Artificial Intelligence Enabled Recruitment and Human Intellectual Development in Small and Medium Enterprises in Lagos, Nigeria

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Abstract: *The growing adoption of Artificial Intelligence (AI) in human resource management is transforming recruitment practices, yet empirical evidence on its implications for human intellectual development and firm performance among small and medium enterprises (SMEs) in developing African economies remains limited. This study examined AI-enabled recruitment on hiring efficiency, hiring quality and human intellectual development among SMEs in Lagos, Nigeria, while assessing the mediating role of intellectual capital and the moderating effects of adoption barriers. Anchored in the Resource-Based View, the study adopted a quantitative cross-sectional survey design. The population comprised 121,239 registered SMEs in Lagos State, from which a sample of 439 respondents was determined using Yamane's formula at a 5% margin of error. Data were collected from SMEs owners and human resource managers using a structured questionnaire and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with 5,000 bootstrap subsamples. The findings revealed that AI-enabled recruitment significantly improved hiring efficiency ($\beta = 0.482$, $p < 0.001$), hiring quality ($\beta = 0.415$, $p < 0.001$), and human intellectual development ($\beta = 0.367$, $p < 0.001$). Intellectual capital partially mediated the relationship between AI-enabled recruitment and SMEs performance, accounting for 38.8% of the total effect. However, infrastructure constraints ($\beta = -0.214$, $p < 0.001$) and cost and skills constraints ($\beta = -0.187$, $p < 0.001$) significantly weakened the positive effects of AI-enabled recruitment. The study concludes that the strategic value of AI in SMEs recruitment extends beyond hiring efficiency to the development of human and organisational intellectual capabilities. It recommends affordable and scalable AI solutions, targeted digital-skills development, improved digital infrastructure, and responsible AI governance to enable SMEs to translate AI adoption into sustainable performance.*

Keywords: artificial intelligence, AI-enabled recruitment, human intellectual development; intellectual capital, SMEs performance.

INTRODUCTION

The rapid diffusion of artificial intelligence (AI) is transforming the way organisations acquire, deploy and develop human resources. The emergence of generative AI, machine learning, natural language processing, predictive analytics and algorithmic decision-making has moved AI in human resource management (HRM) beyond simple administrative automation towards a strategic technology capable of influencing core workforce decisions. Recruitment is particularly amenable to AI applications because it involves large volumes of structured and unstructured information, repetitive screening activities and complex decisions concerning candidate-job fit. AI-enabled recruitment can support activities such as vacancy development, candidate sourcing, résumé screening, chatbot interaction, psychometric assessment, interview analysis and candidate ranking. Consequently, AI has the potential to reduce transaction costs, accelerate recruitment processes and improve the consistency and quality of hiring decisions (Tambe et al., 2019; Pan et al., 2022; Chowdhury et al., 2023).

The growing scholarly interest in AI-enabled HRM reflects the recognition that technological capability alone does not create organisational value; rather, value emerges when AI is effectively integrated with organisational resources, managerial expertise and human judgement. Tambe et al. (2019) argue that the contribution of AI to HRM depends on the availability and quality of organisational data, appropriate technological infrastructure, managerial capabilities and the ability of HR professionals to interpret and utilise AI-generated information. Similarly, Chowdhury et al. (2023), through an extensive review of AI capability in HRM, identify AI resources, employee skills, organisational capabilities, AI–employee collaboration and governance as important conditions for extracting value from AI-enabled HR practices. More recent reviews likewise demonstrate that recruitment and selection have become major application domains of AI in HRM, while simultaneously highlighting unresolved issues concerning transparency, bias, explainability and human oversight (Dadaboyev et al., 2025; Ibitomi , et al., 2026; Lee & Lee, 2026).

Within recruitment, therefore, AI should not be conceptualised merely as a substitute for human labour. Its more consequential role is as an augmentation mechanism through which human decision-makers can process information, identify patterns and make more informed talent decisions. Evidence from the literature suggests that AI can improve the speed and scalability of recruitment by automating repetitive activities and processing applicant information that would otherwise require considerable human effort (Dadaboyev et al., 2025). However, the adoption of AI does not automatically produce superior recruitment outcomes. Pan et al. (2022) found that organisational technological competence and regulatory support facilitate AI adoption, whereas perceived technological complexity constrains adoption. These findings are particularly important for smaller organisations because AI implementation requires not only access to digital tools but also sufficient technological competence, financial resources, organisational readiness and employee capability.

The relevance of these issues is particularly pronounced in small and medium-sized enterprises (SMEs). SMEs constitute an important component of employment generation, entrepreneurship and economic development, yet they typically operate with more constrained financial, technological and managerial resources than large organisations (Ibitomi et al., 2025). Recruitment in many SMEs remains heavily dependent on owner-managers, informal networks, referrals, conventional job advertisements and manual screening. Although such practices may be relatively inexpensive, they can become problematic when firms experience increasing applicant volumes, intensified competition for skilled employees and the need to make timely and accurate hiring decisions. AI-enabled recruitment could potentially provide SMEs with access to sophisticated screening and decision-support capabilities that were previously available mainly to large organisations with specialised HR departments. However, whether such technologies actually generate meaningful human-resource value within resource-constrained SMEs remains an empirical question.

This question is particularly important in the Nigerian context. Nigeria has a large and diverse SMEs sector that provides a substantial foundation for employment, entrepreneurship and private-sector development. Lagos State, as Nigeria's major commercial and technological centre, provides a particularly relevant setting for investigating AI-enabled recruitment because of its concentration of technology firms, financial services, manufacturing businesses, retail enterprises and professional service organisations. At the same time, firms operating in this environment face challenges associated with infrastructure, digital capability, financing and the availability of specialised human resources. These contextual conditions may significantly shape both the adoption and effectiveness of AI-enabled recruitment. Consequently, evidence generated from technologically advanced economies cannot simply be transferred to Nigerian SMEs without considering the institutional, infrastructural and organisational conditions under which recruitment technologies are deployed.

The implication is that recruitment represents an important entry point through which organisations build their human-capital base. If AI-enabled recruitment improves the identification and selection of candidates whose knowledge, skills and capabilities are better aligned with organisational requirements, it may contribute indirectly to the development of a more capable workforce. This possibility provides a stronger theoretical basis for examining AI-enabled recruitment in relation to human intellectual development than an exclusive focus on conventional recruitment indicators such as time-to-hire and recruitment cost. In addition, intellectual-capital research suggests that human-resource practices aimed at acquiring and developing employee capabilities can enhance absorptive capacity and innovation. Soo et al. (2017), for instance, demonstrate that human-capital-enhancing HR practices contribute to absorptive capacity and innovation performance.

Nevertheless, the relationship between AI-enabled recruitment and human intellectual development should not be assumed to be uniformly positive. Algorithmic systems depend on the quality of the data, assumptions and criteria embedded within them. If historical recruitment data contain systematic biases, AI systems may reproduce or amplify those biases rather than eliminate them. Köchling and Wehner (2020), in their systematic review of algorithmic decision-making in HR recruitment and development, show that algorithmic systems can generate discrimination and perceived unfairness when inappropriate or biased data are used. The authors consequently emphasise the importance of transparency, fairness and human oversight in algorithmic HR decisions. Thus, the strategic value of AI-enabled recruitment is likely to depend on the extent to which organisations combine technological capabilities with appropriate human judgement, ethical safeguards and organisational learning.

This issue creates an important research gap. Existing AI-HRM literature has predominantly examined technological adoption, recruitment efficiency, algorithmic decision-making, employee reactions, ethical concerns and organisational performance. Reviews have also noted fragmentation in the theoretical and empirical literature on AI and HRM and have called for more context-sensitive empirical research. Chowdhury et al. (2023) specifically identify SMEs-centric research as an important research priority, while interdisciplinary reviews highlight the need to examine how AI creates value across organisational and employee outcomes rather than treating AI adoption as an end in itself. Recent systematic evidence further shows that AI-recruitment research continues to focus substantially on efficiency, productivity, candidate quality and algorithmic risks, leaving opportunities to examine longer-term human-capital consequences.

Against this background, the present study investigates the effect of AI-enabled recruitment on human intellectual development among SMEs in Lagos State, Nigeria. Specifically, the study conceptualises AI-enabled recruitment as a technological and organisational capability encompassing AI-supported candidate sourcing, résumé screening, candidate assessment, interview support and selection decision-making. Human intellectual development is conceptualised in terms of the extent to which recruitment contributes to the acquisition and utilisation of employees' knowledge, skills, problem-solving capabilities and innovation-oriented competencies. The study further considers intellectual capital as a potential mechanism through which improved recruitment may translate into superior SME outcomes. This positioning integrates the RBV and human capital perspectives and shifts the focus of AI-HRM research from the narrow question of whether AI makes recruitment faster to the more strategically consequential question of whether AI-assisted recruitment contributes to the quality and development of the human resources on which SMEs depend.

The study therefore responds to three interrelated gaps. First, it addresses a contextual gap by providing empirical evidence from SMEs in Lagos, Nigeria, a setting that remains insufficiently represented in the international AI-HRM literature. Second, it addresses a conceptual gap by linking AI-enabled recruitment with human intellectual development and intellectual capital rather than restricting recruitment outcomes to efficiency and cost measures. Third, it addresses a theoretical gap by integrating AI capability with the RBV and human capital perspectives to explain how technology-enabled recruitment may contribute to the development of strategically valuable human resources. Accordingly, the study seeks to determine whether and how AI-enabled recruitment contributes to hiring efficiency and quality, human intellectual development and SME performance, while also examining the mediating role of intellectual capital and the organisational challenges that may constrain effective AI adoption.

The study is consequently guided by the following research questions: i. To what extent do SMEs in Lagos State adopt AI-enabled recruitment technologies? ii. What effect does AI-enabled recruitment have on hiring efficiency and quality? iii. What relationship exists between AI-enabled recruitment and human intellectual development? iv. To what extent does intellectual capital mediate the relationship between AI-enabled recruitment and SME performance? and v. What organisational and technological challenges constrain the effective adoption of AI-enabled recruitment among SMEs in Lagos State?

By addressing these questions, the study contributes to the emerging AI-HRM literature by positioning recruitment as an important mechanism for the formation and development of organisational human capital. It also provides evidence capable of informing SME managers, HR professionals and policymakers about the conditions under which AI can be deployed as an augmentation technology rather than merely an automation instrument. Such an approach is particularly important in emerging economies, where the successful digital transformation of SMEs depends not only on acquiring technology but also on developing the human capabilities required to use that technology productively, ethically and sustainably.

LITERATURE REVIEW

Conceptual Review

Concept of Artificial Intelligence-Enabled Recruitment

Artificial Intelligence (AI) refers broadly to computational technologies capable of performing tasks that traditionally require human cognitive capabilities, including learning, reasoning, pattern recognition, prediction and decision-making. Within human resource management (HRM), AI represents a shift from conventional technology-supported administration towards data-driven and increasingly algorithmic approaches to managing people. Tambe et al. (2019) observe that AI has considerable potential to transform HR activities, particularly recruitment, although its effective application is constrained by the complexity of human behaviour, limitations in available data, ethical concerns and the need for managerial accountability. Thus, AI in HRM should not be regarded simply as an automation technology but as an organisational capability whose value depends on the interaction between technology, data, employees and managerial processes.

AI-enabled recruitment refers to the application of AI technologies to one or more activities involved in attracting, identifying, assessing and selecting prospective employees. Such applications include automated candidate sourcing, résumé and application screening, candidate matching, conversational chatbots, automated interview scheduling, assessment analytics and predictive decision-support systems. Chowdhury et al. (2023) argue that the value of AI in HRM derives from the development of an organisational AI capability involving technological resources, appropriate skills, organisational processes and AI–employee collaboration. Consequently, the effectiveness of AI-enabled recruitment depends not only on whether an organisation possesses an AI tool but also on whether it has the human and organisational capacity to use the technology effectively.

The recruitment function is particularly suitable for AI applications because it involves repetitive information-processing activities and the analysis of large quantities of candidate information. AI systems can assist recruiters in identifying candidates whose qualifications correspond with specified job requirements, reducing the amount of manual effort required for initial screening. Pan et al. (2022), using the technology–organisation–environment framework, found that technological competence and regulatory support facilitate AI adoption in recruitment, whereas perceived technological complexity constrains adoption. These findings suggest that AI-enabled recruitment is both a technological and organisational phenomenon.

The potential benefits of AI-enabled recruitment are particularly significant for small and medium-sized enterprises (SMEs). Unlike large corporations, SMEs often operate with relatively limited financial resources, smaller HR departments and less specialised recruitment infrastructure. Consequently, the automation of routine recruitment activities may enable SMEs to undertake sophisticated recruitment processes without establishing large HR departments. However, Tambe et al. (2019) caution that AI does not eliminate the need for human judgement because recruitment decisions involve complex social and behavioural characteristics that cannot always be captured by algorithms.

Accordingly, this study conceptualises AI-enabled recruitment as the extent to which SMEs employ AI-based technologies to support candidate sourcing, application screening, candidate assessment, interview processes and recruitment decision-making. This conceptualisation recognises AI as an augmentation capability rather than an absolute substitute for human recruiters. It is consistent with Chowdhury et al. (2023), who emphasise AI–employee collaboration as an important component of AI capability in HRM.

AI-Enabled Recruitment and Human Capital Development in SMEs

The concept of human intellectual development occupies an important position in this study because recruitment determines the quality of human resources entering an organisation. However, the term requires conceptual precision. Rather than defining human intellectual development narrowly as formal training, this study conceptualises it as the continuous enhancement and utilisation of employees' knowledge, skills, problem-solving capability, learning capacity, creativity and ability to adapt to changing organisational requirements.

This conceptualisation is closely related to the broader human capital perspective. Human capital represents the knowledge, skills and capabilities embodied in individuals that generate economic and organisational value. Becker's human capital perspective emphasises that investments in knowledge and skills enhance individuals' productive capacity. Empirical evidence further demonstrates that human capital is positively associated with organisational performance. Crook et al. (2011), in a meta-analysis of 66 studies, found a strong relationship between human capital and firm performance, particularly where human capital is firm-specific and difficult to obtain through external labour markets.

Within SMEs, the development of employee intellectual capabilities is especially important because smaller firms often depend heavily on a relatively small number of employees. The loss or underdevelopment of critical employee capabilities can therefore have substantial implications for organisational performance. Ibitomi et al. (2023), in their study of staffing and the development of small-scale enterprises in Owo Local Government, Nigeria, emphasised the importance of adequate staffing for the development of SMEs. Their findings provide contextual support for the proposition that the quality and adequacy of human resources constitute an important foundation for SME development.

AI-enabled recruitment may contribute to human intellectual development indirectly through improved person–job alignment. When recruitment systems are capable of identifying candidates whose competencies correspond more closely with job requirements, organisations may be better positioned to acquire employees with relevant knowledge and capabilities. Better recruitment decisions may consequently reduce skill mismatches and facilitate more effective deployment of employees.

However, recruitment technology alone does not develop human capital. Intellectual development occurs through the interaction of employee capabilities with organisational learning opportunities, managerial support, work experience, training and knowledge-sharing mechanisms. Thus, AI-enabled recruitment should be viewed as an upstream mechanism for improving the quality of human capital acquisition, while subsequent organisational practices determine the extent to which that human capital is developed and transformed into organisational value.

This distinction is important for the present study. AI-enabled recruitment may identify and select individuals with superior learning capacity, technical competence and problem-solving ability, but these capabilities must subsequently be developed and utilised within the organisation. Human intellectual development therefore represents a potential consequence of improved human-resource acquisition rather than an automatic output of AI technology.

The relationship between AI-enabled recruitment and human capital development can be explained through the strategic human-resource perspective. Recruitment constitutes the initial mechanism through which organisations acquire external human resources. If AI improves the accuracy, speed and consistency of recruitment decisions, it may enhance the probability of selecting employees whose capabilities correspond with organisational requirements.

The relevance of this relationship is particularly strong in SMEs because human-resource decisions are often closely associated with owner-manager decisions and organisational survival. Ibitomi et al. (2024), in their study of financial literacy and SME performance in Abuja, demonstrate the importance of knowledge and managerial capabilities for SME outcomes. Their study found that dimensions of financial literacy were positively associated with SME performance, reinforcing the broader proposition that knowledge-based capabilities are important for the effectiveness and development of Nigerian SMEs.

Similarly, Ibitomi et al. (2024) examined the relationship between SMEs and economic growth in Nigeria and demonstrated the broader economic significance of SMEs within the Nigerian context. The study examined SME financing and economic growth using Nigerian time-series data, thereby highlighting the importance of SMEs to economic development.

The implication for the present study is that AI-enabled recruitment may have consequences that extend beyond the immediate recruitment transaction. Improved recruitment can strengthen the human-resource base of SMEs, while stronger human capital may improve organisational learning, innovation, productivity and ultimately enterprise performance. This provides a theoretical bridge between AI-enabled recruitment and human intellectual development.

However, SMES adoption should not be reduced to individual technology acceptance. AI-enabled recruitment requires appropriate infrastructure, digital skills, financial resources, data availability and organisational readiness. Chowdhury et al. (2023) therefore advocate an AI capability perspective that combines technological resources with organisational skills, strategies, governance and AI–employee collaboration.

For SMEs in Nigeria, these considerations are particularly important. Ibitomi et al. (2020), in examining microfinance bank services and small-scale enterprise financing in Abuja, demonstrate that access to financial resources is a significant issue within the Nigerian small-enterprise environment. Their study provides relevant contextual evidence that financial constraints can shape the capacity of small enterprises to access resources necessary for business development. Similarly, Ibitomi et al. (2026) found that government funding interventions can influence the performance of micro and small enterprises in Kogi State, although the effect varies according to the funding institution. These findings are relevant to AI adoption because technology investment ultimately competes with other financial priorities within resource-constrained SMEs.

Thus, the adoption of AI-enabled recruitment in Nigerian SMEs should be examined within the broader realities of SME resource availability, technological capability and institutional support rather than assuming that technologies developed in large corporations can be adopted without adaptation.

This proposed relationship is theoretically consistent with the resource-based view and human capital theory. The RBV explains why valuable human resources can constitute strategic resources, while human capital theory explains why investments in employee knowledge and skills can improve productive capacity. Empirical evidence from SMEs in Nigeria further demonstrates that staffing, financial literacy, access to finance and broader economic conditions are important determinants of SME development and performance (Ibitomi et al., 2020, 2023, 2024, 2026).Small and medium-sized enterprises constitute an important context for examining AI-enabled recruitment because they combine substantial economic importance with relatively constrained organisational resources. The Nigerian SME environment is characterised by firms operating across manufacturing, trade, financial services, technology, professional services and other sectors. Their performance is influenced by financial resources, human-resource capability, economic conditions and institutional support.

The empirical contributions of Ibitomi and colleagues provide useful Nigerian evidence for understanding this environment. Ibitomi et al. (2020) examined microfinance services and small-scale enterprise financing in Abuja, highlighting the financing challenges faced by small enterprises. Ibitomi et al. (2023) focused on staffing and small-scale enterprise development in Owo, demonstrating the importance of adequate staffing to enterprise development. Ibitomi et al. (2024a) examined financial literacy and SME performance in Abuja, while Ibitomi et al. (2024b) investigated the relationship between SME financing and economic growth in Nigeria. More recently, Ibitomi et al. (2026) examined government funding and micro and small enterprise performance in Kogi State. These studies collectively demonstrate that finance, staffing, knowledge and institutional support are central issues in the Nigerian SME environment.

These studies also create an important foundation for the present research. While Ibitomi's previous SMEs studies have examined financing, staffing, financial literacy, economic growth and government funding, the current study extends this line of inquiry into the emerging domain of AI-enabled recruitment and human intellectual development. The proposed study therefore represents a logical extension of existing SME research by examining how a new technological capability may influence the acquisition and development of human resources within Nigerian SMEs.

In this context, SMEs are not treated merely as smaller versions of large organisations. Their resource constraints, informal management structures, limited HR specialisation and dependence on individual employee capabilities make them a distinct organisational context in which the consequences of AI-enabled recruitment require specific empirical investigation.

THEORETICAL FRAMEWORK

Resource-Based View (RBV)

The Resource-Based View (RBV), advanced by Barney (1991), posits that firms achieve sustained competitive advantage when they possess and effectively deploy valuable, rare, difficult-to-imitate and non-substitutable resources. In the context of this study, AI-enabled recruitment capability can be regarded as an organisational resource that enhances the ability of SMEs to identify, attract, screen and select suitable employees efficiently. Beyond the technology itself, competitive value derives from the firm’s capability to integrate AI tools with recruitment processes, managerial expertise and organisational knowledge. Thus, SMEs that develop superior capabilities in applying AI to talent acquisition may improve the quality and speed of recruitment while reducing recruitment-related inefficiencies. RBV therefore provides a useful basis for explaining how AI-enabled recruitment capability can become a strategic resource for strengthening organisational performance and human intellectual development in SMEs.

Human Capital Theory (HCT)

Human Capital Theory, principally associated with Becker (1964), conceptualises employees’ knowledge, skills, competencies and experience as productive assets in which organisations invest to generate economic and organisational returns. The theory suggests that organisational performance is partly determined by the quality and effective utilisation of human capital. In this study, AI-enabled recruitment is relevant because the recruitment process represents an important mechanism through which firms acquire human capital. By improving candidate identification, screening and job–person matching, AI can facilitate the acquisition of employees whose knowledge and competencies are better aligned with organisational requirements. Effective recruitment may subsequently provide a stronger foundation for employee learning, capability development and intellectual contribution. HCT therefore explains the link between AI-enabled recruitment, the quality of human capital acquired, and human intellectual development within SMEs.

Theoretical Relevance to the Study

The two theories provide complementary explanations for the phenomenon under investigation. RBV explains AI-enabled recruitment as a strategic organisational capability, whereas HCT explains the value created through the acquisition and development of employees' knowledge, skills and competencies. Their integration suggests that SMEs can derive greater value from AI when technological recruitment capabilities are effectively deployed to acquire and develop high-quality human capital. Consequently, the combined theoretical perspective provides an appropriate foundation for examining how AI-enabled recruitment contributes to human intellectual development and, ultimately, organisational outcomes in SMEs.

EMPIRICAL REVIEW

The empirical literature on artificial intelligence (AI), recruitment, human resource development and small and medium-sized enterprises (SMEs) is expanding rapidly. Existing studies have examined AI adoption in talent acquisition, applicant reactions to algorithmic recruitment, AI-enabled HR analytics, workforce development and SME performance. However, relatively limited evidence directly connects AI-enabled recruitment with human intellectual development in SMEs, particularly within the Nigerian context.

Raghavan et al. (2020) investigated the adoption of artificial intelligence for talent acquisition in IT/ITeS organisations using the Technology–Organisation–Environment and Task–Technology–Fit frameworks. Data were collected from 562 HR and talent-acquisition managers and analysed using PLS-SEM. The study established that relative advantage, cost-effectiveness, top-management support, HR readiness, competitive pressure and vendor support significantly influenced AI adoption, while security and privacy concerns constrained adoption. The study further showed that AI adoption and task–technology fit influenced actual utilisation of AI in talent acquisition. The findings establish that organisational readiness and perceived technological value are critical to successful AI-enabled recruitment. However, the study focused on IT/ITeS organisations rather than SMEs in developing economies.

Mirowska (2020) examined applicants' reactions to AI-based evaluation during recruitment using a randomised experimental design. Participants were exposed to recruitment scenarios in which prerecorded interviews were evaluated either by humans or by AI. The findings showed that information about AI-based evaluation could influence applicants' application and job-pursuit intentions. The study demonstrates that AI recruitment is not purely a technological process because applicants' perceptions can influence the effectiveness of recruitment outcomes. Nevertheless, the study concentrated on applicant reactions rather than the subsequent quality and development of human capital acquired through AI-supported recruitment.

Mirowska and Mesnet (2022) further investigated potential applicants' reactions to AI evaluation of interviews. The study found evidence of applicant preference and algorithm aversion when AI was involved in evaluating candidates. The findings suggest that organisations cannot assume that technologically efficient recruitment systems will automatically generate positive applicant responses. Trust, perceived fairness and familiarity with technology remain important considerations. This finding is relevant to SMEs because limited organisational reputation and resources may make applicant trust particularly important when introducing AI-enabled recruitment.

Sithambaram and Tajudeen (2023) examined AI use and its effects on HRM among 12 Malaysian companies through in-depth interviews and thematic analysis. The study established that AI was being applied to recruitment, talent management, learning and development, HR analytics and employee self-service. AI adoption generated operational, managerial, strategic, informational and organisational benefits. The findings demonstrate that AI can support both recruitment and employee development rather than functioning merely as a recruitment automation tool. However, the qualitative design and Malaysian context limit direct generalisation to Nigerian SMEs.

Rožman et al. (2022) investigated the integration of AI into talent management and its implications for work engagement and enterprise performance. The study showed that AI-supported talent-management practices can strengthen employee-related outcomes and organisational performance by improving the management and utilisation of human resources. The study is relevant to the present research because it demonstrates that the value of AI extends beyond acquiring employees to improving how employee capabilities are managed and translated into organisational outcomes. Nevertheless, the study did not specifically examine recruitment as the primary mechanism through which human capital is acquired.

França et al. (2023) examined the application of AI to talent identification and employee potential assessment. The findings indicate that AI can support organisations in processing large volumes of employee information and identifying patterns relevant to talent decisions. Such capabilities can improve the objectivity and efficiency of talent-related decisions. The study provides support for the argument that AI can contribute to better human-capital decisions; however, its emphasis on talent assessment rather than SME recruitment leaves room for further empirical investigation.

Pham et al. (2025) examined factors influencing AI adoption in the talent-acquisition process among medium-sized firms in Vietnam. Data were obtained from 297 hiring managers, HR directors and senior executives and analysed using PLS-SEM. The study found that perceived benefits and perceived sacrifices significantly influenced perceived value, which subsequently affected AI adoption. The study confirms that organisational perceptions of value are central to AI adoption in recruitment. Its focus on medium-sized firms makes it particularly relevant to the present study, although it investigated adoption determinants rather than the effect of AI-enabled recruitment on human intellectual development.

Onenyi et al. (2026) investigated AI-enabled HR analytics adoption capability and operational performance among Nigerian SMEs. Survey data were collected from 296 respondents across Lagos, Abuja, Port Harcourt and Kano and analysed using PLS-SEM. The study conceptualised AI-enabled HR analytics adoption capability as a second-order formative construct and established its relationship with SME operational performance. The study provides important Nigerian evidence that AI-enabled HR capabilities can generate organisational value. However, its focus was HR

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analytics and operational performance rather than AI-enabled recruitment and human intellectual development.

Oladejo et al. (2026) examined AI adoption and human-resource upskilling among SMEs in Oyo State, Nigeria. The study directly investigated the relationship between AI adoption and workforce development in an emerging-market SME context. Its findings provide strong evidence that AI adoption is associated with the development of workforce capabilities. The study is particularly important to the present research because it demonstrates the relevance of AI to human-resource development within Nigerian SMEs. However, it examined AI adoption generally rather than isolating AI-enabled recruitment as the mechanism for acquiring and developing human capital.

Malin et al. (2025) investigated job applicants' fairness perceptions of AI-based versus human personnel selection using a vignette experiment involving 921 respondents. The study found that explanations of selection decisions improved perceptions of outcome fairness, process fairness and interpersonal treatment irrespective of whether AI or humans made the decision. The findings indicate that transparency and explainability are important conditions for effective AI-enabled recruitment. The study strengthens the argument that AI recruitment capability should incorporate appropriate human oversight and transparent decision-making. However, it focused on applicant perceptions rather than organisational human-capital outcomes.

Erimife et al. (2026) examined AI-driven HR practices and sustainable workforce performance in Nigerian organisations, considering employee digital adaptability as a mediator. The study covered banking and finance, telecommunications, healthcare and oil and gas organisations in Abuja, Lagos and Port Harcourt, using data from 120 HR managers, executives and AI/IT officers. Regression and mediation analysis revealed that AI-enabled learning and development and employee engagement significantly enhanced sustainable workforce performance, while AI-enabled recruitment and selection and workforce planning were not significant direct predictors. Employee digital adaptability significantly mediated the relationship between AI-driven HR practices and sustainable workforce performance. The finding is particularly important because it suggests that AI recruitment alone may not automatically produce superior workforce outcomes unless employees possess the digital capability required to work effectively within AI-enabled systems.
Xu et al. (2024) examined the relationship between AI investment and labour demand among small and micro enterprises in China. Using data from 127 SMEs across 14 provinces between 2016 and 2020 and a two-way fixed-effects model, the study found that AI investment did not significantly affect overall labour demand. However, significant negative effects were observed among some categories of private and high-technology firms, while positive effects occurred in wholesale and retail firms. The study concluded that AI creates both labour-substitution and labour-creation effects. This finding provides an important counterpoint to the assumption that AI automatically creates employment and suggests that the organisational consequences of AI depend on firm and industry characteristics.

Ibitomi et al. (2023) investigated staffing and the development of small-scale enterprises in Owo Local Government Area, Ondo State, Nigeria. The study established that appropriate staffing and employee placement were significantly associated with SME productivity, with placement and orientation explaining a substantial proportion of the variation in productivity. The authors emphasised the importance of matching employees' skills with appropriate jobs rather than merely increasing employee numbers. This study is highly relevant to the present research because AI-enabled recruitment similarly seeks to improve candidate identification and job person matching. The study therefore provides a Nigerian empirical foundation for examining whether AI can strengthen the quality and effectiveness of recruitment decisions in SMEs.

Ibitomi et al. (2024) examined SMEs and economic growth in Nigeria using annual data covering 1999–2021. The study investigated SME financing through commercial bank loans, private-sector credit and lending rates and assessed their implications for economic growth. The findings provide evidence of the broader economic significance of SMEs and demonstrate that the performance of SMEs is influenced by the resources available to them. Although the study did not examine AI or human-resource development directly, it establishes the importance of strengthening SME capabilities and performance in Nigeria. It therefore provides contextual justification for investigating technological and human-capital mechanisms capable of improving SME outcomes.

Ibitomi et al. (2025) examined the economic environment and SME performance in Nigeria using annual time-series data from 1986–2023. The study assessed inflation, interest rates, exchange rates, tax revenue and electricity consumption as determinants of SME performance and employed ordinary least squares regression. The findings showed that inflation and exchange rates had significant negative effects on SME performance, while tax revenue and electricity distribution had significant positive relationships with SME performance; interest rate was not statistically significant. The study demonstrates that Nigerian SME performance is shaped by both internal and external capabilities and constraints. Its relevance to the present study lies in reinforcing the need to investigate internal organisational resources particularly technology and human capital—that may help SMEs strengthen resilience and performance in a challenging economic environment.

Synthesis of the Empirical Evidence

The reviewed evidence reveals several important patterns. First, AI is increasingly being incorporated into recruitment, talent acquisition, talent management, HR analytics, learning and development and workforce management. Evidence from Malaysia, Vietnam, China, Nigeria and other contexts confirms that AI is moving beyond administrative automation towards strategic human-resource management.

Second, the empirical evidence indicates that AI-enabled recruitment can improve efficiency, candidate screening, talent identification and decision support, but its effectiveness is conditioned by organisational readiness, perceived value, trust, transparency and applicant acceptance. Thus, technological adoption alone may be insufficient to generate superior human-resource outcomes.

Third, the evidence concerning AI and employment is not uniformly positive. Xu et al. (2024), found that AI investment had no significant overall effect on labour demand among small and micro enterprises and produced different effects across industries. This suggests that AI may simultaneously create and substitute labour, making the quality of human-capital management particularly important.

Fourth, Nigerian evidence is beginning to emerge. Onenyi et al. (2026) established a relationship between AI-enabled HR analytics capability and SME operational performance, while Oladejo et al. (2026) provided evidence linking AI adoption with HR upskilling among Nigerian SMEs. Erimife et al. (2026), however, found that AI-enabled recruitment and selection did not significantly predict sustainable workforce performance directly, although employee digital adaptability played a significant mediating role. These findings suggest that the relationship between AI recruitment and human-resource outcomes requires further investigation.

The three studies by Ibitomi and colleagues add an important Nigerian SME perspective. Ibitomi et al. (2023) established that staffing, placement and orientation are important to SME productivity; Ibitomi et al. (2024) demonstrated the broader contribution of SMEs to Nigerian economic growth; while Ibitomi et al. (2025) showed that SME performance is affected by the wider economic environment. Collectively, these studies provide a strong empirical foundation for examining whether AI-enabled recruitment can improve the acquisition and deployment of human capital and consequently contribute to the development and performance of SMEs.

METHODOLOGY

The study adopted a quantitative, cross-sectional survey design to examine the relationships among AI-enabled recruitment, human intellectual development, intellectual capital, adoption barriers and SME performance. The design was considered appropriate because data were collected from multiple SMEs at a defined period and analysed to test the hypothesised relationships among the study constructs.

The study population comprised 121,239 registered SMEs in Lagos State, Nigeria, distributed across the five administrative divisions of Ikeja, Badagry, Ikorodu, Lagos Island and Epe (Lagos State Ministry of Commerce and Industry (LASMCI), 2025). Eligible firms were SMEs employing between 10 and 199 employees, operating for at least two years, and having an owner, HR manager or administrative officer with responsibility for recruitment. These criteria ensured that respondents possessed adequate organisational and recruitment experience to provide informed responses.

The minimum sample size was estimated using Yamane's (1967) formula at a 95% confidence level and 5% margin of error, producing an initial sample of approximately 399 SMEs. Allowing for possible non-response increased the target to approximately 443 respondents. Following field administration and data screening, 439 usable responses were retained for analysis.

A multistage stratified sampling procedure was employed. First, Lagos State was stratified into its five administrative divisions. Second, SMEs were stratified by major sectors, namely technology/fintech, manufacturing, retail/trade, health and professional services. Proportionate allocation was used to determine the number of SMEs selected from each stratum, while simple random sampling was applied within the identified sampling frames. One knowledgeable respondent with direct responsibility for recruitment or HR-related decisions was selected from each participating SME. This procedure enhanced geographical and sectoral representation and reduced the potential for sampling imbalance.

Primary data were collected using a structured questionnaire developed from established measures in the literature and adapted to the Nigerian SME context. The questionnaire comprised six sections. Section A captured respondents' demographic and organisational characteristics. Section B measured AI-enabled recruitment across AI-supported sourcing, screening, interviewing and recruitment analytics. Section C assessed human intellectual development, including employee knowledge, skills, creativity and innovation. Section D measured intellectual capital**,** comprising human, structural and relational capital. Section E captured AI adoption barriers, particularly infrastructure, cost and skills constraints, while Section F measured SME performance.

All substantive constructs were measured using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. Measurement items were adapted from established instruments to enhance content validity and conceptual consistency. Where necessary, wording was modified to reflect the operational realities of SMEs in Nigeria.

The instrument underwent content and face validation before the main survey. Three academics with expertise in human resource management, artificial intelligence and organisational research reviewed the questionnaire for construct relevance, clarity and adequacy of item coverage. A pilot test involving 30 HR-related respondents from SMEs outside the final sample was subsequently conducted to identify ambiguous or poorly worded items and assess the preliminary reliability of the instrument.

The measurement model was assessed using SmartPLS 4**.** Indicator reliability was evaluated using outer loadings, with values of approximately 0.70 or higher considered satisfactory. Convergent validity was assessed using the average variance extracted (AVE**)**, with values above 0.50 regarded as acceptable. Internal consistency was evaluated using Cronbach's alpha and composite reliability**,** with values exceeding 0.70 considered satisfactory. Discriminant validity was assessed using the heterotrait–monotrait (HTMT) ratio, supplemented by the Fornell–Larcker criterion.

Data analysis was conducted using SPSS 27 and SmartPLS 4. Descriptive statistics were initially used to summarise respondent and firm characteristics. Partial Least Squares Structural Equation Modelling (PLS-SEM) was subsequently employed to assess the measurement and structural models. PLS-SEM was considered appropriate because the research model contains multiple latent constructs and incorporates mediation and moderation relationships, while the study also seeks to explain and predict relationships within an emerging research context.

Analysis proceeded in two stages. First, the measurement model was evaluated for indicator reliability, internal consistency, convergent validity and discriminant validity. Second, the structural model was assessed to determine the magnitude and significance of the hypothesised relationships. Path coefficients, coefficients of determination (R^2), effect sizes (f^2) and predictive relevance (Q^2) were reported. Statistical significance was assessed using bootstrapping with 5,000 resamples **and** bias-corrected confidence intervals.

The hypothesised mediation effect was evaluated through the significance of the indirect effect and its bootstrapped confidence interval. Moderation effects were assessed by introducing interaction terms into the structural model. Where relevant, multicollinearity was examined using variance inflation factor (VIF) values.

Because the study relied primarily on self-reported, cross-sectional questionnaire data, procedural and statistical measures were adopted to minimise common method bias. Procedurally, respondents were assured of anonymity and confidentiality, questionnaire items were presented without implying desirable responses, and predictor and outcome constructs were conceptually distinguished. Statistically, collinearity-based diagnostics were examined to determine whether common method bias constituted a serious threat to the results.

The conceptual model specifies AI-enabled recruitment as the principal explanatory construct and human intellectual development as the principal outcome. Intellectual capital and SME performance are incorporated into the model as theoretically specified intervening or outcome constructs, while AI adoption barriers are examined as a contextual moderating factor. The structural relationships were therefore estimated simultaneously using PLS-SEM to determine the direct, indirect and interaction effects among the constructs.

DATA ANALYSIS AND DISCUSSION

A total of 439 questionnaire were distributed to eligible SMEs across the five administrative divisions and five major sectors of Lagos State. Of these, 412 questionnaire were returned, representing a 93.8% return rate. Following systematic data screening for incomplete responses, excessive missing values and influential outliers, 403 questionnaire were retained for the final analysis**,** yielding a 91.8% usable response rate based on the total questionnaires administered. The high usable response rate indicates satisfactory respondent engagement and provides an adequate basis for subsequent statistical analysis. The final sample also exceeded the minimum sample requirement established for the study's PLS-SEM analysis, thereby providing sufficient observations for estimating the hypothesised structural relationships.

DESCRIPTIVE STATISTICS OF CONSTRUCTS

All items were measured on a 5-point Likert scale: 1=Strongly Disagree to 5=Strongly Agree.

Table 1: Descriptive Statistics

Construct	No of Items	Mean	Std. Deviation	Skewness	Kurtosis
AI-Enabled Recruitment	12	3.42	0.87	-0.21	0.34
Hiring Efficiency	4	3.68	0.79	-0.34	0.51
Hiring Quality	4	3.55	0.82	-0.28	0.42
Human Intellectual Development	10	3.61	0.75	-0.19	0.28
Intellectual Capital	9	3.49	0.81	-0.25	0.38
Adoption Barriers	9	3.24	0.91	0.12	-0.15
SME Performance	6	3.57	0.78	-0.31	0.47

Source : Survey, 2026

Table 1 presents the descriptive statistics for the study constructs based on a five-point Likert scale. The mean scores range from 3.24 to 3.68**,** indicating generally moderate-to-high levels of agreement with the measurement items. Hiring efficiency recorded the highest mean (M = 3.68, SD = 0.79), followed by human intellectual development (M = 3.61, SD = 0.75) and SMEs performance (M = 3.57, SD = 0.78). In contrast, adoption barriers recorded the lowest mean (M = 3.24, SD = 0.91), suggesting that respondents experienced relatively moderate constraints to AI adoption. AI-enabled recruitment recorded an overall mean of 3.42 (SD = 0.87)**,** indicating a moderately positive level of AI-enabled recruitment practices among the sampled SMEs.

The relatively low standard deviations (0.75–0.91) indicate reasonable consistency in respondents' perceptions. Skewness values ranged from −0.34 to 0.12, while kurtosis ranged from −0.15 to 0.51, suggesting that the distributions were approximately symmetrical and did not exhibit serious departures from normality. Overall, the descriptive results indicate favourable perceptions of AI-enabled recruitment, human intellectual development and SMEs performance, while adoption barriers remain a notable concern among the sampled SMEs.

MEASUREMENT MODEL ASSESSMENT

Reliability was tested using Cronbach's Alpha and Composite Reliability (CR). Convergent validity was tested using Average Variance Extracted (AVE) and factor loadings. Threshold: $\alpha>0.7$, CR>0.7, AVE>0.5, Loading>0.7 (Hair et al., 2022).

Table 2: Reliability and Convergent Validity Results

Construct	Items	Loading Range	Cronbach α	CR	AVE
AI-Enabled Recruitment	12	0.712 - 0.845	0.912	0.925	0.612
Human Intellectual Development	10	0.701 - 0.832	0.895	0.907	0.584
Intellectual Capital	9	0.721 - 0.819	0.884	0.896	0.571
Adoption Barriers	9	0.705 - 0.801	0.871	0.885	0.559
SME Performance	6	0.734 - 0.856	0.862	0.876	0.603

Source : Survey, 2026.

All constructs met the threshold. This indicates internal consistency and that items measure their intended constructs as they were all above 0.7.

STRUCTURAL MODEL ASSESSMENT

After confirming measurement model, structural paths were tested. Collinearity was checked: all VIF < 3.0, indicating no multicollinearity issue.

Coefficient of Determination R^2 and Predictive Relevance Q^2

Table 3: R^2 and Q^2 Values

Endogenous Construct	R^2	R^2 Adjusted	Q^2
Hiring Efficiency	0.232	0.230	0.141
Hiring Quality	0.172	0.170	0.098
Human Intellectual Development	0.480	0.477	0.274
SME Performance	0.520	0.516	0.311

Following satisfactory assessment of the measurement model, the structural model was evaluated to determine its explanatory and predictive capacity. Collinearity diagnostics showed that all VIF values were below 3.0, indicating that multicollinearity was not a concern and that the structural estimates were sufficiently stable.

Table 3 shows the coefficients of determination (R^2) and predictive relevance (Q^2) for the endogenous constructs. The model explained 23.2% of the variance in hiring efficiency ($R^2 = 0.232$) and 17.2% in hiring quality ($R^2 = 0.172$), indicating relatively modest explanatory power for these outcomes. In contrast, the model demonstrated stronger explanatory power for human intellectual development ($R^2 = 0.480$) and SME performance ($R^2 = 0.520$), indicating that the specified predictors jointly explained 48.0% and 52.0% of their respective variances. The adjusted R^2 values

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were very close to the unadjusted values, suggesting that the explanatory power of the model remained stable after accounting for the number of predictors.

The Q^2 values were positive for all endogenous constructs, ranging from 0.098 to 0.311. This confirms that the model possesses predictive relevance for hiring efficiency, hiring quality, human intellectual development and SME performance. Notably, the highest predictive relevance was observed for SME performance ($Q^2 = 0.311$), followed by human intellectual development ($Q^2 = 0.274$), suggesting that the model has greater predictive capability for these two outcomes.

Effect Size (f^2)

The effect-size results further demonstrate the practical contribution of AI-enabled recruitment to the endogenous constructs. The effect of AI-enabled recruitment on hiring efficiency was medium-to-large ($f^2 = 0.302$), while its effect on hiring quality was medium ($f^2 = 0.208$). Its effect on human intellectual development was also medium ($f^2 = 0.156$). These findings indicate that AI-enabled recruitment makes a meaningful contribution to all three outcomes, with its strongest practical effect occurring in relation to hiring efficiency.

Importantly, the statement that $f^2 = 0.156$ is “large” should be corrected. Based on the conventional thresholds you have adopted (0.02 = small, 0.15 = medium, 0.35 = large), 0.156 represents a medium effect, not a large effect. Thus, your interpretation should read: AI → Human Intellectual Development: $f^2 = 0.156$ (medium effect).

HYPOTHESIS TESTING

Bootstrapping with 5000 subsamples was used to test significance of paths at 95% confidence level.

Direct Effects

Table 4: Direct Path Results

Hypothesis	Path	β	Std Error	t-value	p-value	Decision
H1	AI Recruitment → Hiring Efficiency	0.482	0.058	8.341	0.000	Supported
H2	AI Recruitment → Hiring Quality	0.415	0.058	7.102	0.000	Supported
H3	AI Recruitment → Human Intellectual Dev	0.367	0.059	6.254	0.000	Supported

All direct hypotheses are supported at $p<0.001$.

Mediation Analysis

H4: Intellectual Capital mediates AI Recruitment → SME Performance.
Tested using Preacher and Hayes (2008) bootstrapping approach.

Table 5: Mediation Results

Path	Direct Effect	Indirect Effect	Total Effect	t-value	p-value	Decision
AI → IC → Performance	0.312	0.198	0.510	4.872	0.000	Supported

Result: Partial mediation. 38.8% of total effect is mediated by IC. This means AI improves performance both directly and through building intellectual capital.

Moderation Analysis

H5 and H6: Adoption Barriers moderate the relationship between AI Recruitment and Adoption/Outcomes.

Table 6: Moderation Results

Hypothesis	Path	β	Std Error	t-value	p-value	Decision
H5	Infrastructure × AI → Outcomes	-0.214	0.055	3.891	0.000	Supported
H6	Cost/Skills × AI → Outcomes	-0.187	0.055	3.412	0.000	Supported

Negative coefficients indicate barriers weaken the positive effect of AI. This confirms TAM (Davis, 1989).

DISCUSSION OF FINDINGS

The findings show a consistent and statistically significant positive role of AI-enabled recruitment in SME outcomes, while intellectual capital strengthens the mechanism through which AI creates value and adoption barriers weaken its benefits.

H1: AI-enabled recruitment and hiring efficiency. The result supports H1, showing a positive and significant relationship between AI-enabled recruitment and hiring efficiency ($\beta = 0.482$, $t = 8.341$, $p < 0.001$). This indicates that greater use of AI in recruitment substantially improves the speed and efficiency of hiring. The relatively strong coefficient suggests that AI applications such as candidate sourcing, CV screening and interview scheduling can reduce recruitment delays and administrative workload. Thus, the finding confirms that AI can make the recruitment process faster and more efficient for SMEs.

H2: AI-enabled recruitment and hiring quality. H2 was also supported, as AI-enabled recruitment had a positive and significant effect on hiring quality ($\beta = 0.415$, $t = 7.102$, $p < 0.001$). This means

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that AI-supported recruitment contributes not only to faster hiring but also to better-quality recruitment decisions. The finding suggests that the ability of AI to analyse candidate information and match applicants with job requirements can improve the likelihood of selecting suitable employees. Therefore, AI recruitment provides both an efficiency and quality advantage to SMEs.
H3: AI-enabled recruitment and human intellectual development. The result supports H3, with AI-enabled recruitment significantly influencing human intellectual development ($\beta = 0.367$, $t = 6.254$, $p < 0.001$). This indicates that AI-supported recruitment contributes to the development of employee knowledge, skills and intellectual capabilities. The finding suggests that recruiting employees whose competencies better match organisational requirements can provide SMEs with stronger human-capital foundations for learning, innovation and knowledge creation.

H4: Intellectual capital as a mediator. H4 was supported, demonstrating that intellectual capital partially mediates the relationship between AI-enabled recruitment and SME performance. The direct effect was 0.312, while the indirect effect through intellectual capital was 0.198, producing a total effect of 0.510 ($t = 4.872$, $p < 0.001$). The indirect effect accounts for approximately 38.8% of the total effect, indicating that a substantial proportion of the performance benefits of AI recruitment occurs through the development and utilisation of intellectual capital. The result therefore shows that AI does not improve SME performance only through direct recruitment efficiencies; it also creates value by strengthening the knowledge, skills and capabilities embedded in the organisation.
H5: Infrastructure barriers as a moderator. H5 was supported because infrastructure constraints significantly and negatively moderated the relationship between AI-enabled recruitment and outcomes ($\beta = -0.214$, $t = 3.891$, $p < 0.001$). The negative coefficient indicates that inadequate electricity, internet connectivity, digital systems and related infrastructure reduce the positive benefits that SMEs can obtain from AI recruitment. Thus, even where SMEs are willing to adopt AI, weak infrastructure can limit its effectiveness.

H6: Cost and skills barriers as moderators. H6 was equally supported, with cost and skills constraints exerting a significant negative moderating effect ($\beta = -0.187$, $t = 3.412$, $p < 0.001$). This implies that high implementation costs and inadequate employee skills can weaken the positive contribution of AI-enabled recruitment to SME outcomes. The finding demonstrates that technology adoption alone is insufficient; SMEs require adequate financial resources and appropriate human capabilities to realise the benefits of AI.

Overall, the hypothesis testing demonstrates that AI-enabled recruitment significantly improves hiring efficiency, hiring quality and human intellectual development, with intellectual capital serving as an important pathway through which AI translates into SME performance. However, infrastructure, cost and skills constraints significantly weaken these benefits. The findings therefore suggest that the value of AI recruitment depends not only on adopting the technology but also on creating the organisational and environmental conditions necessary for its effective use.

CONCLUSION AND RECOMMENDATIONS

This study examined the effect of AI-enabled recruitment on human intellectual development among SMEs in Lagos State, Nigeria, with particular attention to hiring efficiency, hiring quality, intellectual capital and the contextual barriers that constrain AI adoption. Based on data obtained from 403 usable responses and analysed using PLS-SEM, the findings provide empirical evidence that AI-enabled recruitment has significant implications for both recruitment outcomes and broader human-capital development.

The study concludes, first, that AI-enabled recruitment significantly improves hiring efficiency ($\beta = 0.482$, $p < 0.001$). The relatively strong effect indicates that AI-supported recruitment can contribute meaningfully to more efficient recruitment processes by improving candidate sourcing, screening and related administrative activities. The finding is particularly relevant to SMEs, where limited managerial and HR resources make recruitment efficiency strategically important.

Second, the study establishes that AI-enabled recruitment significantly improves hiring quality ($\beta = 0.415$, $p < 0.001$). This suggests that the value of AI recruitment extends beyond speed and cost reduction to the quality of person–job matching and selection decisions. The finding supports the Human Capital Theory perspective that the quality of employees acquired through recruitment constitutes an important foundation for subsequent organisational returns.

Third, and most importantly, the study demonstrates that AI-enabled recruitment significantly enhances human intellectual development ($\beta = 0.367$, $p < 0.001$). This finding extends the conventional view of recruitment technology as primarily an administrative or efficiency-enhancing mechanism. It suggests that better recruitment and person–job fit can create conditions for employees to develop knowledge, skills, adaptability and innovative capacity. This represents a central contribution of the study because it connects AI-enabled recruitment with a human-capital outcome that has received comparatively limited empirical attention.

Fourth, the findings establish that intellectual capital partially mediates the relationship between AI-enabled recruitment and SME performance (indirect $\beta = 0.198$, $p < 0.001$). This indicates that the organisational benefits of AI recruitment are realised not only through direct efficiency gains but also through the conversion of employee knowledge and capabilities into organisational resources and relationships. Approximately 38.8% of the effect of AI-enabled recruitment on performance operates through intellectual capital, highlighting the strategic importance of transforming individual employee capabilities into organisational knowledge assets.

Finally, the study establishes that infrastructure barriers and cost/skills barriers significantly weaken the effects associated with AI adoption ($\beta = -0.214$ and $\beta = -0.187$, respectively; $p < 0.001$). Thus, the benefits of AI-enabled recruitment cannot be considered independent of the technological and organisational environment in which SMEs operate. The findings indicate that unequal access to reliable infrastructure, affordable technologies and relevant digital skills may create an uneven distribution of AI-related benefits across SMEs and sectors.

Overall, the study concludes that AI-enabled recruitment represents more than an automation technology for Lagos SMEs; it constitutes a potentially important organisational capability for improving recruitment efficiency and quality and for strengthening human intellectual development**.** However, the realisation of these benefits depends on SMEs' ability to overcome infrastructure, cost and skills constraints and to deliberately convert newly acquired human capabilities into organisational intellectual capital. The findings therefore support an integrated perspective in which technology capability and human-capital development are complementary rather than competing sources of SME advantage.

Based on the empirical findings an conclusion, the study recommends that :
i.SMEs should adopt AI-enabled recruitment strategically, focusing on applications such as candidate sourcing, CV screening, interview scheduling and candidate communication that demonstrably improve recruitment efficiency and quality.
ii. SMEs managers should also maintain meaningful human oversight throughout AI-supported recruitment. AI-generated recommendations should inform rather than replace managerial judgement, particularly at shortlisting and final-selection stages.
iii. SMEs should integrate AI-enabled recruitment with broader human-capital development. Recruitment should be followed by structured onboarding, mentoring, continuous training and knowledge-sharing initiatives so that the capabilities acquired through AI-supported hiring contribute to sustained employee and organisational development.
iv. HR professionals should strengthen digital and AI competencies among recruitment personnel and employees. Training should cover AI literacy, responsible AI use, interpretation of AI-generated outputs, data protection and human oversight.
v. Government agencies and SME-support institutions should reduce the barriers that prevent smaller firms from accessing AI technologies. Targeted support should include affordable AI-enabled recruitment and HR solutions, digital-skills development, technical assistance and financing mechanisms for technology adoption.
vi. AI technology providers should design affordable, scalable and user-friendly recruitment platforms specifically for SMEs. Modular solutions would allow firms to begin with basic recruitment functions and expand their use as financial and technological capabilities improve.

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