

The reliability of the constructs being tested is quantitatively obtained with Cronbach's Alpha reliability measure. With general acceptability defined as anything higher than 0.7 and good to above 0.8 for reliability, its output is examined here. The overall reliability score for all six constructs is 0.908, implying that the internal consistency of the dataset is strong. Among the individual constructs, Customer Trust & Satisfaction has the highest reliability (0.889), followed by Payment Security Systems (0.846) and Transaction Security (0.841). These values are high enough to indicate the presence of a good level of internal consistency with respect to items used to measure these constructs as reliable. AI Techniques has also shown good reliability (0.86), which reflects a well-structured measuring of AI-driven security enhancements in digital banking. Powered Security Systems' slightly lower yet still acceptable reliability score reads 0.776; it indicates a moderate level of internal consistency. However, Digital Banking Platforms has a Cronbach's Alpha value which is notably low at 0.354. This may mean that the survey items are unclear, inter-item correlations are low, or there is a need to refine the measurement scale. Future studies might want to reconsider and expand items for this construct in order to improve reliability. Overall, the constructs have high reliability, thus indicating that the research is valid enough to examine the AI-driven security systems in digital banking.

Table 4: Reliability Analysis

Construct	No. of items	Cronbach Alpha
AI Techniques	5	0.86
Powered Security Systems	5	0.776
Digital Banking Platforms	5	0.354
Transaction Security	5	0.841
Payment Security Systems	5	0.846
Customer Trust & Satisfaction	5	0.889
Overall	6	0.908

Factor Analysis

To validate and test the dimensionality of the constructs applied in the study, factor analysis was performed. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.919, which is well above the recommended threshold of 0.6, meaning that the dataset is suitable for factor analysis. Second, Bartlett's Test of Sphericity was significant (χ^2 = 3750.715, df = 435, $p < 0.001$), with the correlation matrix not being a unit matrix; hence, applying factor analysis could be justified, as it sought to uncover a hidden structure among the data variables. PCA, in this instance, extracted six components that were able to collectively explain 66.51% of the overall variance. It appears that the first component explains about 43.025% variance, followed by 6.289% variance explained by the second component, and 5.426% by the third component. Successive components explained much smaller percent of the variance. The factor solution is good and capable of explaining a great deal of variance in the data set since the cumulative variance explained is more than 60%. The Component Matrix presents the factor loadings of each item on the six components extracted. A loading of an item above 0.5 is considered to have a good correlation with that particular component. The AIT items primarily load onto

Component 1, establishing their internal consistency. The PSS items spread across several components with relatively low loadings; this indicates overlap with other factors. The DBP items are mixed, showing that DBP_1 and DBP_3 load heavily onto Component 3, whereas the rest load elsewhere, meaning there is a bit of inconsistency within this construct. Additionally, Transaction Security (TS) and Payment Security Systems (PASS) items load largely on Component 1, indicating their reliability. Similarly, Customer Trust & Satisfaction (CTS) items load largely on Component 1, showing a close coherence. This implies that trust and satisfaction go together well with security-related concepts, hence validating their role in the research model. From this analysis, it can be concluded that factor analysis supports the dimensionality and validity of most the constructs. However, Digital Banking Platforms show very low factor loadings in most of the domains except for DBP_1 and DBP_3, which may need further investigation. Overall results are that the constructs are well defined and make sense for the present study.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.919
Bartlett's Test of Sphericity	Approx. Chi-Square	3750.715
	Df	435
	Sig.	0.000

Table 5: KMO and Bartlett's Test Results

Component Matrix[a]

	Component					
	1	2	3	4	5	6
AIT_1	.558	.283	.320	.036	-.290	-.098
AIT_2	.751	.289	.194	-.022	-.240	-.091
AIT_3	.682	.337	.039	.008	-.389	.110
AIT_4	.674	.173	-.018	.225	-.335	.145
AIT_5	.702	.136	-.039	.297	-.216	.039
PSS_1	.501	.392	-.094	-.136	.296	.283
PSS_2	.528	.427	-.177	.379	.339	.093
PSS_3	.563	.142	-.124	.490	.121	.176
PSS_4	.525	.493	-.009	.077	.098	-.240
PSS_5	.559	.272	-.183	-.026	.390	-.258
DBP_1	-.022	-.009	.794	.201	.172	.003
DBP_2	.588	.385	.063	-.154	-.011	-.104
DBP_3	-.151	-.124	.741	.217	.110	.130
DBP_4	.664	-.253	-.112	.137	-.010	.246
DBP_5	.661	-.038	.035	-.044	.187	.204
TS_1	.729	.059	.190	-.334	.320	.015
TS_2	.701	-.083	.017	-.260	-.033	-.274
TS_3	.675	-.154	.071	-.063	-.127	-.105
TS_4	.691	-.093	-.154	-.070	-.056	-.360
TS_5	.757	-.310	.061	.196	-.021	-.239
PASS_1	.712	-.352	.007	.017	.135	.080

PASS_2	.736	-.254	-.079	.202	.181	-.142
PASS_3	.669	-.351	.004	.257	.132	-.214
PASS_4	.654	-.246	-.047	.133	-.035	-.192
PASS_5	.738	-.044	-.016	-.295	-.017	.162
CTS_1	.789	.019	.256	-.241	-.021	-.132
CTS_2	.755	-.076	.064	-.308	.058	.175
CTS_3	.776	-.127	.093	-.230	.065	.283
CTS_4	.776	-.320	-.161	.038	-.076	.182
CTS_5	.738	-.146	-.128	.000	-.194	.236

Table 6 Extraction Method: Principal Component Analysis.

Regression Analysis

Dependent Variable: Transaction Security

This is the key model summary table for regression results. The R-value is 0.710, indicating a strong positive correlation between AI Techniques and Powered Security Systems and the dependent variable. The R-Square measures at 0.504, showing that there is a 50.4% explanation variation in the dependent variable for the given set of predictors. Adjusted R-Square at 0.499 adjusts for the number of predictors, thereby confirming good model fit. It reflects the average difference between observed values and predicted values. The average of the estimated standard error is 0.47430, which indicates the model explains most of the variation and thus possesses predictive power.

Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.710[a]	.504	.499	.47430

Table 7 Predictors: (Constant), Powered Security Systems, AI Techniques

The ANOVA table assesses the overall significance of the regression model. The regression sum of squares (45.106) indicates the variation explained by the predictors (AI Techniques and Powered Security Systems), while the residual sum of squares (44.318) represents unexplained variance. The F-statistic (100.252), with 2 and 197 degrees of freedom, is highly significant (p = 0.000), indicating that the model provides a significantly better fit than a model without predictors. Since the p-value is below 0.05, the independent variables significantly contribute to predicting Transaction Security, confirming the model's effectiveness in explaining the dependent variable's variance.

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	45.106	2	22.553	100.252	.000[b]
	Residual	44.318	197	.225		
	Total	89.424	199			

a. Dependent Variable: Transaction Security

b. Predictors: (Constant), Powered Security Systems, AI Techniques

Table 8: Model Fitness

The Coefficients table reveals how each independent variable - AI Techniques and Powered Security Systems - contribute to predicting Transaction Security. The constant is

the expected value of Transaction Security when both independent variables are zero. It is 0.990, p = 0.000. The B coefficient for AI Techniques is 0.476, p = 0.000, indicating that a one-unit increase in AI Techniques results in a 0.476 increase in Transaction Security, all else being held constant. The standardized Beta shows that AI Techniques have the greatest impact among the predictors, which is 0.527. Similarly, the B coefficient for Powered Security Systems is 0.264, p = 0.000, indicating that a one-unit increase in Powered Security Systems increases Transaction Security by 0.264, controlling for AI Techniques. The standardized Beta is 0.250, which indicates a weaker impact than AI Techniques.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.990	.220		4.494	.000
	AI Techniques	.476	.058	.527	8.207	.000
	Powered Security Systems	.264	.068	.250	3.903	.000

a. Dependent Variable: Transaction Security

Table 9: Hypothesis Testing

As both predictors are significant, this model confirms the positive relationship between AI-driven security measures and transaction security. Hence, H1 is accepted and it is inferred that AI Techniques have potent contribution to the enhancement of security than Powered Security Systems as p-value is 0.000 less than the acceptable limit of 0.005.

Dependent Variable: Payment System Security

The Model Summary table analyses the degree to which AI Techniques and Powered Security Systems predict Payment System Security. R-value = 0.660 in which there is much strong variation as predictors have with the dependent variable. The R-Square = 0.436 depicts that 43.6% variation in Payment System Security is accounted for by AI Techniques and Powered Security Systems. The Adjusted R-Square = 0.430, in which sample size adjustment is included, to enhance reliability. The standard error of estimate, being 0.51389, represents the average deviation of the observed values from the predicted ones, thereby depicting moderate accuracy. Overall, the model reflects moderately strong predictability in the context of Payment System Security.

Regression Analysis

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.660[a]	.436	.430	.51389

a. Predictors: (Constant), Powered Security Systems, AI Techniques

Table 10: Regression Analysis

The ANOVA table assesses the model's overall statistical significance. The regression sum of squares (40.254) indicates the explained variance, while the residual sum of squares (52.025) represents unexplained variance. The F-statistic (76.214, p = 0.000) is highly significant, confirming that AI Techniques and Powered Security Systems significantly

contribute to predicting Payment System Security. Since $p < 0.05$, we reject the null hypothesis, concluding that at least one independent variable meaningfully influences the dependent variable. The high F-value suggests a strong model fit, reinforcing that AI-driven security systems effectively enhance Payment System Security in digital banking platforms.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	40.254	2	20.127	76.214	.000[b]
	Residual	52.025	197	.264		
	Total	92.278	199			

a. Dependent Variable: Payment System Security

b. Predictors: (Constant), Powered Security Systems, AI Techniques

Table 11: Model Fitness

The Coefficients table explains the impact of AI Techniques and Powered Security Systems on Payment System Security through regression coefficients. The constant is 1.164, $p = 0.000$, which means that when both predictors are zero, Payment System Security is 1.164 units. This baseline value indicates inherent security factors beyond the model's variables.

The B coefficient for AI Techniques is 0.462, $p = 0.000$, which means that, holding Powered Security Systems constant, a one-unit increase in AI Techniques raises Payment System Security by 0.462. The standardized Beta of 0.503 confirms that AI Techniques has the strongest influence on Payment System Security. Similarly, the B coefficient for Powered Security Systems at 0.232, $p = 0.002$ means that one-unit increase in Powered Security Systems corresponds to a 0.232 increase in Payment System Security net of AI Techniques. The standardized Beta is at 0.217, and although this is an important factor, it follows that AI Techniques are more impactful on securing the payment system. Both the predictors have significant t-values at 7.351 and 3.171, $p < 0.05$, making their effect strong. As p-value is less than 0.005, therefore H2 is accepted and hence it can be concluded that powered security systems play a crucial role in enhancement of payment system security in digital banking platforms.

Dependent Variable: Customer Trust and Satisfaction

The model summary table below gives an indication that the relationship between AI Techniques, Powered Security Systems, and Customer Trust and Satisfaction is very strong. The R-value stands at 0.711, signifying a high positive correlation; meanwhile, R-Square measures to 0.505, showing that the independent variables can explain 50.5% of the variation in Customer Trust and Satisfaction. The Adjusted R-Square value stands at 0.500, hence giving the robustness of the model considering the number of predictors. The standard error of the estimate was at 0.53012, indicating moderate accuracy in the prediction. The model showed significant explanatory power overall and thus explained why AI and security systems were critical to establishing trust among customers of digital banking.

Regression Analysis				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.711[a]	.505	.500	.53012

a. Predictors: (Constant), Powered Security Systems, AI Techniques

Table 12: Regression Analysis

The ANOVA table tests the overall significance of the regression model that predicts Customer Trust and Satisfaction. The sum of squares regression is 56.584, which indicates variance explained by AI Techniques and Powered Security Systems. The residual sum of squares is 55.363, representing unexplained variance. The F-statistic value is 100.673 with a p = 0.000, meaning that the independent variables significantly impact Customer Trust and Satisfaction. The result of the low p-value that is less than 0.05 is the acceptance of the model, indicating that AI-driven enhancements and security systems are very vital in building customer confidence within digital banking environments.

ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	56.584	2	28.292	100.673	.000[b]
	Residual	55.363	197	.281		
	Total	111.947	199			

a. Dependent Variable: Customer Trust and Satisfaction

b.Predictors: (Constant), Powered Security Systems, AI Techniques

Table 13 Model Fitness

The Coefficients table gives an idea about how the AI Techniques and Powered Security Systems affect Customer Trust and Satisfaction in digital banking. The constant value is at 0.750, p = 0.003, which is the baseline level of trust when both independent variables are absent. The B coefficient for AI Techniques is 0.597, p = 0.000, which shows that a one-unit increase in AI Techniques leads to a 0.597 increase in Customer Trust and Satisfaction, showing a strong positive impact. Moreover, the standardized Beta value is 0.589, which further proves that AI Techniques have a higher relative influence on Customer Trust than Powered Security Systems. The B coefficient of Powered Security Systems is 0.205, p = 0.007, which shows that for a one-unit rise in security systems, Customer Trust and Satisfaction improves by 0.205. The standardized Beta value of 0.174, though less than AI Techniques, is also statistically significant for the role played in enhancing trust. Both predictors have p-values less than 0.05, so their effects are highly significant. This analysis points out that AI-driven improvements in security systems are the most important factors in building trust among customers and ensuring a secure and satisfactory digital banking experience.

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	.750	.246		3.045	.003
	AI Techniques	.597	.065	.589	9.196	.000
	Powered Security Systems	.205	.076	.174	2.715	.007

a. Dependent Variable: Customer Trust and Satisfaction

Table 14: Hypothesis Testing

Discussion

The results obtained from this research provide a comprehensive understanding of all the factors, which influence security in digital banking, customer confidence, and ultimately satisfaction. In this respect, it focuses more on the contribution of AI techniques, powered security systems, and digital banking platforms toward security building and, accordingly, customer trust in digital banking services. Analyzing the descriptive statistics, as well as inferential tests such as regression analysis, correlation analysis, and mediation analysis, the study discovers crucial findings to help banks, which intend to enhance their digital banking infrastructure and security measures. The hypotheses of the study, therefore, add clarity on how digital security measures affect customer trust and satisfaction by providing crucial evidence for future advances in the space of digital banking. This section develops the results in greater detail with particular focus on hypotheses.

Descriptive statistics show that respondents have, in general, positive perceptions about the security measures in digital banking. The mean scores for all the variables exceed 3.5 on the 5-point scale, showing a positive view of AI techniques, powered security systems, transaction security, payment system security, and customer trust and satisfaction. The powered security system yields the highest mean score at 3.99, suggesting that respondents have much trust in advanced security technologies. AI techniques also enjoy positive predisposition (mean = 3.81) to play a crucial role in raising the security in digital banking. This indicates that the respondents acknowledge the need for incorporating AI to protect transactions while deterring fraud acts. Considering the technological aspects of AI and machine learning advancements, these opinions reflect that consumers are increasingly looking for AI-enabled security solutions

Most of the skewness scores for the various variables are minus, which states that most have responded positively in their ratings, and this represents that most feel confident about having the security given by digital banks, which represents that a perfect security system retains customers. Skewness and kurtosis of DBP suggest that the responses are highly concentrated at the positive end, suggesting that users find the platforms fairly positive but have a consistency which may not change much across different respondents. On the other hand, this means that there is still room for improvement to create more variability in users' perception of digital banking platforms.

Correlation analysis brings out several significant relationships between the key variables of digital banking security. The findings indicate that AI techniques are significantly positively correlated with transaction security, r =.683, and customer trust and satisfaction, r =.715. These results support the hypothesis that AI-driven security measures have a significant positive impact on both the safety of transactions and customer trust in digital banking platforms. Thus, banks with the aim to reinforce security should offer more AI-based solutions that not only improve technical contents of transaction safety but also psychological contents of customer trust.

Conclusion

The rapid transformation in the banking sector has given rise to a new era with security concerns in digital banking as important as they could ever be. The integration of Artificial Intelligence with new digital banking interfaces has acted as a powerful robust solution for solving most of the issues of security that pertain to transactions, guarding payment systems, and providing good customer trust and satisfaction. This study examined whether AI-based security systems can augment transactional safety, secure pay systems, and strengthen customer trust in digital banks.

This paper focuses on how AI plays an important role in the modern architecture of digital bank security. An AI-based system uses sophisticated algorithms, machine learning, and deep learning to check for fraudulent patterns and anomalies or authenticate transactions. Such technologies largely reduce the chance of cyberattacks, unauthorized transactions, and breaches of data. By inducting AI in the security structures of banks, banking platforms will be able to strengthen their response agility to new cyber threats while continuing to enjoy a strong stance of security.

A key take-away from this research is that AI plays a very important role in transaction security. The backbone of modern banking rests upon digital transactions; thus, this domain of modern banking has become susceptible to fraudulent practices, as well as unauthorized access to digital accounts, without strong security measures. Real-time fraud monitoring, anomaly detection, and behavioral biometrics have brought much greater AI-driven capabilities into transactions. These developments not only guarantee the safety of digital transactions but also make banking operations more efficient, capable of making smooth and safe financial transactions.

The other major area on which this research has focused is the protection of payment systems in digital banking. Payment gateways and online banking services are highly vulnerable to cyberattacks like phishing, ransomware, and identity theft. AI-powered security systems address these weaknesses by engaging in real-time risk assessment, encryption techniques, and predictive analytics. By paying attention to payment activity in real-time and using AI-driven mechanisms for fraud detection, financial institutions minimize fraudulent transactions. This greatly strengthens overall system security. The use of multi-factor authentication, biometric verification, and risk-based authentication by AI enhances user authentication so that only authorized people access and execute financial transactions.

The study also reveals a critical linkage that exists between security in digital banking and customer trust and satisfaction. In the world of digit, trust becomes an essential constituent in customer retention and engagement with a bank's service. Customers insist on safe, reliable, and secure financial portals that assure security for

their information and finances. With AI-based security solutions, such solutions provide extensive protection against cyber threats and improve the user experience to bring about easy and hassle-free transactions. Features like AI chatbots, real-time fraud alerts, and automated dispute resolution add up to make the banking environment secure and customer-friendly. If the customers believe that their financial data is better protected, the confidence with digital platforms is higher, which also brings about higher satisfaction and long-term loyalty.

An additional key benefit is that AI-based security systems support regulatory compliance in the digital banking sector. The very stringent regulations of the banking industry put on strong safety measures to provide safety and security over the customers' data and transactions. AI operates in collaboration with this purpose as it facilitates automated risk assessment, safety reports in real time, and even determines the risk of non-compliance. The banks will adhere to regulatory compliance, avoid hefty penalties, and maintain their reputation in the financial world with the use of AI-driven compliance tools.

Future Recommendations

While AI security systems provide many benefits, the actual implementation comes with its set of challenges. It all starts with questions regarding data privacy and ethics in AI-based digital banking. AI algorithms depend on big data about users to identify patterns and security threats. Unsecured and uncontrolled AI system or handling of data would lead to violation of privacy. Thus, a very strong policy on data governance is to be in place and also have frameworks of AI with transparency in front of which a financial institution adheres strictly with the international standards on data protection such as General Data Protection Regulation (GDPR) and the Payment Card Industry Data Security Standard (PCI DSS).

The other challenge is that AI systems can produce false positives or false negatives in detecting fraud. AI models need to be trained on diverse sets of datasets to reduce the chances of errors and enhance their accuracy in fraudulent activities. Moreover, AI models must be constantly updated and improved to keep abreast with changing threats. Financial institutions need to invest in the expertise and infrastructure of AI and also security audits to continue maintaining their effectiveness in security mechanisms that are AI-driven.

The future of AI in digital banking security seems promising, with ongoing developments in AI technologies leading to more advanced solutions. Blockchain-AI integration is a fast-emerging trend that enhances transactional security and the protection of the payment system. The decentralized nature of blockchain and predictive capabilities of AI can forge a much more resilient and transparent banking ecosystem. Moreover, quantum computing will change AI-driven security through improved encryption methods and faster threat detection processes.

Financial organizations should proactively embrace AI implementation to fully leverage the potential of AI on digital banking security. This involves continuous investment in research and development into AI, collaboration with cybersecurity experts, and a culture of innovation. AI-driven security must be complemented by strong cybersecurity policies that include employee training and awareness among customers so as to establish a comprehensive security structure for digital banking operations.

AI-powered security systems, therefore, are revolutionizing the digital banking landscape by strengthening transactional security and payments and bringing in customer satisfaction and trust. AI equips financial institutions with powerful abilities to detect real-time fraud, strengthen authentication mechanisms, and ensure compliance with regulatory frameworks. However, successful implementation of AI into digital banking security will depend on the ability to overcome challenges linked to data privacy, accuracy, and continuous innovations in AI models. Financial organizations must stay up to date on AI-driven innovations in security and how technology may evolve to give a secure, trustworthy, and resilient digital banking environment. Seamless cooperation between AI and cybersecurity measures will ensure the safety of digital banking for customers as they perform their transactions in an increasingly digital world.

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