IOSR Journal of Humanities and Social Science (IOSR-JHSS)
Volume 31, Issue 6, Series 3 (June, 2026) 64-71
e-ISSN: 2279-0837, p-ISSN: 2279-0845.
www.iosrjournals.org

The Influence of Artificial Intelligence on Recruitment and Selection Practices: Evidence from KPMG East Africa

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Abstract
This study examines the influence of artificial intelligence (AI) technologies on recruitment and selection processes at KPMG East Africa, focusing on their impact on efficiency, candidate experience, and ethical and regulatory considerations. Employing a case study design, data were collected from 50 human resource (HR) professionals using structured questionnaires. Descriptive statistics, Pearson correlation, and multiple linear regression analyses were conducted using SPSS. The findings indicate that AI technologies exert a strong, statistically significant positive effect on recruitment outcomes ($r = 0.695$, $p < 0.01$), while candidate experience also contributes significantly ($r = 0.340$, $p < 0.05$). Regulatory and ethical considerations, however, exhibited a non-significant relationship with recruitment outcomes ($r = 0.277$, $p = 0.052$). The regression model explained 54% of the variance in recruitment and selection outcomes ($R^2 = 0.54$, $F = 17.985$, $p < 0.001$). These results suggest that while AI substantially enhances hiring efficiency and candidate satisfaction, ethical governance frameworks remain underdeveloped in the Kenyan professional services context. The study contributes to the growing body of knowledge on technology-driven human resource management in sub-Saharan Africa and provides practical recommendations for responsible AI integration in recruitment.

Keywords: *artificial intelligence, recruitment, selection, candidate experience, KPMG, Kenya, human resource management, algorithmic bias, Technology Acceptance Model*

Date of Submission: 08-06-2026 Date of Acceptance: 19-06-2026

I. Introduction

The global integration of artificial intelligence (AI) into human resource management has catalysed a fundamental transformation in recruitment and selection processes. Organisations across sectors are increasingly deploying machine learning algorithms, natural language processing (NLP) tools, and predictive analytics to automate and optimise the hiring pipeline, from candidate sourcing through to final selection (Chowdhury et al., 2023). As the war for talent intensifies in competitive professional services markets, the adoption of AI-enabled recruitment tools has emerged not merely as a technological convenience but as a strategic imperative.

KPMG, one of the world's foremost professional services networks, operates across 143 countries with over 273,000 partners and employees. Its East Africa practice, headquartered in Nairobi, serves as the regional coordinating office and employs more than 1,000 professional staff. In a labour market characterised by high graduate unemployment yet critical skills shortages in specialised domains, KPMG's deployment of AI in recruitment represents a particularly instructive case for examining the promises and perils of technology-mediated hiring in a developing economy context.

Despite a growing body of evidence from global organisations such as Google (Bock, 2015), Unilever (Upadhyay & Khandelwal, 2018), and IBM (Van Esch et al., 2019), empirical research on AI-driven recruitment within sub-Saharan African professional services firms remains sparse. Local studies in Kenya have begun to address this gap (Kamau & Wanyonyi, 2020; Ngure & Mwangi, 2021; Kariuki & Njagi, 2018), yet none has focused specifically on the interplay between AI adoption, candidate experience, and ethical governance within a Big Four audit firm.

This study addresses that lacuna by examining three principal determinants of AI-influenced recruitment at KPMG: (1) AI technologies, measured by tool type, integration depth, and usage patterns; (2) regulatory and ethical considerations, assessed through compliance mechanisms and ethical governance frameworks; and (3) candidate experience, captured via perceptions and satisfaction indicators. The dependent variable, recruitment and selection outcomes, is operationalised in terms of effectiveness and efficiency.

Three theoretical frameworks underpin the study. Human Capital Theory (Becker, 1964; Schultz, 1961) provides a lens for understanding how AI-enhanced recruitment optimises the acquisition of high-quality human assets. The Technology Acceptance Model (Davis, 1989) offers a framework for predicting HR professional adoption of AI tools based on perceived usefulness and ease of use. Resource-Based Theory (Barney, 1991; Penrose, 1959) conceptualises AI capabilities as strategically valuable, rare, and non-substitutable organisational resources.

The remainder of this paper is structured as follows. Section 2 reviews theoretical and empirical literature. Section 3 details the research methodology. Section 4 presents data analysis and findings. Section 5 discusses results in light of extant scholarship. Section 6 offers conclusions, recommendations, limitations, and directions for future research.

II. Literature Review

2.1 Theoretical Frameworks

2.1.1 Human Capital Theory

Rooted in the seminal works of Becker (1964) and Schultz (1961), Human Capital Theory posits that investments in workforce knowledge, skills, and capabilities yield measurable productivity gains and competitive advantage. Applied to AI-driven recruitment, the theory suggests that automated tools capable of identifying and attracting superior candidates constitute a form of organisational investment that strengthens human capital quality. By deploying AI to screen and match candidates with greater precision, firms such as KPMG can theoretically build a more capable workforce, thereby enhancing overall organisational performance.Critics, however, argue that Human Capital Theory oversimplifies workforce dynamics by privileging quantifiable inputs over socio-cultural factors (Hanushek, 2015). Furthermore, the model may inadequately capture relational and tacit competencies that AI systems struggle to assess (Finegold & Frenkel, 2006), suggesting the need for complementary human judgement in AI-augmented recruitment.

2.1.2 Technology Acceptance Model (TAM)

Davis (1989) proposed the Technology Acceptance Model to explain the determinants of individual technology adoption. TAM identifies perceived usefulness (PU) and perceived ease of use (PEOU) as the primary antecedents of adoption intention. In the context of AI-driven recruitment, HR professionals who perceive AI tools as improving candidate selection accuracy and reducing administrative burden are more likely to integrate them into daily practice. At KPMG, TAM provides a useful lens for assessing whether AI adoption reflects genuine utility or mere compliance with organisational mandates.

TAM has been criticised for its atomistic focus on individual cognition, which may neglect organisational-level barriers such as institutional inertia, change resistance, and legacy system incompatibilities (Lee et al., 2003; Venkatesh & Davis, 2000). These structural constraints are particularly salient in large professional services firms where established recruitment protocols coexist with emerging AI-driven workflows.

2.1.3 Resource-Based Theory (RBT)

Penrose (1959) and Barney (1991) advanced the Resource-Based View of the firm, arguing that sustainable competitive advantage derives from the possession of resources that are valuable, rare, inimitable, and non-substitutable (VRIN). AI capabilities in recruitment — including proprietary algorithms, data assets, and analytical infrastructure — may qualify as VRIN resources insofar as they are not easily replicated by competitors. For KPMG, embedding AI-driven recruitment tools may represent a strategic differentiator in the competition for talent.

Nonetheless, the model has been challenged for its static orientation. Teece et al. (1997) argue that truly sustainable advantage requires dynamic capabilities — the capacity to continuously renew resources in response to environmental change. Given the rapid obsolescence of AI technologies, KPMG must cultivate adaptive practices that enable ongoing reconfiguration of its AI recruitment infrastructure.

2.2 AI Technologies and Recruitment Practices

AI technologies have profoundly altered the architecture of modern recruitment. Machine learning algorithms automate the initial screening of thousands of resumes, identifying candidates whose profiles most closely match position requirements (Bersin, 2019). NLP tools evaluate written communication quality, vocabulary breadth, and personality indicators from cover letters and open-text application fields (Liebowitz, 2020). Predictive analytics models correlate candidate attributes with historical performance data to forecast future success probabilities.

A noteworthy benefit of AI-mediated screening is its potential to mitigate cognitive biases inherent in human decision-making. By standardising evaluation criteria and anonymising demographic identifiers, AI tools can theoretically promote meritocratic selection (Sujansky, 2020). However, this promise is conditional: if training datasets encode historical hiring patterns that reflect prior discrimination, algorithmic outputs will perpetuate rather than correct those biases (Raghavan et al., 2020). The challenge for organisations is thus to implement AI systems that are not only technically efficient but also epistemically fair.

2.3 Regulatory and Ethical Considerations

The deployment of AI in recruitment occurs within an increasingly complex regulatory environment. In the United States, the Equal Employment Opportunity Commission (EEOC) prohibits employment discrimination on grounds of race, colour, religion, sex, national origin, age, disability, or genetic information (EEOC, 2021). In Europe, the General Data Protection Regulation (GDPR) imposes stringent obligations on the collection, storage, and processing of personal data (GDPR, 2016), with direct implications for candidate databases and AI training sets. Although Kenya does not yet have sector-specific AI legislation, the Data Protection Act (2019) establishes foundational principles of data privacy that bear on AI-driven recruitment.

Ethical dimensions extend beyond legal compliance. Transparency in algorithmic decision-making — enabling candidates to understand how and why they were screened — is increasingly recognised as a prerequisite for fairness (Floridi et al., 2018). The opacity of black-box models, however, renders such transparency technically challenging. Binns (2018) draws on political philosophy to argue that fairness in machine learning requires not merely statistical parity but substantive procedural justice, a standard that current AI recruitment tools rarely meet.

2.4 Candidate Experience

Candidate experience encompassing perceptions of procedural fairness, communication quality, and overall satisfaction with the recruitment process significantly influences both offer acceptance rates and employer brand equity (Hausknecht, Day & Thomas, 2004). Research by Allen, Mahto and Otondo (2007) demonstrates that positive recruitment experiences generate goodwill even among unsuccessful candidates, enhancing the organisation's reputation in the labour market.

AI can enhance candidate experience by enabling rapid, personalised communication through chatbots and automated progress updates, thereby reducing information asymmetry and waiting-time uncertainty (Dineen et al., 2007). Chapman and Webster (2003) further note that the personalisation afforded by AI-driven recommendation systems can create more contextually relevant application journeys. Notwithstanding these benefits, Albert (2019) cautions against over-automation, noting that candidates frequently report diminished satisfaction when AI replaces human interaction at emotionally salient recruitment stages.

2.5 Empirical Evidence

At the global level, a body of case-based empirical literature documents AI's transformative impact on recruitment. Bock (2015) reports that Google's deployment of predictive analytics substantially reduced time-to-hire and improved selection accuracy. Upadhyay and Khandelwal (2018) document how Unilever's gamified AI assessments and digital interviews streamlined screening while enhancing cultural-fit evaluation. Van Esch, Black and Ferolie (2019) find that IBM's AI tools automated administrative tasks and improved diversity by mitigating unconscious bias. Wilson, Daugherty and Morini-Bianzino (2017) demonstrate that Deloitte's AI platform delivered data-driven talent insights and improved diversity outcomes. Albert (2019) highlights L'Oréal's AI-driven improvements in recruitment efficiency, though with caveats about depersonalisation risks.

Within Kenya, empirical research is nascent but growing. Kamau and Wanyonyi (2020) found that AI tools significantly enhanced recruitment efficiency among Kenyan firms, though continuous system updates were identified as a critical implementation challenge. Ngure and Mwangi (2021) documented AI-driven improvements in candidate selection accuracy within Nairobi's banking sector, alongside a pressing need for HR personnel training. Omondi and Otieno (2019) reported that AI improved candidate experience in Kenya's telecommunications industry, particularly through timely feedback mechanisms. Kariuki and Njagi (2018) found that AI applications in manufacturing enhanced operational efficiency but required robust infrastructure support. Muthoni and Njeru (2022) identified transparency and fairness gains in public sector AI recruitment, while flagging unresolved data privacy and algorithmic accountability concerns.

Collectively, these studies reveal a convergent finding: AI adoption accelerates recruitment efficiency and, under favourable conditions, improves candidate experience. However, significant gaps persist regarding the long-term organisational consequences of AI-mediated hiring, the effectiveness of ethical governance mechanisms, and the cultural transferability of AI tools developed in Western contexts to sub-Saharan African organisational environments.

III. Research Methodology

3.1 Research Design

This study employed a quantitative case study design. Case study methodology was selected for its capacity to yield contextually rich, in-depth insights into AI adoption within a specific organisational setting (Yin, 2018). By focusing on KPMG East Africa, the study enables a granular examination of how AI technologies are integrated into recruitment practice, how ethical and regulatory frameworks are navigated, and how candidate experience is perceived and managed.

3.2 Population and Sampling

The target population comprised HR professionals at KPMG East Africa who are directly involved in the recruitment and selection function, including senior managers, talent acquisition specialists, HR business partners, compliance officers, and operations staff. A purposive sampling strategy was employed to identify individuals with direct experience of AI-driven recruitment tools. Five professional categories were identified and ten respondents were sampled per category, yielding a total sample of 50 participants. Purposive sampling is appropriate in case study research where the objective is to capture expert knowledge rather than statistical representativeness (Patton, 2002).

3.3 Data Collection

A structured questionnaire was the primary data collection instrument. The questionnaire comprised four sections: (1) participant background; (2) AI technologies in recruitment; (3) regulatory and ethical considerations; and (4) candidate experience. All items were measured using a five-point Likert scale ranging from 1 (very small extent) to 5 (very high extent). The instrument was pre-tested with five HR professionals not included in the main study to assess clarity and internal consistency. The final questionnaire was distributed to all 50 selected respondents, achieving a 100% response rate.

3.4 Analytical Model

Data were analysed using IBM SPSS Statistics version 25. Descriptive statistics (means and standard deviations) characterised the distribution of each variable. Pearson correlation analysis assessed bivariate relationships between the independent variables — AI Technologies (X_1), Regulatory and Ethical Considerations (X_2), and Candidate Experience (X_3) — and the dependent variable, Recruitment and Selection Outcomes (Y). Multiple linear regression analysis tested the joint predictive capacity of the independent variables:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Where Y = Recruitment and Selection Outcomes; α = constant; β_1, β_2, β_3 = regression coefficients; ε = error term. Model significance was evaluated using ANOVA at a 5% significance level ($p < 0.05$).

IV. Results and Findings

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for all study variables. No missing values were recorded across the dataset.

Table 1. Descriptive Statistics of Study Variables

Variable	N	Mean	Std. Deviation	Minimum	Maximum
Recruitment and Selection Outcomes	50	3.50	1.09	2.00	5.00
AI Technologies	50	3.40	0.99	2.00	5.00
Regulatory and Ethical Considerations	50	3.12	0.87	2.00	5.00
Candidate Experience	50	3.58	1.11	1.00	5.00

Candidate experience recorded the highest mean score (M = 3.58, SD = 1.11), indicating that respondents perceived AI to have had the most pronounced effect on how candidates experience the recruitment process. AI technologies (M = 3.40, SD = 0.99) and recruitment outcomes (M = 3.50, SD = 1.09) were rated at moderate-to-high levels. Regulatory and ethical considerations returned the lowest mean (M = 3.12, SD = 0.87), suggesting these dimensions receive comparatively less attention in day-to-day AI-driven recruitment at KPMG.

4.2 Correlation Analysis

Table 2 presents the Pearson correlation matrix for all variables. AI technologies exhibited a strong, positive, and statistically significant correlation with recruitment and selection outcomes ($r = 0.695$, $p < 0.01$). Candidate experience demonstrated a moderate, positive, and significant correlation with the dependent variable ($r = 0.340$, $p < 0.05$). In contrast, regulatory and ethical considerations showed a weak positive correlation with recruitment outcomes that did not attain statistical significance ($r = 0.277$, $p = 0.052$).

Table 2. Pearson Correlation Matrix

Variable	1. R&S Outcomes	2. AI Technologies	3. Reg. & Ethics	4. Cand. Experience
1. Recruitment & Selection Outcomes	1.000			
2. AI Technologies	0.695**	1.000		
3. Regulatory & Ethical Considerations	0.277	0.332*	1.000	
4. Candidate Experience	0.340*	0.163	−0.012	1.000

Note: ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed). N = 50.

4.3 Regression Analysis

Tables 3, 4, and 5 report the regression model summary, ANOVA results, and coefficient estimates respectively.

Table 3. Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of Estimate
1	0.735	0.540	0.510	0.765

Note: Predictors: (Constant), Candidate Experience, Regulatory and Ethical Considerations, AI Technologies.

Table 4. Analysis of Variance (ANOVA)

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	31.578	3	10.526	17.985	0.000
Residual	26.922	46	0.585		
Total	58.500	49			

Note: Dependent Variable: Recruitment and Selection Outcomes.

Table 5. Regression Coefficients

Variable	B (Unstd.)	Std. Error	Beta (Std.)	t	Sig.
(Constant)	−0.222	0.604		−0.367	0.715
AI Technologies (X_1)	0.745	0.127	0.633	5.872	0.000
Regulatory & Ethical Considerations (X_2)	0.090	0.138	0.069	0.653	0.517
Candidate Experience (X_3)	0.257	0.109	0.238	2.346	0.023

Note: Dependent Variable: Recruitment and Selection Outcomes.

The overall regression model was statistically significant ($F = 17.985$, df = 3/46, $p < 0.001$), with an R^2 of 0.54 indicating that the three independent variables collectively explained 54% of the variance in recruitment and selection outcomes. The remaining 46% is attributable to factors not examined in this study.

AI technologies emerged as the strongest and most significant predictor of recruitment outcomes ($\beta = 0.633$, $t = 5.872$, $p < 0.001$), underscoring its central role in driving hiring effectiveness. Candidate experience was a significant secondary predictor ($\beta = 0.238$, $t = 2.346$, $p = 0.023$). Regulatory and ethical considerations did not attain significance ($\beta = 0.069$, $t = 0.653$, $p = 0.517$). The finalised regression model is expressed as:

$$\hat{Y} = -0.222 + 0.633X_1 + 0.238X_3 + \varepsilon$$

V. Discussion

5.1 AI Technologies and Recruitment Outcomes

The finding that AI technologies are the most powerful predictor of recruitment and selection outcomes ($\beta = 0.633$, $p < 0.001$) is consistent with international evidence demonstrating that AI-driven tools substantially reduce time-to-hire, improve candidate screening accuracy, and enhance the objectivity of selection decisions (Bock, 2015; Van Esch et al., 2019; Albert, 2019). From a Human Capital Theory perspective, these results suggest that KPMG's investment in AI-driven recruitment infrastructure represents an effective strategy for optimising the quality of talent acquisition a core determinant of organisational performance.

The TAM framework also offers explanatory traction: the significant adoption observed among KPMG's HR professionals likely reflects high perceived usefulness, particularly in automating administrative screening tasks that were previously time-intensive. This is consistent with Kamau and Wanyonyi's (2020) finding that Kenyan firms primarily adopted AI tools for efficiency gains in the candidate shortlisting phase.

However, the dominance of AI technology in the regression model invites caution regarding over-reliance. Albert (2019) and Wilson et al. (2017) both caution that heavy automation risks depersonalising the recruitment process, potentially deterring high-calibre candidates who value substantive human engagement. KPMG must therefore design AI deployment strategies that preserve the relational dimensions of hiring, particularly at interview stages where cultural fit and interpersonal dynamics are most consequential.

5.2 Candidate Experience

The significant positive relationship between candidate experience and recruitment outcomes ($\beta = 0.238$, $p = 0.023$) is theoretically coherent: a positive recruitment experience enhances offer acceptance probability and brand perception among unsuccessful applicants (Allen et al., 2007; Dineen et al., 2007). At KPMG, AI tools appear to improve candidate experience primarily through faster communication and reduced waiting times — benefits widely documented across global cases (Upadhyay & Khandelwal, 2018; Omondi & Otieno, 2019).

Yet the relatively modest beta coefficient for candidate experience, compared to AI technologies, suggests that KPMG's AI deployment has not yet fully optimised the candidate journey. Personalisation tailoring application experiences to individual candidate profiles and career aspirations remains a frontier that current AI implementations have only partially addressed. Future investment in AI-driven candidate relationship management systems could yield compounding benefits for both experience satisfaction and outcome quality.

5.3 Regulatory and Ethical Considerations

The non-significant finding for regulatory and ethical considerations ($\beta = 0.069$, $p = 0.517$) is one of the study's most consequential results. It departs markedly from the ethical urgency articulated by Van Esch et al. (2019), Binns (2018), and Floridi et al. (2018), and suggests that governance concerns have not yet been operationalised as active levers of recruitment effectiveness at KPMG East Africa.

Several interpretations warrant consideration. First, Kenya's current regulatory infrastructure for AI in employment while nascent, does not impose the same compliance obligations as GDPR or EEOC frameworks, reducing the perceived salience of regulatory risk among HR professionals. Second, KPMG's AI tools may still be sufficiently new that systematic bias auditing and transparency protocols have not matured into formalised governance mechanisms. Third, the limitation of using HR professionals as sole informants — who may lack visibility into candidates' fairness perceptions could suppress observed correlations between ethics and outcomes.

This finding, however, should not be interpreted as evidence that ethics are irrelevant. On the contrary, the literature consistently documents that unchecked algorithmic systems reproduce historical inequalities (Raghavan et al., 2020), erode candidate trust (Floridi et al., 2018), and expose organisations to reputational and legal risks as regulatory frameworks mature. The absence of a significant effect may therefore reflect a critical governance gap — one that KPMG and similarly positioned firms must urgently address proactively rather than reactively.

5.4 Theoretical Contributions

This study makes several theoretical contributions. First, it extends the application of Human Capital Theory, TAM, and Resource-Based Theory to the AI-recruitment nexus in an East African professional services context, providing empirical grounding for constructs that have predominantly been tested in Western settings. Second, it identifies a disjuncture between the theoretical prominence accorded to ethical governance and its empirical irrelevance in a developing economy AI adoption context a finding with implications for both theory development and policy design. Third, it contributes to the nascent literature on technology-driven HRM in sub-Saharan Africa, responding to calls for more contextually embedded empirical work in this domain.

VI. Conclusion, Recommendations, and Future Research

6.1 Conclusion

This study provides empirical evidence that AI technologies significantly enhance recruitment and selection outcomes at KPMG East Africa, with candidate experience serving as a meaningful secondary driver of effectiveness. Together, these variables account for 54% of variance in recruitment outcomes, validating the case for continued AI investment in HR practice. Regulatory and ethical considerations, while theoretically important, do not currently exert a measurable influence on recruitment outcomes — a finding that signals an urgent governance gap rather than ethical irrelevance.

The results affirm that AI is not merely an operational efficiency tool but a strategically consequential capability that reshapes how organisations attract, assess, and secure talent. However, the responsible exploitation of this capability requires that KPMG and comparable organisations develop robust ethical frameworks commensurate with the sophistication of their AI systems.

6.2 Recommendations

Based on the study findings, the following recommendations are advanced. First, KPMG should continue scaling AI adoption across recruitment stages, particularly resume screening and initial assessments to sustain efficiency gains, while investing in HR professional training to maximise tool utilisation and data interpretation capacity. Second, KPMG should establish a dedicated AI Ethics and Governance Taskforce charged with developing bias-auditing protocols, transparency standards, and compliance frameworks aligned with emerging regulatory requirements, including Kenya's Data Protection Act (2019) and forthcoming AI-specific legislation. Third, KPMG should invest in candidate-facing AI personalisation technologies that enhance the interactive quality of the recruitment journey, particularly at high-engagement touchpoints, to leverage the positive relationship between candidate experience and recruitment outcomes. Fourth, policymakers and professional bodies in Kenya should consider developing sector-specific guidelines for ethical AI use in employment, drawing on established international frameworks such as the EU AI Act and EEOC guidance.

6.3 Limitations

This study is subject to several limitations. The single-organisation case study design constrains the generalisability of findings to other firms and industries. The purposive sample of 50 HR professionals, while appropriate for case study methodology, limits statistical power and representativeness. Furthermore, the exclusive reliance on HR professional perspectives omits the candidate voice a significant limitation given that candidate experience is a key variable. Finally, the cross-sectional design precludes causal inference and analysis of longitudinal dynamics in AI adoption.

6.4 Directions for Future Research

Future research should adopt comparative multi-organisational designs to examine AI-recruitment dynamics across diverse industries, organisational sizes, and cultural contexts within sub-Saharan Africa. Longitudinal studies would help assess the long-term effects of AI adoption on workforce quality, employee retention, and diversity outcomes. Research that centres candidate perspectives through structured surveys or experimental designs would provide crucial insights into the equity and fairness dimensions of AI-driven recruitment. Finally, as Kenya's regulatory environment evolves, studies examining the relationship between compliance obligations and recruitment AI governance will be timely and practically significant.

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