Research Article

Artificial Intelligence and Organisational Performance: An Examination of the Factors Influencing Customers' Perspectives towards Selected Deposit Money Banks in Abuja, Nigeria

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Abstract

This study examines whether the value, rarity, inimitability, and organisational support factors of artificial intelligence influence customers' perspectives of the organisational performance of selected deposit money banks in Abuja, Nigeria. The value, rarity, inimitability, and organisational support factors of artificial intelligence were decoupled into the independent variables, while customers' perspectives of organisational performance of the selected deposit money banks in Abuja were the dependent variables. This study employed a quantitative research method and a cross-sectional research design to achieve its objectives. Access Bank, First Bank, Guaranty Trust Bank, United Bank of Africa, and Zenith Bank were selected for this study. 136 customers from these five deposit money banks were sampled through a convenience sampling technique. This study used Statistical Package for Social Sciences version 26 in conducting the Kruskal-Wallis non-parametric independent sample test. Furthermore, the epsilon-squared effect size calculated the practical significance of this study. The findings suggest that value, rarity, inimitability, and organisational support factors of artificial intelligence have no significant influence on customers' perspectives of artificial intelligence and the organisational performance of the selected deposit money banks in Abuja, Nigeria. Conversely, the epsilon-squared effect size indicates that value, rarity, inimitability, and organisational support factors of artificial intelligence have small effect sizes on customers' perspectives of artificial intelligence and the organisational performance of the selected deposit money banks in Abuja, Nigeria.

Introduction

Background to the study

Artificial intelligence (AI) has been widely recognised as the driver of organisational performance. This is because of its ability to improve operational efficiency in human-to-technology interaction. According to Strykar and Kavlakoglu [1], AI is a technology designed to independently solve problems and improve decision-making. This implies that AI is designed to perform human tasks in a more efficient and effective manner. For example, Graig, Laskowski, and Tucci [2] explain that AI is a technology trained by humans to analyse patterns, make predictions, and engage in interactive communication using vast amounts of data.

The contribution of AI to organisational performance is determined by several strategic factors. These strategic factors are value, rarity, inimitability, and organisational support. The value factor of AI is the perceived benefits derived from the use of AI. For instance, Frery [3] defines the value factor of AI as the ability to use technology to increase the economic value an organisation generates by either increasing customers' willingness to pay for its services, which reduces the costs of its services, or both. This suggests customers value AI in banking transactions when the benefits they derive from such

transactions weigh more than the cost of conducting face-to-face banking transactions. Arguably, the value factor of AI improves organisational performance when its benefits outweigh its cost, which offers benefits that are not readily obtained from traditional face-to-face banking transactions.

Rarity factor of AI occurs when customers find that the promised features and functions of AI during their banking transactions are rare or are not common among business or public organisations' services. For instance, Barney and Clark [4] posit that if the value factor of a business or public organisation's resource or capability is possessed by many competitors, each competitor will exploit the same value (i.e., the features or functions) of AI. Consequently, this leads to common strategies in which customers can not differentiate the value or satisfaction they derive from transacting with AI from when transacting with human agents. Thus, the rarity factor of AI enhances customers' interest in AI when they find it innovatively rare and not common among competitors' services. Therefore, business or public organisations can create a rarity factor of AI through inimitability, which entails making AI satisfaction, features, and functions hard for competitors to imitate.

For a business or public organisation's factors of AI hard for its competitors to imitate, the features and functions of AI must offer promises that meet customers' expectations. According to Frery [3], the inimitability factor of AI is the capability of the technology, which is not replicable by competitors. This entails that business or public organisations' AI integration must proffer solutions that solve customers' needs. Notably, the inimitability of a business or public organisation's features and functions is sustained through its history and corporate reputation among key players in its external environment (i.e., customers, suppliers, etc.).

The value, rarity, inimitability, and organisational factors of AI are made possible by business or public organisational support, which is attained through different levels of management involvement and collaboration. For example, Barney and Clark [4] note that the value, rarity, and inimitability factors of any resources or capabilities can only enhance organisational performance if the organisation is properly structured. This includes the organisation's formal reporting structures, management control systems, and compensation policies that enhance an organisation's potential for achieving organisational performance. This suggests organisational support of AI from all business or public organisations' functional capabilities is what improves organisational performance.

In Europe, governments use AI as a digital transformation for public organisations. This has enabled the delivery of quality services to citizens and stakeholders [5]. For example, Australia's Taxation Office virtual assistant called "Alex" responds to more than 500 questions at a time. It engages in 1.5 million conversations at a go and has resolved over 81% of enquiries at first contact. However, business reports and empirical studies have initially argued that many European business and public organisations were struggling to leverage AI applications. This made it unclear how the factors of AI can be realised from AI investment and its influence on organisational performance [6]. Currently, the European public and business organisations have tackled this uncertainty surrounding their struggle with their AI investment and its leverage on organisational performance. For instance, European banks have employed real-time AI fraud detection technology to save their banks from 90% spoofing losses over the years [7]. This suggests the value, rarity, and inimitability factors of AI depend heavily on the organisational support of the stakeholders with an interest in organisational performance.

In Africa, countries like South Africa and Kenya have employed AI in both business and public organisations. This has enhanced both countries' business and public organisations' performance. In the agricultural sector, for example, South Africa uses "ITIKI" machine learning technology to predict the propensity of droughts. Likewise, the Kenyan government's Forest Guards have employed Microsoft's AI in mitigating illegal logging activities and tackling climate change. Furthermore, the Kenyan government uses "PlantVillageNuru, a state-sponsored machine learning AI, in helping farmers recognise farming plants' diseases. In the financial sector, South Africa's "Mama Money" and Kenya-based "M-KOPA" are AI technologies that enhance both countries' cybersecurity, customer experiences, and inclusive access to financial services [8].

In Nigeria, deposit money banks (DMBs) have employed AI to enhance their organisational performance. For instance, DMBs in Nigeria have employed natural language processing AI in handling customers' everyday transactions and 24 hours support system, which includes resolving banking issues and bank account opening-process assistance. Furthermore, DMBs in Nigeria use machine learning AI to detect customers' banking behaviour and fraudulent transactions [9]. This has enhanced DMBs in Nigeria's organisational performance significantly.

Several DMBs in Nigeria have employed different types of AI to improve their organisational performance. For example, Access Bank, Fidelity Bank, First Bank, Guaranty Trust Bank (GTB), Zenith Bank, First City Monument Bank (FCMB), and United Bank of Africa (UBA) use AI chatbots to handle customers' inquiries and 24-hour service support on digital platforms and devices [9]. These AI chatbots have provided solutions to millions of customers' enquiries on WhatsApp, Facebook, and web chats on these DMB's webpages. Consequently, this has increased the service efficiency and organisational performance of DMBs in Nigeria by 63%, which has increased the foundation for studies on AI and the organisational performance of DMBs in Nigeria.

Recent studies have focused on AI and organisational performance from employees' and management team perspectives. For instance, Okoliko, et al. [10] and Udodiugwu, et al. [11] demonstrate that AI enhances the efficiency, effectiveness, productivity, and enhancement of customer experience in tandem with DMBs' organisational performance. The study was conducted through surveys of employees in DMBs in Nigeria. Additionally, Amado, et al. [12] and

Olumoyegun, Alabi, and Nurudeen [13] highlight that AI has a significant impact on the organisational performance of DMBs in Nigeria. Furthermore, these studies agree that AI influences the efficiency, effectiveness, innovation, risk management, and operational compliance, which translates to the organisational performance of DMBs in Nigeria [10].

Nevertheless, these studies fail to take into account customers' perspectives of AI and the organisational performance of DMBs in Nigeria, which are based on the value, rarity, inimitability, and organisational support. According to Kamba [14], DMBs' financial products or services are becoming increasingly similar. As such, DMBs that master the hyper-personalisation of customer services and prioritise customers will emerge as market leaders in today's AI-driven financial industry. Thus, customers' perspectives of the factors of AI are the ultimate differentiator of DMBs' organisational performance. This entails customers' expectations of personalised and seamless interactions across DMBs' AI multiple channels (i.e., mobile banking, USSD, and WhatsApp banking) are important.

Arguably, DMBs' adoption of AI in Nigeria is still at the infant stage of AI's adoption maturity cycle. According to Price Water Coopers [15], only 10 out of 26 DMBs in Nigeria have employed AI to enhance customer engagement and customer service issue resolutions. As such, DMBs' value, rarity, inimitability, and the organisational support factors of AI that enhance customers' perspectives of the DMBs' organisational performance are yet to be ascertained. This highlights the nuance between the ideal customers' perspectives of AI and the actual customers' perspectives of AI, and the organisational performance of DMBs in Nigeria. For example, Ibrahim and Adepoju [16] claim that DMBs' customers lack trust in AI adoption. This scepticism is based on a lack of trust in AI accuracy, its inability to handle complex queries, and a lack of awareness of AI-driven financial services. Thus, DMBs' customers are more comfortable resolving banking issues through interactions with human agents rather than relying on AI-integrated banking services [17].

Statement of the problem

The influence of AI on customers' perspectives of AI and the organisational performance of DMBs in Nigeria is relatively understudied. Existing studies have largely focused on organisational performance from management and employees' perspectives, which has limited attention to how AI relates to factors that shape customers' perspectives of organisational performance with Nigerian banking sector. As a result, the extent to which the value, rarity, inimitability, and organisational support factors of AI Influence customers' perspectives and the organisational performance of DMBs in Nigeria remains unknown. This gap raises an important strategic question: Does the AI technology used by DMBs possess the value, rarity, inimitability, and organisational support factors that influence customers' perspectives of AI and organisational performance in DMBs in Nigeria?

To address this question, this study adopts the Resource-Based View (RBV), specifically the Value, Rarity, Imitability, and Organisational support (VRIO) framework, to identify the AI factors that influence customers' perspectives of AI and the organisational performance of DMBs in Abuja. This study uses Abuja as a microcosm to reflect the broader operational context of AI on DMBs' organisational performance in Nigeria.

Objectives of the study

To address the identified issues, this study examines whether the VRIO factors of AI influence customers' perspectives of AI and the organisational performance of DMBs in Abuja. The specific objectives of the study are:

I. To determine whether the value factor of AI has a significant influence on the organisational performance of selected DMBs in Abuja;

II. To assess whether the rarity factor of AI has a significant effect on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja;

III. To examine whether the inimitability factor of AI has a significant impact on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja;

IV. And to investigate whether the organisational support factor of AI has a significant influence on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja.

Research questions

In line with the objectives of the study, the following research questions are addressed:

I. Does the value factor of AI significantly influence customers' perspectives of AI and the organisational performance of selected DMBs in Abuja?

II. Does the rarity factor of AI have a significant effect on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja?

III. Does the inimitability factor of AI significantly influence customers' perspectives of AI and the organisational performance of selected DMBs in Abuja?

IV. Does the organisational support factor of AI have a significant influence on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja?

Research hypotheses

Based on the research questions, the following null hypotheses are formulated:

I. H_{01}: The value factor of AI has no significant influence on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja.

II. H_{02}: The rarity factor of AI has no significant effect on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja.

III. H_{03}: The inimitability factor of AI has no significant influence on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja.

IV. H_{04}: The organisational support factor of AI has no significant influence on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja.

Significance of the study

While existing studies of AI adoption in Nigerian DMBs are predominantly organisational performance from management and employee perspectives, this study introduces a novel customer-centric lens. By foregrounding customers' perspectives of AI through the VRIO framework, this study shifts the focus from internal efficiency gains of AI to the externally perceived value of AI. This approach improves the awareness that sustainable organisational performance of AI-driven banking depends on customers' acceptance, trust, and perceived differentiation of AI rather than depending solely on technological deployment.

Scope of the study

The scope of this study covers customers of five selected DMBs operating in Abuja, the Federal Capital Territory of Nigeria. Specifically, the study focuses on customers of banks that have integrated AI into their operations, namely Access Bank, First Bank, Guaranty Trust Bank (GTBank), United Bank of Africa (UBA), and Zenith Bank [18]. This study concentrates on examining the influence of the RBV's VRIO factors of AI on customers' perspectives of AI and the organisational performance of these selected DMBs in Abuja.

The remainder of this study is structured as follows. Section 2 presents the literature review. Section 3 is the research methodology. Section 4 presents the findings and discusses the findings of this study. Lastly, Section 5 is the conclusion of this study.

Literature review

AI has a significant impact on the organisational performance of DMBs. However, operational risks persist in customers' perspectives of the organisational performance of DMBs in Nigeria. While previous studies have focused on AI and organisational performance from the organisation-centric perspective (i.e., management and employees' perspectives) of DMBs in Nigeria, this study examines whether the factors of AI influence customers' perspectives on AI and the organisational performance of selected DMBs in Abuja. To achieve this goal, this study uses the RBV theory and customer expectancy motivation theory to examine the impact that the value, rarity, inimitability, and organisational support factors of AI have on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja.
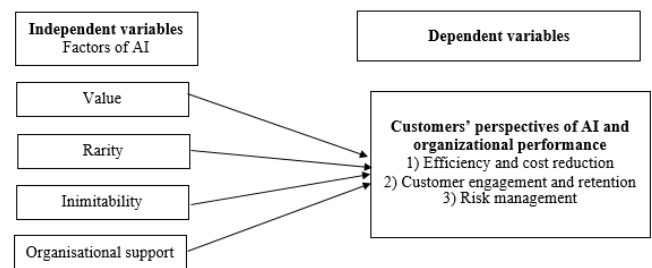

Figure 1: VRIO factors of AI that influence customers' perspectives of AI and the organisational performance of selected DMBs in Abuja.

Conceptual framework

Figure 1 illustrates the connections between decoupled VRIO value factors of AI that influence customers' perspectives of AI and the organisational performance of selected DMBs in Abuja.

Value factor of Artificial intelligence and organisational performance: The value factor of AI and organisational performance refers to an organisation's capacity to reduce operational costs and increase profitability, ultimately leading to enhanced customer satisfaction. For instance, Bellegonds, et al. [19] assert that the factors of AI influence the organisational performance of DMBs through process automation, cost reduction, improved risk assessment, and lower default rates. This means DMBs' employees and management teams see AI as the ultimate solution to customers' issues during banking transactions.

From the customers' perspectives, the value factor of AI refers to the perceived benefits derived from the DMBs' AI-integrated services. For example, customers' recognition of DMBs' organisational performance depends on the functional and economic values of AI. The functional value factor of AI points to how well AI meets customers' practical needs, which includes resolving banking issues or making banking-related inquiries without customers visiting banking premises; while the economic value factor of AI emphasises customers' cost and benefits incurred by interaction AI compared to human agents [20]. This means that customers see the value of AI and organisational performance of DMBs as AI's ability to reduce transaction costs and increase service satisfaction.

Rarity factor of Artificial intelligence and organisational performance: The rarity factor of AI and organisational performance refers to the uniqueness of AI within an industry. For example, a business organisation that has computer-based operations will have advantages in an industry that is dominated by manual or analogue-based operations. This makes this business organisation's computer resources rare to competitors and its customers. Likewise, the rarity factor of AI impacts organisational performance when its applications are unique among DMBs, which will create more value for customers compared to competitors in the industry. However, if DMBs adopt similar AI tools or functions, these tools or functions would not be a rarity factor; consequently, this factor of AI will not contribute to organisational performance [3] For example, two DMBs adopting AI chatbots to interact with customers lack rarity. For the two DMBs, the outcome

of AI chatbots does not rely on the AI resources both DMBs possess; rather, the outcome of both DMBs' organisational performance is based on customers' perspectives of the AI in meeting their banking expectations. Therefore, the rarity factor of AI and organisational performance is defined by their unique applications and differentiation among DMBs. Likewise, customers perceive the rarity factor of AI through service efficiency and differentiation. Despite the value and rarity factors of AI and organisational performance of DMBs, its inimitability factor is sacrosanct.

Inimitability factor of Artificial intelligence and organisational performance: The inimitability factor of AI and organisational performance refers to the difficulty in replicating an organisation's AI factors of AI. For the factors of AI to enhance organisational performance, it must be challenging for competitors to imitate [3]. The inimitability factor of AI impacts organisational performance by deterring competitors from easily replicating existing factors of AI across DMBs. From a consumer's perspective, the imitability factor of AI will be difficult for customers to differentiate from other competitors' AI factors of AI. This increases the cost of the factors of AI awareness. Conversely, inimitable factors of AI will reduce customers' expected costs during customer-to-AI transactions. To ensure the effectiveness of the inimitability factor of AI, there must be an organisational support system for the factors of AI to enhance organisational performance.

Organisational support factor of Artificial intelligence and organisational performance: The organisational support factor of AI and organisational performance involves leveraging the factors of AI to enhance organisational performance. According to Frery [3], the organisational support factor of AI includes effective management control, compensation policies, and strategic planning to maximise organisational performance, which entails having employees with AI knowledge in the different departments of DMBs. This suggests that the organisational support factor of AI affects organisational performance when AI knowledge is part of DMB's culture and policy.

On the other hand, the organisational support factor of AI affects customers' perspective of DMBs' organisational performance because the management and employees of DMBs are committed to enhancing the functionality of AI. For example, customers are impressed when they see that AI is updated regularly, and any glitches or complaints are rectified promptly. This suggests customers' perspectives of AI and organisational performance are centred on seeing DMBs ' efforts in making AI work during their banking transactions. Consequently, the value, rarity, inimitability, and organisational support factors of AI determine customers' perspectives of the organisational performance of DMBs.

Theoretical framework

Resource-Based View (RBV) theory: The Resource-Based View (RBV) theory is a strategic management paradigm that explains how organisations achieve and maintain competitive advantages by effectively employing their unique internal resources or factors. According to Barney and Clark [21], organisational performance improves when a business organisation maximises its internal strengths and minimises its weaknesses by utilising its current resources or factors. This theory explains how business organisations outperform their competitors within an industry. So, resource-based view (RBV) theory highlights and predicts the influence of value, rarity, inimitability, and organisational support on an organisation's performance and its competitive advantage among its competitors. For example, Barney and Clark [4] opine that organisations must possess resources or factors that are valuable, rare, inimitable, and have organisational support. This means that without these qualities, an organisation's resources or factors will not achieve its intended organisational performance, as well as sustainable competitive advantage.

Customers' expectation motivation theory: Customers' expectation motivation theory revolves around an individual's anticipated outcome of an event, situation, or performance based on their past experiences. For instance, Oliver notes that customers' expectations involve comparing an organisation's promised benefits with its actual performance. Customers anticipate the results of an event, situation, or performance based on their own experiences or other sources of information. Therefore, customers' expectations of organisational performance are influenced by post-transaction experience or comparison with offers from competitors [22].

Customers' perspectives of organisational performance rest on business organisations' consistency with their service promises. According to Mulyani and Fitrianti [23], customers' expectations are primarily influenced by enduring service intensifiers, implicit service promises, past experiences, and personal needs. Enduring service intensifiers encompass customers' overall expectations of organisational performance, including the gap between their ideal and actual organisational performance. For instance, customers using a logistics service would expect fast and convenient delivery as a standard for organisational performance. These enduring service intensifiers are essentially implied service promises made by business organisations.

Furthermore, implicit service promises serve as another criterion customers use to assess organisational performance. For example, Parasuraman, Zeithaml, and Berry [24] observe that customers evaluate an organisation's product or service performance based on the promised benefits. Thus, customers' final evaluation depends on whether a business organisation delivered its promised benefits or not.

Empirical review

OKoliko, et al. [10] investigated AI and organisational performance of selected DMBs in Nigeria. The study used a cross-sectional descriptive research design and a structured survey questionnaire. A total of 135 employees from five selected DMBs in Abuja participated in the study. The study used SPSS version 26 to run multiple regression analyses on the data. The main findings of the study revealed that AI significantly increased the efficiency, effectiveness, productivity, customer

satisfaction, and the overall organisational performance of the selected DMBs.

Salemcity, Aiysan, and Japine [25] studied AI adoption and the corporate operating activities of DMBs in Nigeria. The study employed an ex-post facto research design. The findings showed that AI adoption harmed employee costs, while it had a positive effect on the operating systems of DMBs in Nigeria.

OFuani, Omoera, and Akagha [26] examined the integration of AI and the organisational performance at the United Bank of Africa, Nigeria. The study collected primary data from 130 employees and analysed the data with Pearson's correlation. The study found that robotic process automation AI had a significant impact on the bank's organisational performance, while Chatbot and customer service systems had no significant effect on the organisational performance of the DMB.

Chinwendu, Enudu, and Orga [27] investigated AI and the organisational performance of DMBs in the Southeastern region of Nigeria. The study focused on the influence of cardless automated teller machines (ATM) on employee retention and the impact of point-of-sale terminals on loss prevention. The study utilised a survey design research approach and collected primary data from 271 employees in the region. The data was analysed using Pearson's correlation test. Notably, the study revealed that cardless ATMs had a significant influence on employee retention, while point-of-sales terminals had a significant positive effect on loss prevention in DMBs in the Southeastern part of Nigeria.

Udodiugwu, et al. [11] studied the role of AI in enhancing the organisational performance of DMBs in Nigeria. The study focused on Access Bank, Fidelity Bank, Guaranty Trust Bank, and First Bank of Nigeria, while utilising SPSS version 23 for its statistical analysis. The findings showed that AI in customer services improved the non-financial organisational performance of DMBs, while strong cybersecurity AI enhanced their financial organisational performance.

Adepeju, et al. [28] examined AI and risk management of DMBs in Nigeria. The study employed a survey research design. The study reported that AI had a significant impact on GT Bank's credit scoring and enhanced fraud detection in the risk management of DMBs.

Olumoyegun, Alabi, and Nurudeen [13] investigated the contemporary issues on AI and the performance of selected DMBs in Nigeria. The study employed a cross-sectional research design. The findings indicated that Chatbots and robotic advising systems had a significant effect on employees' operational performance.

Unuesiri and Adejuwon [29] investigated the effect of an AI expert system on the financial performance of DMBs in Abuja. The study employed a longitudinal research design, which encompassed Access Bank, Zenith Bank, UBA Bank, and GT Bank's AI adoption from 2015-2023. The findings pointed out that the AI expert system has both positive and significant effects on the operational performance of DMBs in Abuja.

Ogundele, et al. [30] analysed the impact of AI on sustainable banking and service delivery in DMBs in Nigeria. The study included 384 DMBs' customers from Access Bank, Fidelity Bank, Guaranty Trust Bank, and Zenith Bank. The study employed Jarque Beta, correlation analysis, and ordinary least squares. The findings indicated that AI awareness, application, and effectiveness influenced the services of the selected DMBs in Nigeria.

Lastly, Orjinta and Anetoh [31] investigated how AI strategies lead to sustainable performance of DMBs in Nigeria. The study utilised an ex-post facto research design to ascertain these DMBs' operational activities from 2014 to 2023. The findings suggested that AI had a significant effect on the sustainable performance of DMBs in Nigeria.

Appraisal of reviewed literature: This study's appraisal of the reviewed literature is threefold. First, the theoretical framework forms the foundation of this study. Second, the limitations of empirical studies on AI and the organisational performance of DMBs' research designs are identified. Lastly, the significance of the VRIO model in attaining this study's objectives.

First, Mulyani and Fitrianti's [23] factors influencing customers' expectations of service (such as service intensifiers, implicit service promises, past experiences, word of mouth, and personal needs) are most relevant to this study. These customer expectations explain the VRIO factors of AI that influence customers' perspectives of AI and the organisational performance of selected DMBs. Additionally, these customers' expectation factors indicate how the VRIO factors of AI align with customers' perspectives of AI and the organisational performance of the selected DMBs.

Second, empirical studies on AI and organisational performance among DMBs in Nigeria have primarily focused on efficient and effective organisational performance [10,11,26] and employee retention [27](Chinwendu, Enudu, & Orga, 2024). Except for Ogundele, et al.'s [30] study, which focused on AI and the organisational performance of DMBs in Nigeria from customers' perspectives. Furthermore, the empirical studies' findings are based on DMBs' management and employees' perspectives. Notably, Ogundele, et al. [30] highlight customers' perspectives of AI and its effect on organisational performance of DMBs in Nigeria. The study suggests that studies on AI and organisational performance of DMBs in Nigeria are organisation-centric. Furthermore, the findings of these studies are limited by their research designs. These limitations result from a lack of statistical power to ascertain the effect of AI and the organisational performance of DMBs in Nigeria. For example, the ex-post facto research design employed by Salemcity, Aiysan, and Japine [25], as well as Orjinta and Anetoh [1], does not have the capacity to assign research respondents into groups to ascertain each group's unique perspectives on their research topics. As a result, respondents are obliged to give favourable responses. Similarly, Unuseri and Adejewon's longitudinal research design does not encompass customers' perspectives of AI and the organisational performance of DMBs in Nigeria.

Lastly, the VRIO factors of AI (employed from the RBV concept) provide a model to determine which factors of AI are heterogeneous and not transferable across DMBs in Nigeria. Although the VRIO model has not been tested in the context of AI and the organisational performance of DMBs in Nigeria, the model has proven its significance in determining how the VRIO factors of DMBs' resources impact their competitive parity (i.e., to maintain or defend a current position without the intent to outperform competing firms within a strategic group) and competitive advantages. For example, Simamara, Rahayu, and Dirgantari [32] used the VRIO model to ascertain the competitive parity of DMBs' human resources, organisational structure, and products and services. Likewise, the model helped determine the competitive advantages of DMBs' capital resources, information systems, and organisational reputation in Pakistan.

All in all, the value, rarity, inimitability, and organisational support factors of AI indicate how DMBs' organisational performance is differentiated among business organisations. From the customers' perspectives of AI, the value, rarity, inimitability, and organisational support factors of AI notably indicate the dimension of the technology and the organisational performance of selected DMBs in Abuja.

Methodology

This study employed a quantitative research approach. According to Kumar [33], the quantitative research method is effective in testing hypotheses and theories through statistical analysis. For example, Walsh [34] posits that the quantitative research method has objectivity in its procedures and comparability in its results across studies. This suggests that the quantitative research method is suitable for this study because of its effectiveness in hypothesis testing, which makes the findings of this study comparable with other studies on the subject matter.

Research design

In addition to the quantitative research method employed, this study employed a cross-sectional research design. According to Thomas [35], a cross-sectional research design can observe data. This study employed a cross-sectional research design without influencing them or establishing a cause-and-effect relationship between variables. Consequently, the cross-sectional research design is crucial to this study because it increases the observation of preliminary information for subsequent studies [36].

Population of the study

This study engaged the responses of the customers who bank with one or more of the selected DMBs in Abuja. The selected DMBs were Access Bank, First Bank, GT Bank, UBA Bank, and Zenith Bank.

Sample and sampling techniques

This study's sample size was 136 customers of the selected DMBs in Abuja. The sample size of 136 respondents is consistent with similar studies examining AI and organisational performance within the banking context. For example, studies by Okoliko, et al. [10] and Ofuani, et al. [26] used sample sizes of 135 and 130, respectively, to ascertain the impact of AI on the organisational performance of selected DMBs in Nigeria. This suggests that 136 sample size is sufficient for a study exploring an understudied research domain.

Respondents were selected by a non-probability convenience sampling technique. Non-probability convenience sampling technique remains appropriate for capturing preliminary insights in an understudied research domain such as customer-facing AI adoption in Nigerian DMBs. For example, convenience sampling is appropriate for finding initial data, identifying trends, and generating hypotheses for further studies. Notably, non-probability convenience sampling is important when there is no sample frame or available population data to make a probability sampling [37]. Thus, this suggests that 136 respondents and a non-probability convenience sampling technique are appropriate for the generalisability of its findings.

Instrument of data collection

To collect the data suitable for this study, this study employed a survey questionnaire in its data collection. According to Leavy [38], a survey questionnaire offers simplicity in gathering data not easily accessible through secondary sources. This makes the survey questionnaire the best data collection instrument for getting insight into respondents' perspectives on this study's subject matter. Furthermore, the interests and personal information of the respondents who participated in this study were protected through informed consent, which offered the protection of respondents' information and the voluntary participation of respondents.

The survey questionnaire consisted of 19 items categorised into five sections (A-E). Section A (which has 7 items) is the respondents' demographics, including gender, number of accounts with selected banks, awareness of AI applications, and platform interactions. Sections B to E (which have 12 items) were the VRIO constructs of this study, which were measured on a five-point Likert scale. This was scaled from 1 = Strongly Disagree (SD) to 5 = Strongly Agree (SA).

Validity of the instrument

To ensure the validity of the survey questionnaire employed by this study, this study used Principal Component Analysis (PCA) to evaluate the construct validity of the survey questionnaire. According to Ghaza, et al. [39], construct validity determines if a test accurately measures what it claims to measure. Thus, PCA was performed on the 12 items in the survey questionnaire. Consequently, the Kaiser-Meyer-Olkin (KMO) measure confirmed that the study had adequate sampling for the analysis, with a KMO value of 0.69 and significance at a P-value of .001, which indicated that the sample size of this study is adequate [40].

Reliability of instrument

The survey questionnaire was subjected to a Cronbach's alpha reliability test, which ensures internal reliability and

homogeneity across this study's construct. The Cronbach Alpha reliability scores of the four components of this study were as follows. The value factor of the AI construct had a Cronbach's Alpha score of .804. The rarity factor of AI, consisting of 5 items, had a Cronbach's Alpha score of .827. The inimitability of AI, with 2 items, had a Cronbach's Alpha of .792. Furthermore, the organisational support factor of AI, with 3 items in its construct, had a Cronbach's Alpha score of .841. Notably, these scores were above the Cronbach Alpha reliability score of .70 threshold.

Procedure of data collection

This study used self-administered survey questionnaires for respondents. Notably, the procedure of self-administered survey questionnaires was threefold. First, respondents were approached, and their status as customers of one of the selected DMBs in this study was ascertained. Second, respondents' consents to participate in this study were obtained from them. Third, the distribution and collection of the survey questionnaires were based on respondents' convenience.

Method of data analysis

This study used Statistical Package for Social Science (SPSS) version 26 to conduct both its descriptive and inferential statistics. Descriptive statistics categorised respondents according to their bank account operations with the selected DMBs in Abuja. For ease of data analysis, the data collected on each variable of the VIRO construct were transformed into single individual variables. For example, the two variables under the value factor of AI were transformed into a single variable value.

Consequently, an independent sample Kruskal-Wallis non-parametric test was used to conduct the inferential statistics. According to Kaliannan, et al. [41], the independent sample Kruskal-Wallis non-parametric test is ideal for measuring ordinal data. This suggests the Independent sample Kruskal-Wallis non-parametric test is ideal for this study, because of its ability to analyse the interactions between three or more independent variables and dependent variables.

Additionally, the VRIO factors of AI were decoupled into this study's independent variables, while the customers' perspectives of AI and organisational performance were the dependent variables. According to Kaliannan, et al. [41] and Barney and Hesterly [42], the VRIO model presents a practical framework that is easy to comprehend and utilise. This suggests that the VRIO model offers a comprehensive approach to identifying the critical factors of AI that influence customers' perspectives of AI and the organisational performance of the select DMBs in Abuja. Consequently, it distinguishes resources that offer short-term benefits from those that are sustainable.

In addition to the employed independent sample Kruskal-Wallis non-parametric test, this study also employed epsilon squared (E2) to determine the effect sizes of variance between customers' perspectives of organisational performance explained by the VRIO factors of AI. According to Lee and

Bobbitt, effect size suggests the practical implications of a study beyond that of statistical analysis. Thus, the effect size ascertained the practical impact the VRIO factors of AI have on customers' perspectives of AI and the organisational performance of the selected DMBs in Abuja.

The inferential statistics of the independent sample Kruskal-Wallis test were based on a 95% confidence interval and a p-value of .05. As a rule of thumb, a P-value greater than .05 will retain the null hypotheses of this study, while a p-value less than .05 will reject the null hypotheses of this study. In addition, the epsilon-squared effect size employed by this study was calculated manually using the following formula:

$$E2 = (H - K + 1) / (n - k)$$

Where:

H = Kruskal-Wallis H statistics;

K = the number of groups under observation;

n = the total number of observations.

As a rule of thumb, an effect size between .01 and < .06 was considered a small effect size. An effect size within the range of .06 and < .14 was considered a medium effect size, while an effect size that falls above .14 was considered a strong effect size [43].

The adoption of the Kruskal-Wallis non-parametric test represents a methodological strength of this study. According to Kruskal and Wallis [44], the Kruskal-Wallis non-parametric test compares the independent scores among independent groups that come from different populations. This suggests that, given the ordinal nature of Likert-scale data and the absence of normality assumptions, Kruskal-Wallis non-parametric methods offer a robust and conservative approach to hypothesis testing.

Beyond the statistical significance testing, the inclusion of epsilon effect size estimates provides deeper analytical insight into the magnitude of AI-related effects on DMBs' organisational performance. For instance, Beins [45] and Ellis [46] opine that effect size differentiates real world practical significance of a study's findings from that of statistical significance. This dual approach aligns with contemporary best practices in social science studies. For example, the American Psychological Association [47] asserts that empirical studies should adopt effect sizes because effect size improves the interpretation of a study's findings. This advocates moving beyond p-value to assess the practical relevance of empirical findings.

Data presentation

Table 1 presents the concatenation of respondents' demographic characteristics. This study categorised respondents based on the following criteria: gender, primary DMB for transactions, the number of DMB accounts held, alternative DMBs utilised for transactions, awareness of AI integration in the selected DMBs' operations, and the specific

Table 1: Demographic Characteristics of Respondents.

	Access Bank		First Bank		GT Bank		UBA Bank		Zenith Bank		Full sample	
	n	%	n	%	n	%	n	%	n	%	N	%
Gender												
Male	24	50	10	62.5	15	39.5	2	20	5	20.8	56	41.2
Female	24	50	6	37.5	23	60.5	8	80	19	79.2	80	58.8
Total	**48**	**100**	**16**	**100**	**38**	**100**	**10**	**100**	**24**	**100**	**136**	**100**
Number of acct owned												
One acct	11	22.9	5	31.3	7	18.4	5	50	8	33.3	36	26.5
More than one account	37	77.1	11	68.7	31	81.6	5	50	16	66.7	100	73.5
Total	**48**	**100**	**16**	**100**	**38**	**100**	**10**	**100**	**24**	**100**	**136**	**100**
Alternative acct owned												
None	18	37.5	4	25.0	17	44.7	7	70	17	70.8	63	46.3
Access Bank	0	0	3	18.8	0	0	2	20	4	16.6	9	6.6
First Bank	3	6.3	0	0	0	0	1	10	0	0	4	2.9
GT Bank	15	31.3	3	18.8	3	7.9	0	0	0	0	21	15.4
UBA Bank	4	8.3	3	18.8	15	39.5	0	0	0	0	25	18.4
Zenith Bank	8	16.7	3	18.8	3	7.89	0	0	3	12.5	14	10.3
Total	**48**	**100**	**16**	**100**	**38**	**100**	**10**	**100**	**24**	**100**	**136**	**100**
Type of acct												
Saving	32	66.7	13	81.3	27	71.1	5	50	19	79.2	96	70.6
Current	11	22.9	3	18.7	11	28.9	5	50	2	8.3	32	23.1
Fixed	5	10.4	0	0	0	0	0	0	3	12.5	8	5.9
Total	**48**	**100**	**16**	**100**	**38**	**100**	**10**	**100**	**24**	**100**	**136**	**100**
AI awareness												
Yes	32	66.7	8	50	22	57.9	5	50	9	37.5	76	55.9
No	6	12.5	8	50	15	39.5	3	30	0	0	32	23.5
Uncertain	10	20.8	0	0	1	2.6	2	20	15	62.5	28	20.6
Total	**38**	**100**	**16**	**100**	**38**	**100**	**10**	**100**	**24**	**100**	**136**	**100**
AI platform												
Chatbot	14	29.2	2	12.5	5	13.2	2	20	3	12.5	26	19.1
Google	12	25.0	2	12.5	18	47.4	3	30	2	8.3	37	27.2
WhatsApp	9	18.8	3	18.7	7	18.4	3	30	13	54.2	35	25.7
Webpage	13	27.0	9	56.3	8	21.0	2	20	6	25.0	38	28.0
Total	**48**	**100**	**16**	**100**	**38**	**100**	**10**	**100**	**24**	**100**	**136**	**100**

Source: Author's SPSS computation, 2025.

AI platforms of the selected DMBs they use during their banking transactions.

Demographic characteristics of respondents: Table 1 indicates 41.2% of the respondents were male and 58.8% of the respondents were female. Meanwhile, 26.5% of the respondents had one bank account with the selected DMBs in Abuja. 73.5% of the respondents had multiple bank accounts across the selected DMBs in Abuja.

In terms of the percentages of the respondents who had alternative bank transactions across the selected DMBs in Abuja, Access Bank respondents represented 6.6% of the sample population of the customers who had alternative transactions among the selected DMBs in Abuja, while First Bank accounted for 2.9% of the population that had alternative bank transactions across the selected DMBs in Abuja. Furthermore, 18.4% of respondents from UBA Bank and 15.4% from GT Bank had conducted alternative bank transactions across the selected DMBs in Abuja, respectively; while 10.3% of the respondents from Zenith Bank had alternative banking accounts across the selected DMBs in Abuja.

Furthermore, 70.6% of the respondents operated savings accounts with the selected DMBs in Abuja. 23.1% of the respondents operated current accounts, while 5.9% of the respondents operated fixed accounts with the selected DMBs in Abuja.

In terms of respondents' awareness of AI in banking transactions among the selected DMBs in Abuja, 55.9% of the respondents were aware of AI integration in the selected DMBs' transactions, while 23.5% of the respondents were unaware of AI integration among the selected DMBs' bank transactions; while 20.6% of the respondents were uncertain of AI integration in the banking transactions of the selected DMBs in Abuja.

Lastly, in terms of the type of AI-integrated technology platforms respondents have used during their banking transactions with the selected DMBs in Abuja, 28% of the respondents have used DMBs' AI-integrated web pages during their banking transactions with the selected DMBs in Abuja. 25.7% of the respondents have used AI-integrated WhatsApp

platforms during their banking transactions with the selected DMBs in Abuja. Lastly, 27.2% of the respondents have used DMBs' applications on the Google Play Store, while 19.1% of the respondents have interacted with chatbots during their transactions with the selected DMBs in Abuja.

Findings

Table 2 suggests the following findings of this study.

Hypothesis one:

H_{o1}: The value factor of AI has no significant influence on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja. The Kruskal–Wallis non–parametric test indicated value factor of AI has no significant influence on customers' perspectives of AI and the organisational performance of the selected DMBs in Abuja, with $H(4) = 7.02$, p–value = .13, and $E^2 = .02$.

Hypothesis two:

H_{o2}: The rarity factor of AI has no significant effect on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja. The Kruskal–Wallis test suggested the rarity factor of AI has no significant effect on customers' perspectives of AI and the organisational performance of the selected DMBs in Abuja, with $H(4) = 7.23$, p–value = .12, and $E^2 = .03$.

Hypothesis three:

H_{o3}: The inimitability factor of AI has no significant impact on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja. The Kruskal–Wallis test revealed inimitability factor of AI has no significant impact on customers' perspectives of AI and the organisational performance of the selected DMBs in Abuja, with $H(4) = 1.70$, p–value = .79, and $E^2 = -.02$.

Hypothesis four:

H_{o4}: The organisational support factor of AI has no significant influence on customers' perspectives of AI and the organisational performance of selected DMBs in Abuja. Similarly, the Kruskal–Wallis test indicated the organisational support factor of AI has no significant influence on customers' perspectives of AI and the organisational performance of the selected DMBs in Abuja, with $H(4) = 8.28$, p–value = .08, and $E^2 = .03$.

Discussion

This study examined the factors of AI that influence DMBs customers' perspectives of AI and the organisational performance of five DMBs in Abuja, Nigeria. Many studies have been conducted on AI and the organisational performances of DMBs in Nigeria. These studies indicated that AI improves DMBs' organisational performance; however, the findings of these studies were based on the organisational–centric perspectives of DMBs' employees and management. Hence, this study views AI and organisational performance from the customers' perspective, which is based on the value, rarity, inimitability, and organisational factors of AI.

The findings of this study suggest that the value, rarity, inimitability, and organisational support factors of AI have no significant effect on customers' perspectives of AI and the organisational performance of the DMBs examined in Abuja. Consequently, the findings of this study create an interesting scope for discussing the meanings of what was found in this study.

First, customers' perspectives of AI are not influenced by the value factor of AI (ease of service enquiries and trustworthy information feedback). Instead of seeing these services as novel or unique, customers perceive this factor as a normal DMB service package. This suggests customers' expectations of organisational performance have been shaped by failed service assurances, industry norms, and interactions with these selected DMBs' AI. This finding is in line with previous findings from organisational–centric perspectives of AI and organisational performance of DMBs in Nigeria. For example, Ofuani, Omoera, and Akagha [26] found that AI–driven customer service systems have no significant effect on DMBs' organisational performance. This suggests customers' complaints and enquiries are most often resolved by DMBs' human agents rather than AI. Thus, customers do not perceive AI as adding value to the risk management, customer engagement, or customer retention of the selected DMBs in Abuja.

Second, this study suggests that the functions and the features of AI among the selected DMBs are similar, which makes it not rare among its customers. For example, customers perceive homogeneity in the selected DMBs' responses to their banking services enquiries and the service offerings by these selected DMBs. Thus, this suggests customers perceived AI homogeneity across the selected DMBs in Abuja. This finding goes contrary to Okolioko, et al.'s [10] findings, which found

Table 2: Independent-Sample Kruskal-Wallis Test and Epsilon- Squared Effect Size Results.

	p-Value	H-Statistics	Decision	Effect Size (E^2)
Value factor of AI	.13	7.02	Retain the null hypothesis	0.02
Rarity factor of AI	.12	7.23	Retain the null hypothesis	0.03
Inimitability factor of AI	.79	1.70	Retain the null hypothesis	-0.02
Organisational support factor of AI	.08	8.28	Retain the null hypothesis	0.03

Note: p-value is significant at < .05. The epsilon squared effect size was calculated manually with the following equation: $(H − K + 1) / (n − K)$. Where H = Kruskal-Wallis test's H statistic; K = the number of groups observed; and n = the total sample size.

that AI had a significant positive impact on the organisational performance of DMBs. This disparity begs the question of whether Abuja consumers are less aware of AI than those in the Okolioko, et al. [10] study regions. Hence, this suggests that customers may lack the information and exposure necessary to identify variations in AI implementation and how they affect DMBs' organisational performance in Abuja.

Third, AI's inimitability factor, such as distinctive services and corporate reputation, does not affect customers' perspectives of AI and the organisational performance of the selected DMBs. This reveals that customers believe that these AI-related products are not a source of organisational performance, because they are simple to imitate. For example, customers of the selected DMBs interact with the same type of chatbots, which are programmed to communicate the same way across AI platforms. This demonstrates a possible flaw in the way DMBs position or brand their AI. This validates the third hypothesis of the study. This suggests the selected DMBs' AI function in similar ways, and it's easy to imitate among the selected DMBs in Abuja.

Lastly, customers did not consider the organisational support factor of AI (which includes management's commitment to see AI upgrade, employees' AI knowledge transfer) to be significant. This is in contrast to Okolioko, et al. [10], who discovered that the adoption of AI increased the DMBs' efficiency and satisfaction. This suggests the selected DMBs' customers do not perceive management and employees' effort in addressing follow-up on AI-related issues.

This study points to the fact that the selected DMBs' AI adoption and integration are generic. This means that AI applications currently used by the selected DMBs do not have strong value, they lack rarity, they are not inimitable, and they lack organisational support. These findings confirmed Barney and Clark's [21] and Frery's [3] argument, which argues that the factors of AI are not really valuable, rare, inimitable, or have organisational support.

Unarguably, this study's effect sizes are small and not statistically significant; however, they are not entirely devoid of practical meaning. For example, despite the non-significance of the findings, the effect sizes indicated that out of a hypothetical 1 million customers in the selected DMBs in Abuja, 20,000 customers' value expectations will be met by the value factor of AI (i.e., each VRIO factor of AI's effect size multiplied by the hypothetical 1 million customers). 30,000 customers will perceive AI strategic risk management and customer retention to be rare or differentiable across the selected DMBs. 30,000 customers of the selected DMBs will perceive the organisational support to invest in and improve AI and organisational performance. Nevertheless, 20,000 customers will not notice AI function and feature imitation across the selected DMBs in Abuja. Thus, the small effect sizes reflect an early-stage AI adoption environment, which suggests customer-facing benefits are yet to mature. Consequently, the incremental improvement in AI design, transparency, and responsiveness will amplify these effects.

While the conceptual framework presents customers' perspectives of AI and organisational performance as distinct outcomes, this study's empirical analysis operationalises organisational performance through customers' perspectives. This alignment reflects this study's core assumption that customer evaluations serve as a valid proxy for perceived organisational performance in service-driven industries such as DMBs. Accordingly, the framework can be interpreted as modelling perceived organisational performance rather than objective financial outcomes, thereby maintaining conceptual consistency between theory, measurement, and analysis.

Notably, the retention of all of this study's null hypotheses was not a methodological weakness but a theoretically meaningful outcome. The findings challenge prevailing assumptions within AI performance literature, which opine that technological adoption automatically translates to customer-perceived value. Arguably, the findings of this study hinge on two standpoints: theoretical and practical standpoints.

From a theoretical standpoint, the findings suggest that the VRIO factors of AI, while effective in explaining internal competitive advantages among selected DMBs in Abuja, do not directly translate into perceived value at the customer interface. This calls for a refinement of RBV-based applications in banking service contexts, where customers' cognition and expectations play an important role.

From a practical standpoint, these findings imply that AI investment alone is not sufficient to improve perceived organisational performance unless it is visibly differentiated and aligned with customers' expectations.

Notwithstanding, the generalisation of this study's findings has some limitations. First, out of the 10 DMBs that have integrated AI in their services in Nigeria, this study selected 5 DMBs. Thus, the 5 DMBs sampled in this study may not give a proper representation of the selected DMBs' customers' perspectives of AI and their organisational performance across Abuja. Second, the 136 respondents' perspectives of AI and the organisational performance of the selected DMBs in Abuja might not give a proper representation of customers' perspectives. This is because the sample size of this study is too small to give a significant representation of customers' perspectives of AI and the organisational performance of the selected DMBs in Abuja.

In tandem with the identified limitations, this study makes the following suggestions for further studies. First, a larger range of customer viewpoints can be captured by using stratified or cluster sampling, which will show more pronounced patterns of customers' perspectives of AI and the organisational performance of the selected DMBs in Abuja. Second, for a more significant and accurate effect size, future studies should have a larger sample size of the customers of selected DMBs. This improves the significance and effect sizes of the value, rarity, inimitability, and organisational factors of AI on their perspectives of AI and organisational performance. Third, to get a more accurate picture of AI and the organisational performance of DMBs in Abuja, as well as Nigeria, future studies

should expand their scope of study beyond the five selected DMBs in Abuja. Lastly, future should use an AI–Customer Satisfaction Index or an AI Service Equity Index to measure customers' perspectives of AI and organisational performance more precisely. This makes it easy to track the influence the VRIO factors of AI have on customers' perspectives more precisely. Although this study employed VRIO factors of AI as a metric, more focused indices could improve subsequent future studies' findings [48-51].

Conclusion

This study examines the VRIO factors of AI that influence customers' perspectives of AI and the organisational performance of selected DMBs in Abuja. The findings demonstrated that the VRIO factors of AI have no significant influence on customers' perspectives of the selected DMBs' organisational performance. The findings of this study reveal a pronounced expectation gap between DMBs' AI investment and customers' expectations of AI. While DMBs emphasise AI for organisational efficiency, fraud detection, and cost reduction, customers primarily assess AI based on service responsiveness and personal relevance.

Undeniably, customers remain the lifeblood of DMBs in Nigeria. Nonetheless, AI's contribution to organisational performance will be limited if it does not meet customers' expectations. This positions the findings of this study as a new and important factor in AI technology and banking research. This implies that although the selected DMBs may celebrate improvements in internal efficiency, customers' banking expectations are yet to be met. This misalignment suggests AI adoption in Nigerian DMBs is currently technological–driven rather than customer- driven. Until AI systems are repositioned as tools for meaningful engagement and differentiated service delivery among Nigerian DMBs, customers are unlikely to associate AI with organisational performance.

Lastly, to bridge the customers' AI expectation gap, Nigerian DMBs have to move from AI investment and deployment to AI communication, education, and experiential design that visibly improves customers' banking experience. AI is more than just a service tool to improve organisational performance. For AI to improve DMBs' organisational performance, visible customer benefits, awareness, and differentiation are essential. If not, AI will continue to function as a background efficiency mechanism that has no effect on customer loyalty or on the extent to which AI has improved Nigerian DMBs' organisational performance.

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