Journal of Business and Digital Innovation (JBDI)
Volume 1, Issue 2, July 2026, PP 50-62
ISSN 2978-4522 (Print) & ISSN 2978-4530 (Online)
https://doi.org/10.19164/jbdi.v1i2.1881

Exploring How the Adoption of Artificial Intelligence in Human Resource Management Enhances Organizational Performance and Efficiency

[1]Olugbenga Adeyanju Akintola, [2]Samson Onyeluka Chukwuedo,
[3]Imad Yasir Nawaz & [4]Oluwole Shokunbi

[1&3]Northumbria University, London, United Kingdom.
[2]Nnamdi Azikiwe University, Awka, Nigeria
[4]University of Wolverhampton, United Kingdom

Abstract
In the era of the Fourth Industrial Revolution, the use of artificial intelligence (AI) in human resource management (HRM) is increasingly recognized as a powerful tool for improving organizational performance and efficiency. However, despite growing interest in this area, there is still limited and fragmented evidence explaining exactly how AI adoption leads to these improvements. Guided by the Technology Acceptance Model (TAM), the Resource-Based View (RBV), and Dynamic Capabilities Theory (DCT), this study investigates how AI adoption in HRM contributes to organizational performance and efficiency through improvements in HR process efficiency. A cross-sectional survey was conducted among 452 HR personnel and employees working in information technology (IT)-related organizations in Lagos State, South-West Nigeria. Three hypotheses were tested using path analysis. The findings reveal that AI adoption in HRM is positively associated with both organizational performance and organizational efficiency. In addition, HR process efficiency was found to play a mediating role in these relationships, indicating that improvements in HR processes are a key pathway through which AI generates organizational benefits. Overall, this study contributes to the HRM and information systems literature by providing deeper insight into AI-enhanced HRM and offering evidence to support the integration of AI into organizations' day-to-day operations.

Keywords: Artificial intelligence, Human resource management, Organizational performance, Organizational efficiency, technology acceptance, resource-based view.

Wordcount: 200

1.0 Introduction

The rapid development of Artificial Intelligence (AI) has significantly changed the way organizations operate across different industries. AI is reshaping how businesses manage information, make decisions, and improve their processes. In the field of Human Resource Management (HRM), technologies such as machine learning, predictive analytics, natural language processing, and intelligent automation are increasingly being used in key HR activities, including recruitment, employee development, performance management, workforce planning, and talent retention. As organizations strive to remain competitive in fast-changing business environments (Gong, Fan and Bartram, 2025; Vrontis et al., 2022), AI-driven HRM systems have become important strategic tools that help improve operational effectiveness and support organizational goals (Malik, Budhwar and Kazmi, 2023). This growing adoption of AI reflects a broader transition from traditional administrative personnel management to data-driven and strategically aligned HR practices that contribute directly to organizational success.

Recent studies indicate that AI-enabled HRM can improve organizational outcomes in several ways. By automating routine tasks, reducing processing time, improving decision accuracy, and supporting evidence-based workforce management, AI helps organizations operate more efficiently (Zahrani, 2025). AI applications can quickly screen job candidates, provide personalized employee training, monitor performance, and generate predictive workforce insights, making HR functions more responsive and efficient (Yusuf et al., 2025). As a result, organizations are increasingly using AI to streamline HR processes and allow HR professionals to focus on higher-value strategic responsibilities. Previous research has also shown that digital HR systems and AI-supported HRM practices can enhance productivity, workforce agility, and overall organizational effectiveness (Cheng and Zou, 2021; Khudhaire and Fzaea, 2026).

Although the strategic value of AI is widely acknowledged, there is still limited empirical evidence explaining how AI adoption leads to improved organizational performance. Most existing studies have concentrated on the direct relationship between AI implementation and organizational outcomes, while giving less attention to the role of human resource process efficiency as a potential mechanism through which these outcomes are achieved (Malik, Budhwar and Kazmi, 2023). Human resource process efficiency refers to the ability of HR functions to carry out activities with minimal time, cost, and operational errors while maintaining high service quality and responsiveness to employees. From the perspective of the Resource-Based View (RBV), AI can be considered a valuable organizational resource that strengthens capabilities by improving the efficiency and effectiveness of HR processes, which in turn enhances organizational performance (Al-Ayed, 2025).

Emerging research further suggests that HR process efficiency may be a key pathway through which AI-generated capabilities produce measurable organizational benefits. For example, AI-powered recruitment systems, automated performance evaluation tools, and intelligent workforce planning platforms have been found to improve HR process efficiency, which subsequently enhances overall HRM effectiveness and organizational outcomes (Zahrani, 2025). Similarly, studies on electronic and digital HRM systems have identified process optimization and operational efficiency as important mechanisms connecting technology adoption with improved organizational performance (Cheng and Zou, 2021). Despite these findings, the existing literature remains fragmented, and there is still a limited understanding of how HR process efficiency mediates the relationship between AI adoption and organizational performance.

Given the growing investment in AI technologies and the strategic importance of managing human capital effectively, examining the mediating role of human resource process efficiency is both timely and important especially in developing countries like Nigeria where studies about the adoption of AI in HRM are scarcely available. This study therefore addresses population gap (the Nigerian information technology context) and adds to existing literature by investigating how AI adoption in HRM improves organizational performance and efficiency through enhanced HR process efficiency. This study also provides practical guidance for organizations seeking to maximize the value of their AI investments in human resource functions. By bringing together insights from the literature on AI-enabled HRM, process efficiency, and organizational performance, this study contributes to the expansion of extant body of knowledge on digital transformation and strategic HRM (e.g., Margherita, 2023; McCartney and Fu, 2022). Comparatively, to our knowledge. one novelty of this study is that it explored HR process efficiency as a mediator in AI adoption and organizational performance and efficiency links. From extant literature, the study of Chowdhury et al. (2026) explored AI-empowered decision-making as a mediator in the AI adoption in HRM and organizational process level HR outcomes model, while the study of Jangbahadur et al. (2025) examined the mediating role of employee engagement in the relationship between AI adoption in HRM and sustainable organizational performance. Additionally, organizational learning capability and technological trust have been studies as mediators in AI adoption in HRM and organizational effectiveness (Choudhary et al., 2026), while organizational agility was explored as a mediator in the relationship between AI adoption and organizational performance (Aldossary, Ayad and Moustafa, 2026). Thus, this study tends to add to literature by exploring HR process efficiency as a mediator in the AI adoption in HRM and organizational performance and efficiency model.

2.0 Literature Review

Artificial Intelligence (AI) is commonly defined as the study of intelligent agents that perceive their environment and take actions that influence that environment, with the goal of creating rational agents capable of acting autonomously to achieve specific objectives (Russell and Norvig, 2020). Within the context of this study, AI adoption in Human Resource Management (HRM) refers to the organizational use of technologies such as machine learning, natural language processing, robotic process automation, and other intelligent systems to perform or support HR-related activities (Chowdhury et al., 2023; Tambe, Cappelli and Yakubovich, 2019). These technologies are increasingly being applied across a wide range of HR functions, including: (a) recruitment, through resume screening, candidate matching, and chatbot-assisted interviews; (b) onboarding, through automated document processing and personalized training recommendations; (c) performance management, through continuous feedback analytics and productivity prediction; (d) learning and development, through skill-gap analysis and content recommendations; and (e) retention analytics, through employee turnover prediction and engagement sentiment analysis (Malik et al., 2022; Zhou et al., 2021).

Organizational performance refers to the extent to which an organization achieves its strategic and financial goals, including profitability, market share, innovation, and customer satisfaction (Richard et al., 2009). Organizational efficiency, on the other hand, focuses more specifically on the relationship between outputs and inputs—that is, doing things right by maximizing results while minimizing resources. Examples include reducing the cost per hire, shortening the time required to fill vacancies, and minimizing administrative errors (Neely, Gregory and Platts, 2005). Although performance and efficiency are distinct concepts, they are closely interconnected. Improvements in efficiency often enable organizations to redirect resources toward strategic initiatives, which can ultimately enhance overall organizational performance (Di Vaio et al., 2020).

Human resource process efficiency refers to the speed, accuracy, and cost-effectiveness with which core HR activities, such as recruitment, payroll administration, and performance appraisal, are carried out. The adoption of AI has the potential to streamline these processes by automating routine tasks, reducing errors, and accelerating decision-making. As a result, HR professionals can devote more time and effort to strategic responsibilities such as talent development, succession planning, and organizational culture building, all of which contribute to improved organizational performance (Pereira et al., 2021; Chowdhury et al., 2023). Based on this reasoning, we propose that improvements in HR process efficiency serve as a partial mediating mechanism through which AI adoption influences organizational outcomes.

The Fourth Industrial Revolution has positioned Artificial Intelligence (AI) as a key driver of organizational transformation (Di Vaio et al., 2020; Vrontis et al., 2022). In the field of Human Resource Management (HRM), AI applications—ranging from resume screening and candidate matching to performance analytics and personalized learning systems—are increasingly taking over routine administrative tasks (Budhwar et al., 2022; Malik et al., 2022). Advocates of AI argue that by automating these routine functions, HR professionals can dedicate more time to strategic responsibilities, ultimately improving organizational performance and operational efficiency (Chowdhury et al., 2023; Pereira et al., 2021).

Despite its growing adoption, the academic evidence on the benefits of AI in HRM remains mixed. Some studies have reported positive outcomes, including increased productivity and higher employee satisfaction resulting from AI-enabled HRM practices (Prikshat et al., 2023; Zhou et al., 2021). In contrast, other researchers have highlighted challenges associated with AI implementation, such as algorithmic bias, ethical concerns, and the absence of complementary organizational capabilities needed to fully realize AI's potential (Tambe, Cappelli and Yakubovich, 2019; Raghavan et al., 2020). More importantly, much of the existing literature has treated AI as a single, uniform technology and has paid limited attention to the underlying mechanisms (i.e., the "how") through which AI adoption generates improvements in organizational performance (Budhwar et al., 2022; Johnson et al., 2021). This limitation restricts both theoretical advancement and the development of practical guidance for organizations seeking to implement AI effectively.

To address this gap, the present study seeks to answer the following research question: *How and under what conditions does AI adoption in HRM enhance organizational performance and efficiency?* We propose a dual-mechanism model to explain this relationship. First, AI improves HR process efficiency by enabling faster recruitment processes, reducing administrative errors, and streamlining routine HR activities. Second, AI enhances data-driven decision-making through capabilities such as predictive analytics for employee turnover and the identification of workforce skill gaps. We argue that these two pathways serve as important mechanisms through which AI adoption influences organizational outcomes.

The study is grounded in three complementary theoretical perspectives: the Technology Acceptance Model (TAM) (Davis, 1989), the Resource-Based View (RBV) theory (Barney, 1991), and Dynamic Capabilities Theory (Teece, Pisano and Shuen, 1997). From this perspective, AI in HRM is viewed not simply as a technological tool but as a strategic organizational resource that can generate sustainable competitive advantage when combined with complementary human capabilities and skills (Mikalef and Gupta, 2021; Mikalef et al., 2020). Furthermore, Dynamic Capabilities Theory provides a process-oriented lens for understanding how AI contributes to organizational success. Specifically, organizations must develop capabilities for sensing HR-related opportunities and challenges, seizing opportunities through the implementation of AI solutions, and transforming existing HR processes to maximize value creation (Warner and Wäger, 2019). Through these capabilities, AI adoption can lead to enhanced organizational performance and efficiency.

The findings of this study contribute to both theory and practice in two important ways. First, they demonstrate how AI-enhanced HRM environments can improve organizational performance and operational efficiency. Second, the study identifies HR process efficiency as a key mediating mechanism, thereby responding to growing calls for more process-oriented research in the field of AI-enabled HRM (Benabou and Touhami, 2025; Budhwar et al., 2022).

3.0 Theories Underpinning the Study

Three theories shed light to the understanding of this study and the interrelation between the variables, and these are the Technology Acceptance Model (TAM), the Resource-Based View (RBV), and the Dynamic Capabilities Theory (DCT)

Technology Acceptance Model

The Technology Acceptance Model (TAM) was developed by Fred Davis in 1989 to explain how individuals come to accept and use new technologies. In this study, this model specifically explains the variable – AI adoption in HRM since it focuses on how individuals use new technology. According to the model, a person's intention to use a technology is mainly influenced by two key factors: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which an individual believes that a particular technology will enhance job performance, while perceived ease of use describes how effortless the technology is perceived to be. These perceptions shape users' attitudes and behavioural intentions, which in turn influence their actual use of the technology.

Over the years, TAM has been widely used to study the adoption of emerging technologies, including artificial intelligence (AI), across different organizational functions. Within the field of Human Resource Management (HRM), the model provides a valuable framework for understanding how HR professionals and employees accept and use AI-powered tools such as automated recruitment systems, predictive analytics, and employee self-service platforms. Studies have shown that when users perceive AI technologies as both useful and easy to use, they are more likely to adopt them, resulting in improved organizational efficiency and better decision-making processes (Venkatesh and Davis, 2000).

The model has also been expanded over time to strengthen its explanatory power. These extensions include additional factors such as social influence and facilitating conditions, which help provide a more comprehensive understanding of technology adoption (Venkatesh and Bala, 2008). Although TAM has been criticized for being relatively simple, it continues to be regarded as one of the most reliable and widely accepted frameworks for studying technology acceptance. As a result, it offers a strong theoretical basis for examining how AI adoption in HRM can enhance organizational performance and operational efficiency.

In the context of this study, TAM is particularly relevant because this study explored AI adoption, which aligns with the tenet of TAM about how people accept and use new technologies. Similarly, TAM is relevant in this study explored AI applications in HRM such as recruitment automation, employee performance analytics, workforce planning, and chatbot-assisted employee services can only deliver their intended benefits when HR personnel are willing to accept and use them effectively. Therefore, the model helps to explain how the adoption of AI in HRM contributes to improved organizational performance and greater operational efficiency.

Resource-Based View (RBV)

The Resource-Based View (RBV) argues that organizations achieve sustained competitive advantage by possessing resources that are valuable, rare, inimitable, and non-substitutable - VRIN (Barney, 1991). Hence, RBV asks: what resources does organizations have? In other words, RBV framework says that an organization gets competitive advantage not just from what it does in the market, but also from the unique resources it owns and how it uses them. This theory presents AI as a resource that helps an organization to get competitive advantage and perform better. This suggests that RBV specifically applies to organizational performance as a variable measured in this study. In the context of AI-enhanced Human Resource Management (HRM), AI technology itself may not be a unique resource since competing organizations can acquire similar software and tools. However, the way an organization integrates AI into its existing HR processes, combines it with human expertise, and aligns it with its strategic objectives can create the VRIN characteristics necessary for competitive advantage (Mikalef et al., 2020; Wamba-Taguimdje et al., 2020).

For instance, AI applications that are embedded within unique organizational workflows, such as proprietary algorithms trained using company-specific data, become more difficult for competitors to imitate (Shet et al., 2021). This uniqueness enables organizations to derive greater value from AI technologies than competitors who merely adopt similar tools without effectively integrating them into their operations.

Recent developments in RBV further emphasize that technology alone is not enough to create a sustainable advantage. Instead, competitive advantage emerges from the complementary relationship between technology and human capital (Pereira et al., 2021; Prikshat et al., 2023). For example, an AI-powered recruitment system may reduce candidate screening time by as much as 70 percent, but its full value is realized only when HR professionals interpret and apply its recommendations in line with the organization's culture, strategic priorities, and workforce needs (Budhwar et al., 2022).

As applied to this study, the RBV therefore provides a useful framework for understanding how AI-enabled HR systems can become strategic organizational assets or resources. When organizations successfully integrate AI into their HR functions, they can develop unique capabilities that are difficult for competitors to replicate. These capabilities can enhance operational efficiency, strengthen organizational performance, and contribute to long-term competitive advantage.

Dynamic Capabilities Theory

The Dynamic Capabilities Theory (DCT) extends the RBV by explaining how organizations continuously adapt and reconfigure their resources in response to changing environmental conditions (Teece, Pisano and Shuen, 1997). In this study, DCT explains how fast an organization adopts AI in HRM for organizational efficiency. Hence, DCT specifically applies to organizational efficiency as a variable measured in this study. According to Teece (2018), dynamic capabilities are built around three core micro-foundations: sensing, seizing, and transforming. Sensing involves identifying new opportunities and potential threats within the business environment. Seizing refers to mobilizing and deploying resources to take advantage of those opportunities, while transforming focuses on the ongoing renewal and reconfiguration of organizational processes, structures, and capabilities to remain competitive.

In the context of AI-driven Human Resource Management (HRM), sensing may involve using data analytics to identify skill gaps, workforce trends, or operational inefficiencies. Seizing occurs when organizations acquire and implement AI technologies to address these challenges, while transforming involves redesigning HR processes, workflows, and job roles to fully leverage the benefits of AI (Warner and Wäger, 2019; Mikalef and Gupta, 2021).

Empirical studies indicate that organizations with stronger dynamic capabilities tend to achieve greater returns from their AI investments (Mikalef et al., 2020). This is largely because dynamic capabilities help organizations overcome what researchers describe as the “AI implementation gap,” which refers to the delay between adopting AI technologies and realizing measurable improvements in organizational performance (Ransbotham et al., 2017; Vrontis et al., 2022). By effectively sensing opportunities, seizing technological advancements, and continuously transforming their operations, organizations are better positioned to maximize the value of AI and achieve sustained performance improvements.

4.0 Conceptual Framework and Hypothesis Development

The interrelation between the variables of this study is shown in figure 1.

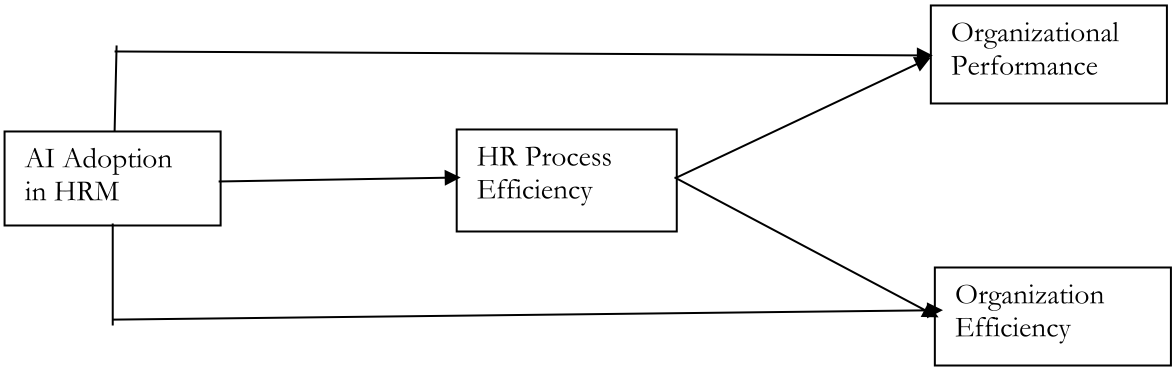

Figure 1. Conceptual Framework: A Simple mediation Model

4.1. Effect of AI Adoption on Organizational Performance

AI-enabled HR systems play an important role in improving organizational effectiveness by supporting data-driven decision-making, automating routine administrative activities, and enhancing the quality and speed of talent management processes. Through advanced analytics and predictive capabilities, these systems enable organizations to optimize key HR functions such as recruitment, employee development, performance management, and workforce planning. As a result, organizations can achieve better resource allocation, increased employee productivity, and more efficient operational processes. As the adoption of AI technologies within HR functions continues to grow, organizations are increasingly positioned to improve both operational efficiency and overall organizational performance. Existing research suggests that digital HR technologies create organizational value by strengthening HR capabilities and aligning HR practices with broader strategic objectives (Marler and Boudreau, 2017). Based on this perspective, the present study proposes that AI adoption in Human Resource Management (HRM) has a positive influence on organizational performance.

Furthermore, AI can enhance organizational performance in several ways. For example, it can improve the quality of talent acquisition through more accurate candidate matching, reduce employee turnover through predictive retention models, and support strategic workforce planning by providing valuable insights into future workforce needs (Budhwar et al., 2022; Prikshat et al., 2023). Evidence from large-scale studies also indicates that organizations that utilize AI in HR functions tend to report higher levels of profitability and productivity compared to those that do not (Budhwar et al., 2022; Zhou et al., 2021).

Hypothesis 1 (H1): AI adoption in HRM is positively related to organizational performance.

4.2 Effect of AI Adoption on Organizational Efficiency

AI technologies have significantly transformed HR operations by automating repetitive and time-consuming tasks, reducing administrative workloads, and enabling faster processing of workforce-related information. Through advanced analytics and intelligent data processing, organizations can make more accurate decisions in areas such as recruitment, performance management, employee scheduling, and workforce planning. The integration of AI into HR processes helps minimize human errors, shorten response times, and optimize the use of organizational resources.

In addition, AI-driven systems support real-time monitoring and evidence-based decision-making, allowing organizations to respond more effectively to operational challenges as they arise. These capabilities help streamline workflows, improve coordination across different functional areas, and enhance the overall efficiency of organizational processes. Consequently, organizations that successfully adopt AI in Human Resource Management (HRM) are more likely to achieve higher levels of operational efficiency and resource productivity.

Previous studies have demonstrated that digital HR technologies can improve both the effectiveness and efficiency of HR functions by promoting data-driven management practices (Strohmeier, 2020). AI systems are particularly effective at handling routine and repetitive HR activities that would otherwise require substantial time and effort from HR personnel. For example, AI-powered chatbots can respond to up to 80 percent of common employee inquiries without human intervention, while AI-driven résumé screening systems can reduce time-to-fill recruitment vacancies by between 40 and 60 percent (Malik et al., 2022; Wamba-Taguimdje et al., 2020). By reducing processing times and minimizing errors, these technologies directly contribute to improved operational efficiency and enhanced organizational performance (Johnson et al., 2021).

Thus: ***Hypothesis 2*** (H2): AI adoption in HRM is positively related to organizational efficiency.

4.3. Mediating Role of HR Process Efficiency

Building on the Resource-Based View (RBV) and perspectives on technology-enabled organizational capabilities, this study argues that HR process efficiency plays a mediating role in the relationship between AI adoption and both organizational performance and operational efficiency. In this context, adopting AI in Human Resource Management (HRM) supports the automation of routine administrative tasks, improves the accuracy of workforce analytics, and enhances both the speed and quality of HR decision-making processes (Marler and Boudreau, 2017).

By streamlining essential HR functions such as recruitment, employee performance management, and workforce planning, AI technologies can significantly increase HR process efficiency. This improvement is reflected in reduced processing times, lower operational costs, and more consistent decision-making outcomes (Strohmeier, 2020). In turn, greater HR process efficiency enables better utilization of organizational resources and improves responsiveness, both of which are essential drivers of overall organizational performance (Becker and Huselid, 2006).

However, research also suggests that the benefits of AI investments are not automatically translated into superior organizational outcomes. Instead, these benefits are realized only when such technologies enhance internal processes and strengthen organizational capabilities that align with strategic objectives (Brynjolfsson and Hitt, 2000).

As a result, HR process efficiency emerges as a crucial mechanism through which AI adoption generates organizational value. This means that organizations that implement AI-enabled HR systems are more likely to experience improved performance and operational efficiency because these technologies strengthen the effectiveness and efficiency of HR processes. Based on this reasoning, it is hypothesized that:

Hypothesis 3 (H3): HR process efficiency positively mediates the relationship between AI adoption and (a) organizational performance (b) organizational efficiency.

5.0 Method

5.1 Sample and Procedure

the participants (*N* = 452) were HR personnels and employees in Information technology (IT) related organizations in Lagos State, South-West Nigeria who were selected using purposive sampling technique since they are particularly involved with IT and HR activities. Lagos State hosts a large and vibrant ecosystem of recruitment and HR agencies alongside one of Africa's most active software and technology sectors, making it Nigeria's leading hub for digital talent and innovation. (Clutch, 2026; Startup Genome, 2024). Among the IT recruitment and HR agencies in Lagos State are DevsData Tech Talent LLC, Andela, BetterWay Devss, Insight Global, Jobbeman Recruitment, DelonApps, Proten International, Winged IT, Remote Team Solution, and Workforce Africa (Clutch, 2026). The IT enterprises are often hired or involved by several organizations (public and privates) to conduct recruitment and other organizational functions that involves the use of technology-enhanced applications. These IT organizations are therefore capable of adopting AI for organizational purposes.

Overall, this study adopted a cross-sectional correlational survey design because it sought to establish the relationship between two or more variables by collecting data from respondents at a single point in time without manipulating the variables (Creswell and Creswell, 2018; Fraenkel, Wallen and Hyun, 2019).

Specifically, the study employed an explanatory correlational survey research design. This is a non-experimental quantitative research design that examines the relationship between two or more variables without manipulating them. The design is appropriate for determining the strength and direction of relationships among variables and for establishing whether one or more independent variables explain or predict variations in a dependent variable (Cohen, Manion and Morrison, 2018; Creswell and Creswell, 2018; Fraenkel, Wallen and Hyun, 2019).

5.2. Measures

To measure all the items of each scale, we used 5-point Likert anchors (1 = strongly disagree, 5 = strongly agree). We also estimated the reliability coefficients of each scale using Cronbach's alpha method. The construct composite reliability of each scale was also established using MacDonald's omega (ϖ) reliability (Hayes and Coutts, 2020), Further, we conducted confirmatory factor analysis for measurement model to determine construct validity of each scale which was based on the following criteria for data fit: CFI = TLI $\geq .950$; SRMR $\leq .060$; RMSEA $\leq .080$ (e.g., Bryn, 2012). The reports are presented as follows:

- AI Adoption in HRM was measure with 6 items - samples: "Our organization uses AI/ML algorithms to screen job applicants" and "We use predictive analytics to forecast employee turnover" - adapted from Mikalef et al., (2020). Reliability coefficients are reported as $\alpha = 0.88$, $\varpi = .91$. The one-factor model yielded satisfactory data fit: $\chi^2 = 34.382$, CFI = .972, TLI = .961, SRMR = .052; RMSEA = .077.
- HR Process Efficiency scale (adapted from Johnson et al., 2021) was a self-report scale and contained 4 items - samples: "Our HR processes are completed faster than industry average" and "The cost per HR transaction has decreased over the past year". Test of reliability yielded coefficients as $\alpha = 0.86$, $\varpi = .88$. for validity, the one-factor model yielded satisfactory data fit: $\chi^2 = 29.262$, CFI = .979, TLI = .976, SRMR = .039; RMSEA = .062.
- Organizational Performance scale (adapted from Richard et al., 2009) has 5 items - samples: "Overall profitability relative to competitors" and "Market share growth". Reliability coefficients are reported as $\alpha = 0.88$, $\varpi = .91$. Supporting validity, the one-factor model yielded satisfactory data fit: $\chi^2 = 33.641$, CFI = .964, TLI = .955, SRMR = .050; RMSEA = .069.
- Organizational Efficiency scale was partly developed by the researchers, but insights drawn from extant literature (e.g., Neely, Gregory and Platts, 2005). It has 4 items with sample as: "We consider recruitment timeline for essential positions" and "HR administrative error rate". Reliability coefficients are reported as $\alpha = 0.90$, $\varpi = .93$. The one-factor model yielded satisfactory data fit: $\chi^2 = 31.211$, CFI = .969, TLI = .963, SRMR = .046; RMSEA = .067.

5.3 Data Collection and Common Method Bias

In this study, data were collected between November 2025 and March 2026. We collected the data from 11 different IT organizations at different times but ensured that no one organization is affiliated to the other to avoid bias and repetition of administration. Although, majority of the survey were administered manually via a research assistant for at least three organizations, a few of the survey was administered online because of the participants who were either on work assignment to other parts of the region or outside the country for that period of time.

To minimize potential common method bias because of self-report measures, we implemented procedural remedies during the design and administration of the survey, following the recommendations of Podsakoff et al. (2003). First, participants were made to understand that participation was voluntary, and respondents were informed that there were no right or wrong answers. This helped to encourage honest responses. Second, we assured the respondents that their responses would remain anonymous and confidential. This approach helped to reduce evaluation apprehension and therefore minimize their tendency to provide socially desirable responses. Third, we used already validated measurement scales for data collection, which were carefully designed using simple, concise, and unambiguous wording to reduce item ambiguity. The use of established and validated scales also helped to enhance construct validity and reliability. Finally, the questionnaire, containing the different scales, was organized logically, with clear instructions and distinct sections separating the measurement of different constructs to reduce respondents' tendency to infer relationships among variables.

5.4. Data Analytical Procedure

To analyse the data, the various items of each measure were aggregated into composite data sets to represent each of the study constructs or variables. Then, the PROCESS Macro for SPSS was employed as a statistical package for data analysis (Hayes, 2013). By adopting the path analysis, we specifically employed the bias-corrected bootstrapping (5,000 resamples) of *Model 4* because it is capable of testing simple mediation effects in the model. Hence, we tested two separate simple mediation models such that one model tested the path containing AI-adoption to HR process to organizational performance, while the other part contains AI-adoption to HR process to organizational effectiveness.

6.0 Results

Table 1

Mean, Standard Deviation and Bivariate Correlation of Variables

Variables	Mean	SD	1	2	3	4
1. AI adoption	3.75	0.65	1			
2. HR process efficiency	4.29	0.58	.234**	1		
3. Organizational performance	3.82	0.55	.327**	.194**	1	
4. Organizational efficiency	4.33	0.61	.422**	.218**	.812**	1

Note. ** $p < .01$, SD = standard deviation

Table 1 presents mean, standard deviations, and correlations. AI adoption correlated positively with organizational performance ($r = 0.327, p < 0.01$) and efficiency ($r = 0.422, p < 0.01$), providing preliminary support for H1 and H2. Additionally, HR process efficiency also correlates with organizational performance ($r = 0.194, p < 0.01$) and efficiency ($r = 0.218, p < 0.01$); which provides preliminary support for H3.

Table 2

Regression of AI Adoption in HRM on Organizational Performance and Efficiency

Paths	R^2	$F(1, 450)$	β(SE)	T	LLCI	ULCI
AI Adoption → Performance	.107	53.913***	.271(.037)	7.343	.199	.344
AI Adoption → Efficiency	.178	97.126***	.348(.035)	9.865	.279	.418

Note. *** $p < .001$, LLCI = lower limit confidence interval, ULCI = upper limit confidence interval

As presented in Table 2, the hypothesized unmediated model reveals significant effects of AI adoption in HRM on organizational performance and efficiency. Table 2 shows that AI adoption has positive significant relationship with organizational performance: $F = 53.913$, $\beta = .271$, $p < .001$, and organizational efficiency: $F = 97.126$, $\beta = .348$, $p < .001$. These results indicate that H1 and H2 are supported.

Table 3

Mediation Analysis of HR Process Efficiency

	Direct Effect Model				Indirect Effect Model		
Mediation Pathways	β(SE)	t	LLCI	ULCI	β(SE)	LLCI	ULCI
AI Adopt. → HR Process → Perf.	.256(.038)	6.738***	,181	.330	.019(.022)	.009	.036
AI Adopt. → HR Process → Effic.	.324(.036)	8.990***	.254	.395	.025(.009)	.009	.045

Note. *** $p < .001$, LLCI = lower limit confidence interval, ULCI = upper limit confidence interval

Results presented in Table 3 reveals the indirect effects of AI adoption in HRM on organizational performance and efficiency via HR process efficiency. The table reveals significant indirect effects on performance: $\beta = 0.019$, 95% CI [0.009, 0.036] and efficiency: $\beta = 0.025$, 95% CI [0.009, 0.045]. Both indirect effects are significant; hence, H3a and H3b are supported. However, the direct effects remain significant for performance ($\beta = 0.256, p < 0.001$) and efficiency ($\beta = 0.324, p < 0.001$), indicating partial mediation.

7.0 Discussion

This study was set out to examine how the adoption of artificial intelligence (AI) in Human Resource Management (HRM) contributes to improved organizational performance and efficiency. Drawing on the Technology Acceptance Model (TAM), the Resource-Based View (RBV), and Dynamic Capabilities Theory (DCT), the study proposed and tested two simple mediation models. The findings provide several important insights.

First, the results show that AI adoption has a significant and positive direct effect on both organizational performance and efficiency (H1 and H2). This suggests that when AI is integrated into organizational routines, it enhances both outcomes simultaneously. Interestingly, the results indicate that the effect on efficiency is stronger than the effect on performance, as reflected in the higher regression estimate for efficiency ($\beta = 0.348$). This suggests that the immediate cost-saving and process-related benefits of AI are more easily realized than longer-term strategic performance gains. From an organizational behavior perspective, these findings reinforce the idea that a technology-enhanced work environment contributes positively to organizational productivity. These findings support previous findings which demonstrated that AI-enabled HRM has positive influence on organizational performance (Aldossary, Ayad and Moustafa, 2026), effectiveness (Choudhary et al., 2026), and employee engagement (Jangbahadur et al. (2025). Overall, these results align with recent meta-analytic evidence (Vrontis et al., 2022; Budhwar et al., 2022) while extending it by focusing specifically on AI applications within HR functions rather than AI adoption in general.

Second, the findings show that HR process efficiency partially mediates the relationship between AI adoption and organizational performance (H3a) as well as between AI adoption and efficiency (H3b). These results extend earlier studies that have often treated efficiency as an outcome rather than as a mechanism through which value is created (e.g., Johnson et al., 2021; Malik et al., 2022). The presence of significant indirect effects suggests that a substantial portion of AI's overall impact on both performance and efficiency operates through improved HR process efficiency. At the same time, the persistence of significant direct effects implies that other, unmeasured mechanisms may also be influencing these relationships. For example, AI adoption may also enhance employee experience, strengthen collaboration, or foster a more innovative organizational climate (Chowdhury et al., 2023). Although the results on mediation are our novel contributions, the findings concur with previous studies (e.g., Choudhary et al., 2026) which found organizational learning capability and technological trust as mediators between AI adoption in HRM and organizational effectiveness These results also complement the findings of Chowdhury et al. (2026) which showed that AI-empowered decision-making is a mediator in the relationship between AI adoption in HRM and organizational process level HR outcomes.

7.1 Theoretical Implications

First, this study extends and reinforces the Technology Acceptance Model (TAM) by showing that when technology is perceived as useful and easy to use within organizational settings, it is more likely to lead to improvements in both performance and efficiency. In other words, positive user perceptions of technology play an important role in translating adoption into tangible organizational benefits.

Second, the study contributes to the Resource-Based View (RBV) by clarifying how AI in Human Resource Management (HRM) can become a source of inimitable competitive advantage. The mediation results indicate that this advantage does not stem from the AI technology itself, since similar systems are widely available to organizations. Instead, it arises from the reconfiguration of organizational processes—particularly improvements in efficiency—that AI enables. This finding extends Barney's (1991) original RBV logic to modern digital and AI-driven organizational contexts.

Third, the study extends Dynamic Capabilities Theory into the domain of HR operations by demonstrating that organizational performance and efficiency are driven through distinct mediating pathways. This highlights how different capability-building mechanisms operate within AI-enabled HR systems to produce separate but related outcomes.

Finally, this research responds to growing scholarly calls for more process-oriented investigations of AI in organizations by moving beyond traditional main-effect studies. In doing so, it aligns with and contributes to recent work emphasizing the need to understand the underlying mechanisms through which AI generates value (Budhwar et al., 2022; Di Vaio et al., 2020).

7.2 Practical Implications

For HR leaders, the findings of this study suggest a sequenced and structured approach to AI implementation. First, organizations should automate routine tasks in order to realize immediate gains in performance. Second, the same automation of routine tasks can also generate short-term improvements in efficiency. Third, and most importantly, organizations should invest significantly in improving HR process efficiency to fully maximize the benefits of an AI-enhanced work environment and achieve higher levels of productivity.

However, simply purchasing and deploying AI software without redesigning existing workflows is unlikely to produce optimal results and may lead to underperformance. In addition, organizations need to systematically measure efficiency-related indicators—such as cost per hire and time to fill positions—in order to accurately capture the full impact of AI adoption in HR processes.

7.3 Limitations and Future Research

We acknowledge some limitations in this study. First, in cross-sectional survey, causality cannot be definitively inferred. We therefore recommend time-lagged study or randomized controlled trials to strengthen causal claims. Second, though partially validated, the use of self-reported performance may inflate relationships. Future research should use alternate measures such as actual recruitment velocity, voluntary turnover rates. Third, our sample was limited to organizations in southwest Nigeria. Hence, we recommend the use of wider sample from different locations.

8.0 Conclusion

This study provides evidence that AI adoption in HRM is positively associated with organizational performance and efficiency. The study also identifies HR process efficiency a mediating mechanism in the relation. Thus, as organizations continue to adopt AI in their day-to-day activities, AT will continue to permeate HR functions. Hence, our findings provide fundamental evidence to understand how AI adoption in HRM could bring future challenge to researchers and practitioners in this perspective.

References

Al-Ayed, S. (2025) 'Role of artificial intelligence in human resource to achieve sustainable organizational performance', *International Journal of Innovative Research and Scientific Studies,* 8(1), pp. 1613–1621. Available at https://doi.org/10.53894/ijirss.v8i1.4709

Aldossary, M. A., Ayad, T. H. and Moustafa, M. A. (2026) 'Artificial intelligence adoption and organizational performance: The role of organizational agility and management commitment in AI-enabled work environment', *Societies,* 16(5), pp. 138. Available at https://doi.org/ 10.3390/soc.16050138

Barney, J. B. (1991) 'Firm resources and sustained competitive advantage', *Journal of Management,* 17(1), pp. 99–120. Available at https://doi.org/10.1177/014920639101700108

Becker, B. E. and Huselid, M. A. (2006) 'Strategic human resources management: Where do we go from here'? *Journal of Management,* 32(6), pp. 898–925. Available at https://doi.org/10.1177/0149206306293668

Bryn, B. M. (2012) *Structural equation modeling with AMOS: Basic concepts, application and programming,* 2nd edn. New York, NY: Routledge, Taylor and Francis Group.

Brynjolfsson, E. and Hitt, L. M. (2000) 'Beyond computation: Information technology, organizational transformation and business performance', *Journal of Economic Perspectives,* 14(4), pp. 23–48. Available at https://doi.org/10.1257/jep.14.4.23

Budhwar, P., Malik, A., De Silva, M. T. T. and Thevisuthan, P. (2022) 'Artificial intelligence – challenges and opportunities for international HRM: A review and research agenda', *The International Journal of Human Resource Management,* 33(6), pp. 1065–1097. Available at https://doi.org/10.1080/09585192.2022.2035161

Cheng, Y. and Zou, Y. (2021) 'Whether and when e-HRM improves organizational performance: A meta-analysis', *Academy of Management Proceedings,* 2021(1), 13990. Available at https://doi.org/10.5465/AMBPP.2021.13

Choudhary, R. K., Singh, A. and Singh, M. (2026) 'AI adoption in HRM, organizational learning capabilities, technological trust, and organizational effectiveness', *Academy of Marketing Studies Journal,* 30(1), pp. 1-5.

Chowdhury, M., Mukherjee, S., Das, M. K. and Chawla, U. (2026) 'Revolutioning AI-driven HR transformation: A study on enhancing workforce efficiency through the technology task fit framework', *Knowledge and Process Management: The Journal of Corporate Transformation*, pp. 1-15. Available at https://doi.org/10.1002/kpm.70096

Chowdhury, S. et al. (2023) 'Unlocking the value of artificial intelligence in human resource management through AI capability framework', *Human Resource Management Review,* 33(1), 100899. Available at https://doi.org/10.1016/j.hrmr.2022.100899

Clutch. (2026). *Top Recruiting Firms in Lagos*. Available at https://clutch.co/ng/hr/recruiting/lagos

Cohen, L., Manion, L. and Morrison, K. (2018) *Research methods in education*, 8th edn. Abingdon, Oxon: Routledge.

Creswell, J. W. and Creswell, J. D. (2018) *Research design: Qualitative, quantitative, and mixed methods approaches*, 5th edn. Thousand Oaks, CA: SAGE Publications.

Benabou, A. and Touhami, F. (2025) 'Empowering human resource management through artificial intelligence: A systematic literature review and bibliometric analysis', *International Journal of Production Management and Engineering,* 13(1), pp. 59–76. Available at https://doi.org/10.4995/ijpme.2025.21900

Di Vaio, A., Palladino, R., Hassan, R. and Escobar, O. (2020) 'Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review', *Journal of Business Research*, 121, pp. 283–314. Available at https://doi.org/10.1016/j.jbusres.2020.08.019

Fraenkel, J. R., Wallen, N. E. and Hyun, H. H. (2019) *How to design and evaluate research in education*, 10th edn. New York, NY: McGraw-Hill Education.

Gong, Q., Fan, D. and Bartram, T. (2025) 'Integrating artificial intelligence and human resource management: A review and future research agenda', *International Journal of Human Resource Management,* 36(1), pp. 103–141. Available at https://doi.org/10.1080/09585192.2024.2440065

Hayes, A. F. (2013) *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, 2nd edn. New York, NY: The Guilford Press.

Hayes, A. F. and Coutts, J. J. (2020) 'Use omega rather than Cronbach's alpha for estimating reliability. But…', *Communication Methods and Measures,* 14(1), pp. 1-24. Available at https://doi.org/10.1080/19312458.2020.1718629

Jangbahadur, U., Ahlawat., S., Rozera, P. and Gupta, N. (2025) 'The effect of AI-enabled HRM dimensions on employee engagement and sustainable organizational performance: Fusion skills as a moderator', *Evidenced-based HRM: A Global Forum for Empirical Scholarship,* 13(1), pp. 85-107. Available at https://doi.org/10.1108/EBHRM-02-2023-0038

Johnson, R. D., Ruel, H., Stone, D. L. and Lukaszewski, K. M. (2021) 'The benefits of eHRM and AI for talent acquisition' *Journal of Tourism Futures,* 7(1), pp. 40–52. Available at https://doi.org/10.1108/JTF-02-2020-0013

Shet, S. V., Poddar, T., Wamba, S. F. and Dwivedi, Y. K. (2021) 'Examining the determinants of successful adoption of data analytics in human resource management: A framework for implications', *Journal of Business Research,* 131, pp. 311–326. Available at https://doi.org/10.1016/j.jbusres.2021.03.054.

Khudhaire, S. J. and Fzaea, A. J. (2026) 'Digital transformation of human resource management and its impact on employee efficiency: A systematic literature review' *American Journal of Management Practice,* 3(1), pp. 84–100. Available at https://doi.org/10.51699/ajmp.v3i1.3529.

Malik, A., Budhwar, P., Patel, C., and Srikanth, N. R. (2022) 'May the bots be with you! Delivering HR cost-effectiveness and individualised employee experiences in an MNE', *The International Journal of Human Resource Management,* 33(6), pp. 1148–1178. Available at https://doi.org/10.1080/09585192.2020.1859582

Malik, A., Budhwar, P. and Kazmi, B. A. (2023) 'Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework', *Human Resource Management Review,* 33(1), 100940. Available at https://doi.org/10.1016/j.hrmr.2022.100940

Marler, J. H. and Boudreau, J. W. (2017) 'An evidence-based review of HR Analytics', *The International Journal of Human Resource Management,* 28(1), pp. 3–26. Available at https://doi.org/10.1080/09585192.2016.1244699

McCartney, S. and Fu, N. (2022) 'Bridging the gap: Why, how and when HR analytics can impact organizational performance', *Management Decision,* 60(13), pp. 25–47. Available at https://doi.org/10.1108/MD-12-2020-1581

Mikalef, P. and Gupta, M. (2021) 'Artificial intelligence capability', *Journal of Business Research,* 128, pp. 548–560.

Mikalef, P., Krogstie, J., Pappas, I. O. and Pavlou, P. A. (2020) 'Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities', *Information & Management,* 57(2), pp. 103169. Available at https://doi.org/10.1016/j.im.2019.05.004

Neely, A., Gregory, M. and Platts, K. (2005) 'Performance measurement system design: A literature review and research agenda', *International Journal of Operations & Production Management,* 25(12), pp. 1228–1263. Available at https://doi.org/10.1108/01443570510633639

Pereira, V., Hadjielias, E., Christofi, M. and Vrontis, D. (2021) 'A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective', *Human Resource Management Review,* 33(1), 100857. Available at https://doi.org/10.1016/j.hrmr.2021.100857

Podsakoff, P. M., Mackenzie, S. B., Lee, J-Y. and Podsakoff, N. P. (2003) 'Common method biases in behavioral research: A critical review of the literature and recommended remedies', *Journal of Applied Psychology,* 88(5), pp. 879-903. Available at https://doi.org/10.1037/0021-9010.88.5.879.

Prikshat, V. et al. (2023) 'AI-augmented HRM: Literature review and a proposed multilevel framework for future research', *Technological Forecasting and Social Change,* 193, pp. 122645. Available at https://doi.org/10.1016/j.techfore.2023.122645

Raghavan, M., Barocas, S., Kleinberg, J. and Levy, K. (2020) *Mitigating bias in algorithmic hiring: Evaluating claims and practices*. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 469–481). Association for Computing Machinery. Available at https://doi.org/10.1145/3351095.3372828

Ransbotham, S., Kiron, D., Gerbert, P. and Reeves, M. (2017), *Reshaping business with artificial intelligence: Closing the gap between ambition and action*. Available at https://web-assets.bcg.com/img-src/Reshaping%20Business%20with%20Artificial%20Intelligence_tcm9-177882.pdf

Richard, P. J., Devinney, T. M., Yip, G. S. and Johnson, G. (2009) 'Measuring organizational performance: Towards methodological best practice', *Journal of Management,* 35(3), pp. 718–804. Available at https://doi.org/10.1177/0149206308330560

Startup Genome. (2024) *The Global Startup Ecosystem Report 2024*. Startup Genome. Available at https://startupgenome.com/report/gser2024

Strohmeier, S. (2020) 'Digital human resource management: A conceptual clarification' *German Journal of Human Resource Management,* 34(3), pp. 345–365. Available at https://doi.org/10.1177/2397002220921131

Tambe, P., Cappelli, P. and Yakubovich, V. (2019) 'Artificial intelligence in human resources management: Challenges and a path forward', *California Management Review,* 61(4), pp. 15–42. Available at https://doi.org/10.1177/0008125619867910.

Teece, D. J. (2018) 'Business models and dynamic capabilities', *Long Range Planning,* 51(1), 40–49. Available at https://doi.org/10.1016/j.lrp.2017.06.007.

Teece, D. J., Pisano, G. and Shuen, A. (1997) 'Dynamic capabilities and strategic management', *Strategic Management Journal,* 18(7), pp. 509–533. Available at https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z.

Vrontis, D. et al. (2022) 'Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review', *International Journal of Human Resource Management,* 33(6), pp. 1237–1266. Available at https://doi.org/10.1080/09585192.2020.1871398

Wamba-Taguimdje, S., Wamba, S. F., Robbert, K. K. J. and Tchatchouang C. E. W. (2020) 'Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects', *Business Process Management Journal,* 26(7), pp. 1893–1924. Available at https://doi.org/10.1108/BPMJ-10-2019-0411

Warner, K. S. R. and Wäger, M. (2019) 'Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal', *Long Range Planning,* 52(3), pp. 326–349. Available at https://doi.org/10.1016/j.lrp.2018.12.001

Yusuf, M., Mulyadi, Chadafi, M. F. and Muchsin. (2026) 'The influence of artificial intelligence adoption in HRM on recruitment and selection efficiency', *Jurnal Ilmiah Manajemen Kesatuan,* 14(1), pp. 289–300. Available at https://doi.org/10.37641/jimkes.v14i1.4600.

Zahrani, A. A. (2025) *AI in HRM: A unified model of AI capabilities and process efficiency for enhanced HRM effectiveness*. *Research Square* [Preprint]. Available at https://doi.org/10.21203/rs.3.rs-7685386/v1

Zhou, Y., Liu, G., Chang, X. and Wang, L. (2021) 'The impact of HRM digitalization on firm performance: Investigating three-way interactions', *Asia Pacific Journal of Human Resources,* 59(1), pp. 20–43. Available at https://doi.org/10.1111/1744-7941.12258.