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The Effect of Artificial Intelligence on Organizational Resilience in Deposit Money Banks

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Abstract: *The aim of this paper was to find how artificial intelligence (AI) affected organizational resilience in Bauchi State, Nigeria's Deposit Money Banks (DMBs). With an eye toward helping banks to become more flexible, resilient, and successful in the face of challenges, it specifically looks at how artificial intelligence affects strategic, operational, and financial resilience. Emphasizing an organization's capacity to recognize, grab, and use resources in response to changing surroundings, the study was based on the Dynamic Capabilities Theory. Understanding how artificial intelligence helps banks to improve their resilience by predictive analytics, automation, and process innovation calls especially on this theoretical framework. 121 staff members of three different banks in Bauchi State answered self-administered questionnaires forming a cross-sectional survey design. The sample size was calculated from the Krejcie and Morgan Table; descriptive and inferential statistics—including Linear Regression at a 0.05 significance level—were then applied in data analysis. Results show that strategic, operational, and financial resilience in DMBs benefits much from artificial intelligence. By means of scenario planning and long-term adaptability, operational resilience through automation and real-time monitoring, and financial resilience by means of resource allocation and guarantees of liquidity during economic crisis, artificial intelligence strengthens strategic resilience. The study recommended that DMBs to invest in AI-driven tools for scenario planning and predictive analytics to boost strategic resilience, apply AI-powered automation and monitoring systems to strengthen operational resilience, and employ AI for financial modeling and cost control to so increase financial resilience. To further reduce the risks connected with the use of artificial intelligence, banks should also implement strong governance systems and ethical issues.*

Keywords: Artificial Intelligence; Organizational Resilience; Deposit Money Banks; Dynamic Capabilities Theory; Strategic Resilience; Operational Resilience and Financial Resilience.

Keywords: *Artificial Intelligence; Organizational Resilience; Deposit Money Banks; Dynamic Capabilities; Adaptability*

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1.0 Introduction

Artificial intelligence (AI) has quickly changed many sectors, including the banking sector (Umamaheswari & Valarmathi, 2023). Increasingly adopting AI-driven technologies to improve operational efficiency, customer experience, and decision-making processes, Deposit Money Banks (DMBs), which are vital in financial intermediation and economic stability, are being adopted by AI-driven technologies (Nambie et al., 2024) Artificial intelligence applications including predictive analytics, natural language processing, and machine learning are being used to automate daily chores, identify fraudulent activity, and offer customized financial services (Hassan et al., 2023). But as the banking industry depends increasingly on artificial intelligence, concerns regarding how technology affects organizational resilience—that is, institutions' capacity to adjust, bounce back, and flourish in the face of upheavals (Deng, 2024). Particularly in an era of technical, financial, and legal uncertainty, this paper aims to investigate how artificial intelligence shapes the resilience of DMBs.

Particularly in the face of obstacles including cyberattacks, economic downturns, and legislative changes, organizational resilience in the banking industry is very vital for preserving financial stability and customer confidence (Dupont, 2019). Resilience has long been connected historically to strong risk management systems, agile decision-making, and flexible corporate cultures (Holbeche, 2019). But the incorporation of artificial intelligence presents opportunities as well as difficulties for these systems of resilience-building. On the one hand, artificial intelligence can improve prediction skills so that banks may more precisely foresee and reduce risks (Ashta & Herrmann, 2021). Conversely, over-reliance on artificial intelligence systems could expose weaknesses including algorithmic biases, data privacy issues, and the possibility of systematic failures (Lockey et al, 2021). DMBs must be able to negotiate the complexity of the digital age by knowing the double functions of artificial intelligence in promoting and diminishing resilience.

The dynamic character of the financial ecosystem adds much more complexity to the acceptance of artificial intelligence in DMBs. Rapid technology advances, changing client expectations, and strict regulatory demands define the environment in which banks work (Obeng et al, 2024). AI needs large expenditures in infrastructure, people, and governance even as it can help banks remain competitive by raising efficiency and innovation (Boobier, 2020). Furthermore, the opaque character of artificial intelligence algorithms presents difficulties for openness and responsibility, which are very important for preserving stakeholder confidence (Obeng et al, 2024). This paper seeks to analyze how DMBs could balance using artificial intelligence for competitive advantage with making sure the inherent hazards of AI technology do not damage their resilience.

With little regard for the banking industry, existing research on artificial intelligence and organizational resilience has mostly concentrated on manufacturing, healthcare, and supply chain management. Although some studies have shown how artificial intelligence could improve operational efficiency and risk management in banks, knowledge of how AI affects the more general aspects of organizational resilience—including strategic adaptability, employee preparedness, and customer confidence—is lacking. By looking at the interaction between artificial intelligence adoption and resilience-building techniques in DMBs, this paper aimed to close this disparity. By doing this, it hopes to offer insights that would enable banks to create AI plans that not only boost innovation but also increase their resilience to the ability to bounce back from disruptions.

The study provided answers to the following questions:

i. What effect does artificial intelligence have on strategic resilience of Deposit Money Banks in Bauchi State, Nigeria?
ii. What effect does artificial intelligence have on operational resilience of Deposit Money Banks in Bauchi State, Nigeria?
iii. What effect does artificial intelligence have on financial resilience of Deposit Money Banks in Bauchi State, Nigeria?

1.1 Literature Review

Section 2.0 provides a comprehensive literature review that sets the foundation for understanding how organizations build resilience and adapt to rapidly changing environments. This section explores key concepts related to organizational resilience, such as proactive planning, risk management, and agile innovation, while also considering the challenges posed by volatile, unpredictable, complex, and ambiguous conditions. The review draws upon a broad range of studies to illuminate how firms can anticipate, respond to, and recover from disruptions while maintaining long-term success.

1.1.1 Theoretical Framework

Section 2.1 narrows the focus to the theoretical framework that underpins this study, with a particular emphasis on Dynamic Capabilities Theory. Originally proposed by Teece, Pisano, and Shuen in 1997, this theory emerged as a response to the limitations of the resource-based view, arguing that competitive advantage depends not only on possessing valuable resources but also on the ability to sense opportunities, seize them, and continuously transform organizational processes. Despite criticisms regarding its abstract nature and measurement challenges, the theory remains highly relevant for examining how organizations, especially in dynamic sectors like banking, integrate advanced technologies such as artificial intelligence to enhance resilience and adaptability.

Dynamic Capabilities Theory

David Teece, Gary Pisano, and Amy Shuen first proposed dynamic capabilities theory in their key 1997 paper, Dynamic Capabilities and Strategic Management. Faced with the constraints of the firm's resource-based view (RBV), which concentrated on stationary resources as the basis of competitive advantage (Kero & Bogale, 2023), the theory developed as a reaction. Teece and his colleagues contended that organizations need dynamic capacities to adapt, innovate, and reinterpret their resources and processes in fast changing surroundings than only valued resources (Pitelis et al., 2024). According to the theory, dynamic capabilities—that is, the capacity of the organization to combine, develop, and reconfigure internal and external skills to fit evolving conditions—are what enable it to Sensing (identifying opportunities and dangers), seizing (mobilizing resources to capitalize on opportunities), and transforming (continuously renewing and reconfiguring the organization to sustain competitiveness) are three basic processes under which these capabilities fall (Malik, 2023).

Dynamic Capabilities Theory has not been without controversy even if it is somewhat popular. Its seeming ambiguity and lack of operationalizability are among main criticisms. Critics contend that the theory is overly abstract and impossible to measure or implement in useful settings (Ince & Hahn, 2020). Furthermore, some academics argue that the theory lacks originality since it greatly overlaps with already accepted ideas such organizational learning and creativity. Others note that the theory's high degree of managerial foresight and agility—which might not always be present in companies, particularly in highly regulated sectors like banking—is assumed by it. These objections underline the need of more empirical study to improve and validate the constructions of the theory, especially in particular environments like the banking industry.

Notwithstanding these criticisms, Dynamic Capabilities Theory is still very relevant and best underlines the research on how artificial intelligence affects organizational resilience in Deposit Money Banks (DMBs) (Ince & Hahn, 2020). The emphasis of the theory on adaptation, creativity, and reconfiguration fits very well the possibilities and difficulties provided by artificial intelligence acceptance in the banking industry. By means of predictive analytics and real-time monitoring, AI helps DMBs to improve their sensing capacities; by means of optimal decision-making and resource allocation, it helps them to increase seizing capabilities; and by means of automation and process innovation, it drives transformation (Arokodare & Asikhia, 2020). Moreover, the emphasis of the theory on ongoing education and renewal fits the feature of cultural and human resilience that is essential for effective integration of artificial intelligence. Dynamic Capabilities Theory allows the research to methodically investigate how artificial intelligence affects the resilience of DMBs, so offering a strong basis for knowledge of the dynamic interaction between technology and organizational flexibility in a fast changing financial environment.

1.2 Conceptual Review

1.2.1 Concept of Organizational Resilience

Organizational resilience is the capacity of a company to foresee, get ready for, react to, and adjust to disturbances, crises, or environmental changes while keeping continuous operations and accomplishing long-term success (Duchek, 2020). It covers the ability to bounce back from shocks, fast recuperate, and even come out of hardship stronger. Resilience is about surviving in the face of adversity by using strengths, learning from events, and encouraging adaptability—not only about survival but also about In the volatile, unpredictable, complex, and ambiguous (VUCA) environment of today, when businesses run across a wide spectrum of hazards including technological disruptions, economic instability, cyber attacks, and legislative changes (Komytska, 2023), this idea is especially important. Many times seen as a complex concept with strategic, operational, financial, cultural, and human aspects each adding to the general ability of the company to negotiate uncertainty.

Fundamentally, organizational resilience is developed from proactive planning, strong risk management, and an agile and innovative culture (Johnson & Walker, 2023). It calls on companies to create systems and procedures that let them spot possible hazards early on, handle crises, and modify their operations and plans to fit new conditions (Duchek, 2020.). A strong company might, for instance, make investments in duplicate systems to guarantee business continuity, build a culture of learning and teamwork to improve staff readiness, and keep financial buffers to help to withstand economic shocks. Crucially, resilience is a dynamic capacity that develops over time by constant learning and progress rather than a fixed quality (Barinua & Nwimua, 2022). Organizations can not only withstand shocks but also grab new possibilities by including resilience into their DNA, therefore guaranteeing sustainable development and competitiveness in a terrain always shifting.

1.3 Measures of Organizational Resilience

There are various measures of organizational resilience however, this study adopted the following:

1. 3.1 Strategic Resilience

A crucial component of organizational resilience, strategic resilience emphasizes on an entity's capacity to modify its long-term objectives, plans, and business models in reaction to changing surroundings (Herbane, 2019). It requires foresight, adaptability, and the ability to turn around when confronted with disturbances to make sure the company stays competitive and sustainable over time. In dynamic sectors like banking, where technology developments, legislative changes, and changing consumer expectations can quickly affect the competitive environment, strategic resilience is especially vital (Iriani et al., 2024). High strategic resilience organizations are keen in spotting new trends, spotting possible hazards, and reorganizing their plans to grab fresh prospects. By matching its long-term objectives with changing market conditions, a bank that proactively embraces digital transformation strategies to meet the rising demand for online banking services, therefore demonstrating strategic resilience (Napier, et al., 2024).

Evaluating strategic resilience is determining how creatively innovative, flexible, and strategically agile a business can be. Important markers include the organization's research and development (Iriani et al., 2024), the speed and accuracy of decision-making procedures, and the success of scenario planning. Strategic resilience also distinguishes itself in the ability to balance long-term strategic aims with short-term operational needs. Strategic resilience is shown, for example, by a bank that invests in AI-driven technology to improve customer experience while preserving financial stability or diversifies income sources (Nosike et al., 2024). Organizations can increase their strategic resilience by encouraging a culture of lifelong learning and innovation, therefore helping them to negotiate uncertainty and come out from disturbances stronger. This aspect of resilience guarantees that companies not only overcome obstacles but also set themselves for continuous development and success in an always changing surroundings.

1.3.2 Operational Resilience

A fundamental component of organizational resilience, operational resilience emphasizes on an organization's capacity to sustain important operations and provide services both during and following disturbances (Annarelli, et al., 2020). It underlines how strong systems, infrastructure, and processes are to resist shocks and bounce back fast, therefore guaranteeing little disturbance of operations. In sectors like banking, where service continuity is crucial to keeping customer confidence and regulatory compliance, operational resilience is especially significant (Dupont, 2019). proactive measures like business continuity planning, disaster recovery systems, and redundancy in important operations constitute this dimension. For instance, a bank with geographically scattered data centers and a well-tested disaster recovery strategy can keep running smoothly even amid cyberattacks or natural catastrophes, hence proving great operational resilience (Holloway, 2023).

Measuring operational resilience means assessing how well an organization's contingency planning, risk management systems, and reaction systems work. Important markers include the speed of disruption recovery, IT system dependability, and incident response team (Rahi, 2019) efficiency. Furthermore essential for operational resilience is the capacity to spot and minimize weaknesses in operational systems. Strong operational resilience is shown, for example, by a bank that routinely tests its systems and changes its policies in response to past disruptions (Karakasiloti, 2024). Organizations can increase their capacity to endure and recover from disruptions by investing in robust infrastructure, encouraging cross-functional cooperation, and always refining operational processes, therefore guaranteeing ongoing service delivery and long-term success (Rahi, 2019).

1.3.3 Financial Resilience

A key component of organizational resilience, financial resilience gauges a company's capacity to withstand financial shocks and maintain operations under times of economic crisis (Zahedi et al., 2022). It shows the financial strength of a company including its liquidity, capital fit, and capacity for efficient cost control. In volatile sectors like banking, where economic downturns, market volatility, and legislative changes can dramatically affect income sources and profitability, financial resilience is especially crucial (Hussain & Papastathopoulos, 2022). High financial resilience companies are better able to negotiate uncertainty, make investments in expansion prospects, and keep stakeholder confidence. Strong capital buffers, varied income streams, and careful risk management techniques, for instance, let a bank survive economic crises—such as recessions or unexpected market collapses—without sacrificing operational stability (Hussain & Papastathopoulos, 2022).

Evaluating important financial indicators including debt-to---equity ratios, liquidity ratios, and emergency fund availability helps one to measure financial resilience. Crucially also markers of financial resilience are capacity to control expenses, maximize resource allocation, and create sustainable income sources (Grzelczak et al., 2024). Strong financial resilience can be shown, for example, by a bank with a good balance sheet, routinely stress-tested financial models, and with contingency funding plans in place. Organizations that give financial stability a priority will be confident they have the means to withstand disruptions, make investments in innovation, and grab fresh possibilities (Iriani et al., 2024). In an uncertain economic environment, financial resilience not only protects an organization's immediate survival but also sets it for long-term development and competitiveness.

1.4 Concept of Artificial Intelligence

Artificial intelligence (AI) is the replication of human intellect in computers built to complete activities usually needing human cognition, including learning, reasoning, problem-solving, and decision-making (Korteling et al., 2021, Ariyibi et al., 2024). Using algorithms, data, and processing capability, artificial intelligence systems examine trends, generate forecasts, and automate tasks. These systems can be classified as general AI, which seeks to duplicate human-like intelligence over a broad spectrum of activities, and narrow AI, which is intended for certain tasks (e.g., facial recognition or language translation). By improving efficiency, accuracy, and invention, artificial intelligence technologies—machine learning, natural language processing, and computer vision—are revolutionizing sectors (Olowu et al., 2024). In the banking industry, for instance, artificial intelligence is applied for customer service chatbots, fraud detection, and tailored financial suggestions, so transforming bank operations and client interaction.

The aim behind artificial intelligence is to design tools that might either replicate or surpass human capacity in particular fields. To train models, increase accuracy, and over time react to new information, it depends on enormous volumes of data (Markauskaite et al., 2022). Although artificial intelligence presents major advantages including higher production and better decision-making, it also presents ethical, societal, and technological problems. Problems include algorithmic bias, data privacy, and possible employment displacement call for rigorous thought and control (Kuhl et al., 2020). Driven by developments in processing power, data availability, and algorithmic innovation, artificial intelligence keeps developing fast despite these difficulties (Adako et al., 2024). Understanding its capabilities and constraints becomes crucial as companies embrace artificial intelligence (AI) more and more in order to maximize its possibilities while lowering risks and so guarantee that AI helps to ensure that society and the economy advance (Adeusi et al., 2024).

1.4.1 Empirical Review

Gupta et al. (2021) investigated how strong information systems might help to reduce the degree of risk in supply chain operations' disruption scenarios. The paper is done in the qualitative approach using a semistructured interview schedule for supply chain specialists. Emerging categories have been developed by means of a theme analysis. The results of this paper show important shortcomings in present information systems and show how artificial intelligence-oriented solutions might help the ecosystem of disrupted supply chains to reduce money and increase efficiency on several criteria. The paper also suggests a conceptual framework wherein architectural elements and organizational principles can be seen together for suitable business decisions in complicated and uncertain disruptions. The framework shows the interactions among artificial intelligence, information systems, and supply chains disturbance. Along with information system infrastructure, installing appropriate AI-based data acquisition, processing, and self-training capabilities will help companies minimize the impact of supply chain disturbance and guarantee geographically appropriate supply chains and cybersecurity, so aligning the transportation network. At last, the consequences for theory and practice with regard to the constraints and extent of future study are discussed.

Emphasizing the difficulty firms have in juggling agility and resilience during disaster responses, Dubey et al., (2022) investigates the role of artificial intelligence-driven big data analytics capabilities (AI-BDAC) in humanitarian assistance operations. Although academics in operations management differ on whether responsiveness should take precedence over efficiency, the paper contends that managing unforeseen occurrences like disasters depends critically on both agility and resilience. Previous studies have used the resource-based view (RBV) or dynamic capability view (DCV) to describe how combinations of resources and capabilities—e.g., technology, agility, resilience—afford performance. With 171 responses gathered via a web survey of international non-governmental organizations (NGOs), the study tests its assumptions using Partial Least Squares (PLS) analysis. The results show that in humanitarian supply chains AI-BDAC greatly improves agility, robustness, and performance. Moreover, it simplifies information complexity (IC), thereby enhancing the links among agility, resilience, and performance. The study comes to the conclusion that although the PBV provides a more efficient theoretical lens, the RBV and DCV are insufficient for adequately reflecting the actual dynamics of humanitarian supply chains. The paper also notes its constraints and offers recommendations for next investigations.

Gupta et al., (2023) investigated empirically the ability of AI and BT to determine their part in supply chain financial resiliency. Additional research takes into account the environmental dynamism controlling the link between artificial intelligence and BT resulting in supply chain financial resilience. Using a multi-methodological approach, we investigate the relationship between artificial intelligence, BT, and supply chains' financial resilience by means of an empirical and qualitative research. While the qualitative study gathered responses from 25 supply chain experts using semi-structured interviews and the grounded approach, 202 survey responses from supply chain professionals were gathered to evaluate the theoretical model in data collecting. Our results show that, under the moderating effect of environmental dynamism, blockchain technology is stronger in enabling financial resilience of a supply chain than artificial intelligence after structural equation modeling for the quantitative data analysis. Thematic analysis for the qualitative study show how blockchain in seizing and financial resilience in reconfiguring the prospects reside in supply chain, and how artificial intelligence senses. AI is fit for blockchain implementation and perceiving the corporate surroundings. This

paper presents a theoretical contribution as well as pragmatic ramifications for managers.
Under a dynamic and supply chain uncertainty framework, Belhadi et al., 2024 looked at the direct and indirect impacts of artificial intelligence, SCRes, and SCP. By doing thus, we have conceived the use of artificial intelligence in the supply chain on the organizational information processing theory (OIPT). Structural equation modeling (SEM) was used to assess the created framework. Data on surveys was gathered from 279 companies spanning several nations, sectors, and sizes. Although artificial intelligence directly affects SCP in the near future, our results imply that itis advised to take use of its information processing capacity to develop SCRes for long-term SCP. Among the first to offer practical data on optimizing the advantages of artificial intelligence capacity to produce continuous SCP is this work. One could extend the study by means of a longitudinal research to investigate other aspects of the phenomena.

Operational Framework

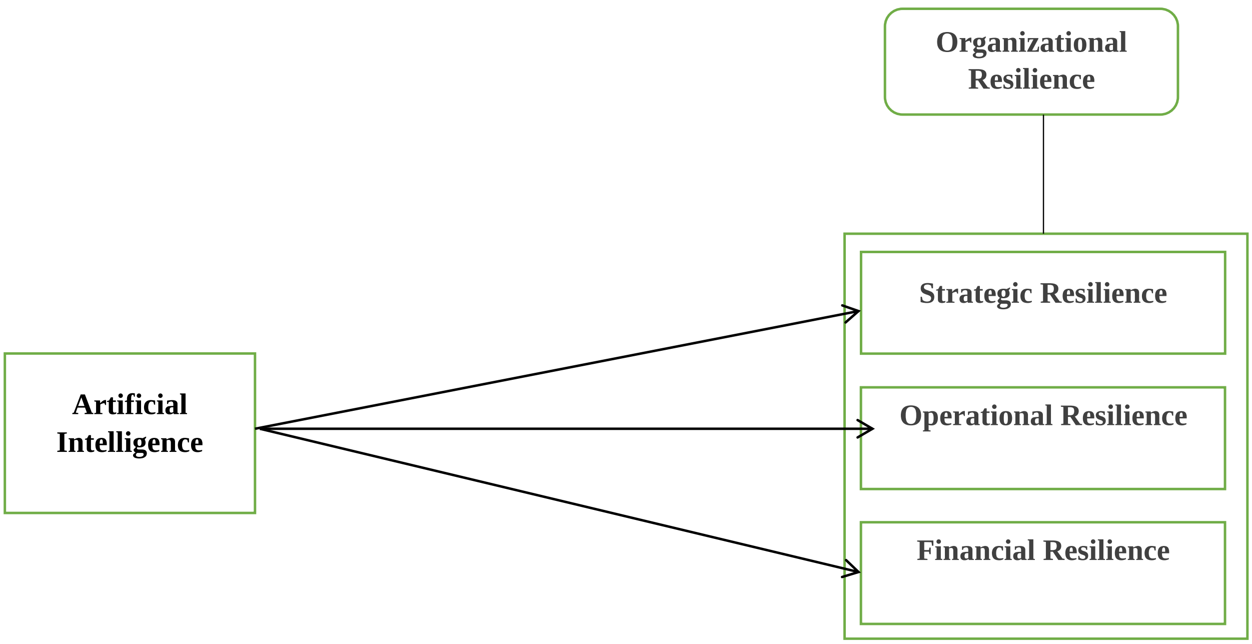

Fig. 1: **Operational Framework of the Study Showing Relationship of the study variables**
Source: **Author's Desk Research, 2025**

The following hypotheses were drawn:

$H0_1$: Artificial intelligence does not significantly affect strategic resilience of Deposit Money Banks in Bauchi State, Nigeria

$H0_2$: Artificial intelligence does not significantly affect operational resilience of Deposit Money Banks in Bauchi State, Nigeria

$H0_3$: Artificial intelligence does not significantly affect financial resilience of Deposit Money Banks in Bauchi State, Nigeria

2.0 Materials and Method

This study adopted a cross-sectional survey design to investigate the impact of artificial intelligence on organizational resilience in Deposit Money Banks in Bauchi State, Nigeria.

Data were collected through self-administered questionnaires, which served as the primary instrument for capturing responses from bank staff. The target population consisted of staff from three major banks in Bauchi State: 47 employees from Guarantee Trust Bank, 59 from First Bank Plc, and 66 from United Bank for Africa, totaling 172 respondents.

Using the Krejcie and Morgan (1970) table as a guide, a sample size of 121 respondents was determined to be representative of the population. Participants were selected through a simple random sampling technique to ensure that every member of the population had an equal chance of inclusion in the study.

The questionnaire underwent expert review and evaluation, and the reliability of the instrument was confirmed with a Cronbach's Alpha coefficient exceeding 0.70 for all items. Data analysis was conducted using both descriptive and inferential statistical methods. The study tested its hypotheses through linear regression analysis, employing a significance level of 0.05 and a 95% confidence interval to determine statistical significance.

3.0 Results and Discussion

The results of this study examine the impact of Artificial Intelligence (AI) on the resilience of Deposit Money Banks (DMBs) in Bauchi State, Nigeria. The analysis involves assessing strategic, operational, and financial resilience using statistical models. Each table is introduced, interpreted, and discussed before the test of hypotheses.

3.1 Strategic Resilience Analysis

Table 1 provides a model summary that evaluates the relationship between artificial intelligence (AI) and strategic resilience in Deposit Money Banks. The table shows an R value of 0.780, indicating a strong positive correlation between the two variables. Additionally, the R Square value of 0.609 signifies that approximately 61% of the variance in strategic resilience can be explained by the integration of AI. This robust level of explained variance suggests that AI plays a critical role in enhancing the strategic resilience of these banks.

Table 1: Model Summary (Strategic Resilience Analysis)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.780	0.609	0.605	0.66591
a. Predictors: (Constant), Artificial Intelligence				

Table 2 presents the ANOVA results for the regression model examining the relationship between artificial intelligence and strategic resilience. The table indicates that the regression sum of squares is 70.456, while the residual sum of squares is 45.231, resulting in a total sum of squares of 115.687. With 1 degree of freedom for the regression and 102 degrees of freedom for the residual, the mean square for the regression is 70.456. The model's F-statistic is 158.884, accompanied by a p-value of 0.000, which is well below the conventional significance level of 0.05. These results confirm that the regression model is statistically significant, meaning that artificial intelligence is a significant predictor of strategic resilience in Deposit Money Banks.

Table 3 presents the regression coefficients for the model predicting strategic resilience. The constant is estimated at 0.637 with a standard error of 0.251, yielding a t-value of 2.540 and a p-value of 0.013, indicating that it is statistically significant. The coefficient for artificial intelligence is 0.803 with a standard error of 0.064, a standardized beta of 0.780, and a t-value of 12.605, with a p-value of 0.000. These results confirm that artificial intelligence is a strong and statistically significant predictor of strategic resilience in Deposit Money Banks.

Table 2: ANOVA (Strategic Resilience Analysis)

Model	Sum of Squares	df	Mean Square	F	Sig.
1	70.456	1	70.456	158.884	0.000
Residual	45.231	102	0.443		
Total	115.687	103			

a. Dependent variable: strategic resilence, b, predictors (constant, AI)

Table 3: Regression Coefficients (Strategic Resilience Analysis)

Model	Variable	Unstandardized Coefficients (B)	Std. Error	Standardized Coefficients (Beta)	t	Sig.
1	(Constant)	0.637	0.251		2.540	0.013
	Artificial Intelligence	0.803	0.064	0.780	12.605	0.000
a. Dependent Variable: Strategic Resilience						

The coefficient table shows that AI has a significant effect on strategic resilience (p = 0.000). Since the p-value is less than 0.05, the null hypothesis is rejected, confirming that AI significantly influences strategic resilience in DMBs.

3.2 Operational Resilience Analysis

Table 4 summarizes the model's performance in explaining the relationship between artificial intelligence and the dependent variable. The R value of 0.899 indicates a strong positive correlation, while the R Square value of 0.809 shows that about 81% of the variance in the dependent variable is explained by the model. The Adjusted R Square of 0.807 confirms that this relationship remains robust even after accounting for the number of predictors, and the standard error of 0.48170 reflects a reasonably low level of prediction error.

Table 4: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.899	0.809	0.807	0.48170
a. Predictors: (Constant), Artificial Intelligence				

The R value of 0.899 indicates a very strong relationship between AI and operational resilience, with R Square showing that AI explains 81% of the variance.

Table 5 presents the ANOVA results for the model evaluating the impact of artificial intelligence on operational resilience. The analysis shows a regression sum of squares of 100.241 and a residual sum of squares of 23.667, resulting in a total sum of squares of 123.908. With an F value of 432.010 and a p-value of 0.000, the model demonstrates a highly significant effect of artificial intelligence on operational resilience, confirming that the predictor significantly explains the variability in the dependent variable.

Table 5: Table 5: ANOVA Analysis for Operational Resilience Model

Model	Sum of Squares	df	Mean Square	F	Sig.
1	100.241	1	100.241	432.010	0.000
Residual	23.667	102	0.232		
Total	123.908	103			
a. Dependent Variable: Operational Resilience					
b. Predictors: (Constant), Artificial Intelligence					

The ANOVA results show a significant effect of AI on operational resilience (F = 432.010, p = 0.000). Table 6 displays the regression coefficients for the operational resilience model. The constant (or intercept) is estimated at 0.188 with a standard error of 0.181, yielding a t-value of 1.036 (p = 0.303), which is not statistically significant. However, the coefficient for Artificial Intelligence is 0.958, with a standard error of 0.046 and a standardized beta of 0.899, resulting in a t-value of 20.785 and a p-value of 0.000. This highly significant result ($p < 0.05$) indicates that artificial intelligence has a substantial and statistically significant positive impact on operational resilience in Deposit Money Banks.

Table 6: Table 6: Regression Coefficients for Operational Resilience

Model	Variable	Unstandardized Coefficients (B)	Std. Error	Standardized Coefficients (Beta)	t	Sig.
1	(Constant)	0.188	0.181		1.036	0.303
	Artificial Intelligence	0.958	0.046	0.899	20.785	0.000
a. Dependent Variable: Operational Resilience						

Since the p-value is 0.000, the null hypothesis is rejected, confirming that AI significantly impacts operational resilience in DMBs.

3.3 Financial Resilience Analysis

Table 7 presents the model summary, illustrating the overall fit of the model. Table 8 details the ANOVA results that confirm the model's statistical significance, and Table 9 displays the regression coefficients, indicating the strength and direction of the relationship between artificial intelligence and financial resilience.

Table 7: Financial Resilience Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.833	0.694	0.691	0.54811

a. Predictors: (Constant), Artificial Intelligence

This table shows that the model has an R value of 0.833, indicating a strong positive correlation between artificial intelligence and financial resilience. The R Square value of 0.694 suggests that approximately 69% of the variance in financial resilience is explained by the model, which confirms a good fit for the predictor variable..

The ANOVA table (Table 8) demonstrates that the model is statistically significant, with an F value of 230.863 and a p-value of 0.000. This indicates that the variation explained by the model is significant and that artificial intelligence is a critical predictor of financial resilience.

Table 8: ANOVA Results for Financial Resilience Model

Model	Sum of Squares	df	Mean Square	F	Sig.
1	69.356	1	69.356	230.863	0.000
Residual	30.643	102	0.300		
Total	99.999	103			

a. *Dependent Variable: Financial Resilience*
b. *b. Predictors: (Constant), Artificial Intelligence*

Table 9 indicates that the constant is 0.786 and that the coefficient for artificial intelligence is 0.796 with a standardized beta of 0.833. The t-value of 15.194 and a p-value of 0.000 for artificial intelligence confirm that the effect is statistically significant. Since the p-value is less than 0.05, we reject the null hypothesis, confirming that artificial intelligence has a significant positive influence on financial resilience.

Table 9: Regression Coefficients for Financial Resilience Model

Model	Variable	Unstandardized Coefficients (B)	Std. Error	Standardized Coefficients (Beta)	t	Sig.
1	(Constant)	0.786	0.206		3.807	0.000
	Artificial Intelligence	0.796	0.052	0.833	15.194	0.000

a. Dependent Variable: Financial Resilience

Test of Hypotheses

Hypothesis 1:

H_0: Artificial intelligence does not significantly affect the strategic resilience of Deposit Money Banks in Bauchi State, Nigeria.

To test this hypothesis, the model yielded an R value of 0.780 and an R^2 of 0.609, indicating that approximately 61% of the variance in strategic resilience is explained by artificial intelligence. The ANOVA results produced an F value of 158.884 with a p-value of 0.000, and the coefficient for artificial intelligence was significant ($p = 0.000$). Based on these statistical parameters, the null hypothesis is rejected, demonstrating that artificial intelligence significantly influences strategic resilience.

Hypothesis 2

H_0: Artificial intelligence does not significantly affect the operational resilience of Deposit Money Banks in Bauchi State, Nigeria.

The model for operational resilience revealed an R value of 0.899 and an R^2 of 0.809, meaning that 81% of the variance in operational resilience is attributed to artificial intelligence. The ANOVA table showed an F value of 432.010 with a p-value of 0.000, and the coefficient for the predictor was highly significant (p = 0.000). These results lead to the rejection of the null hypothesis, indicating that artificial intelligence significantly impacts operational resilience.

Hypothesis 3

H_0: Artificial intelligence does not significantly affect the financial resilience of Deposit Money Banks in Bauchi State, Nigeria.

For financial resilience, the model produced an R value of 0.83 and an R^2 of 0.694, suggesting that 69% of the variance is explained by artificial intelligence. The ANOVA analysis resulted in an F value of 230.863 and a p-value of 0.000, and the coefficient for artificial intelligence was statistically significant (p = 0.000). These findings compel us to reject the null hypothesis, confirming that artificial intelligence significantly influences the financial resilience of the banks.

Overall, the statistical evidence across all three hypotheses demonstrates that artificial intelligence plays a crucial role in enhancing strategic, operational, and financial resilience in Deposit Money Banks in Bauchi State, Nigeria.

3.4 Discussion of Findings

Table 10 shows detailed discussion and comparison of the findings for the three hypotheses, presented in a chart format along with an interpretative narrative that links these results to the relevant literature.

Table 10: Chart: Comparison of Results and Discussion for the Three Hypotheses

Hypothesis	Key Statistics	Interpretation	Comparison with Literature	Implications for DMBs
H_1: Strategic Resilience (AI's effect on long-term adaptability)	R = 0.780 R^2 = 0.609 F = 158.884 p = 0.000 Coefficient p = 0.000	AI explains 61% of the variance in strategic resilience, indicating a significant impact. This suggests that AI adoption strongly contributes to a bank's ability to adapt its strategic orientation and long-term planning in response to environmental changes.	These results support the views of Teece et al. (1997) and Malik (2023), who emphasize the importance of dynamic capabilities for strategic flexibility. Gupta et al. (2021) also noted that AI can drive enhanced decision-making and strategic reconfiguration.	DMBs that integrate AI may achieve improved strategic resilience by better identifying opportunities, managing risks, and continuously realigning their long-term objectives.
H_2: Operational Resilience (AI's effect	R = 0.899 R^2 = 0.809 F = 432.010	AI explains 81% of the variance in operational resilience,	This finding is consistent with the work of Dubey et al. (2022) and Annarelli	With the integration of AI, DMBs can achieve higher

on day-to-day efficiency)	p = 0.000 Coefficient p = 0.000	underscoring its significant role in enhancing daily operational efficiency. The high R^2 suggests that nearly all variations in operational performance can be attributed to the influence of AI.	et al. (2020), who demonstrated that AI-driven systems substantially improve operational efficiency, risk management, and service continuity.	levels of operational efficiency, reduce downtime, and maintain continuous service even during disruptions, thereby boosting overall performance.
H_3: Financial Resilience (AI's effect on resource management and stability)	R = 0.83 R^2 = 0.694 F = 230.863 p = 0.000 Coefficient p = 0.000	AI accounts for 69% of the variance in financial resilience, signifying a strong effect on the banks' ability to manage financial resources and sustain economic stability.	The results align with findings by Dupont (2019) and related studies, which highlight that AI improves financial performance through enhanced resource allocation and risk prediction.	Implementing AI in financial processes may enable DMBs to optimize resource allocation, improve risk assessment, and ultimately sustain financial stability in a competitive market.

The analysis of the three hypotheses reveals that artificial intelligence significantly affects all three dimensions of organizational resilience in Deposit Money Banks in Bauchi State, Nigeria. For strategic resilience, an R^2 of 0.609 indicates that 61% of the variability in strategic adaptability is explained by AI, reinforcing the idea that AI plays a critical role in shaping long-term strategic planning and adaptive capabilities. These findings are supported by the theoretical framework proposed by Teece et al. (1997) and further elaborated by Malik (2023), which stress the importance of dynamic capabilities in a changing environment. Gupta et al. (2021) similarly argued that AI-driven insights foster strategic agility, enabling organizations to realign their strategies in response to external shocks.

Operational resilience demonstrated an even stronger relationship with AI, as evidenced by an R^2 of 0.809. This high value implies that nearly 81% of the variation in day-to-day operational performance can be attributed to the use of AI. The operational benefits are in line with the conclusions of Dubey et al. (2022) and Annarelli et al. (2020), who highlighted that real-time monitoring and predictive maintenance—key features of AI systems—are critical for ensuring continuous and efficient operations. In practical terms, the adoption of AI in DMBs can reduce downtime and enhance service reliability, which is particularly vital during periods of disruption.

Financial resilience is also significantly influenced by AI, with an R^2 of 0.694 indicating that 69% of the variance in financial stability is due to AI. This relationship confirms that AI is instrumental in improving resource management, risk assessment, and overall financial performance. These results resonate with the findings of Dupont (2019) and related studies, which have shown that AI integration leads to more effective financial decision-making and resource optimization. For banks, this means that leveraging AI can enhance financial stability and support sustainable growth, even in a competitive and uncertain economic environment.

Overall, the empirical evidence from this study demonstrates that artificial intelligence plays a pivotal role in enhancing strategic, operational, and financial resilience in Deposit Money Banks. The consistent statistical significance across all three dimensions underscores the transformative potential of AI in the banking sector. These findings not only add to the existing body of literature on AI and organizational resilience but also provide practical implications for financial institutions seeking to maintain competitiveness in rapidly evolving environments. By integrating AI technologies, banks can achieve superior adaptability, efficiency, and stability, positioning themselves to navigate future challenges effectively.

4.0 Conclusion

This study investigated the impact of artificial intelligence on organizational resilience in Deposit Money Banks in Bauchi State, Nigeria, revealing that AI significantly enhances strategic, operational, and financial resilience. The findings demonstrated that AI accounts for 61% of the variance in strategic resilience, 81% in operational resilience, and 69% in financial resilience, with all statistical tests indicating strong significance. The research confirms that integrating AI into banking operations not only strengthens decision-making and resource optimization but also supports continuous service delivery and financial stability. In conclusion, artificial intelligence emerges as a pivotal tool for enhancing resilience in the banking sector, enabling institutions to adapt more effectively to environmental changes and disruptions. It is recommended that banks invest in advanced AI technologies and develop comprehensive risk management frameworks to mitigate potential vulnerabilities such as algorithmic bias and data privacy issues. Future research should explore the long-term effects of AI integration and consider the role of regulatory compliance in sustaining technological innovations within the financial industry.

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Compliance with Ethical Standards

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