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Mediating Role of AI-Human Collaboration in the Relationship Between Artificial Intelligence Adoption and Employee Performance

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Abstract

This study examines the effect of Artificial Intelligence (AI) adoption on employee performance in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria, with a focus on the mediating role of AI-Human Collaboration. A cross-sectional research design was adopted. The population comprised clinical and non-clinical healthcare workers in selected public healthcare institutions in Nigeria. Using a multistage sampling technique 520 questionnaires were distributed, of which 371 valid responses were analyzed. SmartPLS 4 was employed for data analysis. Findings reveal that AI adoption significantly enhances both AI-human collaboration and employee performance. AI-human collaboration also has a significant positive effect on employee performance and significantly mediates the relationship between AI adoption and employee performance. The study concludes that AI adoption improves employee performance both directly and indirectly through enhanced collaboration between employees and AI systems. It recommends that healthcare institutions should strengthen AI-human collaboration through continuous training and integration of AI technologies to maximize performance outcomes. These measures are essential for improving workforce efficiency and achieving sustainable performance in Nigeria's healthcare sector.

Keywords: Artificial Intelligence Adoption; AI-Human Collaboration; Employee Performance; Healthcare Sector

Introduction

Healthcare sector is regarded as a driver of socio-economic development. Healthcare sector contributes to overall population health outcomes, workforce productivity, and overall economic stability (World Health Organization [WHO], 2023; World Bank, 2024). Across both developed and developing economies, healthcare institutions play a vital role in improving life expectancy, reducing disease burden, and ensuring equitable access to quality medical services. In high-income countries such as the United States and the United Kingdom, digital transformation has significantly reshaped healthcare delivery through the integration of artificial intelligence (AI), electronic health systems, and data-driven clinical decision-making tools (Organisation for Economic Co-operation and Development [OECD], 2023; McKinsey & Company, 2023). Similarly, an emerging economies such as India and South Africa have increasingly adopted digital health technologies to improve service efficiency and expand access to good healthcare services. In Nigeria, Federal Teaching Hospitals (FTHs) and Federal Medical Centres (FMCs) represent key institutions within the national healthcare system, providing healthcare, specialist services, and medical training. Despite their strategic importance, the Nigerian healthcare system continues to face persistent structural and operational challenges, including inadequate infrastructure, workforce shortages, and inefficiencies in service delivery (Federal Ministry of Health Nigeria, 2024; WHO, 2023). These constraints often result in long patient waiting times, administrative bottlenecks, and reduced operational efficiency, thereby limiting optimal employee performance in public healthcare institutions (World Bank, 2024).

Universally, healthcare systems are undergoing rapid technological transformation driven by artificial intelligence and related digital innovations. AI applications such as clinical decision-support systems, predictive analytics, automated diagnostics, and health information management systems are increasingly being deployed to enhance efficiency, improve diagnostic accuracy, and support clinical decision-making (OECD, 2023; McKinsey & Company, 2023). Evidence from McKinsey & Company (2023) indicates that AI adoption in healthcare can improve operational efficiency and reduce administrative workload, while the WHO (2023) highlights its potential to strengthen health system responsiveness. However, despite these improvements, the translation of AI adoption into improved workforce performance is not automatic, as it depends ominously on how effectively human actors interact with these systems. Emerging literature suggests that the benefits of AI in organizational settings are highly dependent on complementary human capabilities, especially the ability of employees to interpret, collaborate with, and effectively utilize AI-generated outputs (Brynjolfsson & McAfee, 2017; Autor et al., 2022). In healthcare environments, AI systems do not operate independently but function as decision-support tools that need human judgment, validation, and integration into clinical workflows. Thus, the effectiveness of AI in improving employee performance is gradually understood to be contingent on the quality of

AI–human collaboration, rather than technology adoption alone (Jarrahi, 2018; Seeber et al., 2020).

In developing countries such as Nigeria, this challenge is more prominent due to uneven digital infrastructure, limited technological readiness, and varying levels of digital competency among healthcare workers (Federal Ministry of Health Nigeria, 2024; WHO, 2023). Although Nigerian Federal Teaching Hospitals and FMCs have begun adopting digital health systems such as electronic medical records, telemedicine platforms, and hospital information systems, their utilization remains inconsistent across institutions and departments. This raises important concerns regarding the extent to which AI adoption translates into measurable improvements in employee performance within the public healthcare sector. Empirical studies on AI in organizational contexts have largely focused on adoption determinants and direct performance effects, with limited attention to the mechanisms through which AI influences employee outcomes. While some studies report positive relationships between digital technology adoption and performance, others emphasize that such outcomes are contingent upon human-technology interaction and organizational integration processes (Brynjolfsson & McAfee, 2017; World Economic Forum, 2024). More specifically, there remains a scarcity of empirical research examining AI–human collaboration as a mediating mechanism in the relationship between AI adoption and employee performance, particularly within public healthcare institutions in developing economies.

Therefore, despite increasing investment in artificial intelligence and digital health technologies within Nigerian Federal Teaching Hospitals and Federal Medical Centres, there is still limited understanding of how AI adoption influences employee performance and the extent to which AI-human collaboration explains this relationship. Without such understanding, healthcare institutions risk underutilizing technological investments and failing to achieve expected gains in productivity and service delivery. In response to this gap, this study examines the effect of artificial intelligence adoption on employee performance, with a specific focus on the mediating role of AI-human collaboration in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria. The study contributes to existing literature by providing empirical evidence from a developing healthcare system and by advancing understanding of the human-AI interaction mechanism in explaining employee performance outcomes in the era of digital transformation

Literature Review and Hypotheses Development

Theoretical Literature

Socio-Technical Systems Theory

Socio-Technical Systems Theory was developed by Trist (1981) and posits that organizational effectiveness depends on the joint optimization of social systems (employees) and technical systems (technology). The theory argues that technological systems alone cannot guarantee improved organizational performance unless they are effectively integrated with human capabilities and work processes. In AI-enabled work environments, employees must interact with, interpret, and utilize intelligent systems effectively for organizations to realize performance gains. Within healthcare settings, artificial intelligence systems function primarily as decision-support technologies requiring human interpretation and validation. Therefore, the theory provides a relevant foundation for explaining how AI-human collaboration influences employee performance in healthcare institutions.

Human Capital Theory

Human Capital Theory, advanced by Becker (1993), emphasizes that employees' knowledge, competencies, and skills are important determinants of productivity and organizational performance. The theory suggests that investments in employee capabilities enhance work efficiency and performance outcomes. In digital work environments, human capital increasingly includes technological competence and the ability to work effectively with intelligent systems. Thus, employees who possess the necessary digital and collaborative capabilities are more likely to effectively utilize AI systems and improve workplace performance. The theory is relevant to this study because it explains how employee capability enhances AI-human collaboration and performance outcomes in healthcare institutions.

Conceptual Literature

Concept of Artificial Intelligence Adoption

Artificial intelligence adoption refers to the extent to which organizations integrate and utilize AI-enabled technologies such as machine learning systems, predictive analytics, automation tools, and intelligent decision-support systems into operational and decision-making processes (Russell & Norvig, 2021; OECD, 2023). In healthcare systems, AI adoption is increasingly applied in clinical diagnostics, patient monitoring, administrative automation, and resource optimization. The World Health Organization (2023) notes that AI has the potential to improve healthcare efficiency, reduce diagnostic errors, and enhance service delivery. Similarly, McKinsey & Company (2023) reports that AI technologies can significantly improve productivity in healthcare operations by automating repetitive tasks and supporting clinical decision-making. However, the effectiveness of AI adoption depends not only on technological availability but also on organizational readiness and employee capability integration. In this study, AI adoption refers to the extent of integration and utilization of AI-enabled systems in healthcare operations within selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria.

Concept of AI-Human Collaboration

AI-human collaboration refers to the interactive process through which employees work jointly with artificial intelligence systems to accomplish tasks, make decisions, and improve performance outcomes. It reflects a socio-technical relationship in which human judgment and machine intelligence complement one another to improve work effectiveness (Jarrahi, 2018; Seeber et al., 2020). In healthcare environments, AI systems operate primarily as decision-support tools rather than autonomous actors. Consequently, healthcare professionals are required to interpret AI-generated outputs, validate recommendations, and integrate system-generated insights into clinical workflows. According to Raisch and Krakowski (2021), organizations derive greater value from AI when employees effectively collaborate with intelligent systems. Therefore, AI-human collaboration is considered an important mechanism for enhancing efficiency, service delivery, and employee productivity in healthcare institutions.

Concept of Employee Performance

Employee performance is a multidimensional construct reflecting the extent to which employees effectively execute assigned tasks and contribute to organizational objectives. It is commonly measured using indicators such as task efficiency, productivity, quality of output, and goal attainment (Campbell & Wiernik, 2015; Koopmans et al., 2014). In contemporary digital work environments, employee performance increasingly includes adaptability, problem-solving capability, and the ability to work effectively with digital technologies and intelligent systems (World Economic Forum, 2024). In healthcare settings, employee performance is particularly important because it directly influences service quality, patient safety, and operational efficiency. Healthcare employees are expected not only to perform routine clinical and administrative functions but also to effectively utilize digital health systems such as electronic medical records and AI-enabled decision-support tools. Therefore, in this study, employee performance is conceptualized as a composite construct reflecting task efficiency, productivity, quality service delivery, and effective utilization of AI-enabled systems within Federal Teaching Hospitals and Federal Medical Centres in Nigeria.

Empirical Literature and Hypotheses Development

Artificial Intelligence Adoption and Employee Performance

Empirical evidence suggests that artificial intelligence adoption positively influences employee performance across organizational settings. Brynjolfsson et al. (2021) found that AI adoption improves productivity, particularly when organizations redesign workflows to complement human capabilities. Similarly, McKinsey & Company (2023) report that AI technologies improve operational efficiency by automating repetitive tasks and supporting data-driven decision-making. In healthcare institutions, AI-enabled systems such as electronic medical records and clinical decision-support systems contribute to improved accuracy, reduced workload, and enhanced service delivery. Acemoglu and Restrepo (2020) further argue that AI technologies improve performance when they complement rather than replace human labor. Based on these empirical arguments, this study proposes that AI adoption enhances employee performance in healthcare institutions.

H_1: Artificial intelligence adoption has a significant positive effect on employee performance in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria.

Artificial Intelligence Adoption and AI-Human Collaboration

Artificial intelligence adoption is increasingly associated with improved interaction and collaboration between employees and intelligent systems. Ransbotham et al. (2020) found that organizations with higher AI maturity levels experience stronger integration between employees and AI-enabled technologies. Similarly, Brynjolfsson and McAfee (2017) argue that AI systems generate greater value when employees actively interact with and utilize machine-generated insights in organizational processes. In healthcare environments, the adoption of AI systems requires healthcare workers to collaborate with intelligent technologies during diagnosis, patient monitoring, and administrative operations. Thus, increased AI adoption is expected to strengthen AI-human collaboration within healthcare institutions.

H2: Artificial intelligence adoption has a significant positive effect on AI-human collaboration in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria.

AI-Human Collaboration and Employee Performance

Studies increasingly show that effective collaboration between employees and artificial intelligence systems enhances employee performance. Dellermann et al. (2019) found that hybrid intelligence systems combining human and AI capabilities outperform standalone human or machine systems. Similarly, Seeber et al. (2020) report that AI-human collaboration improves decision quality, operational efficiency, and service delivery in complex organizational settings. In healthcare environments, employees who effectively collaborate with AI systems are more likely to improve diagnostic accuracy, reduce errors, and enhance workflow efficiency. Therefore, AI-human collaboration is expected to positively influence employee performance in healthcare institutions.

H3: AI-human collaboration has a significant positive effect on employee performance in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria.

AI-Human Collaboration as a Mediator

The mediating role of AI-human collaboration between AI adoption and employee performance is grounded in socio-technical systems theory, which posits that organizational performance depends on the effective interaction between technological systems and human capabilities (Bostrom & Heinen, 1977; Trist, 1981). AI adoption alone may not automatically improve employee performance unless employees effectively collaborate with AI systems. Jarrahi (2018) argues that AI technologies should be viewed as collaborative partners that augment human decision-making rather than replace human workers. Empirical evidence supports this argument. Brynjolfsson et al. (2021) found that productivity gains from AI are significantly enhanced when organizations integrate human judgment with machine intelligence. Similarly, Seeber et al. (2020) emphasize that AI-human collaboration is essential for realizing the performance benefits of AI systems. In healthcare settings, employees must interpret AI outputs and integrate them into clinical workflows for improved performance outcomes. Therefore, AI-human collaboration is expected to mediate the relationship between AI adoption and employee performance.

H_4: AI-human collaboration significantly mediates the relationship between artificial intelligence adoption and employee performance in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria.

Research Model

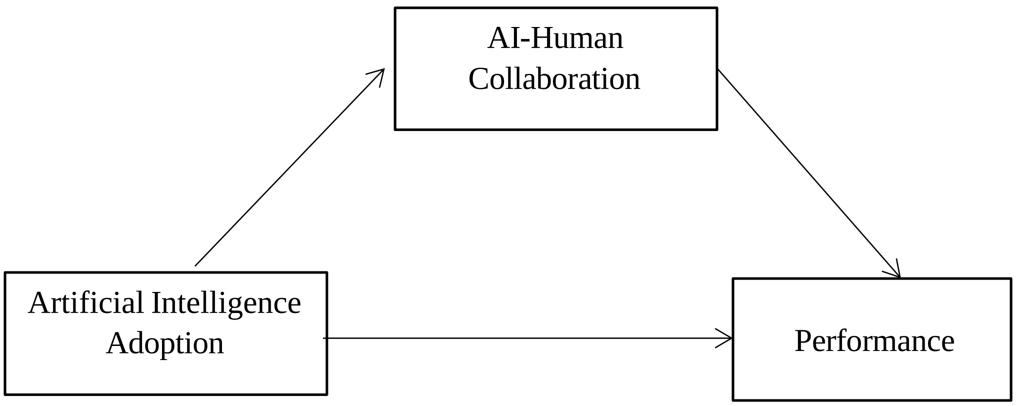

Fig. 1: Conceptual model

Methodology

Research Design

This study adopted a quantitative cross-sectional survey research design. The design is appropriate for examining causal relationships among variables at a single point in time using numerical data. It was employed to investigate the effect of Artificial Intelligence (AI) adoption on employee performance, with AI-human collaboration as a mediating variable. The study is grounded in a positivist research paradigm, which assumes that relationships among variables can be objectively measured and statistically tested.

Population of the Study

The population of this study comprised clinical and non-clinical healthcare workers in selected Federal Teaching Hospitals (FTHs) and Federal Medical Centres (FMCs) in Nigeria. The selected healthcare institutions were purposively chosen from selected geopolitical zones based on their level of digital health infrastructure and the adoption of AI-enabled healthcare technologies Based on records obtained from the selected healthcare institutions, the total population across the selected institutions was 12,436 employees.

Table 1: Selected Institutions

Institution	State	Geopolitical Zone
Ahmadu Bello University Teaching Hospital	Kaduna State	North West
Aminu Kano Teaching Hospital	Kano State	North West
Federal Medical Centre Katsina	Katsina State	North West
University of Nigeria Teaching Hospital	Enugu State	South East
University College Hospital	Oyo State	South West
Federal Medical Centre Owerri	Imo State	South East

Source: Researcher (2026)

Sample Size and Sampling Technique

This study adopted a multistage sampling technique to ensure representativeness across selected geopolitical zones, healthcare institutions, and professional categories within Federal Teaching Hospitals and Federal Medical Centres in Nigeria. In the first stage, Nigeria was stratified into geopolitical zones, from which selected states in the North West, South East, and South West were purposively chosen based on the presence of Federal Teaching Hospitals and Federal Medical Centres with established digital health infrastructure and artificial intelligence-enabled healthcare systems. In the second stage, Federal Teaching Hospitals and Federal Medical Centres within the selected states were purposively selected based on their level of adoption of digital health technologies such as electronic medical records, hospital information systems, telemedicine platforms, and AI-enabled decision-support systems. In the third stage, proportionate allocation was used to distribute the sample size across the selected hospitals based on the size of their eligible healthcare workforce, ensuring proportional representation. Finally, healthcare workers within each hospital were stratified into professional categories, including doctors, nurses, pharmacists, laboratory scientists, ICT personnel, medical records officers, and administrative staff, and simple random sampling was employed to select respondents from each stratum, ensuring equal chance of selection for all eligible participants. The sample size for the study was determined using Yamane’s (1967) sample size determination formula:

$$n = \frac{N}{1 + N(e)^2}$$

Where:
(n) = sample size
(N) = population size
(e) = level of precision (0.05)
Given a study population of 12,436 healthcare workers, the sample size was computed as follows:

$$n = \frac{12436}{1 + 12436(0.05)^2} = 387$$

The computed sample size was approximately 387 respondents. However, to accommodate possible non-response and incomplete questionnaires, to accommodate possible non-response and incomplete questionnaires, the sample size was increased by approximately 30%, resulting in the distribution of 520 questionnaires. This is consistent with the recommendations of Israel (1992) and Baruch & Holtom (2008). Out of the 520 questionnaires distributed, 371 valid and usable responses were retrieved, representing a response rate of approximately 71.3%, which is considered adequate for survey-based research (Baruch & Holtom, 2008). The final sample size exceeded the minimum threshold required for Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 and was considered adequate for reliable statistical analysis (Hair et al., 2021).

Instrument for Data Collection and Measurement of Variables

Data were collected using a structured questionnaire comprising four sections: demographic characteristics, Artificial Intelligence Adoption, AI–Human Collaboration, and Employee Performance. All items were measured on a 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

Artificial Intelligence Adoption was measured using a 7-item reflective scale adapted from the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology (Davis, 1989; Venkatesh et al., 2003). AI–Human Collaboration was measured using a 6-item reflective scale adapted from prior human–AI interaction studies (Jarrahi, 2018; Seeber et al., 2020). Employee Performance was measured using a 5-item reflective scale adapted from the Individual Work Performance Scale (Koopmans et al., 2014; Pradhan & Jena, 2017).

Method of Data Analysis

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.

Data Analysis, Results and Discussion

Demographic Characteristics of Respondents

Before presenting the measurement and structural model results, the demographic characteristics of the respondents were analyzed to provide an overview of the sample distribution. The demographic variables considered in this study include gender, age, educational qualification, professional category, and years of work experience. The analysis indicates that the respondents were adequately distributed across different demographic categories, thereby ensuring broad representation of healthcare workers in the selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria.

Table 2: Demographic Characteristics of Respondents (N = 371)

Variable	Category	Frequency	Percentage (%)
Gender	Male	214	57.7
	Female	157	42.3
Age	20–30 years	74	19.9
	31–40 years	146	39.4
	41–50 years	102	27.5
	51 years and above	49	13.2
Educational Qualification	Diploma	41	11.1
	Bachelor’s Degree	183	49.3
	Master’s Degree	109	29.4
	PhD/Others	38	10.2
Professional Category	Doctors	78	21.0
	Nurses	126	34.0
	Pharmacists	34	9.2
	Laboratory Scientists	42	11.3
	ICT Personnel	29	7.8
	Administrative Staff	62	16.7
Work Experience	1–5 years	96	25.9
	6–10 years	141	38.0
	11–15 years	82	22.1
	Above 15 years	52	14.0

Source: Field Survey (2026)

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The results in Table 2 show that the majority of the respondents were male (57.7%), while female respondents constituted 42.3% of the sample. Most respondents were between 31 and 40 years of age (39.4%), indicating that the study largely captured active working professionals within the healthcare sector. In terms of educational qualification, respondents with Bachelor's degrees constituted the largest proportion (49.3%), followed by respondents with Master's degrees (29.4%). Regarding professional category, nurses represented the largest group (34.0%), followed by doctors (21.0%) and administrative staff (16.7%). Furthermore, most respondents had between 6 and 10 years of work experience (38.0%), suggesting that the respondents possessed sufficient professional experience to provide reliable responses regarding AI adoption, AI-human collaboration, and employee performance within healthcare institutions.

Measurement Model

The measurement model was assessed using indicator loadings, internal consistency reliability, convergent validity, and multicollinearity diagnostics. Indicator reliability was evaluated using outer loadings. As presented in Table 3 and Figure 1, all indicator loadings exceeded the recommended threshold of 0.70, confirming satisfactory indicator reliability (Hair et al., 2022).

Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability (CR). All constructs recorded Cronbach's Alpha and Composite Reliability values above the recommended threshold of 0.70, indicating satisfactory reliability and internal consistency (Hair et al., 2022).

Convergent validity was evaluated using the Average Variance Extracted (AVE). As shown in table 3, the AVE values for all constructs exceeded the recommended minimum threshold of 0.50, confirming that the indicators adequately explained the variance of their respective latent constructs (Fornell & Larcker, 1981; Hair et al., 2022).

To assess multicollinearity among indicators, Variance Inflation Factor (VIF) values were examined. As shown in table 3, all VIF values were below the conservative threshold of 5.0, indicating the absence of multicollinearity problems among the measurement items (Hair et al., 2022).

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Table 3: Item Loadings, Internal Consistency, and Average Variance Extracted

Construct	Item	Loading	VIF	AVE	CR	Cronbach's Alpha
AIA	AIA1	0.836	2.304	**0.704**	**0.943**	**0.930**
	AIA2	0.853	2.767			
	AIA3	0.830	2.655			
	AIA4	0.835	2.443			
	AIA5	0.858	2.464			
	AIA6	0.816	2.762			
	AIA7	0.828	2.665			
AHC	AHC1	0.840	2.517	**0.672**	**0.935**	**0.919**
	AHC2	0.821	2.288			
	AHC3	0.829	2.421			
	AHC4	0.784	2.001			
	AHC5	0.815	2.274			
	AHC6	0.823	2.292			
	AHC7	0.826	2.351			
EP	EP1	0.860	2.761	**0.736**	**0.944**	**0.928**
	EP2	0.860	2.680			
	EP3	0.853	2.605			
	EP4	0.853	2.646			
	EP5	0.870	2.866			
	EP6	0.852	2.611			

Source: SmartPLS Output (2026)

Table 3 above compiles the loadings, whereas figure 1 below displays the study's graphical loadings. According to Fornell and Larcker (1981), only elements with loadings greater than 0.50 should be retained in the measurement model.

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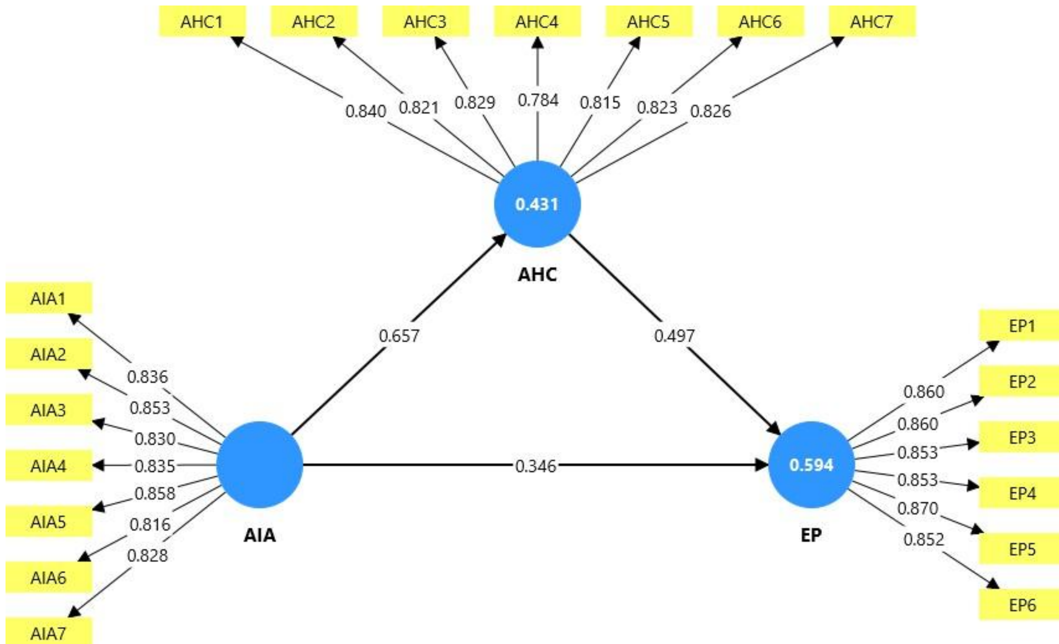

Figure 1: Measurement Model with Loadings
Source: SmartPLS Output (2026)

Discriminant Validity (HTMT Criterion)

The Heterotrait-Monotrait ratio (HTMT) was used to assess discriminant validity among the study constructs. The HTMT values reported are as follows: Artificial Intelligence Adoption and AI–Human Collaboration (0.710), AI-Human Collaboration and Employee Performance (0.784), and Artificial Intelligence Adoption and Employee Performance (0.724). All HTMT values are below the recommended threshold of 0.85 (Henseler et al., 2015), indicating that discriminant validity is established. This suggests that each construct, Artificial Intelligence Adoption, AI-Human Collaboration, and Employee Performance is empirically distinct and measures a unique concept within the model.

Table 4: Discriminant Validity (HTMT Criterion)

	AHC	**AIA**	**EP**
AHC			
AIA	0.710		
EP	0.784	0.724	

Source: SmartPLS Output (2026)

Structural Model

Table 5 provides a summary of the overall path coefficient data and the hypothesis testing. A t-test and a bootstrapping approach were applied to 5,000 resamples.

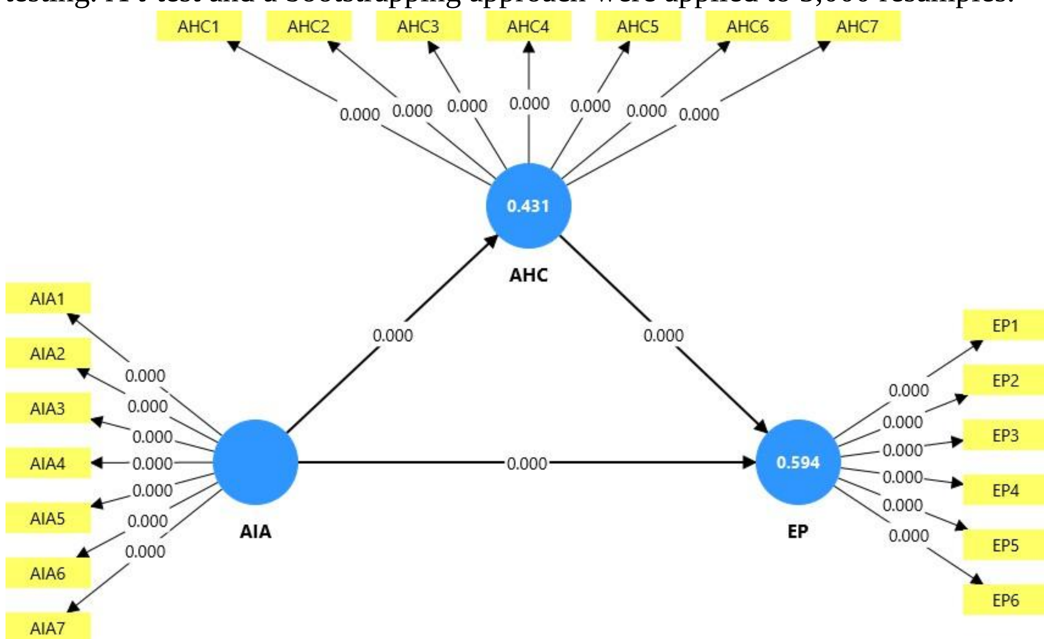

Figure 2: Structural Model
Source: SmartPLS Output (2026)

Table 5: Summary of the Structural Model

	Original sample (O)	Standard deviation	T statistics (|O/STDEV|)	P values
AHC -> EP	0.497	0.040	12.406	0.000
AIA -> AHC	0.657	0.032	20.339	0.000
AIA -> EP	0.346	0.039	8.986	0.000
AIA -> AHC -> EP	0.327	0.030	10.745	0.000
R^2 (EP)	0.594			

Source: SmartPLS Output (2026)

As presented in Table 5, the results of the structural model analysis revealed that Artificial Intelligence Adoption (AIA) has a significant positive effect on AI–

Human Collaboration (AHC) with β = 0.657, t = 20.339, p = 0.000. Therefore, the study rejects the null hypothesis (H01) and concludes that AI adoption significantly enhances AI–human collaboration among healthcare workers in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria. Similarly, Artificial Intelligence Adoption (AIA) has a significant positive effect on Employee Performance (EP) with β = 0.346, t = 8.986, p = 0.000. Hence, the study rejects the null hypothesis (H02) and concludes that AI adoption directly improves employee performance.

Furthermore, AI-Human Collaboration (AHC) has a significant positive effect on Employee Performance (EP) with β = 0.497, t = 12.406, p = 0.000. Therefore, the study rejects the null hypothesis (H03) and concludes that effective collaboration between employees and artificial intelligence systems significantly enhances employee performance in healthcare institutions. In addition, the indirect effect of Artificial Intelligence Adoption (AIA) on Employee Performance (EP) through AI-Human Collaboration (AHC) is significant with β = 0.327, t = 10.745, p = 0.000. This indicates that AI-human collaboration significantly mediates the relationship between artificial intelligence adoption and employee performance. Thus, the study rejects the null hypothesis (H04) and confirms the presence of a significant mediation effect.

The R-square value of 0.594 indicates that Artificial Intelligence Adoption and AI-Human Collaboration jointly explain 59.4% of the variance in employee performance, which is considered moderate to substantial explanatory power (Hair et al., 2021). Overall, these findings suggest that Artificial Intelligence Adoption improves employee performance both directly and indirectly through AI-Human Collaboration, confirming a partial mediation effect and highlighting the importance of human–technology interaction in realizing the benefits of AI in healthcare settings.

Discussion of Results

The findings revealed that Artificial Intelligence Adoption (AIA) has a significant positive effect on AI-Human Collaboration (AHC) among healthcare workers in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria. This implies that increased adoption of AI technologies enhances the level of interaction, coordination, and synergy between employees and AI-enabled systems in the workplace. As AI systems become more integrated into clinical and administrative processes, healthcare workers are increasingly required to interpret outputs, validate recommendations, and incorporate machine-generated insights into decision-making. This finding is consistent with Brynjolfsson, Li, and Raymond (2021), who empirically demonstrated that AI adoption improves worker productivity when it is combined with complementary human capabilities and workflow redesign. Similarly, Ransbotham et al. (2020) found that organizations with higher AI maturity levels experience improved human–machine integration and decision-making efficiency.

The findings further revealed that Artificial Intelligence Adoption (AIA) has a significant positive effect on Employee Performance (EP). This suggests that AI technologies enhance employee efficiency, accuracy, and productivity through automation of routine tasks, improved information processing, and support for clinical decision-making. In healthcare settings, AI systems such as electronic medical records and decision-support tools reduce administrative burden and allow employees to focus on higher-value tasks. This result aligns with Brynjolfsson, Rock, and Syverson (2021), who provide firm-level empirical evidence that AI adoption significantly improves productivity when combined with organizational adaptation. Similarly, Acemoglu and Restrepo (2020) empirically show that automation technologies increase productivity when they complement rather than substitute human labor. Furthermore, OECD (2023) reports across healthcare systems indicate that AI adoption enhances operational efficiency and service delivery outcomes, particularly in data-intensive environments.

The results also showed that AI-Human Collaboration (AHC) has a significant positive effect on Employee Performance (EP). This implies that employees who effectively collaborate with AI systems are more likely to perform better in terms of task efficiency, decision quality, and service delivery. In healthcare environments, collaboration with AI tools enables workers to interpret complex data, reduce diagnostic errors, and improve workflow efficiency. This finding is supported by Seeber et al. (2020), who empirically demonstrate that human–AI collaboration significantly improves decision-making performance in complex organizational settings. Similarly, Dellermann et al. (2019) provide evidence that hybrid intelligence systems combining human and AI capabilities outperform standalone human or machine systems. In addition, Raisch and Krakowski (2021) argue that organizational performance gains from AI are largely dependent on the quality of human-AI interaction and integration.

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Finally, the findings revealed that AI-Human Collaboration (AHC) significantly mediates the relationship between Artificial Intelligence Adoption (AIA) and Employee Performance (EP). This indicates that AI adoption improves employee performance both directly and indirectly through enhanced collaboration between humans and AI systems. In other words, the performance benefits of AI are maximized when employees actively engage with AI systems rather than merely adopting them. This finding is consistent with Brynjolfsson et al. (2021), who demonstrate that productivity gains from AI are significantly higher when organizations redesign tasks to support AI-human complementarity. Similarly, Seeber et al. (2020) empirically confirm that AI-human collaboration serves as a key mechanism through which AI generates performance improvements. Furthermore, Acemoglu and Restrepo (2020) argue that the economic impact of AI is strongly mediated by task reallocation and human adaptation. These findings reinforce socio-technical systems theory, which posits that optimal organizational performance is achieved through the joint optimization of technological systems and human capabilities.

Conclusion and Recommendations

Conclusion

The study concludes that Artificial Intelligence Adoption plays a significant role in enhancing Employee Performance in selected Federal Teaching Hospitals and Federal Medical Centres in Nigeria, both directly and indirectly through AI-Human Collaboration. The findings demonstrate that AI adoption not only improves operational efficiency, decision-making processes, and service delivery in healthcare institutions, but also strengthens the interaction between employees and AI-enabled systems. This enhanced collaboration enables healthcare workers to better interpret AI-generated outputs, integrate technological insights into clinical and administrative tasks, and improve overall job effectiveness. The results further establish that AI-Human Collaboration is a critical determinant of employee performance, as it facilitates the effective use of AI technologies in daily work activities. In addition, the study confirms that AI-Human Collaboration serves as a significant mediating mechanism in the relationship between Artificial Intelligence Adoption and Employee Performance. This implies that the full benefits of AI technologies in healthcare settings can only be realized when employees actively engage with and collaborate alongside AI systems. Overall, the study reinforces Socio-Technical Systems Theory, which emphasizes that organizational performance improvement depends on the joint optimization of technological systems and human capabilities (Trist, 1981; Bostrom & Heinen, 1977).

Recommendations

The study recommends that Federal Teaching Hospitals and Federal Medical Centres in Nigeria should intensify the adoption and integration of artificial intelligence technologies across clinical and administrative operations in order to enhance efficiency, accuracy, and overall employee performance. Expanding the use of AI-driven systems such as electronic medical records, clinical decision-support systems, and automated workflow tools will significantly improve the speed and quality of healthcare service delivery while reducing administrative burden on healthcare workers. Furthermore, healthcare institutions should prioritize continuous training and capacity-building programmes aimed at strengthening employees' ability to effectively collaborate with artificial intelligence systems. Such programmes should include workshops, seminars, and hands-on practical training designed to improve AI literacy and digital competence among healthcare workers, thereby enhancing AI–human collaboration in daily operations.

In addition, hospital management should align investments in artificial intelligence with human resource development strategies. This involves integrating structured AI training and digital collaboration skills into staff development policies to ensure that technological advancement is matched with adequate human capability for effective utilization. Policy makers in the Nigerian health sector are also encouraged to develop and implement national frameworks that support responsible and ethical adoption of artificial intelligence in healthcare delivery. Such frameworks should ensure that AI integration is not only technology-driven but also supported by adequate human capacity development to guarantee sustainable improvements in employee performance and healthcare service delivery.

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