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EFFECT OF ARTIFICIAL INTELLIGENCE AND BIG DATA ON PERFORMANCE OF DEPOSIT MONEY BANKS IN NORTHEASTERN NIGERIA: MEDIATING ROLE OF ABSORPTIVE CAPACITY

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Abstract
Deposit Money Banks (DMBs) plays a crucial role in the economic transformation of developing nations, addressing various challenges such as weak international trade support, economic instability and inflation, inefficient payment system, and capital scarcity. Despite their significant contribution to economic growth, these banks have faced numerous challenges such as high operational costs, fraud, and intense competition, which have constrained their performance. Many challenges faced by these bank, however, stem from non-adopting of artificial intelligence (AI) and big data (BD) technologies. While existing research has practically acknowledged the growing adoption of AI and BD technologies in the global banking sector, there is limited empirical evidence on how these technologies influence the performance of DMBs in Nigeria. Furthermore, the role of absorptive capacity (AC) in enhancing the effectiveness of these technologies remains underexplored. This knowledge gap calls for an empirical study of the phenomenon. This study adopted a survey research design. Copies of questionnaire were administered to 375 staff of DMBs operating in the Northeastern Nigeria. Utilizing Structural Equation Modeling (SEM) with Smart PLS 4, the study aimed to examine the mediating role of absorptive capacity on the relationship between artificial intelligence and big data and performance of deposit money banks. The findings from the empirical study reveal that artificial intelligence has positive and significant effects on the performance of DMBs. In contrast, big data was found to have a weak and insignificant effect on DMBs performance. Moreover, on the indirect effect, knowledge transformation of absorptive capacity fully mediates the relationship between artificial intelligence and DMBs performance. Furthermore, transformation do not mediates the relationship between big data and DMBs performance. In the light of these findings, the study among other things recommends that deposit money banks should continue investing in AI-powered solutions such as chatbots, fraud detection systems, and predictive analytics to further enhance performance; and also prioritized employee training on AI applications to maximize efficiency and innovation.

Keywords: Absorptive capacity; artificial intelligence; Big data; deposit money banks; oganizational performance.

Introduction

In today's era of rapid industrialization, industries worldwide are being reshaped by technologies such as artificial intelligence (AI) and big data (BD), which are revolutionizing how businesses operate and interact with customers (Desai, 2014). In the banking sector, these technologies are playing a pivotal role in enhancing customer experiences, streamlining operations, and improving decision-making processes. For instance, AI enables banks to automate routine tasks, reduce errors, lower costs, and offer personalized services (Bag et al., 2021), while big data allows banks to analyze vast amounts of customer information to gain deeper insights into behavior, preferences, and market trends (Gandomi & Haider, 2021). These advancements not only improve service quality but also drive profitability and customer satisfaction.

In Nigeria, the adoption of AI and BD in the banking sector has been growing, with notable innovations in digital and mobile banking platforms (Abubakar et al., 2023). However, the pace of adoption still lags behind global standards due to challenges such as infrastructural deficits, regulatory constraints, and a shortage of skilled personnel (Ansoff & Bamidele, 2023). Despite these hurdles, Nigerian banks are increasingly leveraging these cutting-edge technologies to enhance operational efficiency and customer engagement.

A critical factor in the successful implementation of these technologies is absorptive capacity (ACAP), which refers to an organization's ability to recognize, assimilate, and apply new knowledge to achieve commercial ends (Cohen & Levinthal, 2022). ACAP is essential for fostering innovation and gaining a competitive edge (Zahra & George, 2002). Studies have shown that firms with strong ACAP are better equipped to integrate external knowledge with existing knowledge, leading to improved performance and innovation (Engelman et al., 2017). For example, research has demonstrated that banks utilizing AI-driven analytics have significant improvements in operational efficiency and customer satisfaction (Afolabi & Mohammed, 2023), with ACAP playing a key mediating in enhancing these outcomes (Abou-Foul et al., 2023).

Despite the promising potential of AI and BD, there is a scarcity of empirical studies examining their combined impact on organizational performance, particularly in the banking sector. Moreover, the role of ACAP as a mediating factor in this relationship remains underexplored (Ghasemghaei, 2019). Prior studies have shown the role of ACAP as a mediating factor. For instance, Tsai (2021) found that banks with higher ACAP were more successful in leveraging AI for fraud detection and customer service automation, leading to improved financial performance. Similarly, Al-Sulaiti et al. (2023) demonstrated that BD positively impacts bank profitability, but only when mediated by the firm's ability to absorb and apply data-driven insights. Furthermore, the dynamic capability theory (Teece et al., 1997) provide a theoretical foundation for the mediation. The theory posit that that a firm's ability to integrate and exploit external knowledge (e.g., AI and BD) determines its competitive advantage. This study aims to address these gaps by investigating how AI and BD influence the performance of deposit money banks in Northeastern Nigeria, with a focus on how absorptive capacity through knowledge transformation (TS) mediates this relationship.

This paper was guided by the following research questions:

i. Does artificial intelligence significantly affect performance of deposit money banks in Northeastern Nigeria?

ii. Does big data significantly affect performance of deposit money banks in Northeastern Nigeria?

iii. Does absorptive capacity mediate the relationship between artificial intelligence and performance of deposit money banks in Northeastern Nigeria?

iv. Does absorptive capacity mediate the relationship between big data and performance of deposit money banks in Northeastern Nigeria?

Literature Review

Concept of Organizational Performance

The concept of organizational performance is explored through various approaches and measures. Performance is broadly defined as the degree of success, achievement, and competitiveness of an organization, alongside its efforts to optimize the present and secure its future (Richard et al., 2009). It remains a critical criterion for evaluating organizations, their actions, and their environments, consistently serving as a dependent variable in numerous studies. Organizational performance, particularly in the banking sector, is multidimensional and encompasses both financial and non-financial metrics. Financially, performance is often measured through profitability indicators such as Return on Assets (ROA), Return on Equity (ROE), and cost-to-income ratios (Ogundele & Popoola, 2022). Non-financial performance metrics, including customer satisfaction, operational efficiency, service quality, and innovation capacity, are also critical in assessing the success of banks in meeting their objectives (Duru & Nwachukwu, 2021).

Artificial Intelligence

Artificial intelligence is relatively new technology in the space of the business and banking world. It is affirmed that, artificial intelligence technology ensures quality decision making and trust credible outcome of operations. According to Novillo et al. (2022), the adoption of AI opens opportunities for businesses including banking industries. According to Antonescu (2018), AI is an intelligent system that is created to use data analysis, and observations to perform tasks without needing to be programmed to do so. Borana (2016), defined AI as the intelligence that is exhibited by an artificial entity in order to solve complex problems, and such a system is generally assumed to be a computer or machine. Adding to the literature, Plastino and Purdy (2018) describe AI as a category of technology which involves a capital–labour hybrid with the ability to self-learn, continuously improve, and be rapidly scaled-up.

The overarching goal of AI implementation is to improve the quality of operations across various sectors. Harfouche et al. (2019) assert that AI is aimed at uplifting operational standards and promoting greater efficiency in business processes. This aligns with findings of The AI Journal (2020), which revealed that industry leaders are optimistic about AI's future impact. According to the survey, 74% of respondents anticipate that AI will enhance business processes by increasing efficiency. Additionally, over half of the respondents believe that AI will facilitate creation of new business models, thereby leading to development of innovative products and services.

More so, in the area of automation, Gbolagade, Alao and Mashi (2021) study revealed that firms that adopt automation amazingly experienced more business expansion, generated more profit, and employed more labour than those that are yet to embrace the use of automation. Furthermore, chatbots has led to a change in the bank-customer interface and communication. With the aid of these artificial chatbots, people's interactions, including past conversations, are used to improve and expand databases. These chatbots work to answer unclear or ambiguous questions and can also generate responses on their own with the aid of processing technology (Joshi, 2018).

Big Data

Big data refers to extensive datasets containing information across various domains, including business, human behaviors, and industries. These datasets require specific techniques and methods for analysis to derive meaningful insights or predict future trends. As highlighted by Labrinidis and Jagadish (2012), BD encompasses structured, semi-structured and unstructured data that are mined to enhance operations. Big data has the potential to transform business processes fundamentally. According to Snijders, Matzat, and Reips (2012), BD presents companies with the opportunity to analyze vast, complex datasets using advanced data management techniques to derive valuable insights. This means companies will obtain a better understanding of their market position and to make informed decisions aimed at improving competitiveness and expanding market share.

The study of Al-Dmour et al. (2021) conclude that the application of big data positively impacts banks' performances, particularly in areas such as customer relationship management (CRM), fraud detection and prevention, and risk management within investment banking. Deposit money banks, which possess extensive volumes of customer transactional and behavioral data, and demographic data, benefit significantly from the value and usage of big data, particularly in improving marketing and risk management performance (Lee, 2017).

Concept of Absorptive Capacity

The concept of absorptive capacity has been widely recognized in scientific literature as a key driver of innovation and knowledge transfer within organizations (Cohen & Levinthal, 1990). Zou et al. (2018) define ACAP as an organization's ability to renew its knowledge base and achieve innovative outcomes, though they acknowledged that it does not directly improve performance. Instead, financial gains arise when companies effectively transform absorbed knowledge into competitive advantages through products and services. Wang and Chen (2022) define ACAP as an organization's ability to continuously identify, interpret, and reconfigure external knowledge into actionable insights, emphasizing agility in rapidly changing technological environments.

Absorptive capacity is typically divided into two main components: potential absorptive capacity and realized absorptive capacity (Lane et al., 2006). Potential absorptive capacity refers to the ability to acquire and assimilate external knowledge, while realized absorptive capacity involves the transformation and exploitation of this knowledge for competitive advantage (Cohen & Levinthal, 1990).

Prior research shows that ACAP can mediate the relationship between technological innovation and organizational performance. Tsai (2021) found that firms with higher absorptive capacity were more successful in leveraging AI for fraud detection and customer service automation, leading to improved financial performance. Similarly, Al-Sulaiti et al. (2023) demonstrated that BD positively impacts bank profitability, but only when mediated by the firm's ability to absorb and apply data-driven insights. In addition, Obeidat et al. (2022) examined Middle Eastern banks and found that ACAP significantly mediated the relationship between digital transformation (including AI and BD) and operational efficiency. The authors' structural equation modeling (SEM) analysis confirmed that banks with well-developed ACAP experienced higher returns on investment in AI technologies compared to those with weaker knowledge transformation capability. Furthermore, the dynamic capability theory (Teece et al., 1997) provide a theoretical foundation for the mediation. The theory posit that a firm's ability to integrate and transform external knowledge (e.g., AI and BD) determines its competitive advantage. Empirical studies consistently show that without sufficient ACAP, investments in advanced technologies yield suboptimal results (Camison & Fores, 2010).

Theoretical Review

This study shall be underpin by three theories.

The Resource-Based View (RBV): The RBV theory was primarily introduced by Wernerfelt in 1984. However, the RBV theory was further developed and popularized by Barney in 1991. This theory posits that organizations gain a competitive advantage by leveraging valuable, rare, inimitable, and non-substitutable resources and capabilities. In the context of this study, artificial intelligence and big data are viewed as technological resources that can help banks enhance their operational capabilities and improve performance. The RBV suggests that organizations that successfully deploy these technologies can achieve superior outcomes, such as increased efficiency, enhanced customer satisfaction, and reduced operational costs (Barney, 1991). Furthermore, the RBV underscores the importance of absorptive capacity, which enables organizations to effectively acquire, assimilate, and apply external knowledge, especially in the context of advanced technologies like AI and BD (Cohen &Levinthal, 1990).

Dynamic Capability (DC) Theory: The DC theory was propounded by Teece, Pisano, and Shuen in 1997. The dynamic capability refer to an organization's capacity to build, integrate, and reconfigure its internal resources and external competencies in response to changing technological and market conditions.

Absorptive Capacity Theory (ACT): The ACT introduced by Cohen and Levinthal (1990), describes an organization's ability to recognize, assimilate, and apply new external knowledge. It is composed of two key components: the ability to acquire external knowledge and the ability to assimilate and apply this knowledge effectively. In this study, absorptive capacity is considered a mediating variable, playing a central role in determining whether the adoption of AI and BD translates into improved performance. It implies that a bank's ability to process and leverage these technologies for innovation, improved decision-making, and better customer service depends on its absorptive capacity. Specifically, banks with higher absorptive capacity are more likely to gain a competitive advantage through the integration of AI and BD, leading to enhanced performance (Zahra & George, 2002).

Review of Empirical Studies.

Adeyemo and Okoronkwo (2024) examine artificial intelligence and operational efficiency of deposit money banks in Lagos state, Nigeria. The study identified the types of AI technologies that are used by banks and examined the impact of the different types of technologies on the operational efficiency of five deposit money banks. The study revealed that AI-powered technologies (deep learning, automation and fraud detection) had positive and significant effects on the operational efficiency of banks, while chatbots had a positive but insignificant effect. In a related study, Luo, Yang and Wu (2023) investigated the influence of big data technology on the profitability of China's City Banks. The findings suggest that the adoption of BD technology had a negative impact on bank profitability. The authors propose that the costs and challenges associated with implementing BD technologies may have outweighed the benefits in the short term. Similarly, Dick, Elekwachi and Nwosu (2023) examined the relationship between diagnostic big data and the performance of deposit money banks in Rivers State, Nigeria. The findings indicated that diagnostic big data positively impacted the performance of deposit money banks in terms of customer satisfaction and return-on-investment (ROI). Aziz, Fei, and Wan (2023) investigated the impact of big data analytics capability (BDAC) on firm performance within the Malaysian Banking Sector. Utilizing partial least squares structural equation modelling (PLS-SEM), he study findings revealed that big data significantly influences firm performance in the banking sector.

Furthermore, Umamaheswari, Valarmathi, and Lakshmi (2023) investigated the role of artificial intelligence (AI) in the banking sector in India. Employing a systematic review approach, the study found that automation enabled institutions to improve profitability, overall performance, and reduce dependence on human resources. Additionally, the study revealed that AI-powered virtual assistants enhanced business process performance across various sectors, particularly in banking, by providing speed, reliability, and independence from human intervention. Gbolagade, Alao, and Mashi (2022) investigated the contributions of I4.0 to entrepreneurial performance in Katsina State. Their findings suggested that I4.0 represents a significant revolution contributing to enhanced performance. Additionally, entrepreneurs adopting and implementing I4.0 technologies experienced more business expansion, generated more profit, and employed more labour. Patimah and Taufik (2021) investigated the mediating role of absorptive capacity in the relationships between industry 4.0 and organizational performance. The study results indicated that absorptive capacity partially mediates the relationship between industry 4.0 and organizational performance in the Indonesian context. Similarly, Hasan et al. (2021) investigated the influence of big data on banking operations, utilizing a qualitative research method. The findings indicated that big data has a substantial impact on different facets of banking operations. Data mining technology, for instance, holds promising market prospects in decision support and various business management applications within the banking sector, such as database marketing, customer segmentation, credit scoring, fraud detection, and market analysis. Additionally, big data management was found to play a critical role in mitigating banks' vulnerabilities to external cyber-attacks and internal security risks. Christiana (2017) evaluated the influence of digital adoption, absorptive capacity, and risk management implementation on organizational resilience in the Indonesian Banking industry. The study found a non-significant role of absorptive capacity through the transformation capacity on the banks' performance

Similarly, Serge-Lopez et al. (2020) investigated the impact of artificial intelligence (AI) on firm performance, particularly by examining the business value of AI-based transformation projects. The findings revealed that AI technologies offer numerous benefits and services, significantly enhancing organizational performance and potentially revolutionizing various aspects of daily life. Furthermore, Bajari et al. (2019) investigated impact of big data on firm performance in United States. The study found that, in some cases, the adoption of big data technologies did not lead to immediate performance improvements. The authors suggest factors such as high implementation costs, lack of skilled personnel, and integration challenges as potential reasons for the negative impact on performance. Furthermore, Rehman et al. (2020) study finding suggests the positive mediating role of transformation in the relationship between artificial intelligence and firm performance.

Review of the literature highlights several important gaps and opportunities for further research in the field of digital technologies and its influence on organizational performance, particularly in the banking sector. First, although there is a wealth of research on AI's applications in banking, limited studies focus on how AI adoption impacts the non-financial performance of Nigerian banks specifically. More importantly, few studies have examined the mediating role of absorptive capacity in maximizing AI's benefits in this context. Second, while big data's benefits in banking are widely recognized, there is a gap in understanding how absorptive capacity influences the ability of Nigerian banks to capitalize on BD. Moreover, few studies explore the combined effects of AI and BD on non-financial performance in the Nigerian banking sector. Lastly, the existing literature on AI and BD and performance is predominantly based on studies conducted in developed economies (e.g., Bajari et al., 2019). The Nigerian context presents unique challenges, such as infrastructure limitations, regulatory frameworks, varying levels of technological literacy among customers, and specific socio-economic factors. These contextual factors may significantly influence the relationship between AI and BD and performance. Therefore, it is crucial to investigate this relationship within the specific context of the Nigerian banking sector to generate relevant and applicable insights.

Methodology

This paper adopts cross-sectional, survey research design. The study focused on Domestically Systematically Important Banks (First Bank, UBA, GT Bank, Access Bank, Ecobank, Fidelity Bank Plc and Zenith Bank) (CBN, 2023) and their branches in Bauchi, Borno, Gombe, Taraba and Yobe states, all in Northeast Nigeria. The banks were chosen due to their significant investment in cutting-edge technology (Ighosewe et al., 2024). Preliminary investigations revealed that a typical commercial bank in Nigeria has a minimum of five (5) branch management team who are the core staff (Yunana et al., 2024). The population of this study is 375 staffs of the D-SIBs. The study adopted census method. Survey questionnaire was used for data collection. The questionnaire has been constructed in 4 sections. Section A is related to the demographic profile of respondents. While sections B, C, and D, the respondents are requested to tick the five-point Likert scale. The independent variables are artificial intelligence and big data. AI items were adapted from Vasiljeva and Lukanova (2016) and Makridakis (2017). The items for BD were adapted from Wang, Kung and Byrd (2018) and Gupta and George (2016). The dependent variable in this study is organizational performance (OP), with ten items adapted from DeLone and McLean (2003) and Wu and Ko (2013). While the mediating variable, absorptive capacity (i.e., knowledge transformation), with 8 items adapted from Flatten et al., (2011) and Zahra and George (2002). In addition, Partial Least Squares Structural Equation Modelling (PLS-SEM) is used for the data analysis with the support of SmartPLS 3.0 software.

Results and Discussion

The researcher distributed a total of 375 questionnaires, with 363 successfully returned from the different banks. This yielded a response rate of 97%, while the remaining 3% represented unreturned questionnaires. However, out of the 363 returned responses, there are only 357 (i.e., 95%) that are valid to be analyzed. Six responses (i.e. 2%) have to be deleted due to invalid answers, and some of the questions are not entirely answered. This response rate surpasses the minimum threshold advocated by Rogelburg and Stanton (2007), who submitted for a response rate of 35% - 40% for organizational-level studies and 50% for individual-level surveys. Following these guidelines, the response rate for this study is deemed excellent.

Measurement Model Assessment

In this study, the researcher uses PLS-SEM to analyze the data. Therefore, this study applied two types of validity, convergent validity and discriminant validity, to assess the measurement model. Fig. 1 shows the modified PLS path model.

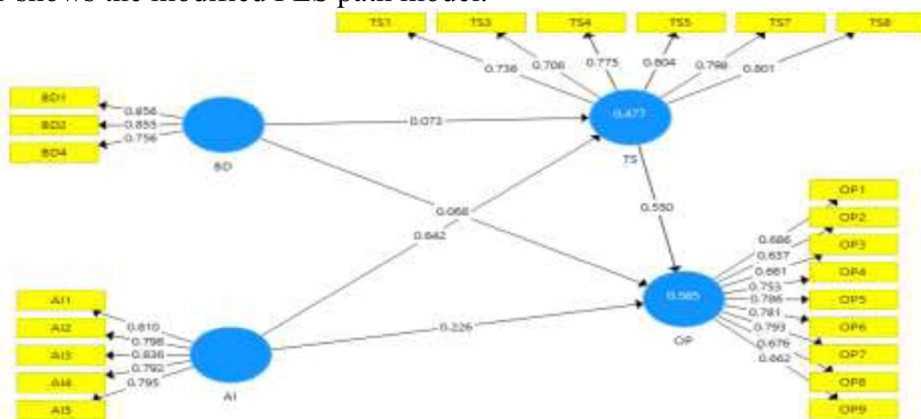

Fig. 1: Modified PLS Path Model

Internal Consistency

The acceptable value for outer loading must be above 0.50 (Hair et al. (2016). Therefore, the factor loading less than 0.50 should be considered to be deleted. In this study, 5 items with factor loading lower than 0.50 have been deleted to achieve dimensionality among the measurement items in the model. As shown in Fig.1, the construct of BD (big data) is only two items deleted out of a total of five items, followed by TS (knowledge transformation) with two items deleted out of eight items. Lastly is OP (organizational performance) with one deleted item out of a total of ten items.

Convergent Validity

The researcher assessed the convergent validity by considering the factor loading, average variance extracted (AVE) and composite reliability (CR). Elements incurred under convergent validity are AVE and CR. AVE value should be greater than 0.50 so that a satisfactory model has been achieved (Fornell & Larcker, 1981). Higher AVE values indicate that the construction in the model measurement is more than 50% of the respective item variance (Hair et al., 2012). Furthermore, according to Henseler et al. (2015), to reach the level of confirmatory, the acceptance value of CR must be more than 0.7. CR value equal to or greater than 0.80 is considered good for confirmatory research, while greater than 0.90 represent high reliability. Table 4.2 shows the results summary of the measurement model.

Table 2. Measurement model (results).

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
AI	0.865	0.868	0.903	0.650
BD	0.762	0.769	0.863	0.678
OP	0.883	0.886	0.905	0.515
TS	0.863	0.862	0.898	0.594

Source: Researcher's compilation in PLS-SEM 3.0

Table 4.2 shows that the value for every AVE fell between 0.515 - 0.678, which exceeds the suggested value of 0.50. While, all CR fell in between 0.863 and 0.905, which exceeds 0.7, which means that all the constructs are high reliability.

Discriminant Validity

This study selected Heterotrait-monotrait (HTMT) instead of Fornell-Larcker criterion because HTMT can better detect discriminant validity. Henseler et al. (2015) added that the discriminant validity could be established between a given pair of reflective constructs if and only when the HTMT value is below 0.90. Table 3 below shows that all the constructs have achieved the requirement of discriminant validity.

Table 3. Heterotrait–monotrait ratio of correlations (HTMT).

	AI	BD	OP	TS
AI				
BD	0.773			
OP	0.727	0.582		
TS	0.786	0.582	0.797	

Source: Researcher's compilation in PLS-SEM 3.0

Structural Model Assessment

The key indicators considered in the evaluation of the structural model include, determination of coefficient (R^2), predictive relevance (Q^2), path coefficients' size and significance, as well as the effect sizes (f^2 and q^2), as put forward by Hair et al., (2020).

For the coefficients determination (R^2), it is suggested that values equal to or greater than 0.10 are deemed adequate for the variance explained in endogenous constructs (Falk & Miller, 1992). Q2 values greater than zero indicate the predictive relevance of the exogenous construct for the considered endogenous construct. Table 4 below depicts the (R^2).

Table 4. Coefficient of Determination

	R-Square	R-Square adjusted
OP	0.57	0.585
TS	0.59	0.477

Source: Researcher's compilation in PLS-SEM 3.0

Effect sizes (f^2) of 0.02, 0.13, and 0.26 indicate weak, moderate, and strong effects of an exogenous construct in an endogenous construct, respectively (Cohen, 1988). Effect size values less than 0.02 imply no effect (Hair et al., 2020; Ringle & Sarstedt, 2022). Table 5 below shows the effect size.

Table 5. Assessment of Effect Size (f^2)

	OP	Effect Size	TS	Effect Size
AI	0.050	Small	0.474	Moderate
BD	0.007	Small	0.006	Small
TS	0.382	Medium	N/A	N/A

Source: Researcher's compilation in PLS-SEM 3.0
Note: *AI = artificial intelligence, BD = big data, TS = transformation, OP = organizational performance*

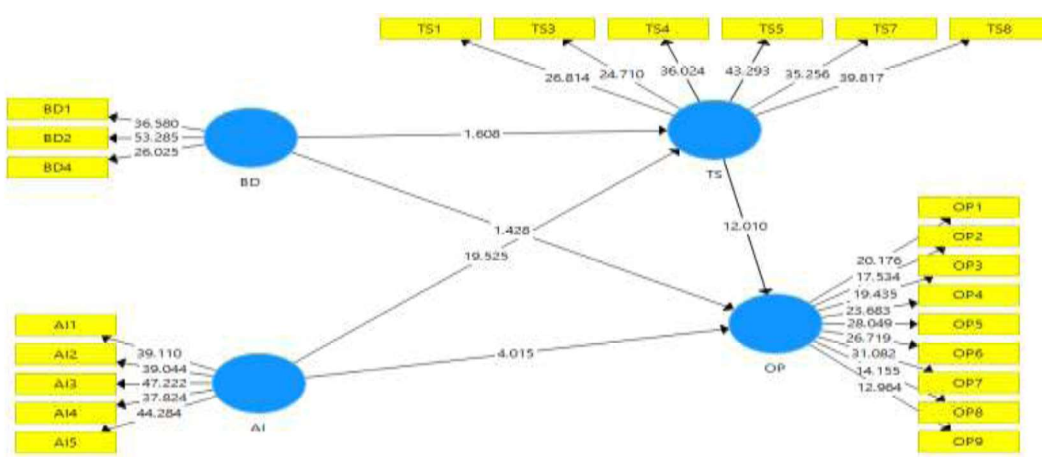

Fig. 2 PLS-SEM Structural Model

In this study, there are a total of two directional hypotheses that are being tested and two indirect hypotheses. Table 6 below shows the results of hypotheses testing for both direct and indirect hypotheses.

Table 6. Structural model (results).

Hypotheses	Beta Values	Standard (STDEV)	Deviation	T (|O/STDEV|)	Statistics	P Values	Sig
AI -> OP	0.232	0.056		4.015		0.000	Yes
AI -> TS	0.643	0.033		19.525		0.000	Yes
BD -> OP	0.068	0.048		1.428		0.154	Yes
BD -> TS	0.074	0.046		1.608		0.108	Yes
TS -> OP	0.547	0.046		12.010		0.000	Yes

Note: Significant at the $p < 0.05$ level

The above table (Table 6) shows the indirect effect of the study variables. From the table, it shows that adoption of artificial intelligence has a positive and significant correlation to organizational performance with β=0.232 and t= 4.015. The findings also suggests that artificial intelligence has effect on transformation with a beta value of 0.643. Similarly, the table reveals that big data has no significant effect on organizational performance.

Discussion of Findings

H_1 evaluated whether artificial intelligence significantly and positively influences the performance of DMBs. The PLS-SEM result revealed that artificial intelligence have a significant and positive influence on the DMBs performance (β = 0.232, t = 4.015 and p = 0.000). Therefore, H_1 was supported. Previous studies (Adeyemo & Okoronkwo, 2024; Umamaheswari et al., 2023; Serge-Lopez et al., 2020) have supported this, revealing that empirically it has been established that artificial intelligence significantly influence the performance of DMBs. The outcome of this study implies that the adoption of artificial intelligence by DMBs have an impact on operational efficiency.

H_2 investigated whether big data adoption significantly and positively influence the performance of DMBs. The results showed that big data have an insignificant influence on the DMBs performance (t=1.428, β=0.068 and p = 0.154). Hence H_2 was not supported. Previous studies (Luo, Yang & Wu, 2023; Bajari et al., 2019) have supported this, indicating that big data negatively impact on DMBs performance. However, it contrasts with the findings of Aziz et al. (2023) and Dick et al. (2023), whose studies indicated a significant and positive relationship between big data and DMBs performance.

H_3 evaluated whether absorptive capacity mediates the relationship between artificial intelligence and performance of DMBs. The result revealed that absorptive capacity through transformation (TS) have a positive and significant mediation. The significant relationship between AI -> TS and TS -> OP suggest that TS fully mediates the relationship between AI and OP. This is because the direct effect of AI on OP (AI -> OP) is significant. Therefore, the indirect beta value of 0.127 shows a positive and significant mediation. Hence, H_3 was supported. This finding is in agreement with the findings of Rehman et al., (2020).

H_4 evaluated whether absorptive capacity mediate through transformation on the relationship between big data and DMBs performance. The PLS-SEM result revealed that absorptive capacity through transformation have an insignificant relationship between big data and performance, with beta value of 0.037. Therefore, H_4 was not supported. The findings is supported by Christiana (2017).

Overall, the study findings suggest that while artificial intelligence significantly influence DMBs performance, big data do not have a notable impact. This highlights the importance of artificial intelligence technologies for operational efficiency and overall performance of DMBs. Furthermore, while absorptive capacity significantly mediates the relationship between artificial intelligence and DMBs performance, it revealed insignificant mediation in the relationship between big data and DMBs performance. This highlights the importance of role of absorptive capacity on technological adoption.

Conclusion and Recommendations

This study examined the effect of artificial intelligence and big data on organizational performance of DMBs in Northeastern Nigeria, with particular focus on the mediating role of absorptive capacity. Based on the result of first objective, the study established that the adoption of AI allows for greater scalability, cost savings, and better management of banking operations, thus enhancing organizational performance. This also implies that when firms take advantage of knowledge transformation, it will lead to high improvement.

Therefore, the study recommends that DMBs should continue investing in AI-powered solutions such as chatbots, fraud detection systems, and predictive analytics to further enhance performance. Also employee training on AI applications should be prioritized to maximize efficiency and innovation. That, DMBs should leverage hybrid cloud models to balance security with scalability. Additionally, regulatory frameworks for cloud adoption should be strengthened to ensure compliance while maintaining operational flexibility. Furthermore, DMBs should invest in enhancing their absorptive capacity by fostering a culture of learning and innovation. This will ensure they are able to effectively absorb and apply new technologies such as AI and BB which in turn will improve their performance.

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