

AI ADOPTION AND OPERATIONAL PERFORMANCE OF COMMERCIAL BANKS IN GHANA: *THE MODERATING ROLE OF EMPLOYEE TECHNOLOGY SKILLS*

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Abstract

The study examined of the adoption of artificial intelligence (AI) on operational performance within Ghana Commercial Banks by considering the moderating role of employee technological skills. A sample size of 136 employees from Ghana Commercial Bank comprised the population of the study, which employed a quantitative methodology. The research samples were chosen using the convenience sampling technique. The instrument used to collect the data was a structured questionnaire. Data for the study was analysed using Amos' Structural Equation Model (SEM) (version 23). Findings from this study showed that, AI adoption leads to significant improvements in operational metrics, such as cost reduction and service efficiency. Again, the path coefficient for employee technological skills to operational performance (0.345; $p < 0.001$) shows that employee technological skills are a critical factor in improving operational performance of banks. Also, the results of the study showed that, employee skills moderated the relationship between AI adoption and operational performance of banks in Ghana. However, demographic factors, such as work experience, age, gender, and education, are not significant predictors of operational performance in the context of AI adoption, underscoring the importance of technological readiness over traditional demographic measures. It was suggested that banks prioritize the development of their employees' technological skills and make investments in AI technology and system upgrades to satisfy operational needs. Banks should also create precise metrics to evaluate how the use of AI affects operational performance. Furthermore, banks have to make sure that training initiatives for staff members correspond with the particular objectives and features of the AI systems they are putting into place.

Keywords: Artificial Intelligence, Technology, Banks, Operations, Performance, Employee skills

Introduction

In professional contexts, information technology (ITs) are ubiquitous and have a profoundly disruptive and influencing impact on all essential operations and activities. Integration of IT into the business ecosystem can have a significant impact, especially on how businesses engage with their partners, customers, and prospects (Lauterbach, 2019; Nwamen, 2006). Artificial intelligence (AI) is one of the many IT applications that is most notable, having grown at an extraordinary rate in the last few decades (Lee et al., 2018; Wiljer & Hakim, 2019). Artificial Intelligence is described as a collection of theories and methods used to build machines that can mimic human intelligence. The generic term artificial intelligence (AI) refers to the modeling of intelligent behavior by a computer with little to no human interaction (Haenlein & Kaplan, 2019).

Business and organizational processes are being radically transformed by artificial intelligence (AI) and associated technologies, including chatbots, neural networks, deep learning, machine

learning, and virtual assistants (PwC, 2019). The rapid deployment of artificial intelligence technologies has resulted in significant transformations within banks. Artificial Intelligence is being utilized more and more to enhance customer service, increase operational efficiency, and simplify bank processes. Numerous applications, including risk management, fraud detection, automated customer care, and predictive analytics, are among the banking industry's use of AI (Accenture, 2018). Therefore, the requirement to maintain competitiveness in a market threatened by Fintechs and shifting consumer expectations has an impact on the transition toward AI adoption (Deloitte, 2020). The potential for transforming banking operations through the automation of repetitive processes, acceleration of decision-making, and reduction of human error lies in the integration of AI technologies. PwC (2022) asserts that AI-driven automation can replace time-consuming and repetitive jobs like data entry, transaction processing, and basic client contacts, resulting in a considerable increase in efficiency. For example, AI-powered chatbots can respond accurately and quickly to a large number of customer inquiries at once, increasing customer satisfaction while freeing up human staff to work on more intricate, high-value tasks (Vinoth & Chinnasamy, 2024; Mori & Du, 2023). Additionally, AI systems are adept at processing and analyzing large datasets, which is critical for banks in areas such as risk management and fraud detection. By identifying patterns and anomalies in real-time, AI can provide early warnings of potential risks, enabling banks to take proactive measures to mitigate them. This capability not only enhances the bank's operational efficiency but also strengthens its overall risk management framework, leading to more secure and reliable banking operations.

Therefore, the ability of employees in using technologies plays a critical role in determining the extent to which AI will be able to have positive impacts on banks' operational performance. Banks require a workforce that is not only competent in basic digital skills but can also understand, manage, and optimize AI tools (Mazurchenko et al., 2022). Such technical competencies must be instilled in the employees to facilitate the interpreting of AI-generated insights, implement AI-driven process execution, and troubleshooting for any issues related to such processes (Lavrinenko & Shmatko, 2019; Mazurchenko et al., 2022; Pradhan & Saxena, 2023). Absence of such skills can result in less-than-optimal usage of AI technologies, thus eroding potential benefits and maybe even causing operational disruptions. This makes continuous upskilling and reskilling initiatives within banks very important in ensuring that employees can make optimum use of AI technologies in routine tasks (Pradhan & Saxena, 2023).

The interaction between AI adoption and employee technological skills also points to broader implications for workforce management and organizational strategy within the banking sector (Chuang, 2024). As AI continues to evolve in the coming years, so does the demand for specific skill sets that would foster shifts in job roles and responsibilities within banks (Biswas et al., 2020). Strategic investments in employee training and development are hence imperative to align the workforce with the technological advancements being implemented (Morandin et al., 2023). Banks that actively act on this need are more likely to make a smoother transition to AI-driven operations and thereby get an upper hand in the banking sector (Mahapatra & Singh, 2021; Christensen, 2021; Rahman et al., 2023).

Adoption of artificial intelligence (AI) technology has potential for transforming operational procedures, improving efficiency, and providing better client experiences in the dynamic world of modern banking (Tiwari et al., 2021; Doumpos et al., 2023). However, staff members' technological proficiency plays a major role in the effectiveness of AI integration into banking

processes. Although the banking industry is placing more and more emphasis on the use of AI, little is known about how employee technological proficiency affects how AI adoption affects operational performance. There is still more research to be done, particularly in Ghana, on the effects of artificial intelligence technology adoption on banks' operational performance, the role that employee technological skills play in this relationship, and the kinds of technological competencies or skills that are particularly important in maximizing the advantages of AI adoption for banking operational performance. Addressing these gaps is crucial for banks seeking to maximize the benefits of AI adoption while effectively leveraging the capabilities of their workforce. Therefore, this study attempts to breach the identified gaps in literature.

The study seeks to achieve the following objectives; (1) assess the effect of artificial intelligence adoption on the operational performance of banks; (2) examine the impact of employee technological skills on the operational performance of banks; (3) ascertain the moderating role of employee technological skills in the relationship between artificial intelligent adoption and operational performance of banks.

Theoretical underpinning of the study

This study is supported by two main theories; 1) the resource-based view theory and 2) innovation diffusion theory.

The Resource-based View Theory (RBT)

The RBV developed by Barney (1981) can be regarded as a conceptual instrument applied to explain how unique resources and capabilities that are available in a firm contribute to its competitive advantage and performance. In view of the above, one is presented with the opportunity to bring out the importance of technological skills by employees as far as AI adoption is concerned in banks and its effects on operational performance. The RBV stresses that firms have resources and capabilities that are unique to them, which, if properly harnessed and utilized, can enable the firm to attain a competitive advantage. In this case, the main resources would be AI technology and employee technological skills. Such AI technologies as machine learning algorithms, natural language processing, and robotic process automation are related and valuable resources for banks. These technologies can improve operational efficiency, customer service, risk management, and decision-making processes of a bank.

RBV highlights the importance of human capital in leveraging technological resources effectively. In the context of AI adoption, employee technological skills such as data analysis, programming, AI algorithm development, and understanding of AI applications become critical. RBV suggests that resources and capabilities should complement each other to create value. In this case, the adoption of AI technology is complemented by the presence of skilled employees who can effectively utilize and manage these technologies. Through the combination of AI technology and skilled employees, banks can achieve a competitive advantage in terms of operational efficiency, customer experience, risk management, and innovation. Banks with superior AI capabilities and well-trained employees are better positioned to adapt to changing market dynamics and gain market share. RBV would argue that, the combination of AI adoption and employee technological skills positively influences operational performance metrics such as cost efficiency, productivity, accuracy, customer satisfaction, and innovation. RBV suggests that sustainable competitive advantage arises when resources and capabilities are valuable, rare, inimitable, and non-substitutable (VRIN). In the case of AI adoption, continuous investment in employee training and

development of technological skills ensures the sustainability of the competitive advantage derived from AI.

Innovation Diffusion Theory

Innovation Diffusion Theory (IDT) is a theoretical construct that facilitates the comprehension of the diffusion and adoption of novel concepts, technologies, or innovations in a given community or institution. It investigates how innovations spread over time among members of a social system through certain routes. According to IDT, an innovation's adoption rate is influenced by a few key features. The rate and degree to which banks adopt AI technology will depend on a number of factors, including complexity, compatibility with current systems, and the belief that AI will improve operational efficiency and customer service. IDT highlights the significance of communication channels for the dissemination of innovative information. Banks may rely on various channels such as industry publications, conferences, and professional networks to learn about AI technologies and their potential benefits.

The adoption of AI in banks is significantly influenced by the social system, which includes employee attitudes, leadership support, and corporate culture. Banks that have an innovative and learning-oriented culture are more likely to successfully implement AI technologies. Support from the leadership is also crucial for allocating funds and advancing AI projects. IDT acknowledges that innovations are adopted gradually and along a particular path, usually beginning with inventors and early adopters and progressing to the bulk of users. Early adopters of AI in banking could be more technologically astute institutions that see the benefits of AI right away in terms of enhanced operational efficiency.

IDT highlights the importance of the skills and capabilities of individuals within the organization in the adoption of innovations. In the case of AI adoption in banks, employees need to have the necessary technological skills to understand, implement, and utilize AI technologies effectively. These skills may include data analysis, programming, machine learning, and AI-specific knowledge. IDT provides a framework for understanding the adoption of AI technologies in banks and their impact on operational performance. By examining factors such as innovation characteristics, communication channels, the social system within banks, the passage of time, and the role of employee technological skills, researchers and practitioners can gain insights into how AI adoption can be facilitated to improve operational performance in the banking sector.

Hypothesis Development and Conceptual Model

Artificial Intelligence Adoption on the Operational Performance of banks

In the context of the banking sector, AI is utilized to enhance productivity and improve customer experiences by automating processes that were traditionally performed by humans. According to Davenport and Ronanki, (2018), AI technologies such as machine learning and natural language processing help in the automation of routine tasks, which aids in enhancing efficiency and productivity (Venkatesh et al., 2024). It is in regard to streamlining organizational processes, reducing human error, and resource allocation that organizations can indeed benefit from these technologies toward driving operational excellence. Automation frees up human resources to deal with more strategic, creative, high-value-added activities, which in effect enhances productivity and operational performance.

Similarly, Brynjolfsson and McAfee (2017), explain how AI-driven automation might realize appreciable cost savings through the optimization of resource use. Using AI, companies can do predictive maintenance in order to reduce equipment and machinery downtime, elongating their life and rendering production processes continuous and efficient. Such proactive maintenance not only reduces the costs related to repair and replacement but also ensures continuous and efficient production. Moreover, AI's capability for the analysis of big datasets makes organizations more informed in decision-making, hence inventory management, less wastage, and efficient supply chains. Therefore, the integration of AI in operations leads to a leaner organization that is more agile and can respond promptly to market demands and changes. Karthiga et al. (2024) investigated the impact of AI on the banking sector, providing a comprehensive analysis of its effects. Their study highlights several key areas where AI is making a difference, including credit scoring, operational efficiency, fraud detection, personalized financial services, customer service, predictive analytics, and regulatory compliance. Additionally, AI algorithms have bolstered security measures by detecting fraudulent activities and improving credit scoring and loan underwriting processes (Karthiga et al., 2024; Noreen et al., 2023; Boustani et al., 2022). Furthermore, AI-powered predictive analytics enable banks to make informed, data-driven decisions in financial markets, while automation has notably increased operational efficiency (Karthiga et al., 2024). Umamaheswari et al. (2023) examined the role of AI in the banking industry and found that, adopting AI can improve both the operations and overall performance of banks. Therefore, it is hypothesized that;

H1: Artificial intelligent has a positive influence on banks operational performance.

Employee Technological Skill and Operational Performance.

Previous literature is dedicated to in-depth empirical research on the relationship between employee technological skill and operational performance, focusing on the former (Rusilawati, 2023; Pinto et al., 2020; Hasan & Chowdhury, 2023; Jaiswal et al., 2023; Maisiri et al., 2019). Many such studies report findings that firmly confirm the enormous difference that highly technologically skilled employees can make in organizational performance. For instance, Ahearne Atefi and Lam (2020); González-Lloret (2020); Tavakoli et al., (2021), prove that a technological workforce not only multiplies the gains made in investments in information technology but also creates efficiency, acts as an underpinning of innovation, and places organizational activity on the road to success. This means that for top operational performance to be achieved with continuous competitive advantage, the technological skills of the workforce need to be developed. Heuser, Letmathe, and Schinner al. (2023), emphasize that enhanced technological skills among employees lead to improved operational efficiency, as skilled workers can leverage technology to streamline processes and reduce errors. Similarly, Fitri et al. (2022), found that organizations with a workforce proficient in technology experience higher levels, attributing this to the ability to adapt quickly to technological changes and innovations. Oira (2021) supports this by highlighting that employee training in technological skills not only boosts individual performance but also fosters a culture of continuous improvement within teams, ultimately enhancing overall operational performance. However, Wijayanti and Sari (2020) caution that the mere presence of technological skills is insufficient; organizations must also cultivate an environment that encourages the application of these skills to realize performance gains. Abireza and Faris (2023) further note that while technological skills are crucial, the integration of these skills into operational strategies is vital for maximizing performance outcomes. Thus, while the evidence strongly supports a positive

relationship between employee technological skill and operational performance, the context and organizational support play critical roles in determining the extent of this impact. As noted by Adesina et al. (2024), employees with advanced technological skills can streamline processes, reduce operational costs, and improve overall efficiency. Also, Kyambade et al., (2024), highlight that skilled employees are crucial for implementing new technologies, which directly influences the innovation process in banking institutions. Similarly, Vo, et al. (2024), found employee digital skill to have a significant effect on operational performers. From the above, we therefore hypothesise that;

H2: Employee technological skill has a positive effect on banks operational performance.

The Moderating Role of Employee Technological Skill in the relationship Between Artificial intelligent Adoption and Operational Performance.

The moderating role of employee technological skill in the relationship between artificial intelligence (AI) adoption and operational performance is significant. Employee technological skills are crucial in ensuring that AI technologies are effectively implemented and utilized within an organization. According to Huang and Rust (2018), employees with high technological competence are more likely to embrace AI tools, leading to a more seamless integration and better operational performance. Conversely, a lack of technological skills can hinder the effective use of AI, resulting in lower productivity and inefficiencies (Tambe, 2014). Therefore, the technological skills of employees can be seen as a moderating factor in the relationship between AI adoption and operational performance (Khin & Ho, 2019). Research indicates that higher levels of employee technological skills enhance the effectiveness of AI integration, leading to improved operational outcomes. For instance, Chen, Zhang and Wang (2024), highlights that skilled employees can leverage AI tools more effectively, resulting in better decision-making and efficiency gains. Similarly, Sharma and Saxena emphasize that technological proficiency among employees is crucial for maximizing the benefits of AI, as it facilitates smoother implementation and utilization of these technologies. Moreover, Sahoo, Kumar, Donthu and Singh (2024), found that organizations with a workforce adept in technology experience a more pronounced positive impact on operational performance post-AI adoption, suggesting that employee skills act as a critical enabler in this context. However, the disparities in technological skills can lead to uneven performance outcomes, indicating a need for targeted training programs to bridge skill gaps (West, Kraut and Ei Chew, 2019; Bishop, 2019). Based on the discussions above, it is hypothesized that;

H3: Employee technological skill moderate the relationship between AI adoption and banks operational performance.

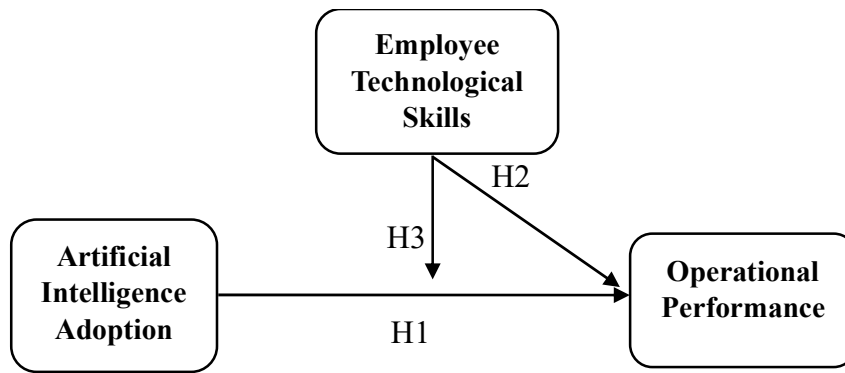


Figure 1: Conceptual Framework

Source: Researcher's Construct, 2024

Methodology

This study used a survey design approach to investigate how the use of artificial intelligence (AI) affected the operational performance of Ghana's banking industry. The descriptive survey indicated that a quantitative technique was employed in the investigation. The Ghana Commercial Banks in the Ashanti Region of Ghana make up the population. There are 1100 workers in the area overall. Convenience sampling is a non-probability sampling technique used in this study. Using this approach, study volunteers are chosen based on their availability and willingness to take part. The 136 research participants are based on the work of Krejcie and Morgan (1970). Data for the study was collected using a structured questionnaire. Printed questionnaires were utilized, which were divided into four sections. Section A was dedicated to gathering demographic information from the respondents. Section B included measurement items related to Artificial Intelligence Adoption, and Employee Technological Skills. Section C consisted of questions Operational Performance. In Sections B and C, respondents provided their responses on a Likert scale, ranging from 1 (Strongly disagree) to 5 (Strongly agree). To ensure that the study's variables meet the established criteria for validity and reliability, Cronbach's Alpha was calculated for all the variables used. Based on the results, it was confirmed that all the variables were suitable for further investigation because they were all above the > 0.70 criteria. Furthermore, exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) will be carried out within the framework of SEM analysis, and discriminant validity will be assessed. These processes are essential for confirming the accuracy and consistency of the measurements of the variables.

Exploratory Factor Analysis (EFA)

To determine if measurement items were correctly loaded onto their respective latent variables, EFA is used. SPSS (v. 25) was used to conduct EFA. There were three (3) latent variables, which were, Artificial Intelligence Adoption, Employee Technological Skills and Operational Performance. Originally (from the questionnaire – Appendix I), Artificial Intelligence Adoption had six (6) measurement items, Employee Technological Skills had five (5) measurement items and Operational Performance had Six (6) measurement items. Measurement items loading on various or multiple constructs and having weak factor loadings (less than 0.5) were removed from the analysis during the EFA. After eliminating items with factor loadings of less than 0.5 or cross-loading on several constructs, Table 1 lists the items that were kept.

At 79.285%, the total variance extracted (TVE) from the data exceeded the minimal threshold required of 50%. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, which should be at least 0.6, gives the current study a score of 0.923, indicating good sample adequacy. To confirm EFA and show the strength of the correlations between the variables, the Bartlett's Test of Sphericity results also need to be statistically significant. The collected data ($X^2 = 3245.791$; Sig. 0.000) showed that there was enough correlation between the variables to support an appropriate EFA. The Determinant of Correlation should also not equal zero (zero) as an indication of positive definiteness in the estimation data. $3.700E7$ was the EFA determinant, meaning it is greater than zero (0).

Table 1: Exploratory Factor Analysis (EFA)

Measurement Items	Components		
	1	2	3
ETS1			.835
ETS2			.886
ETS3			.874
ETS4			.841
AIA1	.763		
AIA2	.756		
AIA3	.869		
AIA4	.867		
AIA5	.847		
AIA6	.818		
OP1		.622	
OP2		.828	
OP3		.855	
OP4		.820	
OP5		.725	
<i>Total Variance Explained</i>			79.285%
<i>Kaiser-Meyer-Olkin Measure of Sampling Adequacy</i>			.923
<i>Bartlett's Test of Sphericity</i>			Approx. Chi-Square 3245.791

<i>Df</i>	105
<i>Sig.</i>	.000
<i>a. Determinant</i>	3.700E-7

Source: Researcher's Field Work (2024)
Confirmatory Factor Analysis (CFA)

Table 2 displays the estimated CFA findings following the EFA's meeting of the respective thresholds. As predicted, all of the standardized factor loadings for the measurement variables were more than 0.5. This indicates that every measurement item successfully captured the meaning of its underlying variable. The measurement variables exhibited good internal reliability because all latent variables had Cronbach's Alphas (CA) above the lower limit of 0.7. The requirements set out by Fornell and Larcker (1981) for composite reliability (CR) and average variance extracted (AVE) were all met for every construct. CR had to be at least 0.7 and AVE had to be at least 0.5. This indicates that convergent validity was achieved. The pictorial representation of CFA is depicted in Figure 1.

In the present study, the following criteria were used to evaluate the model fitness: CMIN/DF should be ≤ 3 , GFI $\geq .8$, PClose > 0.05 , TLI $\geq .9$, CFI $\geq .9$, RMSEA $\leq .08$, and RMR $\leq .08$. All of these requirements were found to be met by the data shown in Table 2, which led to the conclusion that the dataset accurately fit the expected model.

Table 2: Confirmatory Factor Analysis (CFA)

Model-fit Indices	Factor Loading
CMIN=152.834; DF=84; CMIN/DF=1.819; GFI=.921; TLI=.973; CFI=.979; RMSEA=.060; RMR=.050; PClose=.129	
ARTIFICIAL INTELLIGENCE ADOPTION (AIA): CA=.942; CR=.925; AVE=.675	
AIA1	.763
AIA2	.756
AIA3	.869
AIA4	.867
AIA5	.847
AIA6	.818
EMPLOYEE TECHNOLOGICAL SKILLS (ETS): CA=.943; CR=.919; AVE=.738	
ETS1	.835

ETS2	.886
ETS3	.874
ETS4	.841

OPERATIONAL PERFORMANCE (OP): CA=.912; CR=.881; AVE=.600

OP1	.622
OP2	.828
OP3	.855
OP4	.820
OP5	.725

Source: Researcher's Field Work (2024)

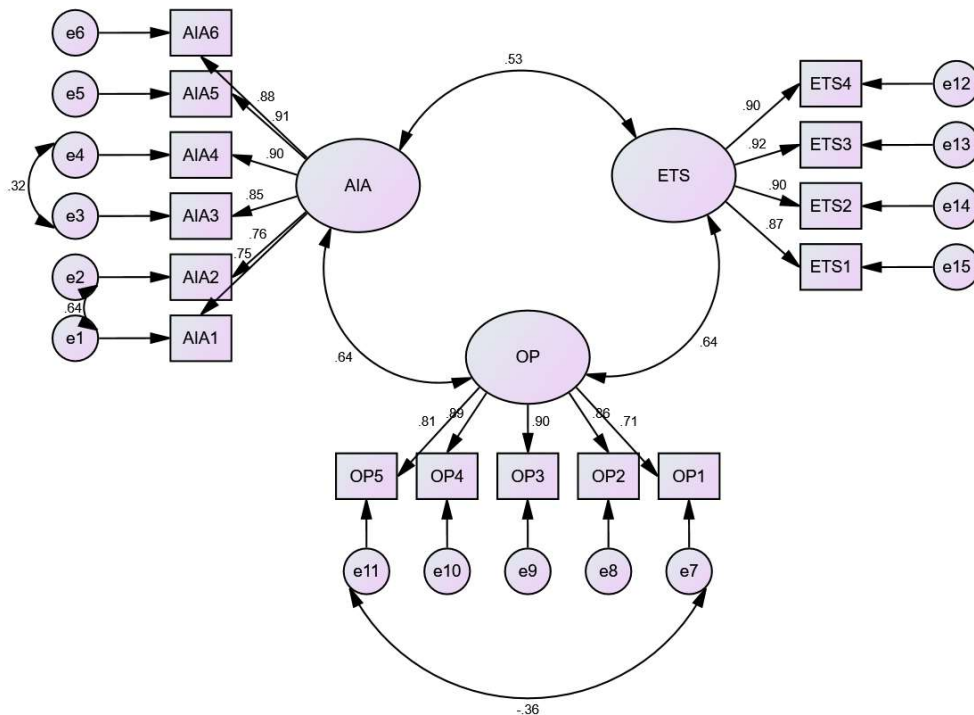


Figure 2: Confirmatory Factor Analysis

Source: Researcher's Field Work (2024)

Discriminant Validity

In order to assess discriminant validity, the researcher examined the relationship between the inter-correlation coefficients and the square root of the average variance extracted ($\sqrt{\text{AVE}}$). The correlation coefficients between the variables were consistently lower than the $\sqrt{\text{AVE}}$ values, which are indicated in bold and italics. There was a 0.630 association between the use of artificial intelligence and operational effectiveness, with the lowest $\sqrt{\text{AVE}}$ being 0.775. As shown in Table 3.3, this highest correlation of 0.630, being below 0.7, indicates that multicollinearity is not a concern within the dataset. Therefore, the data derived from the confirmatory factor analysis (CFA) is deemed valid for structural model estimation.

Table 3: Discriminant Validity

	Gender	Age	Education	Work Experience	AIA	ETS	OP
Gender	-						
Age	.011	-					
Education	-.043	.031	-				
Work Experience	.078	.010	.081	-			
AIA	-.051	.214**	.199**	-.051	0.822		
ETS	.069	.158*	.169*	-.032	.501**	0.859	
OP	.010	.167*	.199**	-.025	.630**	.604**	0.775

** ~ Correlation is significant at the 0.01 level (2-tailed); * ~ Correlation is significant at the 0.05 level (2-tailed); $\sqrt{\text{AVE}}$ ~ Bold and Italics.

Source: Researcher's Field Work (2024)

Results of the study

Demographics of Respondents

Relevant background profiles of the workers were determined. These include their gender, age, education and work experience. Table 4 projects the contextual physiognomies of the respondents.

Table 4: Table Demographics of Respondents

Variable		Frequency	Percent
Gender	Male	79	58.1
	Female	57	41.9
	Total	136	100.0
Age	25-30 years	17	12.5
	31-40 years	39	28.7

	41-50 years	63	46.3
	51-60 years	17	12.5
	Total	136	100.0
Education	HND/Diploma	20	14.7
	1st Degree	85	62.5
	Post-Graduate Degree	31	22.8
	Total	136	100.0
Work Experience	5-10 years	36	26.5
	11-15 years	38	27.9
	16-20 years	33	24.3
	Above 20 years	29	21.3
	Total	136	100.0

Source: Researcher's Field Work (2024)

Table 4 presents the demographic characteristics of the respondents. The study indicates that out of One-hundred and thirty-six (136) respondents, seventy-nine (79) were male representing 58.1% while the remaining Fifty-Seven (57) were female at 41.9%. Also, majority of the respondents 46.3% are with the age range of 41-50 years. Hundred and Thirty-Six (136) between the ages range of Twenty-five (25) to Sixty (60) years. The predominant group of respondents holds a first degree, with a total of eight-five (85) representing 62.5% indicating a strong foundational knowledge base within the banking sector. The largest group of respondents has 11-15 years of experience representing 27.9%.

Path Analysis

Table 5 presents a path analysis of the many direct effects of the study's hypotheses. The path analysis provides a method of separating the association between the numerous independent variables and the dependent variable, supporting theories put forth by previous scholars. Structural Equation Model (SEM) from Amos (ver. 23) was used to examine this. Table 4.3 showed the interaction between the independent (latent) factors (Artificial Intelligence, and Employee technological skills) and the dependent variable (Operational performance) for the control variables (gender, age, education and work experience).

Table 5: Path Coefficients

Paths	Unstd. Estimates	S. E.	C. R.	P
A_I_A → O_P	.365	.059	6.211	***
E_T_S → O_P	.345	.049	7.017	***
AIAXETS_Interaction → O_P	.067	.031	2.118	.034

Work Experience → O_P	.000	.030	.004	.997
Gender → O_P	.001	.069	.017	.987
Age → O_P	.022	.040	.548	.584
Education → O_P	.044	.050	.883	.377

Source: Researcher's Field Work (2024)

This analysis uses Path Coefficients (Table 5) to assess the relationship between Artificial Intelligence (AI) adoption, operational performance (OP), and the moderating role of employee technological skills (ETS) in Ghana Commercial Banks. The table also includes control variables such as work experience, gender, age, and education, but the primary focus is on the paths that show significant relationships. The path coefficient is 0.000 with a non-significant p-value ($p = 0.997$), indicating that work experience has no significant impact on operational performance in this context. This suggests that technological skills, rather than general experience, are more critical for banks to maximize the benefits of AI adoption. The path coefficients for gender (0.001, $p = 0.987$), age (0.022, $p = 0.584$), and education (0.044, $p = 0.377$) are all non-significant. These demographic variables do not seem to influence operational performance in a meaningful way in the context of AI adoption in the banking sector. This result highlights that specific technological skills are more influential than demographic factors in determining the success of AI adoption. The lack of significance for gender, age, and education implies that the benefits of AI are accessible to all employees, regardless of demographic differences, provided they possess the necessary technological skills. This reinforces the importance of targeted skills training over demographic considerations in AI adoption strategies.

AI Adoption on Operational Performance (AIA → OP)

The path coefficient from AI adoption to operational performance is 0.365 with a significant p-value ($p < 0.001$). This indicates a strong, positive relationship between AI adoption and improvements in operational performance in the banking sector. AI adoption leads to enhancements in service quality, cost reduction, flexibility, and productivity, as suggested by previous tables on operational performance. The standardized estimate of 0.365 means that for each unit increase in AI adoption, operational performance improves by 0.365 units.

The strong and significant relationship between AI adoption and operational performance indicates that AI technologies can greatly enhance banking operations. These improvements likely manifest in quicker service delivery, reduced operational costs, and increased flexibility and productivity. This finding aligns with the descriptive data provided in earlier tables, where respondents acknowledged the positive impact of AI on key performance indicators.

Employee Technological Skills on Operational Performance (ETS → OP)

The path coefficient for employee technological skills to operational performance is 0.345, also with a highly significant p-value ($p < 0.001$). This shows that employee technological skills are a critical factor in improving operational performance. When employees have the skills to use AI and other technologies, it enhances the operational performance of the bank, enabling smoother processes, faster service delivery, and better customer experiences. The significant path between

employee technological skills and operational performance emphasizes the critical role that skill development plays in maximizing AI's potential. Banks should prioritize upskilling their workforce in relevant technologies to fully leverage AI systems and improve operational outcomes.

Interaction of AI Adoption and Employee Technological Skills on Operational Performance ($AI \times ETS \rightarrow OP$)

The interaction term between AI adoption and employee technological skills is 0.067 with a significant p-value ($p = 0.034$). Although the coefficient is smaller than the direct paths, this result is important because it suggests that the effect of AI on operational performance is moderated by employee technological skills. Specifically, the positive impact of AI on operational performance is stronger when employees have higher technological skills. In banks where employees are more proficient in technology, AI adoption has a greater impact on improving operational outcomes. The significant interaction term suggests that technological skills amplify the impact of AI on performance. Employees with stronger technological skills are better able to interact with AI systems, leading to greater gains in efficiency, customer satisfaction, and overall operational success.

In conclusion, this analysis shows that the adoption of AI in Ghana Commercial Banks has a direct and positive impact on operational performance. Employee technological skills not only enhance operational performance on their own but also amplify the positive effects of AI adoption. The interaction between AI and employee skills underscores the importance of investing in technological skill development to fully realize the benefits of AI systems. Control variables such as work experience, gender, age, and education do not play a significant role, suggesting that success in AI adoption is primarily dependent on technological readiness rather than demographic factors.

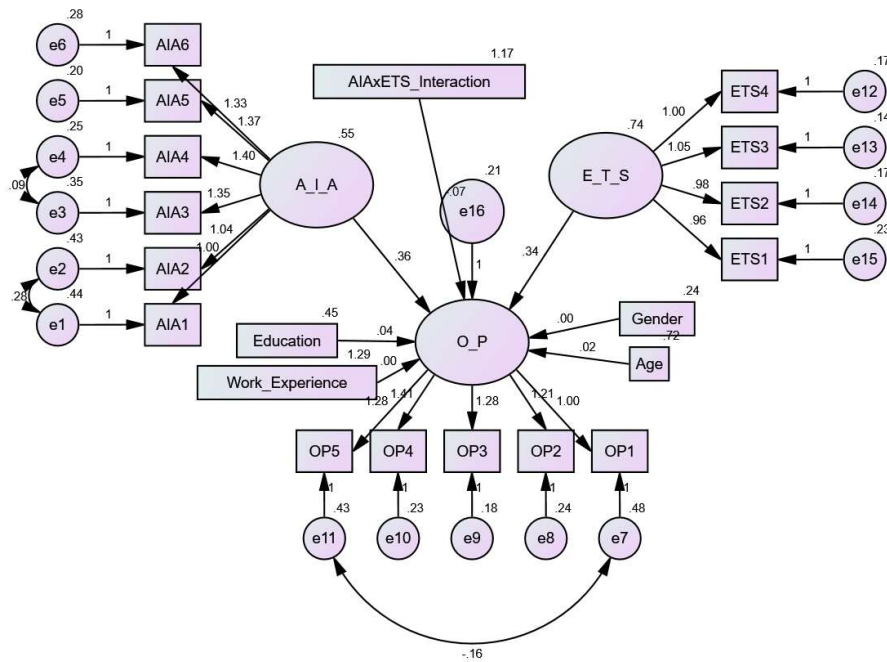


Figure 3: Structural Equation Model

Source: Researcher's Field Work (2024)

In conclusion, the structural equation model confirms that AI adoption positively impacts operational performance, with the effect being stronger when employees have higher technological skills. The interaction between AI and employee skills plays a key role in maximizing operational improvements, while demographic factors (gender, age, education, work experience) have minimal impact. This suggests that Ghana Commercial Banks should focus on both AI implementation and continuous upskilling of their workforce to enhance operational performance.

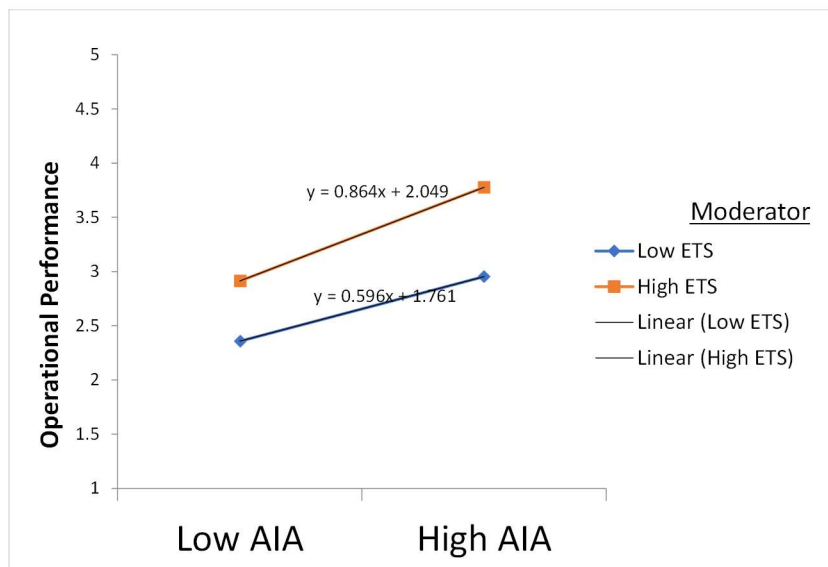


Figure 4: Two-Way Interaction between AI Adoption and Employee Technological Skills.

Source: Researcher's Field Work (2024)

Interpretation of the Two-Way Interaction Graph between AI Adoption and Employee Technological Skills.

This graph above (Figure 4) shows a two-way interaction between Artificial Intelligence Adoption (AIA) and Employee Technological Skills (ETS) on Operational Performance (OP) in Ghana Commercial Banks. The graph compared the effects of high and low levels of employee technological skills on operational performance, contingent on the extent of AI adoption. High ETS where ($y = 0.864x + 2.049$), This slope is steeper, indicating that when employee technological skills are high, AI adoption has a more significant positive impact on operational performance. As AI adoption increases, operational performance improves substantially. Low ETS where ($y = 0.596x + 1.761$), This slope is flatter, showing that for banks with low employee technological skills, the positive impact of AI adoption on operational performance is smaller. Even when AI adoption is high, the operational performance does not improve as much as in the high ETS case. Therefore, it is significant to demonstrate that, employee technological skills significantly moderate the relationship between AI adoption and operational performance. The effect of AI adoption is more pronounced in banks where employees have high technological skills, allowing them to better utilize AI technologies to enhance operational efficiency, customer service, and overall productivity.

Discussions of Results

Empirical evidence strongly supports the analysis of AI adoption and its impact on operational performance in the banking sector, particularly within Ghana (Goyal & Varma, 2022; Deloitte, 2023; Osei, Mensah and Adom, 2022). Goyal and Varma (2022) study in both Indian and Ghanaian banks showed a positive correlation between AI implementation and the efficiency of service delivery, reduction in operational costs, and customer satisfaction. That is, this study's findings

suggests that, AI adoption leads to significant improvements in operational metrics, such as cost reduction and service efficiency. Similarly, a 2023 report from Deloitte on AI in African banking systems corroborates these findings. It shows that AI adoption leads to 35% increased efficiency in operational performance in banks across Africa, including Ghana, through optimized workflow automation, customer service chatbots, and data analytics tools that reduce decision-making time. Also, employee technological skills are crucial in realizing these performance gains, with proficient employees enabling smoother AI integration and more effective operations. A study by Osei et al. (2022) on the role of technological skills in Ghanaian banks revealed that, in banks, where employees possessed higher technological competencies experienced greater improvements in operational performance. Specifically, their ability to interact with AI tools, such as data analytics platforms and automated customer service systems, resulted in faster response times and reduced error rates in service delivery. Moreover, a 2023 PwC Ghana study on technological readiness in financial institutions highlighted that banks investing in employee upskilling saw a 25% increase in productivity post-AI adoption. Employees who were proficient in technology were more capable of leveraging AI systems to streamline daily operations, leading to a significant operational uplift.

Regarding the moderating effect of employee skills in AI adoption and operational performance link, this study found that employee skills moderated that relationship. This corroborates earlier findings (Mensah, Osei & Adom, 2023). Research from Accenture's AI in Banking Report (2023) provides empirical support for the moderating role of employee skills in AI adoption. Their study of African banks, including those in Ghana, found that AI's impact on operational performance was amplified by the technological proficiency of employees. In banks where employees were trained in AI tools and data analysis, the improvements in operational performance were 40% higher compared to banks with less technologically adept staff. This finding aligns with the interaction term in the path coefficient analysis, which shows that technological skills enhance the positive effect of AI on operational performance. However, on Control Variables which includes Work Experience, Gender, Age, and Education, several studies conducted have shown that demographic factors such as age, gender, and education have minimal impact on the operational success of AI adoption when compared to technological skills. A study by Mensah et al. (2023) analyzed demographic factors in Ghanaian banks and concluded that age, gender, and work experience do not significantly affect the efficiency gains from AI adoption. Instead, the key factor driving performance improvements was the level of employee technological skills, reinforcing the need for skill-based training programs rather than focusing on demographic diversity alone.

Theoretical Contributions

The Resource-Based View (RBV) theory asserts that a firm's competitive advantage stems from its unique resources and capabilities, which are valuable, rare, inimitable, and non-substitutable (Barney, 1991). In the context of adopting AI in operational performance within the banking sector, RBV highlights how AI technology can serve as a strategic resource for Ghanaian commercial banks. As a strategic resource in banks, AI offers banks the ability to improve operational efficiency, reduce transaction costs, enhance decision-making processes, and deliver better customer services. By leveraging AI, banks can harness data-driven insights to streamline operations, predict market trends, and optimize workflow automation. However, to fully realize the benefits of AI as a resource, banks must combine it with other organizational resources such as employee skills, infrastructure, and strategic alignment. Secondly, Employee Technological

Skills as a Complementary Capability: The technological skills of employees play a critical role in AI adoption.

AI implementation alone cannot enhance operational performance without employees who possess the knowledge and skills to effectively manage and utilize AI systems. Employees' ability to engage with AI tools, troubleshoot issues, and optimize usage becomes a complementary capability that allows banks to fully leverage the value of AI. From an RBV perspective, this interaction between AI systems (resource) and employee technological competence (capability) can create a sustainable competitive advantage for Ghanaian banks. Also, Innovation Diffusion Theory (IDT) describes how new technologies are adopted and spread within organizations. The theory outlines factors that influence the rate and success of innovation adoption, including relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). When applied to AI adoption in the banking sector, IDT sheds light on how AI systems spread within the organization and the role employee technological skills play in this process.

Conclusion

The study examined the effect of artificial intelligence (AI) adoption on operational performance within the banking sector in Ghana. Based on the findings AI adoption leads to significant improvements in operational metrics, such as cost reduction and service efficiency. Employee technological skills are crucial in realizing these performance gains, with proficient employees enabling smoother AI integration and more effective operations. The interaction of AI and technological skills enhances AI's benefits, amplifying its positive effect on operational performance. However, demographic factors, such as work experience, age, gender, and education, are not significant predictors of operational performance in the context of AI adoption, underscoring the importance of technological readiness over traditional demographic measures.

Recommendations

The present study examined the adoption of artificial intelligence (AI) on operational performance within the banking sector by considering the moderating role of employee technological skills in Ghana Commercial Banks. In as much as the study provided some interesting findings, these recommendations are inspired;

Banks should Invest in AI Technology and Upgrade AI Systems to meet operational needs. Banks should invest in advanced AI technologies that can enhance operational performance. This includes integrating AI tools for automation, data analytics, and customer service. AI systems should be tailored to address specific banking operations, such as fraud detection, credit scoring, and personalized customer interactions. Also, there should be Continuous Improvement. Regularly update and maintain AI systems to keep up with technological advancements and changing market needs. This ensures that the AI tools remain effective and relevant.

Again, banks should **Prioritize Employee Technological Skills Development**. Implement comprehensive training programs to enhance employees' technological skills. Focus on equipping staff with the necessary competencies to effectively use AI systems, such as data analysis, machine learning basics, and AI tool management. Promote continuous learning opportunities through workshops, seminars, and online courses. Encourage employees to stay updated with the latest technological trends and AI advancements. Create an organizational culture that embraces technological change and innovation. Encourage employees to be open to new technologies and

to actively seek ways to integrate AI into their daily tasks. Provide resources and incentives for employees to experiment with new AI applications and to propose innovative solutions for improving banking operations.

Suggestion for Further Studies

The study only focused on the effect of employee technological skills on the operational performance of commercial banks in Ghana. Further studies can consider the role of employees' technological competencies in the development and implementation of new banking products and services. Also, future research can compare the impact of technological skills on operational performance in Ghanaian banks with banks in other regions or countries with similar or different technological landscapes.

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