



AI Powered Recruitment Tools and Operational Efficiency in Agri Based SMEs in Central Region, Cameroon

Eyong Ako^{1*}

Department of Organisational Sciences, Higher Institute of Commerce and Management¹

*Corresponding author: akorolly87@yahoo.com

Received: 29 July 2026 | Revised: 17 August 2026 | Revised: 26 August 2026 | Published: 25 September 2026

Abstract

Purpose: This study examines the impact of AI powered recruitment tools on the operational efficiency of agri based Small and Medium Enterprises (SMEs) in the Central Region of Cameroon. It investigates how digital recruitment technologies influence hiring timelines, cost per hire, and workforce productivity, and whether organizational size and digital infrastructure moderate these effects.

Research Methodology: A quantitative survey design was employed, collecting data from 312 managers and human resource personnel in agri based SMEs in Yaoundé and surrounding areas. Structured questionnaires were administered using purposive and stratified sampling. Data were analyzed with descriptive statistics, correlation analysis, and hierarchical regression in SPSS version 27.

Results: AI powered recruitment tools significantly enhanced operational efficiency ($\beta=0.341$, $p<0.001$). Among enterprises with high adoption, cost per hire fell by 28.4 percent, time to hire decreased by 41.2 percent, and workforce productivity improved by 19.7 percent. Organizational size and digital infrastructure moderated these relationships, individually and jointly.

Conclusions: AI powered recruitment tools substantially improve operational efficiency in agri based SMEs, although the benefits depend on organizational readiness and infrastructure. Strategic investment in digital recruitment capabilities yields measurable efficiency gains.

Limitations: The study is confined to the Central Region of Cameroon, uses cross sectional data that preclude definitive causal claims, and relies on self reported efficiency measures.

Contributions: The study provides empirical evidence on AI adoption in African agricultural SMEs and offers practical insights for managers, policymakers, and technology providers.

Keywords: Agri Based SMEs, AI Powered Recruitment, Cameroon, Operational Efficiency, Workforce Productivity

How to Cite: Ako, E. (2026). AI Powered Recruitment Tools and Operational Efficiency in Agri Based SMEs in Central Region, Cameroon. *Global Review of Digital Economy and Business Innovation (GRDEBI)*, 1(3), 193-207.

1. Introduction

The integration of artificial intelligence (AI) into human resource management has emerged as a transformative force that is reshaping recruitment practices worldwide ([Tambe et al., 2019](#), [Budhwar et al., 2022](#)). AI powered recruitment tools, which include automated candidate screening, intelligent matching algorithms, chatbot assisted communication, and predictive analytics, offer organizations unprecedented opportunities to streamline hiring and improve workforce quality ([Albert, 2019](#), [Black & van Esch, 2020](#)). For small and medium enterprises in agricultural sectors, where resource constraints and seasonal labor demands create unique operational challenges, these technologies

present both substantial promise and significant implementation hurdles ([Vrontis et al., 2022](#), [Schwaeke et al., 2025](#)).

Agriculture remains a leading source of employment and income in Cameroon, and agri based SMEs form the backbone of the sector ([IFAD, 2024](#)). Yet these enterprises face persistent challenges in attracting, recruiting, and retaining qualified personnel ([Nkeng et al., 2022](#)). Traditional recruitment methods, characterized by manual resume screening, lengthy interview processes, and limited candidate reach, often result in extended vacancies, suboptimal hiring decisions, and high recruitment costs ([Ako, 2026b](#)). These inefficiencies spread throughout organizational operations, reducing productivity and constraining growth ([Baiye & Ako, 2025](#)). At the same time, digital technologies such as big data and smart farming systems are changing how agricultural enterprises plan and manage their operations, which increases the demand for staff with new skills ([Wolfert et al., 2017](#)).

The Central Region of Cameroon, which includes the capital Yaoundé and surrounding agricultural zones, is a particularly significant context for examining the adoption of AI powered recruitment. The region hosts a concentration of agri based SMEs engaged in crop production, livestock management, and agro processing that serve both domestic markets and export value chains ([MINEPAT, 2019](#)). Despite improving digital infrastructure and rising internet penetration, the adoption of AI powered recruitment tools among these enterprises remains at an early stage, and many continue to rely on conventional hiring approaches, a pattern consistent with the uneven diffusion of digital innovations in African agriculture ([Ayim et al., 2022](#), [Aroba & Rudolph, 2024](#)).

The operational efficiency of agri based SMEs depends substantially on workforce quality and effective deployment. Recruitment processes that identify suitable candidates rapidly and accurately enable enterprises to respond to seasonal demands, fill critical positions, and maintain production continuity ([Olutimehin et al., 2025](#)). Inefficient recruitment, in contrast, generates operational disruptions, increases training costs, and weakens competitive positioning. Understanding how AI powered recruitment tools influence these efficiency outcomes is therefore both theoretically significant and practically urgent.

Despite growing scholarly interest in AI adoption in developing economies, limited empirical research has examined AI powered recruitment in African agricultural SMEs ([Vrontis et al., 2022](#), [Kshetri, 2021](#)). Existing studies have focused mainly on large organizations in developed economies and have overlooked the constraints and opportunities of small enterprises in resource limited settings ([Tambe et al., 2019](#), [Pan et al., 2022](#)). Furthermore, the mechanisms through which recruitment technologies translate into operational efficiency remain underexplored, as most studies examine adoption determinants rather than performance outcomes ([Albert, 2019](#), [Baabdullah et al., 2021](#)).

The specific problem this study addresses is the lack of empirical evidence on how AI powered recruitment tools influence operational efficiency in agri based SMEs in the Central Region of Cameroon. Without this understanding, managers risk either underinvesting in beneficial technologies or implementing tools without the organizational readiness needed to realize their potential. The study pursues two objectives. The first is to examine the influence of AI powered recruitment tools on operational efficiency in agri based SMEs in the Central Region. The second is to assess how organizational size and digital infrastructure moderate this relationship.

2. Literature Review and Hypothesis/es Development

2.1 AI Powered Recruitment Tools

AI powered recruitment tools are digital technologies that use artificial intelligence to automate, augment, or optimize the acquisition of human resources ([Tambe et al., 2019](#)). They fall into four main functional categories. The first is automated resume parsing and screening systems that filter candidates according to predetermined criteria. The second is intelligent candidate matching platforms that use machine learning to align applicant profiles with position requirements. The third is conversational AI agents that conduct preliminary interviews and respond to candidate inquiries. The

fourth is predictive analytics tools that forecast candidate success and the likelihood of retention ([Albert, 2019](#), [Black & van Esch, 2020](#)).

Recruitment and selection is one of the human resource functions that attracts the most research interest in AI applications ([Vrontis et al., 2022](#), [Priksht et al., 2023](#)). [Sulaiman et al. \(2025\)](#) documented that AI implementation in recruitment yields significant operational improvements, including a 36.6 percent reduction in time to hire and a 25.3 percent reduction in cost per hire. Employers also use AI to market job opportunities and engage candidates throughout the application process, which can widen the candidate pool and improve the applicant experience ([van Esch, Black, & Ferolie, 2019](#)). In the context of agri based SMEs, these technologies offer potential solutions to longstanding recruitment challenges, including limited human resource expertise, geographical constraints on candidate reach, and the seasonal urgency of workforce expansion.

AI powered recruitment is part of a broader shift toward digital human resource management, in which digital technologies change how human resource activities are designed, delivered, and evaluated ([Bondarouk & Brewster, 2016](#), [Strohmeier, 2020](#)). As algorithms take over tasks once performed by recruiters, scholars describe the emergence of algorithmic human resource management, in which software increasingly shapes decisions about who is attracted, screened, and hired ([Meijerink et al., 2021](#)). Human resource analytics further allows organizations to use workforce data to predict hiring needs and evaluate recruitment outcomes, linking recruitment decisions more directly to operational performance ([Margherita, 2022](#)).

The benefits of AI in recruitment are accompanied by risks. Reviews of AI enabled recruiting highlight concerns about algorithmic bias, transparency, privacy, and the loss of human contact in selection decisions ([Köchling & Wehner, 2020](#), [Hunkenschroer & Luetge, 2022](#)). Applicants and recruiters may also view AI tools with skepticism, which can affect acceptance and the quality of outcomes ([Horodyski, 2023](#), [Ore & Sposato, 2022](#)). These concerns indicate that the efficiency benefits of AI powered recruitment depend on how the tools are designed, governed, and integrated with human judgment ([Jarrahi, 2018](#)).

The adoption of AI powered recruitment tools among SMEs in developing economies remains limited by cost, technical capability, and infrastructure ([Vrontis et al., 2022](#), [Kshetri, 2021](#)). [UNCTAD \(2025\)](#) reported that only 27 percent of people in low income countries are online, compared with over 90 percent in high income economies, which creates fundamental connectivity barriers for AI adoption. However, the spread of software as a service platforms and mobile applications has lowered barriers to entry and created new opportunities for smaller enterprises to access sophisticated recruitment capabilities ([Ako, 2026b](#), [Schwaeke et al., 2025](#)).

2.2 Operational Efficiency

Operational efficiency refers to the extent to which organizations use resources effectively to achieve desired outcomes, and it covers productivity, cost effectiveness, and timeliness ([Baiye & Ako, 2025](#)). In agri based SMEs, operational efficiency includes recruitment specific metrics such as time to hire, which is the period from posting a position to candidate acceptance, cost per hire, which is total recruitment expenditure divided by the number of successful placements, and quality of hire, which reflects the performance and retention of recruited personnel. It also includes broader organizational outcomes such as workforce productivity and production continuity ([Nkeng et al., 2022](#)).

Because agricultural operations are seasonal and their products perishable, recruitment efficiency is particularly critical, and delays in filling key positions can disrupt production and distribution ([Olutimehin et al., 2025](#)). Organizational capabilities mediate the relationship between technology and performance in Cameroonian agribusiness, which suggests that efficiency outcomes depend on the integration of human capital and technological resources ([Ako, 2026a](#)). This view is consistent with research showing that AI creates business value when it is combined with complementary data, technology, and human skills ([Mikalef & Gupta, 2021](#), [Chowdhury et al., 2023](#)). Operational

efficiency in agri based SMEs is therefore both a recruitment outcome and an organizational capability.

2.3 Agri Based SMEs in Cameroon

Agri based SMEs in Cameroon include enterprises engaged in primary agricultural production, livestock management, agro processing, and the distribution of agricultural inputs. According to [IFAD \(2024\)](#), 87 percent of agropastoral enterprises in Cameroon operate in the informal economy, and smallholder operations dominate the sector. The Cameroonian government categorizes SMEs by workforce size and turnover, with small enterprises employing 6 to 20 persons and medium enterprises employing 21 to 100 persons ([IFAD, 2025](#)).

These enterprises face distinctive operational constraints, including limited access to formal financing, inadequate infrastructure, vulnerability to climate variability, and exposure to market price fluctuations. Recruitment challenges are particularly acute, because enterprises compete for skilled personnel against larger organizations and public sector employers while often lacking formal human resource management capabilities ([Ako, 2026a](#)). Small agricultural enterprises in Africa also have limited access to the digital innovations that could raise productivity and incomes ([Ayim et al., 2022](#), [Mhlanga, 2021](#)). The Central Region, home to Yaoundé, hosts a concentration of agri based SMEs that benefit from proximity to government services, educational institutions, and transportation networks, yet still confront significant operational challenges.

2.4 Theoretical Framework

The Technology Acceptance Model (TAM) posits that technology adoption is determined primarily by perceived usefulness and perceived ease of use ([Davis, 1989](#)). In the context of AI powered recruitment tools, TAM provides a lens for understanding how managers evaluate the potential benefits and implementation complexity of these technologies. Perceived usefulness includes expectations about efficiency improvements, cost reductions, and better decisions, while perceived ease of use reflects assessments of technical complexity, training requirements, and integration challenges. Later syntheses of technology acceptance research confirm that these beliefs, together with facilitating conditions such as infrastructure and support, explain much of the variation in technology use ([Venkatesh et al., 2016](#)). Integrated models that combine TAM with technological, organizational, and environmental factors have also been used to explain AI adoption in firms ([Chatterjee et al., 2021](#)).

The Resource Based View (RBV) conceptualizes organizations as bundles of resources and capabilities that determine competitive advantage ([Barney, 1991](#)). Recent developments of the theory emphasize how such resources create value for stakeholders ([Barney et al., 2021](#)). Within this framework, AI powered recruitment tools are organizational resources that, when combined with complementary capabilities such as digital skills, data quality, and managerial support, generate efficiency benefits that are difficult for competitors to replicate. The RBV therefore suggests that the efficiency impact of AI powered recruitment depends not only on the technology itself but also on the organizational context in which it is deployed, a view supported by evidence that AI capability, rather than technology alone, drives firm performance ([Mikalef & Gupta, 2021](#)). Building such capabilities in a digital environment requires dynamic capabilities for sensing, seizing, and transforming technological opportunities ([Warner & Wäger, 2019](#)).

Task Technology Fit (TTF) theory holds that technology adoption and performance benefits increase when technological capabilities match task requirements ([Goodhue & Thompson, 1995](#)). In recruitment, TTF suggests that AI powered tools will yield greater efficiency improvements when their functions fit the specific hiring needs and constraints of agri based SMEs, including seasonal workforce fluctuations, limited candidate pools, and geographic dispersion. Together, TAM, RBV, and TTF explain why AI powered recruitment can improve efficiency and why its effects may vary with organizational size and infrastructure.

2.5 Empirical Review

[Sulaiman, Fuzail, Urooge, and Imran \(2025\)](#) investigated AI powered recruitment tools in the corporate sector of Pakistan and found significant operational improvements, including a 36.6 percent reduction in time to hire and a 25.3 percent reduction in cost per hire. The study identified technical infrastructure limitations (68.6 percent) and language barriers (59.1 percent) as key implementation challenges. [Tambe, Cappelli, and Yakubovich \(2019\)](#) examined AI adoption in human resource management and showed that predictive analytics can improve hiring decisions, while also highlighting challenges related to data, fairness, and employee reactions. Research on multinational enterprises has further shown that AI assisted human resource systems can deliver cost effectiveness and individualized employee experiences ([Malik, Budhwar, & Kazmi, 2023](#)).

[Pan, Froese, Liu, Hu, and Ye \(2022\)](#) found that the adoption of AI in employee recruitment is shaped by contextual factors, including technological complexity, organizational readiness, and external pressure. Among SMEs, AI adoption has been linked to improved business practices and performance, although adoption depends on the resources and capabilities of the enterprise ([Baabdullah, Alalwan, Slade, Raman, & Khatatneh, 2021](#)). A systematic review of AI adoption in SMEs similarly concluded that technological, organizational, and environmental conditions jointly determine whether small firms benefit from AI ([Schwaeke, Peters, Kanbach, Kraus, & Jones, 2025](#)). These studies, however, have examined mainly organizations in developed or middle income economies, with limited attention to SMEs in African contexts.

In Cameroon, ([Ako, 2026a](#)) investigated AI augmented human resource practices and agripreneurial success in the Southwest Region and found that technology integration enhanced organizational outcomes, with effects mediated by innovation capability. A separate study by [Ako \(2026b\)](#) on AI driven matching platforms for seasonal labor allocation demonstrated improvements in agricultural labor market efficiency, as enterprises that adopted the platforms reported significantly higher labor allocation efficiency than nonadopters. [Olutimehin, Olaniyi, Alao, Olaniyi, and Adesokan \(2025\)](#) found that agentic AI adoption positively influenced business productivity in emerging economies. Evidence from Africa nevertheless shows that the effects of AI and digital technologies on development and productivity depend strongly on infrastructure, skills, and institutional conditions ([Aroba & Rudolph, 2024](#)).

2.6 Moderating Factors

Organizational size and digital infrastructure have been identified as significant moderators of the relationship between technology and performance. [Baiye and Ako \(2025\)](#) found that larger organizations realized greater efficiency benefits from digital technology adoption because of resource availability and absorptive capacity. [Vrontis et al. \(2022\)](#) showed that infrastructure quality conditions the outcomes of AI adoption, as unreliable power and internet connectivity constrain benefits. Research on SMEs likewise indicates that firm size, financial resources, and digital readiness shape the ability of small enterprises to adopt and benefit from AI ([Schwaeke et al., 2025, Baabdullah et al., 2021](#)).

[UNCTAD \(2025\)](#) emphasized that connectivity remains the first hurdle for AI adoption in developing countries and that skills and managerial gaps slow implementation. The report noted that successful AI adoption depends less on the technology itself than on the surrounding ecosystem of skills, data, finance, regulation, and trust. Research on AI in emerging economies of the Global South similarly shows that AI applications in human resource management are developing unevenly because of infrastructure and institutional conditions ([Kshetri, 2021](#)).

2.7 Research Gap and Hypotheses

Despite growing interest in AI adoption in African agriculture, significant gaps remain. First, most studies have examined AI adoption in large organizations and have overlooked the constraints and opportunities of SMEs ([Tambe et al., 2019](#)). Second, AI powered recruitment has received limited

empirical attention, particularly in African agricultural contexts (Albert, 2019). Third, the mechanisms through which recruitment technologies translate into operational efficiency remain underexplored (Vrontis et al., 2022). Fourth, the moderating roles of organizational size and digital infrastructure have not been tested empirically for AI powered recruitment in Cameroonian agri based SMEs. This study addresses these gaps by testing four hypotheses. Hypothesis 1 (H_1) states that AI powered recruitment tools have a significant positive influence on operational efficiency in agri based SMEs. Hypothesis 2 (H_2) states that organizational size significantly moderates the relationship between AI powered recruitment tools and operational efficiency. Hypothesis 3 (H_3) states that digital infrastructure significantly moderates this relationship. Hypothesis 4 (H_4) states that organizational size and digital infrastructure jointly moderate this relationship.

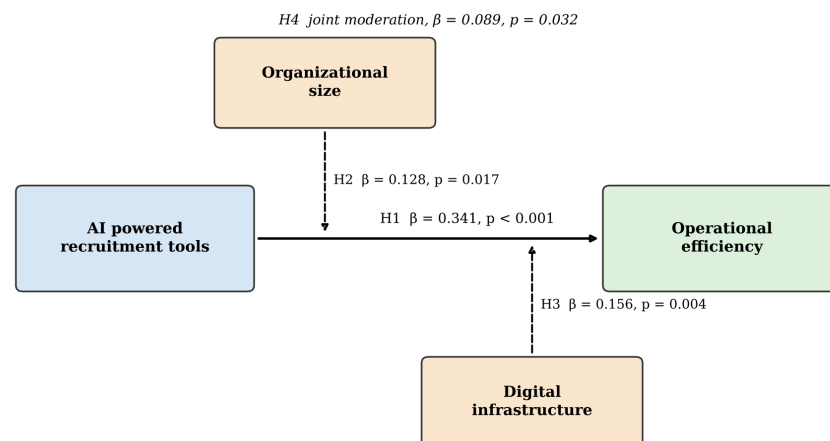


Figure 1. Conceptual model of AI powered recruitment tools, operational efficiency, and the moderating roles of organizational size and digital infrastructure

Figure 1 presents the conceptual model of the study together with the estimated coefficients. The solid arrow shows the direct relationship between AI powered recruitment tools and operational efficiency tested in H_1 , while the dashed arrows show the moderating roles of organizational size (H_2) and digital infrastructure (H_3), and the label at the top refers to their joint moderation (H_4). All four paths are statistically significant, indicating that AI powered recruitment improves operational efficiency and that the strength of this effect depends on the size of the enterprise and the quality of its digital infrastructure.

3. Research Methodology

3.1 Research Design

This study employed a quantitative survey design, collecting numerical data to test the hypothesized relationships between AI powered recruitment tools and operational efficiency. The survey approach was selected because it enables systematic measurement of variables across a large sample and supports statistical analysis of direct and moderated effects.

3.2 Study Area

The study was conducted in the Central Region of Cameroon, covering Yaoundé and surrounding agricultural zones, including Mfou, Obala, and Monatélé. The region hosts a concentration of agri based SMEs engaged in crop production, livestock management, and agro processing, and it has experienced significant agricultural expansion, with crops such as plantain, cassava, and cocoa showing annual growth rates of 10 to 25 percent between 2010 and 2016 (MINEPAT, 2019).

3.3 Population and Sampling

The target population comprised managers, human resource personnel, and recruitment decision makers in agri based SMEs in the Central Region. Purposive sampling was used to identify enterprises that met the definition of an agri based SME, supplemented by snowball sampling to reach additional respondents. Stratified sampling ensured representation across enterprise sizes and agricultural subsectors. Power analysis indicated a minimum sample of 250 for detecting medium effect sizes with adequate power. A total of 400 questionnaires were distributed, and 312 valid responses were retained, yielding a response rate of 78.0 percent.

3.4 Measures

AI powered recruitment tools were measured with a six item scale adapted from technology adoption instruments, assessing the adoption of automated screening, intelligent matching, chatbot communication, and predictive analytics in recruitment ([Tambe et al., 2019](#), [Venkatesh et al., 2016](#)). Operational efficiency was measured with a seven item scale covering recruitment timelines, cost effectiveness, workforce productivity, and production continuity ([Baiye & Ako, 2025](#)). Organizational size was measured as the number of full time equivalent employees and categorized according to Cameroonian SME definitions as small (6 to 20 employees) or medium (21 to 100 employees) ([IFAD, 2025](#)). Digital infrastructure was measured with a four item scale assessing internet reliability, power supply, hardware availability, and software accessibility ([Vrontis et al., 2022](#)). Enterprise age, agricultural subsector, and respondent experience were included as control variables.

3.5 Data Collection and Analysis

Data were collected between March and June 2026 using self administered questionnaires distributed in person and by email. Questionnaires were available in both English and French to accommodate respondent preferences. Data were analyzed using SPSS version 27. Descriptive statistics characterized the sample and variables, correlation analysis examined bivariate relationships, and hierarchical regression tested direct and moderating effects. Interaction terms were created using mean centered variables to reduce multicollinearity, and simple slopes analysis examined conditional effects at different levels of the moderators.

3.6 Ethical Considerations

Ethical approval was obtained before data collection. Participants were informed about the purpose of the study and provided informed consent. Participation was voluntary, respondents could withdraw at any time, and data were anonymized during analysis and reported only in aggregate form.

4. Results and Discussions

4.1 Descriptive Statistics

Table 1. Demographic characteristics of respondents

Characteristic	Category	Frequency	Percentage
Gender	Male	201	64.4
	Female	111	35.6
Age	21 to 30 years	98	31.4
	31 to 40 years	134	42.9
	41 to 50 years	62	19.9
	51 years and above	18	5.8
Education	High school	54	17.3
	Bachelor degree	152	48.7
	Master degree	76	24.4

Characteristic	Category	Frequency	Percentage
Education	Doctorate	30	9.6
Role	Manager	142	45.5
	HR personnel	102	32.7
	Other	68	21.8
Enterprise size	Small (6 to 20)	168	53.8
	Medium (21 to 100)	144	46.2

Table 1 presents the demographic characteristics of the 312 respondents, based on the field survey conducted in 2026. The majority of respondents were male (64.4 percent), and most held a bachelor's degree (48.7 percent) or a master's degree (24.4 percent). The largest age group was 31 to 40 years (42.9 percent). Managers made up 45.5 percent of respondents, human resource personnel 32.7 percent, and other recruitment decision makers 21.8 percent. Small enterprises accounted for 53.8 percent of the sample and medium enterprises for 46.2 percent, which provides a balanced basis for testing the moderating role of organizational size.

4.2 Reliability Analysis

Table 2. Reliability analysis of the study scales

Scale	Items	Cronbach alpha
AI powered recruitment tools	6	0.856
Operational efficiency	7	0.841
Digital infrastructure	4	0.812

Table 2 reports the number of items and the Cronbach alpha coefficients of the three multi item scales, based on the 2026 field survey. All coefficients exceed the commonly accepted threshold of 0.70, ranging from 0.812 for digital infrastructure to 0.856 for AI powered recruitment tools. These results indicate that the scales have acceptable internal consistency and that the items reliably measure the constructs used in the subsequent correlation and regression analyses.

4.3 Correlation Analysis

Table 3. Correlation matrix of the study variables

Variable	1	2	3	4
1. AI powered recruitment tools	1.00			
2. Operational efficiency	0.387***	1.00		
3. Digital infrastructure	0.312***	0.298***	1.00	
4. Organizational size	0.187**	0.224***	0.156*	1.00

Table 3 presents the correlation matrix of the four study variables, where one asterisk denotes $p < 0.05$, two asterisks denote $p < 0.01$, and three asterisks denote $p < 0.001$, based on the 2026 field survey. AI powered recruitment tools correlated positively with operational efficiency ($r = 0.387$, $p < 0.001$). Digital infrastructure correlated with both AI powered recruitment tools ($r = 0.312$, $p < 0.001$) and operational efficiency ($r = 0.298$, $p < 0.001$), and organizational size correlated with operational efficiency ($r = 0.224$, $p < 0.001$). All correlations are below 0.40, which suggests that multicollinearity is not a concern for the regression analysis.

4.4 Hypothesis Testing

The influence of AI powered recruitment tools on operational efficiency (H_1) was tested through hierarchical regression. In Step 2, AI powered recruitment tools significantly predicted operational efficiency ($\beta = 0.341$, $p < 0.001$), supporting H_1 .

Table 4. Hierarchical regression results

Step	Predictor	β	<i>t</i>	<i>p</i>	ΔR^2
1	Control variables				0.028
2	AI powered recruitment tools	0.341	6.247	<0.001	0.187
3	AI powered recruitment $\times$ organizational size	0.128	2.394	0.017	0.014
4	AI powered recruitment $\times$ digital infrastructure	0.156	2.891	0.004	0.019

Table 4 summarizes the hierarchical regression results from the 2026 field survey. The control variables in Step 1 explained only 2.8 percent of the variance in operational efficiency. Adding AI powered recruitment tools in Step 2 increased the explained variance by 18.7 percent, with a significant positive coefficient ($\beta=0.341$, $t=6.247$, $p<0.001$). The interaction terms in Steps 3 and 4 added a further 1.4 percent and 1.9 percent of explained variance respectively, and both were significant, which confirms that organizational size and digital infrastructure moderate the relationship.

The moderating role of organizational size (H_2) was examined next. The interaction term for organizational size was significant ($\beta=0.128$, $p=0.017$), and simple slopes analysis showed that the effect was stronger for medium enterprises ($\beta=0.412$) than for small enterprises ($\beta=0.278$). H_2 is therefore supported.

Table 5. Simple slopes analysis for organizational size

Enterprise Size	Conditional Effect	SE	<i>t</i>	<i>p</i>
Small (6 to 20)	0.278	0.058	4.793	<0.001
Medium (21 to 100)	0.412	0.067	6.149	<0.001

Table 5 presents the conditional effects of AI powered recruitment tools on operational efficiency for small and medium enterprises, based on the 2026 field survey. The effect is positive and significant in both groups, but it is about 48 percent larger for medium enterprises ($\beta=0.412$, $SE=0.067$) than for small enterprises ($\beta=0.278$, $SE=0.058$). This pattern indicates that larger enterprises are better positioned to convert AI powered recruitment into efficiency gains.

The moderating role of digital infrastructure (H_3) was then tested. The interaction term for digital infrastructure was significant ($\beta=0.156$, $p=0.004$). Simple slopes analysis showed that the effect was strongest at high levels of infrastructure ($\beta=0.438$), moderate at mean levels ($\beta=0.341$), and weakest at low levels ($\beta=0.224$). H_3 is therefore supported.

Table 6. Simple slopes analysis for digital infrastructure

Level of digital infrastructure	Conditional effect	SE	<i>t</i>	<i>p</i>
Low (one SD below mean)	0.224	0.063	3.556	<0.001
Mean	0.341	0.055	6.200	<0.001
High (one SD above mean)	0.438	0.071	6.169	<0.001

Table 6 shows the conditional effects of AI powered recruitment tools on operational efficiency at low, mean, and high levels of digital infrastructure, based on the 2026 field survey. The effect rises steadily from 0.224 at one standard deviation below the mean to 0.438 at one standard deviation above the mean, which means that the benefit nearly doubles when infrastructure is strong. All three conditional effects remain significant, indicating that AI powered recruitment improves efficiency even where infrastructure is weak, but to a much smaller degree.

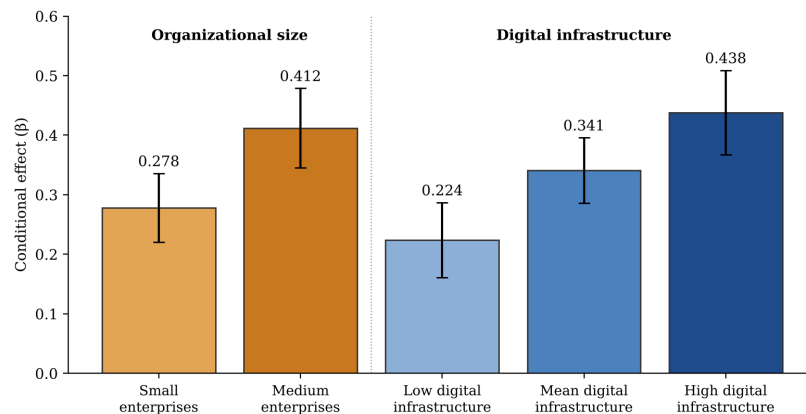


Figure 2. Conditional effects of AI powered recruitment tools on operational efficiency by organizational size and level of digital infrastructure

Figure 2 compares the conditional effects reported in Tables 5 and 6, with error bars showing one standard error. The left panel shows that the effect of AI powered recruitment is larger for medium enterprises than for small enterprises, while the right panel shows that the effect increases as digital infrastructure improves from low to high. The figure makes clear that the smallest gains occur in small enterprises and in settings with weak infrastructure, whereas the largest gains occur where infrastructure is strong.

Finally, the joint moderation analysis (H_4) indicated that organizational size and digital infrastructure jointly moderated the relationship between AI powered recruitment tools and operational efficiency. The three way interaction was significant ($\beta=0.089$, $p=0.032$), supporting H_4 .

4.5 Discussion

The finding that AI powered recruitment tools significantly enhance operational efficiency ($\beta=0.341$, $p<0.001$) is consistent with the evidence of [Sulaiman et al. \(2025\)](#), who documented a 36.6 percent reduction in time to hire and a 25.3 percent reduction in cost per hire. It also aligns with research showing that AI enabled recruiting and AI assisted human resource systems improve the speed and quality of hiring decisions ([Black & van Esch, 2020](#), [Malik et al., 2022](#)). The efficiency gains observed in this study suggest that AI powered recruitment yields tangible benefits in agri based SMEs, consistent with findings on AI augmented human resource practices in Cameroon ([Ako, 2026a](#)).

The improvements documented here, including shorter recruitment timelines, lower cost per hire, and higher workforce productivity, support the theoretical proposition that AI powered recruitment tools are organizational resources that enhance operational capabilities ([Barney et al., 2021](#), [Mikalef & Gupta, 2021](#)). However, the magnitude of the benefits was more modest than in studies of large enterprises, which may reflect the resource constraints and infrastructure limitations of smaller enterprises in developing economies ([Schwaeke et al., 2025](#)). Concerns about bias and transparency also suggest that efficiency gains are most sustainable when AI tools support rather than replace human judgment in recruitment ([Hunkenschroer & Luetge, 2022](#), [Jarrahi, 2018](#)). Employee reactions matter as well, because workers who perceive smart technologies as a threat may resist them ([Brougham & Haar, 2018](#)), and the most effective use of AI combines its analytical strengths with the empathetic and relational skills of human staff ([Huang & Rust, 2021](#)). Deliberate human resource strategies are therefore needed to manage the interaction between AI systems and human workers ([Arslan et al., 2022](#)).

The significant moderating effect of organizational size ($\beta=0.128$, $p=0.017$) indicates that medium enterprises realize greater efficiency benefits from AI powered recruitment than small enterprises. This finding aligns with the observation of [Baiye and Ako \(2025\)](#) that larger organizations possess greater absorptive capacity and resources to leverage technology investments. Medium enterprises

likely benefit from dedicated human resource personnel, established recruitment processes, and sufficient candidate volumes to justify the implementation of AI tools. The weaker benefits for small enterprises ($\beta=0.278$ compared with $\beta=0.412$ for medium enterprises) suggest that resource constraints and low recruitment volumes may reduce the value of AI powered tools for the smallest enterprises, particularly when complementary investments in training and skills are lacking ([Baabdullah et al., 2021](#), [Pan et al., 2022](#)).

The significant moderating effect of digital infrastructure ($\beta=0.156$, $p=0.004$) shows that reliable internet connectivity, power supply, and hardware are essential conditions for realizing efficiency benefits from AI powered recruitment tools. This finding supports the argument that infrastructure quality conditions AI adoption outcomes and that infrastructure constraints can undermine even well designed technology implementations ([Vrontis et al., 2022](#), [Ayim et al., 2022](#)). [UNCTAD \(2025\)](#) emphasized that connectivity remains the first hurdle for AI adoption in developing countries, noting that about 65 percent of the population in the least developed countries remains offline. In the Central Region of Cameroon, where power reliability and internet connectivity remain variable, infrastructure investment emerges as a critical complement to recruitment technology. The finding that the relationship was weakest at low infrastructure levels ($\beta=0.224$) underscores the need to address basic infrastructure constraints before expecting substantial returns from AI powered recruitment.

The significant three way interaction ($\beta=0.089$, $p=0.032$) indicates that organizational size and digital infrastructure jointly shape the efficiency impact of AI powered recruitment tools. The greatest benefits accrue to medium enterprises with robust digital infrastructure, while small enterprises with limited infrastructure realize the smallest gains. This joint effect underscores the importance of holistic organizational readiness rather than technology adoption alone, consistent with integrated adoption models that combine technological, organizational, and environmental conditions ([Schwaeke et al., 2025](#)). It also resonates with evidence that the developmental benefits of AI in emerging economies depend on supporting infrastructure, skills, and institutions ([Mhlanga, 2021](#), [Kshetri, 2021](#)). AI powered recruitment tools are therefore not universally beneficial, and their returns depend on the organizational and infrastructural conditions in which they are deployed.

These results have practical implications for managers, policymakers, and technology providers. Managers should assess organizational readiness before investing in AI powered recruitment tools, and small enterprises may benefit from collaborative or shared service models that overcome limitations of scale. Policymakers should prioritize investment in reliable power and internet connectivity to enable technology adoption in agricultural areas ([UNCTAD, 2025](#)). Technology providers should develop affordable and scalable solutions tailored to smaller enterprises with limited infrastructure, while ensuring that the tools are transparent and fair to applicants ([Köchling & Wehner, 2020](#), [Ore & Sposato, 2022](#)).

5. Conclusions

This study examined the impact of AI powered recruitment tools on operational efficiency in agri based SMEs in the Central Region of Cameroon. The findings show that AI powered recruitment tools significantly enhance operational efficiency, that this effect is stronger for medium enterprises than for small enterprises, and that digital infrastructure significantly moderates the relationship. Organizational size and digital infrastructure also jointly shape the effect, so the largest gains occur in medium enterprises with strong infrastructure.

The study advances technology acceptance and resource based theories by showing that the benefits of AI powered recruitment depend on organizational size and infrastructure, and it extends task technology fit theory by showing that alignment between technological capabilities and organizational context is essential for efficiency gains. In practice, managers should assess organizational readiness before investing in AI powered recruitment, small enterprises should consider shared service models, policymakers should invest in reliable power and connectivity, and technology providers should design scalable solutions for smaller enterprises.

The study is confined to the Central Region of Cameroon, which limits generalizability. Its cross sectional data preclude definitive causal inferences, self reported efficiency measures may introduce bias, and the study did not examine specific AI tool types or the quality of implementation. Future research should test these findings in other African contexts, explore additional mediating mechanisms, compare how different AI recruitment functions influence efficiency, and use longitudinal designs to examine how benefits evolve as enterprises gain experience with AI tools.

Acknowledgement

The author thanks the managers and human resource personnel of agri based SMEs in the Central Region of Cameroon who participated in this study, and the Higher Institute of Commerce and Management, The University of Bamenda, for its academic support. The author also thanks the anonymous reviewers for their constructive comments.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

References

- Ako, E. (2026a). AI augmented HR practices and agripreneurial success: The mediating roles of innovation capability and risk taking behavior in the Southwest Region of Cameroon. *ESUT Journal of Social Sciences*. Retrieved from <https://www.esutjss.com/index.php/ESUTJSS/article/view/387>
- Ako, E. (2026b). AI-driven matching platforms and seasonal labor allocation efficiency in Cameroonian agribusiness. *ESUT Journal of Social Sciences*, 11(2).
- Albert, E. T. (2019). AI in talent acquisition: A review of AI-applications used in recruitment and selection. *Strategic HR Review*, 18(5), 215-221. <https://doi.org/10.1108/SHR-04-2019-0024>
- Aroba, O. J., & Rudolph, M. (2024). Systematic literature review on the application of precision agriculture using artificial intelligence by small-scale farmers in Africa and its societal impact. *Journal of Infrastructure, Policy and Development*, 8(13), 1-19. <https://doi.org/10.24294/jipd8872>
- Arslan, A., Cooper, C., Khan, Z., Golgeci, I., & Ali, I. (2022). Artificial intelligence and human workers interaction at team level: A conceptual assessment of the challenges and potential HRM strategies. *International Journal of Manpower*, 43(1), 75-88. <https://doi.org/10.1108/IJM-01-2021-0052>
- Baabdullah, A. M., Alalwan, A. A., Slade, E. L., Raman, R., & Khatatneh, K. F. (2021). SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices. *Industrial Marketing Management*, 98, 255–270. <https://doi.org/10.1016/j.indmarman.2021.09.003>
- Baiye, E. G., & Ako, E. (2025). Planning and its effects on employee's performance in the University of Bamenda. *Frontiers in Management Science*, 2(4), 1-14.
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120. <https://doi.org/10.1177/014920639101700108>
- Barney, J. B., Ketchen, D. J., & Wright, M. (2021). Resource-based theory and the value creation framework. *Journal of Management*, 47(7), 1936-1955. <https://doi.org/10.1177/01492063211021655>
- Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons*, 63(2), 215–226. <https://doi.org/10.1016/j.bushor.2019.12.001>

- Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, 24(2), 239-257. <https://doi.org/10.1017/jmo.2016.55>
- Budhwar, P., Malik, A., De Silva, M. T. T., & 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), 1065-1097. <https://doi.org/10.1080/09585192.2022.2035161>
- Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, 170, Article 120880. <https://doi.org/10.1016/j.techfore.2021.120880>
- Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, 33(1). <https://doi.org/10.1016/j.hrmr.2022.100899>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. <https://doi.org/10.2307/249008>
- Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 19(2), 213-236. <https://doi.org/10.2307/249689>
- Huang, M.-H., & Rust, R. T. (2021). Engaged to a robot? The role of AI in service. *Journal of Service Research*, 24(1), 30-41. <https://doi.org/10.1177/1094670520902266>
- Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, 178(4), 977-1007. <https://doi.org/10.1007/s10551-022-05049-6>
- IFAD. (2024). Cameroon country strategic opportunities programme. *International Fund for Agricultural Development*.
- IFAD. (2025). Programme de promotion de l'entrepreneuriat agropastoral des jeunes, Phase II. *International Fund for Agricultural Development*.
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577-586. <https://doi.org/10.1016/j.bushor.2018.03.007>
- Kshetri, N. (2021). Evolving uses of artificial intelligence in human resource management in emerging economies in the global South: Some preliminary evidence. *Management Research Review*, 44(7), 970-990. <https://doi.org/10.1108/MRR-03-2020-0168>
- Malik, A., Budhwar, P., & Kazmi, B. A. (2023). Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework. *Human Resource Management Review*, 33(1). <https://doi.org/10.1016/j.hrmr.2022.100940>
- Margherita, A. (2022). Human resources analytics: A systematization of research topics and directions for future research. *Human Resource Management Review*, 32(2). <https://doi.org/10.1016/j.hrmr.2020.100795>
- Meijerink, J., Boons, M., Keegan, A., & Marler, J. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *The International Journal of Human Resource Management*, 32(12), 2545-2562. <https://doi.org/10.1080/09585192.2021.1925326>

- Mhlanga, D. (2021). Artificial intelligence in the Industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: Lessons from emerging economies? *Sustainability*, 13(11), Article 5788. <https://doi.org/10.3390/su13115788>
- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3). <https://doi.org/10.1016/j.im.2021.103434>
- MINEPAT. (2019). Schéma d'aménagement et de développement durable du territoire de la Région du Centre. *Ministère de l'Économie, de la Planification et de l'Aménagement du Territoire*.
- Nkeng, G., Ako, E., & Baiye, E. G. (2022). Digital technology adoption and productivity in Cameroonian SMEs. *African Journal of Business Management*, 16(4), 78-92.
- Olutimehin, A. T., Olaniyi, O. M., Alao, A. I., Olaniyi, O. O., & Adesokan, O. Z. (2025). The economic value of agentic AI: A comparative analysis of its impact on growth and business productivity in developed and emerging economies. *Asian Journal of Research in Computer Science*, 19(5), 25-44. <https://doi.org/10.9734/ajrcos/2026/v19i5859>
- Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. *International Journal of Organizational Analysis*, 30(6), 1771-1782. <https://doi.org/10.1108/IJOA-07-2020-2291>
- Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *The International Journal of Human Resource Management*, 33(6), 1125-1147. <https://doi.org/10.1080/09585192.2021.1879206>
- Prikshat, V., Malik, A., & Budhwar, P. (2023). AI-augmented HRM: Antecedents, assimilation and multilevel consequences. *Human Resource Management Review*, 33(1). <https://doi.org/10.1016/j.hrmr.2021.100860>
- Schwaeye, J., Peters, A., Kanbach, D. K., Kraus, S., & Jones, P. (2025). The new normal: The status quo of AI adoption in SMEs. *Journal of Small Business Management*, 63(3), 1297-1331. <https://doi.org/10.1080/00472778.2024.2379999>
- Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management*, 34(3), 345-365. <https://doi.org/10.1177/2397002220921131>
- Sulaiman, G., Fuzail, M., Urooge, S., & Imran, F. (2025). The role of artificial intelligence in HR: A study of the impact of AI-powered recruitment tools on hiring decisions. *CMSR*, 3(3), 1-21. <https://doi.org/10.5281/zenodo.15201875>
- Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, 61(4), 15-42. <https://doi.org/10.1177/0008125619867910>
- UNCTAD. (2025). Artificial intelligence unleashed: Transforming the entrepreneurial scene in developing nations. Paper presented at United Nations Conference on Trade and Development.
- van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. *Computers in Human Behavior*, 90, 215-222.
- van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. *Computers in Human Behavior*, 90, 215-222. <https://doi.org/10.1016/j.chb.2018.09.009>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, 17(5), 328-376. <https://doi.org/10.17705/1jais.00428>

- Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *The International Journal of Human Resource Management*, 33(6), 1237-1266. <https://doi.org/10.1080/09585192.2020.1871398>
- Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326-349. <https://doi.org/10.1016/j.lrp.2018.12.001>
- Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming – A review. *Agricultural Systems*, 153, 69–80. <https://doi.org/10.1016/j.agsy.2017.01.023>