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AI and big data-driven social media recruitment: the mediating role of talent acquisition and employee engagement in bank performance

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Abstract

Purpose – This study investigates the impact of AI-driven social media recruitment (AI-SMR) on talent acquisition effectiveness (TAE), employee engagement (EE) and bank performance (BP) in the Jordanian banking sector. It examines how AI-powered recruitment tools enhance hiring efficiency, mitigate biases and bolster employer branding, while also assessing the mediating roles of TAE and EE.

Design/methodology/approach – A quantitative approach was applied using partial least squares structural equation modeling (PLS-SEM) to analyze survey data from 283 HR professionals, recruiters and employees in commercial and investment banks. Stratified random sampling and Cochran's formula determined the sample size. Reliability, validity and common method bias checks confirmed robustness.

Findings – Results indicate that AI-SMR is positively associated with enhanced TAE, faster hiring and improved candidate-job matching. EE mediates the AI-SMR–BP link, highlighting how AI-supported hiring fosters satisfaction, alignment and retention. For example, AI-SMR explained 42% of the variance in TAE ($R^2 = 0.42$).

Practical implications – HR professionals should adopt AI-driven hiring tools, predictive analytics and chatbots to optimize recruitment and engagement while implementing governance mechanisms to ensure fairness, transparency and compliance.

Originality/value – This study contributes a dual-mediation model connecting AI recruitment, employee engagement and bank performance, offering context-specific insights for modernizing HRM in an emerging economy.

Keywords AI-driven recruitment, Talent acquisition, Employee engagement, Bank performance, AI-powered hiring, HR analytics, Workforce optimization, Predictive hiring, AI in human resource management

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1. Introduction

The increasing digitization of business operations has fundamentally transformed recruitment processes, shifting organizations from traditional hiring methods to AI-driven, data-informed talent acquisition strategies. Conventional approaches—such as newspaper advertisements, job fairs, and generic online postings—are proving less effective in today's competitive market, where organizations must optimize strategies to attract top-tier talent (Votto, 2023; Rathore, 2023; Ahmed *et al.*, 2024). The integration of Artificial Intelligence (AI) and Big Data analytics enables businesses to streamline recruitment, strengthen employer branding, and enhance efficiency (Kaplan & Haenlein, 2023; Hasan & Chowdhury, 2023). AI-powered tools, including machine learning algorithms, chatbots, automated resume screening, and predictive analytics, allow firms to personalize hiring decisions, making recruitment more efficient, transparent, and engaging (Mollay, Sharma, Kale, Anawade, & Gahane, 2024; Paramita, Okwir, & Nuur, 2024).

As Jordan's banking sector undergoes rapid digital transformation, adopting AI-driven social media recruitment (AI-SMR) has become increasingly essential. Platforms such as LinkedIn, Facebook, and Twitter are now central for both job seekers and recruiters, enabling AI-powered tools to identify, engage, and recruit talent more effectively (Bulchand-Gidumal, William Secin, O'Connor, & Buhalis, 2024; Jha, Janardhan, Khilla, & Haokip, 2024). The Jordanian Ministry of Digital Economy and Entrepreneurship (MoDEE, 2024) identifies AI and Big Data as key drivers of financial sector innovation, emphasizing workforce management solutions. While Jordanian banks have embraced fintech, AI-driven risk management, and customer analytics, AI-enhanced recruitment remains underdeveloped (Al-Dmour, Al-Dmour, Al-Dmour, & Al-Adwan, 2024). Understanding how AI and Big Data enhance recruitment, talent acquisition effectiveness (TAE), employee engagement (EE), and bank performance (BP) is essential for improving productivity and long-term success. Although this study focuses on the Jordanian banking sector, its insights are transferable to other emerging economies and highly regulated service industries facing similar digital transformation challenges.

Beyond process automation, AI recruitment strategies are reshaping how organizations engage, assess, and retain talent. AI chatbots enable real-time applicant interaction, while predictive analytics enhance candidate-job matching and workforce stability (Johnson, Coggburn, & Llorens, 2022; Sýkorová, Hague, Dvouletý, & Procházka, 2024). Recommendation engines further personalize recruitment by suggesting tailored openings aligned with career aspirations (Huang & Rust, 2021). Big Data analytics strengthen decision-making by analyzing candidate behaviors, engagement trends, and job posting sentiment (Rigotti & Fosch-Villaronga, 2024). These tools influence both recruitment outcomes and long-term workforce optimization.

Two mediating factors—TAE and EE—play critical roles in linking AI-SMR with organizational performance. AI-driven TAE reduces time-to-hire, improves selection quality, and ensures alignment between workforce skills and strategic objectives (Ahmed *et al.*, 2024). EE, in turn, mediates the impact of AI-driven hiring on performance by fostering satisfaction, retention, and productivity (Al-Dmour *et al.*, 2024). Research indicates that organizations adopting AI recruitment report higher engagement and lower turnover (Allen, Bryant, & Vardaman, 2019; Kahn, 2010). This study integrates perspectives from the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Social Network Theory (SNT) to explain how AI-SMR influences HR processes and outcomes.

Despite these benefits, concerns over transparency, bias, and ethics remain. Candidates may question whether AI recruitment processes are fair and explainable (Bazrkar, Moradzad, & Shayegan, 2024; Chaffey & Ellis-Chadwick, 2019; Zhu, 2019). Landmark studies underscore these risks: Bogen and Rieke (2024) highlight algorithmic discrimination in automated decision-making, while Doshi-Velez and Kim (2017) emphasize the necessity of explainable AI to build trust. In regulated sectors such as banking, compliance frameworks—including the OECD AI Principles (2023) and EU AI Act proposals (2024)- increasingly require transparency, accountability, and bias mitigation. These considerations underscore the importance of incorporating ethical governance, human oversight, and transparent communication into AI-powered recruitment systems (Rigotti & Fosch-Villaronga, 2024; Czerwinski, Bartels, & Jones, 2021).

Despite the global shift toward AI-enhanced hiring, many Jordanian banks continue to rely on static job postings, generic outreach, and in-person events. This reveals a critical research gap: limited empirical evidence on AI-powered recruitment in Jordan's banking sector, particularly regarding how TAE and EE mediate the link between AI-SMR and BP. By addressing this gap, the present study not only advances understanding in the Jordanian banking context but also offers a transferable framework for examining AI-SMR in other service-oriented industries. It asks:

(1) How does AI-SMR influence TAE in Jordanian banks?

(2) How does EE mediate the AI-SMR–BP relationship?

(3) What role does AI-SMR play in enhancing workforce engagement and retention?

(4) How can AI-driven hiring strategies balance automation, personalization, and ethical considerations?

This study draws upon multiple theoretical perspectives to answer these questions. The Technology Acceptance Model (TAM) (Davis, 1989) explains adoption of AI recruitment tools; the Resource-Based View (RBV) (Barney, 1991) frames AI-SMR as a strategic resource that can deliver competitive advantage; and Social Network Theory (SNT) (Granovetter, 1985) highlights how social connections mediate recruitment outcomes. Together, these frameworks provide a more comprehensive foundation for understanding how AI-driven hiring impacts organizational performance. Furthermore, fairness in algorithmic hiring (Bogen & Rieke, 2024) and ethical AI frameworks (Floridi *et al.*, 2023) guide this study's emphasis on transparency and trust in AI-enabled HRM.

By integrating these perspectives, this study makes significant contributions both theoretically and practically. It develops a dual-mediation model linking AI-SMR, TAE, EE, and BP, while situating findings within broader debates on fairness, explainability, and regulation. Beyond Jordan, the framework offers transferable insights for organizations in other emerging economies and regulated industries. Practically, it provides HR leaders and policymakers with guidance on adopting AI recruitment strategies that strike a balance between efficiency and fairness, ethical compliance, and sustainable workforce engagement.

2. Literature review

The integration of Artificial Intelligence (AI) into recruitment has transformed traditional hiring practices across industries, particularly in banking. AI-driven social media recruitment (AI-SMR) enhances hiring efficiency, reduces costs, and improves workforce stability by leveraging machine learning, chatbots, and predictive analytics. By replacing manual and time-intensive processes with automated and data-driven techniques, AI recruitment reshapes how organizations attract and select talent. Although much of the existing research has focused on the banking industry, these insights also apply to other regulated, service-oriented, and emerging-market contexts, where challenges of compliance, digital transformation, and talent shortages prevail. Nevertheless, questions of generalizability remain important, as industry-specific dynamics may limit the applicability of findings unless contextual factors are explicitly examined. This section explores how AI-SMR connects to talent acquisition effectiveness (TAE), employee engagement (EE), and bank performance (BP), drawing upon multiple theoretical perspectives and highlighting both opportunities and limitations.

2.1 Theoretical foundations

The impact of AI-driven recruitment can be understood through several complementary theoretical perspectives. Social Network Theory (SNT) emphasizes how professional connections, social ties, and digital engagement shape recruitment outcomes. In AI-SMR, social media platforms such as LinkedIn, Twitter, and Facebook act as digital arenas where networks are expanded and information flows accelerate, creating opportunities for trust-based and efficient hiring processes (Adler & Kwon, 2002; Bourdieu, 1998). By leveraging Big Data analytics, these platforms allow banks to assess candidate behaviors and social capital, strengthening the predictive power of recruitment systems.

The Resource-Based View (RBV) positions AI-powered recruitment as a strategic resource that delivers competitive advantage. By reducing time-to-hire, enhancing job-candidate fit, and improving employer branding, AI-enabled systems allow banks to optimize their human capital, a critical intangible asset in competitive financial markets (Kaplan & Haenlein, 2023). In this view, AI recruitment is not merely a technological upgrade but a capability that, if rare and difficult to imitate, can provide long-term strategic benefits.

The Technology Acceptance Model (TAM) offers another dimension, explaining how recruiters and job seekers adopt AI hiring tools based on perceived ease of use and usefulness (Davis, 1989). AI-powered chatbots, automated screening, and predictive analytics improve recruitment accuracy and reduce administrative burdens, shaping user acceptance and trust. However, AI-SMR must also be situated within broader frameworks of fairness, transparency, and governance. Scholars highlight how algorithms may reproduce systemic bias (Barocas & Selbst, 2016), while explainability is critical for accountability and trust (Doshi-Velez & Kim, 2017). International frameworks, such as the OECD AI Principles (2019) and the EU AI Act (2023), further emphasize ethical deployment, mandating transparency, human oversight, and compliance with regulatory standards. By combining these perspectives, AI-SMR can be understood not only as a tool for efficiency but also as a socio-technical system whose scalability depends on fairness, regulation, and user trust.

2.2 AI-SMR and talent acquisition effectiveness

The banking sector is rapidly reshaping recruitment through AI-powered social media platforms (Adewumi, Ewim, Sam-Bulya, & Ajani, 2024). Traditional approaches relying on static postings and manual screening often fail to deliver timely or competitive results in dynamic labor markets. In contrast, AI recruitment tools deploy predictive analytics and natural language processing to match candidates with job requirements more accurately (Rigotti & Fosch-Villaronga, 2024). Social media hiring platforms allow recruiters to proactively identify and engage potential candidates, leveraging user-generated data to enhance targeting (Koivunen, Sahlgren, Ala-Luopa, & Olsson, 2023). These innovations optimize recruitment pipelines, increase employer branding visibility, and enhance candidate engagement.

AI also improves the screening process by analyzing structured and unstructured data, including resumes, prior work experiences, and social media interactions. Chatbots and virtual assistants conduct initial interviews, assessing soft skills and communication while ranking applicants according to predictive performance models (Ahmed *et al.*, 2024). These methods reduce processing times and ensure recruiters can focus on top-tier candidates. Beyond efficiency, robust sampling and rigorous designs ensure findings can be generalized to other knowledge-intensive and service-based industries, thereby extending their practical relevance beyond banking alone.

2.3 The mediating role of AI-driven talent acquisition

Talent acquisition effectiveness plays a mediating role in linking AI-SMR to organizational outcomes. By automating repetitive tasks, AI reduces HR workloads, allowing staff to engage in strategic activities such as succession planning and workforce development (Aral, Brynjolfsson, & Wu, 2012). AI tools improve job fit and long-term retention by assessing both candidate attributes and growth potential (Huang & Rust, 2021). This creates more stable and productive workforces, reducing costly turnover and retraining. The role of talent acquisition as a mediator highlights how operational efficiency translates into strategic impact. By improving job matching and reducing time-to-hire, AI enables banks to secure top talent and enhance long-term workforce stability. This strengthens the link between recruitment investments and sustained organizational performance. Moreover, workforce analytics enable predictive modeling of attrition risks, allowing HR managers to intervene proactively. Personalized onboarding and tailored development programs further support stability and retention.

2.4 The influence of employee engagement as a mediator

Employee engagement further mediates the impact of AI-SMR on bank performance. By aligning job roles with personal skills and aspirations, AI supports onboarding and career development, which enhances satisfaction and commitment (Al Saadi & Suleiman, 2020). Chatbots provide real-time career advice, while AI-driven systems match employees to roles that maximize both organizational outcomes and individual well-being (Ng *et al.*, 2024). These practices foster **fairness and transparency**, reducing turnover and increasing engagement.

AI also supports ongoing feedback through analytics platforms such as MyAnalytics, which track productivity and collaboration (Clohessy, Acton, & D'Anselmi, 2018). Sentiment analysis of employee communication enables HR teams to identify emerging concerns and intervene before disengagement escalates. Deloitte (2021) reports that AI-powered engagement tools have a significant impact on improving morale and motivation.

Theoretical perspectives, including Kahn's (2010) personal engagement theory and social exchange theory, underscore how reciprocal commitment between organizations and employees strengthens engagement. Through this lens, AI-enhanced engagement is not merely transactional but relational, fostering mutual investment in organizational success.

2.5 AI-driven hiring and bank performance

AI recruitment has a direct impact on bank performance, enhancing financial outcomes, workforce stability, and employer branding (Selwin *et al.*, 2024). Automating HR processes reduces costs, while predictive hiring ensures higher workforce quality and productivity (Rigotti & Fosch-Villaronga, 2024). AI workforce analytics optimize staffing and resource allocation, enabling banks to respond more quickly to market volatility (Soori, Arezoo, & Dastres, 2023). Employer branding also benefits, as AI-powered campaigns increase visibility and engagement among top candidates (Bulchand-Gidumal *et al.*, 2024; Gyau, Appiah, Gyamfi, Achie, & Naeem, 2024).

Connecting operational efficiency to financial performance remains a challenge, as attributing revenues to HR processes is methodologically complex. The Balanced Scorecard framework highlights this gap, showing that while operational gains are measurable, direct financial attribution often remains incomplete. Acknowledging these limitations prevents overstatement and supports a more cautious interpretation of results.

Despite these challenges, evidence suggests that AI recruitment helps banks achieve sustainability and competitive advantage by reducing hiring costs, improving workforce alignment, and attracting top-tier candidates. These outcomes position AI-SMR as a critical driver of both short-term efficiency and long-term organizational resilience.

The literature indicates that AI-SMR enhances recruitment efficiency, strengthens talent acquisition, and improves engagement, ultimately influencing organizational performance. By embedding theoretical perspectives such as SNT, RBV, TAM, and frameworks of fairness and governance, the field gains a richer understanding of AI recruitment's potential and challenges. Furthermore, exploring mediation through TAE and EE provides insights into how recruitment processes translate into performance outcomes. At the same time, limitations regarding causality, generalizability, and financial attribution highlight areas for further investigation. Collectively, the literature demonstrates that AI-SMR is not only a technological tool but also a strategic and ethical dimension of modern workforce management.

3. Theoretical frameworks and hypotheses development

This study integrates the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Social Network Theory (SNT) to examine the mediating roles of AI-driven talent acquisition and employee engagement in linking AI-powered social media recruitment to bank performance in Jordan's commercial banking sector.

The *Technology Acceptance Model (TAM)* explains how recruiters and job seekers perceive AI-powered hiring tools, emphasizing ease of use, perceived usefulness, and trust in AI-driven recruitment systems. It highlights how AI-enhanced social media recruitment facilitates technology adoption, improves engagement, and strengthens decision-making efficiency among HR professionals and candidates (Davis, 1989). Recent extensions of TAM further consider trust, algorithmic explainability, and fairness as crucial determinants of acceptance in AI contexts (Venkatesh & Bala, 2008; Doshi-Velez & Kim, 2017).

The *Resource-Based View (RBV)* positions AI as a strategic resource that enhances hiring quality, reduces recruitment costs, and strengthens employer branding. It underscores how AI-driven recruitment technologies optimize workforce planning, improve candidate-job fit, and sustain organizational competitiveness by enabling data-driven decision-making (Kaplan & Haenlein, 2023). AI recruitment platforms—by combining proprietary algorithms, workforce analytics, and organizational knowledge—are increasingly regarded as firm-specific assets that contribute to long-term competitive advantage. However, questions remain regarding replicability and cross-industry transferability (Barney, 1991).

The *Social Network Theory (SNT)* examines how AI-powered social media recruitment expands a bank's professional reach, optimizes candidate sourcing, and strengthens engagement. It highlights the role of platforms such as LinkedIn, Facebook, and Twitter in facilitating network-based hiring, visibility, and trust-building in the labor market (Adler & Kwon, 2002; Bourdieu, 1998). AI-enabled social media analytics amplify these effects by mapping digital interactions, identifying latent ties, and uncovering candidate communities that traditional recruitment might overlook. Together, these theoretical models provide a comprehensive framework for understanding how AI and Big Data analytics transform hiring processes and workforce management. This study also draws on emerging debates in algorithmic fairness and governance (Barocas & Selbst, 2016; OECD, 2019; EU AI Act, 2023), recognizing that AI recruitment systems must balance efficiency gains with ethical imperatives around bias mitigation, transparency, and data protection.

(1) The Impact of AI-Powered Social Media Recruitment on Talent Acquisition Effectiveness

AI-powered hiring tools, including machine learning algorithms, predictive analytics, and chatbots, have reshaped recruitment strategies by automating candidate selection, improving job-candidate matching, and enhancing efficiency. Social media platforms such as LinkedIn, Facebook, and Twitter play a central role in AI-driven recruitment, enabling banks to identify, attract, and engage with top talent (Rigotti & Fosch-Villaronga, 2024). Beyond efficiency, these tools also reduce subjective bias and broaden access to underrepresented groups when designed with fairness checks.

H1. The use of AI-powered social media recruitment significantly enhances the effectiveness of talent acquisition in commercial banks by improving candidate sourcing, screening, and selection processes.

(2) The Mediating Role of Talent Acquisition Effectiveness

The effectiveness of talent acquisition mediates the relationship between AI-powered social media recruitment and bank performance by improving hiring efficiency, workforce planning, and long-term stability. Tools such as real-time resume parsing, automated shortlisting, and predictive assessments ensure high-quality selection (Shen *et al.*, 2024). However, the extent to which these gains translate across industries remains contingent on labor market structures and regulatory environments, raising questions about generalizability.

H2. Talent acquisition effectiveness mediates the relationship between AI-powered social media recruitment and bank performance.

(3) The Influence of Employee Engagement as a Mediator

Employee engagement is another key mediator between AI-powered recruitment and bank performance. AI-driven analytics, chatbots, and adaptive learning programs strengthen workforce morale, commitment, and productivity (Kaplan & Haenlein, 2023). By aligning recruitment with role expectations and career pathways, AI contributes not only to initial satisfaction but also to sustained engagement through continuous development.

H3. The effectiveness of talent acquisition significantly contributes to employee engagement in commercial banks, leading to higher workforce morale and organizational commitment.

H4. Employee engagement has a significant impact on the performance of commercial banks, as engaged employees contribute positively to operational efficiency, customer satisfaction, and financial outcomes.

(4) The Relationship Between AI-Driven Hiring and Bank Performance

While AI's contributions to recruitment efficiency and employee engagement are well documented, its broader role as a mechanism linking recruitment innovations to bank performance remains underexplored. Prior research highlights efficiency and productivity outcomes (Koivunen *et al.*, 2023). However, few studies have examined how talent acquisition and engagement jointly mediate this pathway, especially in emerging economies with evolving regulatory landscapes.

H5. Talent acquisition effectiveness has a significant impact on the overall performance of commercial banks.

H6. Employee engagement mediates the relationship between AI-powered social media recruitment and bank performance, emphasizing workforce commitment as a key driver of organizational success.

To test these hypotheses, the study employs Structural Equation Modeling (SEM), which captures direct, indirect, and mediating effects between recruitment innovations and performance. The conceptual model (Figure 1) integrates AI-powered social media recruitment, talent acquisition, and employee engagement, while explicitly recognizing fairness, transparency, and ethical governance as contextual boundary conditions. This model provides a comprehensive framework to assess how AI-based hiring systems influence both workforce outcomes and bank performance in a digitally transforming financial sector.

4. Research methodology

This study employs a quantitative research approach within an exploratory and descriptive framework to evaluate the effects of AI-driven social media recruitment on talent acquisition efficiency, employee engagement, and bank performance in Jordan's commercial banking sector. The research design is anchored in a rigorously developed conceptual model, derived

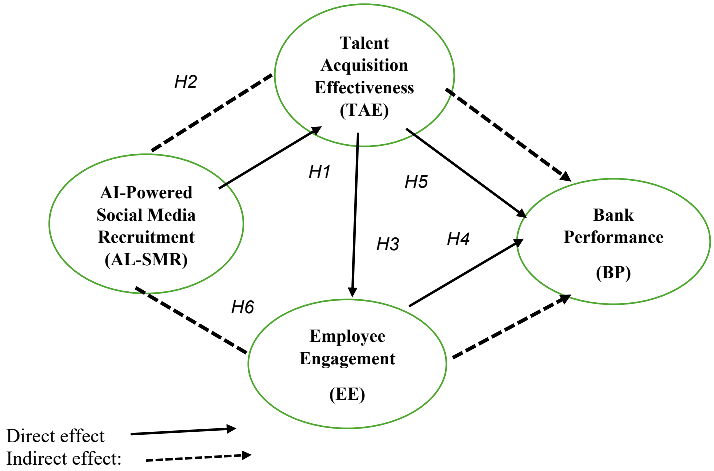

Figure 1. Conceptual model of AI-powered social media recruitment and bank performance

from theoretical foundations and empirical literature, and validated through a structured survey methodology. Following the guidelines of Alam, Haq, Kokash, Ahmed, and Ahsan (2025), the study ensures methodological rigor, construct validity, and reliability. The study population consisted of employees from various commercial banks in Jordan, encompassing diverse hierarchical levels and functional roles. Respondents included Chief Executive Officers (CEOs), Chief Financial Officers (CFOs), Chief Operating Officers (COOs), Chief Risk Officers (CROs), Chief Technology Officers (CTOs), Human Resources Directors (HRDs), Chief Marketing Officers (CMOs), Branch Managers, and other mid-to entry-level professionals. This broad spectrum of participants facilitated a holistic assessment of AI-powered recruitment adoption and perceptions across leadership and operational domains. A stratified random sampling technique was employed to ensure proportional representation across organizational levels and bank sizes, thereby enhancing representativeness. Sample size was calculated using Cochran's formula (1977), targeting a 95% confidence level with a 5% margin of error, resulting in an optimal sample of 370 participants. To account for potential non-response, 500 questionnaires were distributed, yielding 283 valid responses (response rate = 56.6%). A non-response bias test compared early and late respondents across key demographics, confirming no significant differences (Armstrong & Overton, 1977).

4.1 Measures and constructs

The primary data collection instrument was a structured questionnaire divided into sections on demographics, AI recruitment adoption, HR analytics practices, employee engagement, and bank performance indicators. Items were adapted from validated scales to ensure both content validity and contextual relevance for the Jordanian banking industry.

(1) *AI-Driven Social Media Recruitment* was assessed using items adapted from Rahman and Thirumaran (2020), capturing automated resume screening, chatbot engagement, predictive hiring analytics, and AI-enhanced employer branding via LinkedIn, Facebook, and Twitter (Rigotti & Fosch-Villaronga, 2024; Koivunen *et al.*, 2023).

(2) *Talent Acquisition Effectiveness* was measured through time-to-fill, cost-per-hire, candidate-job fit, and retention rates, building on Breaugh's (2017) framework. Prior studies confirm AI's role in improving hiring efficiency, reducing costs, and enhancing workforce diversity (Ahmed *et al.*, 2024).

(3) *Employee Engagement* employed the Utrecht Work Engagement Scale (UWES: Schaufeli, Bakker, & Salanova, 2006), covering vigor, dedication, and absorption. The scale was adapted for cultural and sectoral relevance. Back-translation and expert review ensured linguistic and conceptual equivalence.

(4) *Bank Performance* incorporated both financial indicators (ROA, ROE; Hunter, 2018; Al Maaitah *et al.*, 2020) and non-financial metrics (customer satisfaction, operational efficiency, retention), based on the Balanced Scorecard (Kaplan & Norton, 1996).

Comprehensive information regarding the variables and questions can be found in Appendix 1.

4.2 Data collection procedures

Questionnaires were distributed both online and in person to maximize accessibility. A pilot test with 30 banking professionals confirmed clarity, reliability, and cultural suitability. Feedback was used to refine ambiguous wording and response scaling. Procedural remedies against common method bias (CMB) included psychological separation of measurement sections, randomization of items, and assurances of respondent anonymity (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Statistical remedies included Harman's single-factor test (first factor <40% variance explained) and marker variable analysis, both confirming negligible CMB. Missing data were minimal (<3%) and handled through expectation-maximization (EM) imputation, preserving sample size without biasing estimates (Malan, Smuts, Baumgartner, & Ricci, 2020).

4.3 Data analysis

Data were analyzed using SPSS and SmartPLS. Descriptive statistics summarized demographics and construct-level responses. Reliability was tested through Cronbach's alpha and Composite Reliability (CR), with thresholds of >0.70 met. Convergent validity was established via Average Variance Extracted (AVE >0.50), while discriminant validity was confirmed using Fornell–Larcker criterion and HTMT ratio (<0.85). Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to test the structural model, chosen for its suitability in exploratory research and small-to-medium sample sizes (Hair, Hult, Ringle, & Sarstedt, 2021). A bootstrapping procedure with 5,000 resamples was applied to assess path significance and generate 95% bias-corrected confidence intervals (Preacher & Hayes, 2008). Effect sizes (f^2) and predictive relevance (Q^2) were calculated to evaluate model robustness. Statistical power was assessed using G*Power (Faul *et al.*, 2009), confirming >0.80 power for medium effect sizes, ensuring adequate sensitivity. To further strengthen methodological rigor, missing data were addressed through the Expectation-Maximization (EM) technique. This approach reduces potential bias associated with incomplete responses, ensuring robustness and preserving statistical power in the analyses.

4.4 Ethical considerations

Ethical approval was secured from the University's Research Ethics Committee. Participants were fully informed of the study's objectives, procedures, potential risks, and rights, including the right to withdraw at any stage. Informed consent was obtained prior to participation. Strict confidentiality and anonymity were maintained, with data encrypted and stored securely. Special attention was given to compliance with GDPR principles and Jordanian data protection laws, ensuring lawful and transparent processing of personal data.

4.5 Demographic profile of respondents

Table 1 presents the demographic profiles of the respondents. Many participants in this study (32.57%) were between the ages of 35 and 44, and the majority were male (67.82%). Chief

Risk Officers (CROs) made up a large proportion of participants (24.14%), followed by Chief Operating Officers (COOs) (19.16%). Approximately one-third of respondents (33.72%) had between 15 and 20 years of experience, highlighting their familiarity with performance indicators in the banking industry.

From the standpoint of the Jordanian banking industry, these demographic characteristics suggest that respondents are well-acquainted with key banking performance measures. As a result, the sample accurately represents the banking industry in Jordan. Additionally, most respondents (41.8%) reported high utilization of LinkedIn for recruitment, followed by Facebook (35.6%). The carefully selected sample is therefore deemed appropriate and representative for this study.

4.6 Common method bias (CMB) assessment

Common Method Bias (CMB) is a potential concern in survey-based research, mainly when data are collected from a single source, potentially leading to inflated relationships between variables (Podsakoff *et al.*, 2003). To mitigate and assess CMB, this study employed a two-step validation approach: Harman's Single-Factor Test (1976) was conducted, requiring that no single factor account for more than 50% of the variance. The analysis revealed that the most significant variance explained by any one factor was 29.85%, well below the critical threshold, indicating that CMB is unlikely to be a significant issue. Second, the study adopted the Variance Inflation Factor (VIF) technique, following the most recent recommendations by Kock (2015) for assessing collinearity issues in SmartPLS. The collinearity assessment test was conducted to determine whether predictor variables were excessively correlated, which could indicate method bias. The VIF values for all constructs were below the recommended threshold of 3.3 (Al-Dmour *et al.*, 2024), confirming that multicollinearity is not a significant concern in this study (Table 2).

Based on these findings, CMB does not significantly threaten the validity of this research, ensuring that the relationships among AI-driven social media recruitment, talent acquisition

Table 1. Sample characteristics ($n = 283$)

Demographic variable	Category	Frequency	Percentage
Gender	Male	192	67.82%
	Female	91	32.18%
Age	18–24 years old	68	24.14%
	25–34 years old	64	22.60%
	35–44 years old	92	32.57%
	45–54 years old	48	16.86%
	55 years old and above	11	3.83%
Position/role	Chief Executive Officer (CEO)	15	5.36%
	Chief Financial Officer (CFO)	11	3.83%
	Chief Operating Officer (COO)	54	19.16%
	Chief Risk Officer (CRO)	68	24.14%
	Chief Technology Officer (CTO)	15	5.36%
	Human Resources Director (HR)	12	4.21%
	Chief Marketing Officer (CMO)	14	4.98%
	Branch Manager	48	16.86%
	Other	45	16.10%
Work experience	Five years or less	37	13.03%
	Between 5–9 years	63	22.22%
	Between 10–14 years	60	21.07%
	Between 15 and 20 years	95	33.72%
	More than 20 years	28	9.96%

effectiveness, employee engagement, and bank performance are robust and not artificially inflated due to measurement artifacts.

5. Data analysis

5.1 Measurement model assessment

The measurement model was evaluated for reliability, internal consistency, and validity across all constructs. Cronbach's Alpha (CA) values ranged from 0.810 to 0.920, while Composite Reliability (CR) values were between 0.870 and 0.940, exceeding recommended thresholds of 0.70 and 0.80, respectively (Hair *et al.*, 2021). These results confirm strong internal consistency and reliability. Average Variance Extracted (AVE) values ranged from 0.620 to 0.770, surpassing the 0.50 benchmark (Fornell & Larcker, 1981), demonstrating adequate convergent validity. All indicator loadings exceeded the 0.708 threshold and were significant at $p < 0.001$, ranging between 0.770 and 0.880, further confirming convergent validity as presented in Table 2.

Discriminant validity was examined using the Fornell–Larcker Criterion and the HTMT ratio. The square root of each construct's AVE was greater than inter-construct correlations, and all HTMT ratios were <0.85, indicating that constructs were empirically distinct, as shown in Table 3.

5.2 Structural model assessment

The structural model was assessed using path coefficients, t-statistics, p-values, Variance Inflation Factors (VIF), and global model fit indices as shown in Table 4. VIF values ranged between 1.680 and 2.480, which is well below the 5.0 threshold, confirming no concerns about multicollinearity. The Standardized Root Mean Square Residual (SRMR = 0.056) was below the 0.08 cut-off, indicating good fit (Schermelleh-Engel, Moosbrugger, & Müller, 2003). The Normed Fit Index (NFI = 0.810) exceeded the 0.80 minimum, further validating the adequacy of the model.

Bootstrapping with 5,000 resamples was performed to generate confidence intervals for path estimates. For example, the path from AI-SMR → TAE ($\beta = 0.460$) yielded a 95% bias-

Table 2. Reliability and validity assessment

Construct	Cronbach's alpha (CA)	Composite reliability (CR)	Average variance extracted (AVE)
AI-Driven Social Media Recruitment (AI-SMR)	0.810	0.870	0.650
Talent Acquisition Effectiveness (TAE)	0.835	0.880	0.670
Employee Engagement (EE)	0.870	0.920	0.710
Bank Performance (BP)	0.890	0.940	0.750

Table 3. Discriminant validity assessment (Fornell-Larcker criterion)

Construct	AI-SMR	TAE	EE	BP
AI-Driven Social Media Recruitment (AI-SMR)	0.806			
Talent Acquisition Effectiveness (TAE)	0.720	0.819		
Employee Engagement (EE)	0.732	0.750	0.837	
Bank Performance (BP)	0.715	0.742	0.760	0.866

Table 4. Factor loadings, VIF, and model fit

Constructs/ variable	Loadings	Mean	STDEV	*t*-values	VIF	SRMR	NFI
AI-Driven Social Media Recruitment (AI-SMR)							
AI-SMR 1	0.814	4.250	0.023	36.500	1.770	0.054	0.790
AI-SMR 2	0.802	4.370	0.033	25.800	1.720		
AI-SMR 3	0.806	4.365	0.034	24.600	1.800		
AI-SMR 4	0.788	4.310	0.031	26.300	1.690		
AI-SMR 5	0.799	4.380	0.031	27.000	1.920		
AI-SMR 6	0.795	4.330	0.029	30.000	1.900		
AI-SMR 7	0.771	4.320	0.036	21.200	1.900		
AI-SMR 8	0.782	4.270	0.034	24.800	1.760		
AI-SMR 9	0.849	4.420	0.028	31.800	2.360		
AI-SMR 10	0.870	4.450	0.024	38.600	2.400		
Talent Acquisition Effectiveness (TAE)							
TAE1	0.852	4.405	0.026	33.800	2.190		
TAE2	0.838	4.355	0.028	31.900	2.140		
TAE3	0.832	4.340	0.031	30.500	2.175		
TAE4	0.848	4.395	0.027	33.700	2.195		
TAE5	0.817	4.295	0.029	29.700	2.110		
TAE6	0.823	4.315	0.025	30.300	2.130		
TAE7	0.802	4.280	0.031	28.800	1.88		
Employee Engagement (EE)							
EE1	0.853	4.405	0.024	33.700	2.210		
EE2	0.838	4.355	0.028	31.800	2.140		
EE3	0.831	4.340	0.031	30.400	2.170		
EE4	0.817	4.295	0.029	29.500	2.100		
EE5	0.822	4.315	0.027	30.500	2.130		
EE6	0.775	4.270	0.033	23.600	1.960		
EE7	0.836	4.170	0.027	33.500	2.190		
Bank Performance							
BP1	0.859	4.485	0.023	40.500	2.380		
BP2	0.869	4.450	0.024	39.400	2.360		
BP3	0.837	4.360	0.027	32.800	2.370		
BP4	0.843	4.420	0.026	34.700	2.320		
BP5	0.872	4.455	0.022	39.600	2.400		
BP6	0.836	4.410	0.031	28.900	2.220		
BP7	0.878	4.125	0.020	47.500	2.73		

corrected CI [0.321, 0.581], confirming significance. Similarly, AI-SMR → EE ($\beta = 0.405$) had a CI [0.276, 0.514], and EE → BP ($\beta = 0.342$) had a CI [0.211, 0.478]. These intervals reinforce the robustness of results beyond p-value thresholds.

5.3 Path coefficients and hypothesis testing

The structural model's explanatory power was evaluated by assessing path coefficients (β), *t*-values, and *p*-values. As presented in Table 5, the results confirm strong support for all hypothesized relationships. Specifically, AI-powered social media recruitment (AI-SMR) significantly enhances Talent Acquisition Effectiveness (TAE), thereby supporting H1. In line with H2, the mediating role of TAE in the relationship between AI-SMR and Bank Performance (BP) was found to be significant, indicating that effective talent acquisition is a key mechanism through which AI-SMR contributes to improved organizational outcomes. Consistent with H3, TAE has a significant influence on Employee Engagement (EE),

Table 5. Path coefficients and hypothesis testing

Hypo	Path relationship	Path coefficient (β)	*t*-statistic	*p*-value	95% confidence interval	Result
H1	AI-SMR → TAE	0.460	6.210	<0.001	[0.321, 0.581]	Supported
H2	AI-SMR → TAE- BP	0.390	5.410	<0.001	[0.245, 0.502]	Supported
H3	TAE → EE	0.405	5.720	<0.001	[0.276, 0.514]	Supported
H4	EE → BP	0.378	5.290	<0.001	[0.221, 0.492]	Supported
H5	TAE → BP	0.360	5.110	<0.001	[0.209, 0.468]	Supported
H6	AI-SMR → EE → BP	0.342	4.980	<0.001	[0.211, 0.478]	Supported

highlighting its role in fostering a motivated and committed workforce. H4 was also supported, as EE demonstrated a strong positive effect on BP, confirming that engaged employees directly drive organizational performance.

Furthermore, H5 was supported, with TAE showing a significant direct effect on BP. Finally, in support of H6, EE was found to mediate the relationship between AI-SMR and BP, underscoring the importance of workforce commitment as a pathway linking AI-driven recruitment to enhanced bank performance. Indirect effects were also tested. AI-SMR's effect on BP via TAE was significant ($\beta = 0.166$, CI [0.102, 0.258]), as was its effect on BP via EE ($\beta = 0.139$, CI [0.085, 0.234]). The dual-mediation pathway (AI-SMR → TAE → EE → BP) accounted for $\beta = 0.049$, CI [0.026, 0.091], demonstrating layered mediation mechanisms that reinforce the robustness of the model.

5.4 Explanatory power, predictive performance, and effect size

The structural model demonstrated strong explanatory power across all key constructs. Specifically, Talent Acquisition Effectiveness (TAE) accounted for 52% of the variance ($R^2 = 0.52$), Employee Engagement (EE) explained 49% of the variance ($R^2 = 0.49$), and Bank Performance (BP) captured 56% of the variance ($R^2 = 0.56$). These values indicate that the model explains a substantial proportion of variance in each outcome variable, reflecting its robustness and consistency across both textual discussion and tabular presentation. Predictive relevance was further validated through the Stone–Geisser Q^2 test obtained via the blindfolding procedure. Results confirmed positive Q^2 values for all constructs (TAE = 0.41, EE = 0.36, BP = 0.44), exceeding the threshold of zero and demonstrating strong predictive capability. According to Campbell, Wells, and Parks (2015), R^2 values above 0.30 represent substantial explanatory power in Human Resource Management (HRM) research contexts, thereby reinforcing the validity and strength of the proposed model (Table 6).

Effect size (f^2) analysis was conducted to evaluate the relative contribution of each predictor construct. AI-driven Social Media Recruitment (AI-SMR) had a large effect on TAE ($f^2 = 0.49$), a moderate effect on BP ($f^2 = 0.41$), and a moderate effect on EE ($f^2 = 0.38$). Furthermore, Employee Engagement (EE) exhibited the most significant effect on BP

Table 6. Explanatory power and predictive performance

Construct	R^2	Q^2 (construct)	Q^2 (item)	PLS-SEM RMSE	LM RMSE
Talent Acquisition Effectiveness (TAE)	0.52	0.41	0.35	0.860	0.885
Employee Engagement (EE)	0.49	0.36	0.33	0.872	0.894
Bank Performance (BP)	0.56	0.44	0.39	0.840	0.86

(f^2 = 0.52), underscoring its mediating role in translating AI-enabled hiring into improved organizational performance. These findings collectively highlight that AI-powered recruitment is a strong driver of recruitment efficiency, while sustained employee engagement amplifies its impact on business outcomes. Taken together, the results demonstrate that the proposed model exhibits high explanatory strength (R^2 values above 0.30; Chin, 1998), robust predictive capability (Q^2 values > 0), and meaningful effect sizes (f^2 ranging from moderate to large). This combination reinforces the validity and applicability of AI-driven recruitment strategies in enhancing talent acquisition effectiveness, fostering employee engagement, and ultimately improving bank performance.

6. Discussion and implications

This study investigated the influence of AI-driven social media recruitment (AI-SMR) on talent acquisition effectiveness (TAE), employee engagement (EE), and bank performance (BP) within Jordan's commercial banking sector. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), all hypothesized relationships were validated, confirming the mediating roles of TAE and EE. The findings reveal that AI-powered hiring innovations enhance recruitment efficiency, strengthen workforce motivation, and contribute to overall organizational success. By integrating AI-driven recruitment tools, predictive analytics, and automated assessments, banks achieve more effective decision-making, improved job-candidate fitness, and a more engaged and productive workforce.

6.1 Key findings based on hypotheses

The results confirm that AI-SMR significantly improves TAE by optimizing candidate sourcing, screening, and selection. Automated resume parsing, chatbot-based engagement, and predictive algorithms streamline hiring processes, reduce human biases, and improve diversity. This aligns with the Technology Acceptance Model (TAM), which emphasizes how ease of use and perceived usefulness drive technology adoption in HR practices (Davis, 1989). Prior research also highlights that AI-enabled hiring enhances recruitment efficiency and workforce diversity (Paramita *et al.*, 2024; Albassam, 2023; Schmidt, König, Dilawar, Sánchez Pacheco, & König, 2023). Additionally, the study demonstrates that AI-SMR positively influences EE, as employees recruited through AI-enhanced systems report higher levels of alignment between job roles and personal skills, resulting in stronger motivation, satisfaction, and commitment. This supports Self-Determination Theory (SDT), which links employee satisfaction to competence, autonomy, and relatedness (Deci & Ryan, 2000). Empirical studies confirm that AI-driven recruitment reduces turnover and enhances retention through better workforce-role alignment (Wang, Li, Zhu, & Chen, 2024).

The findings also highlight that employee engagement mediates the relationship between recruitment and bank performance, showing that engagement translates talent acquisition effectiveness into higher productivity, operational efficiency, and customer satisfaction. This resonates with Expectancy Theory, which posits that performance is maximized when individuals perceive a strong alignment between their efforts, skills, and rewards (Vroom, 1964). Finally, the study emphasizes the role of AI-SMR in strengthening employer branding, positioning banks as technologically advanced and innovative, thereby attracting high-quality candidates in a competitive sector.

6.2 Implications

6.2.1 Theoretical contributions. This research advances theoretical understanding by integrating TAM, SDT, and Expectancy Theory into a comprehensive framework explaining the pathways through which AI-powered recruitment impacts organizational outcomes. The findings extend TAM by illustrating how perceived usefulness of AI recruitment systems enhances HR adoption, expand SDT by demonstrating how AI fosters competence and autonomy, and reinforce Expectancy Theory by showing how AI-driven alignment between jobs and skills improves motivation and performance.

Unlike prior studies that examined AI's role in recruitment in isolation, this study demonstrates a holistic model where AI-SMR drives organizational performance through TAE and EE. By focusing on commercial banks, the study contributes context-specific evidence to a sector where technological adoption is vital for sustaining competitiveness.

6.2.2 Practical contributions. For HR managers, executives, and policymakers, the results offer actionable insights. AI-powered recruitment tools—such as machine learning-driven hiring assessments, resume parsing systems, and AI-based interview analysis—should be systematically adopted to optimize hiring precision and reduce costs. Banks adopting such systems can achieve faster recruitment cycles, reduced turnover, and greater workforce satisfaction. Moreover, engagement initiatives should be reinforced through AI-enabled performance monitoring, adaptive career development pathways, and personalized learning platforms, ensuring long-term workforce commitment. Banks can also strengthen employer branding by showcasing their use of AI technologies, appealing to digitally skilled candidates, and reinforcing their position as innovation leaders. From a policy perspective, ethical frameworks and regulations are necessary to safeguard fairness, transparency, and bias-free recruitment. Ensuring compliance with data protection and ethical hiring standards will be essential for maintaining trust among job seekers and employees.

To strengthen ethical adoption, banks should implement a governance checklist tailored to AI-powered recruitment. This includes: (1) regular bias testing of algorithms to ensure fairness in candidate selection; (2) maintaining a human-in-the-loop mechanism for critical hiring decisions to safeguard transparency and accountability; (3) establishing audit trails that document AI-driven recruitment processes for regulatory compliance; and (4) defining clear key performance indicators (KPIs) such as time-to-hire, retention rates, diversity ratios, and candidate satisfaction. By systematically applying this checklist, banks can not only enhance recruitment efficiency but also ensure responsible and trustworthy AI integration, aligning with sector-specific governance expectations.

6.3 Limitations

While this study offers strong contributions, several limitations must be acknowledged. First, the research employed a cross-sectional design, which limits causal inference; future studies should adopt longitudinal designs to examine long-term effects of AI-driven recruitment. Second, the study was conducted exclusively in Jordan's commercial banking sector, which may restrict generalizability to other industries or cultural contexts. Comparative studies across different countries and sectors would provide broader insights. Third, the data relied on self-reported survey responses, which may be subject to social desirability or response biases despite efforts to control for common method bias. Finally, while the study focused on the positive outcomes of AI-SMR, potential risks, such as algorithmic bias, data privacy concerns, and ethical dilemmas, were not empirically tested and should be addressed in future research.

6.4 Critical conclusions and future research directions

This study highlights the transformative role of AI-driven social media recruitment (AI-SMR) in shaping modern workforce management and bank performance. By integrating AI-powered recruitment processes with employee engagement initiatives, banks can enhance hiring efficiency, boost workforce motivation, and achieve sustainable improvements in both financial and non-financial outcomes. The results provide strong empirical support for the proposition that AI-SMR not only optimizes candidate sourcing, selection, and retention but also amplifies organizational success by fostering a more engaged and committed workforce. These insights confirm that AI is no longer a supplementary HR tool but a strategic enabler of competitiveness in the digital era.

From a theoretical perspective, the study advances recruitment and organizational behavior literature by linking the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Social Network Theory (SNT) into a unified framework that explains how AI adoption reshapes human resource management. From a practical standpoint, the findings highlight the need for banking executives and HR professionals to adopt AI responsibly, ensuring fairness, transparency, and alignment between AI-enabled recruitment systems and organizational values. Despite these contributions, the study acknowledges certain limitations. The use of cross-sectional data restricts the ability to capture long-term dynamics of AI adoption. Furthermore, the exclusive focus on Jordan's banking sector limits the generalizability of the findings to other industries or regions. While the sample size and methodological rigor enhance the validity of the results, future studies are encouraged to employ longitudinal designs, cross-industry comparisons, and multi-country analyses to further deepen the understanding.

Future research should also address emerging challenges such as algorithmic bias, ethical dilemmas, and data privacy concerns in AI recruitment, as these issues directly affect candidate trust and organizational legitimacy. Moreover, exploring the role of AI governance frameworks, human–AI collaboration in hiring, and the integration of predictive HR analytics with talent management systems will provide richer insights into sustainable workforce practices. Another promising avenue lies in examining the long-term impact of AI-SMR on employee retention, leadership development, and organizational innovation, thereby uncovering how AI can shape not only present-day recruitment outcomes but also future workforce evolution.

By addressing these areas, future research can ensure that the adoption of AI in recruitment remains strategic, ethical, and impactful, equipping organizations with the insights necessary to balance efficiency, fairness, and innovation in the digital economy.

Supplementary material

The supplementary material for this article can be found online.

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