

The Augmented Recruiter: Examining AI Integration and Decision-Making Dynamics in Qatar's Organisational Hiring Practices

AJONBADI, Hakeem, ADEKOYA, Olatunji <<http://orcid.org/0000-0003-4785-4129>>, MAHMOUD, Somaya, MANSOUR, Yumna, DAHER, Kounouz and OWOLEWA, Mutiat Ayodele

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Citation:

AJONBADI, Hakeem, ADEKOYA, Olatunji, MAHMOUD, Somaya, MANSOUR, Yumna, DAHER, Kounouz and OWOLEWA, Mutiat Ayodele (2026). The Augmented Recruiter: Examining AI Integration and Decision-Making Dynamics in Qatar's Organisational Hiring Practices. *Journal of Work-Applied Management*. [Article]

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The augmented recruiter: examining AI integration and decision-making dynamics in Qatar's organisational hiring practices

Journal of Work-
Applied
Management

Hakeem Ajonbadi

University of Doha for Science and Technology, Doha, Qatar

Olatunji David Adekoya

Sheffield Hallam University, Sheffield, UK

Somaya Mahmoud, Yumna Mansour and Kounouz Daher

University of Doha for Science and Technology, Doha, Qatar, and

Mutiati Ayodele Owolewa

Birmingham City University, Birmingham, UK

Received 9 October 2025

Revised 17 February 2026

Accepted 23 March 2026

Abstract

Purpose – This study explored the implementation of artificial intelligence (AI) in recruitment processes within Qatari organisations, focussing on how these technologies impact organisational efficiency, human judgement in decision-making and recruitment outcomes.

Design/methodology/approach – The research employed an interpretivist philosophy and a case study design, investigating two prominent Qatari firms with contrasting AI recruitment implementation approaches. Data were collected through semi-structured interviews with twenty-two participants across various organisational roles and hierarchical levels. The thematic analysis framework was used to identify patterns and relationships within the data.

Findings – Four key themes emerged, including (1) process optimisation through AI integration, (2) subjectivity in AI-powered recruitment, (3) recruitment strategies in the age of AI and (4) strategic investments in AI. The research found that AI significantly enhanced efficiency through process standardisation and automation, but functioned optimally as an augmentative rather than a replacement technology.

Practical implications – Organisations should approach AI recruitment tools as augmentative technologies, invest in customisation capabilities, implement comprehensive change management strategies and maintain robust post-hire evaluation procedures.

Originality/value – The research shifts focus to under-researched non-Western workplace settings, particularly in technologically advancing Middle Eastern economies like Qatar.

Keywords AI recruitment tools, Augmented technology, AI augmented hiring, Artificial intelligence, Qatari organisation, Decision making

Paper type Research article

Introduction

The integration of artificial intelligence (AI) into human resource management (HRM), particularly in recruitment and selection processes, represents one of the most significant technological disruptions in contemporary organisational practice (Nawaz *et al.*, 2024; Shams *et al.*, 2025). As organisations worldwide grapple with the complexities of talent acquisition in increasingly competitive labour markets, AI-powered recruitment tools offer potential

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Journal of Work-Applied Management
Emerald Publishing Limited
e-ISSN: 2205-149X
p-ISSN: 2205-2062
DOI 10.1108/JWAM-10-2025-0193

solutions to longstanding challenges of efficiency, objectivity and effectiveness (Budhwar *et al.*, 2022). These technologies promise to transform recruitment from a predominantly manual, time-intensive process to one characterised by automation, data-driven decision-making and predictive capabilities (Madanchian, 2024).

The adoption of AI in recruitment encompasses diverse applications, including applicant tracking systems (ATS), CV screening algorithms, automated interview scheduling, chatbots for candidate engagement and predictive analytics for candidate assessment (Tambe *et al.*, 2019). While proponents advocate that these tools enhance organisational efficiency and reduce human bias (Boateng, 2021), critical perspectives highlight concerns regarding algorithmic bias, candidate experience and the diminution of human judgement in selection decisions (Madanchian, 2024). This tension between technological optimisation and human-centred recruitment practices forms the conceptual backdrop against which this study is situated.

Despite growing scholarly and practitioner interest in AI-powered recruitment, empirical research examining organisational outcomes of AI recruitment implementation remains limited, with existing studies predominantly focused on technical capabilities rather than practical implications (van Esch *et al.*, 2019). Second, there is little research exploring stakeholder experiences across organisational hierarchies, with most studies privileging executive perspectives over those of recruitment specialists, line managers and other affected employees (Vardarlier and Zafer, 2020). Third, geographical imbalance in existing research has resulted in limited understanding of AI recruitment in non-Western contexts, particularly in technologically advancing Middle Eastern economies like Qatar (Al-Shaiba *et al.*, 2020).

This study addresses these gaps by examining how the implementation of AI-powered recruitment processes impacts organisational efficiency within Qatari companies. Drawing on qualitative data from key stakeholders across two prominent Qatari organisations, the research explores how AI recruitment tools are reshaping traditional hiring practices, the challenges and opportunities they present and their implications for organisational effectiveness. While existing research has predominantly focused on Western settings (Bankins *et al.*, 2024; Madanchian, 2024; Shams *et al.*, 2025) and technical implementation aspects (van Esch *et al.*, 2019), this study provides empirically grounded insights into how AI recruitment technologies interact with the unique socio-cultural dynamics of Qatari organisations. By situating this analysis within Qatar's unique socioeconomic context, characterised by rapid technological advancement alongside distinctive cultural and institutional arrangements, this study offers valuable insights for both theory and practice.

The research is guided by the following objectives: (1) to understand how AI integration affects recruitment process efficiency in Qatari organisations; and (2) to explore the connection between AI systems and human judgement in recruitment decision-making.

The remainder of this paper proceeds by reviewing the literature on AI-enabled recruitment, organisational efficiency and technology adoption in Middle Eastern contexts. We then outline the research methodology and analytical approach, present findings structured around four themes and discuss theoretical and practical implications, before concluding with limitations and directions for future research.

Literature review and theoretical perspective

Artificial intelligence and the transformation of recruitment

The integration of AI into recruitment marks a significant shift within HRM, reshaping how organisations attract, assess and select talent. Although early conceptual discussions of AI-supported HRM emerged in the 1990s (Lawler and Elliot, 1996), sustained scholarly attention has intensified only in the past decade alongside advances in machine learning, big data analytics and digital platforms (Budhwar *et al.*, 2022). Despite this growth, conceptual clarity regarding AI's strategic role in HRM remains limited, particularly in relation to contextual, institutional and ethical dimensions (Priksat *et al.*, 2023). Recruitment has become the

primary domain for AI adoption, driven by organisational pressures to enhance efficiency, manage large applicant volumes and improve decision consistency (van Esch *et al.*, 2019; Tambe *et al.*, 2019).

Early e-recruitment systems largely digitised administrative tasks such as job advertising and CV screening (Tambe *et al.*, 2019). Contemporary AI-enabled recruitment tools extend beyond digitisation to incorporate predictive analytics, automated screening algorithms and conversational agents that interact with candidates in real time (Li *et al.*, 2023). These developments reflect Davenport and Ronanki's (2018) framework of AI applications, including process automation, cognitive insight and cognitive engagement, which are increasingly embedded within recruitment workflows (Bankins *et al.*, 2024). Empirical studies suggest that AI adoption can enhance recruiter productivity, accelerate decision cycles and improve candidate communication, with many HR professionals reporting perceived improvements in hiring outcomes (Ebrahim and Rajab, 2025; Stefanowicz, 2025).

Recruitment effectiveness has traditionally been assessed using metrics such as time-to-hire, cost-per-hire and quality-of-hire (Phillips and Gully, 2015). AI technologies have been associated with improvements across these indicators, particularly through automating high-volume screening and standardising evaluation criteria (El Ouakili, 2025). By processing large datasets rapidly and applying consistent decision rules, AI systems can reduce administrative burdens and enable recruiters to focus on higher-value activities. Additionally, AI-driven chatbots and recommendation systems may enhance candidate engagement through timely feedback and personalised interaction (Nawaz *et al.*, 2024).

However, efficiency gains do not necessarily equate to improved decision quality or fairness. Scholars caution that algorithmic screening systems may exclude qualified candidates whose profiles deviate from historically dominant career patterns or predefined keyword parameters (Tambe *et al.*, 2019). Evidence indicates that rigid filtering mechanisms can disadvantage individuals with non-linear career trajectories or unconventional educational pathways, potentially narrowing the diversity of applicant pools (El Ouakili, 2025). These risks are compounded by AI's limited capacity to interpret contextual nuance, non-standard CV formats and culturally embedded indicators of competence (Rathore, 2023), highlighting tensions between standardisation and inclusivity.

Ethical concerns surrounding algorithmic bias and governance have therefore become central to debates on AI-driven recruitment. AI systems are shaped by the data on which they are trained, and where historical datasets reflect structural inequalities, algorithms may reproduce and amplify those biases (Raghavan *et al.*, 2020; Boateng, 2021). Such concerns extend beyond technical bias to broader issues of transparency, accountability and legitimacy in automated decision-making. In recruitment contexts, opaque algorithmic processes may undermine trust among candidates and practitioners while exposing organisations to reputational and regulatory risks.

These challenges are particularly pronounced in non-Western and multicultural labour markets. Many AI recruitment tools are developed within Western institutional contexts and may embed assumptions about qualifications, career progression, or behavioural indicators that do not translate seamlessly across regions (Al-Shaiba *et al.*, 2020; Adekoya *et al.*, 2024). In Gulf Cooperation Council (GCC) countries, recruitment is further shaped by nationalisation policies, sponsorship systems and socio-cultural norms related to nationality and gender (Budhwar and Mellahi, 2016; Waxin and Bateman, 2016). Comparative studies in GCC and emerging economy contexts suggest that while AI adoption can enhance operational efficiency, persistent concerns remain regarding algorithmic transparency, fairness and alignment with local labour regulations (Trigui *et al.*, 2024; Albous *et al.*, 2025).

In response, the literature increasingly advocates "responsible AI" approaches that integrate ethical oversight, bias auditing, explainability and human accountability into recruitment systems (Wilson and Daugherty, 2018; Papagiannidis *et al.*, 2025). This has shifted the scholarly consensus away from narratives of technological replacement toward models of human-AI augmentation. Under such approaches, AI functions as a decision-

support tool that enhances human judgement while leaving context-dependent, ethical and relational evaluations to human recruiters (Karaboga and Vardarlier, 2020). Hybrid “human-in-the-loop” configurations enable organisations to harness AI’s computational strengths while mitigating risks associated with bias, opacity and decontextualised decision-making (Mori *et al.*, 2025).

Despite its potential, the organisational integration of AI in recruitment remains challenging. Resistance to change, concerns about job displacement and limited digital capabilities among HR professionals can constrain adoption (Horodyski, 2023). Moreover, increasing regulatory scrutiny and societal expectations for algorithmic transparency require organisations to invest in governance capabilities alongside technological infrastructure. These dynamics underscore that AI-driven recruitment constitutes not merely a technical innovation, but a broader socio-organisational transformation requiring alignment between technology, human agency and institutional context.

The Co-alignment of social and technical architectures

To explore how AI-powered recruitment systems are understood and enacted within Qatar’s socio-cultural and institutional environment, this study draws on socio-technical systems (STS) theory (Trist and Bamforth, 1951; Mumford, 2006) alongside context-sensitive technology adoption models (Bagozzi, 2007; Venkatesh *et al.*, 2003, 2016). Together, these frameworks provide a lens for interpreting how AI technologies are embedded within organisational practices, social relationships and contextual norms.

Originating from Trist and Bamforth (1951), STS theory conceptualises organisations as comprising interdependent social and technical subsystems whose alignment shapes organisational functioning (Mumford, 2006). From this perspective, technological change is not treated as a discrete intervention but as a socially mediated process that reconfigures roles, workflows and decision authority. In AI-enabled recruitment, algorithms do not merely automate screening tasks; they also reshape how competence is defined, how evaluation criteria are constructed and how accountability is negotiated (Leicht-Deobald *et al.*, 2019). Within HRM research, STS has been used to interpret how digital tools interact with organisational routines and professional identities (Makarius *et al.*, 2020). This perspective is therefore valuable for understanding how recruiters make sense of AI systems and how organisational actors adapt to emerging technological affordances (Fenwick *et al.*, 2024).

Complementing STS, the Unified Theory of Acceptance and Use of Technology highlights how technology adoption is shaped by user perceptions, organisational readiness and institutional expectations (Venkatesh *et al.*, 2003, 2016). Unlike earlier models such as TAM (Davis, 1989), UTAUT2 incorporates demographic and cultural moderators, making it particularly relevant in cross-cultural settings. In the Middle East, institutional logics, religious norms and labour policies such as Qatarisation influence how recruitment technologies are interpreted and legitimised (Budhwar and Mellahi, 2016; Waxin and Bateman, 2016). By integrating STS and context-sensitive adoption models, this study conceptualises AI recruitment as a socially constructed and institutionally embedded process rather than a purely technical innovation.

Methodology

Research design

This study adopted an interpretivist research philosophy, recognising that organisational experiences with AI recruitment technologies are shaped by the perceptions, meanings and interactions of various stakeholders (Saunders *et al.*, 2019). Given the socio-technical complexity of AI and the relative novelty of its application in Middle Eastern recruitment practices, this philosophical lens enabled contextual sensitivity and the exploration of subjective experiences often overlooked in positivist approaches (Baroudi *et al.*, 1986). The

research followed an abductive reasoning approach, which involves an iterative movement between theory and empirical data (Saunders *et al.*, 2019).

We adopted a case study design, focussing on two prominent Qatari organisations. These organisations were purposively selected based on three criteria: (1) recent implementation of AI-driven recruitment tools (within 12–18 months), (2) representation of different AI adoption approaches within Qatar’s diversified business sector and (3) organisational willingness to provide access across hierarchical levels. Both firms are large, diversified business groups employing over 500 staff. Firm A integrated an ATS with AI screening capabilities, while Firm B used AI tools, including ChatGPT, for CV screening. Their shared national context but differing implementation pathways offer valuable comparative insights into organisational adaptation (Yin, 2018), representing broader trends in Qatar’s business landscape where organisations adopt AI incrementally alongside existing systems. Figure 1 shows a snapshot of the methodological process.

Sampling and data collection

Purposive sampling was used to identify individuals directly involved with or significantly exposed to AI recruitment technologies (Patton, 2015). Twenty-two participants were recruited across both organisations, reflecting representation at multiple organisational levels: top-level executives ($n = 4$), mid-level managers ($n = 11$) and lower-level staff ($n = 7$). This distribution ensured hierarchical diversity in perspectives on AI-enabled recruitment (See Table 1).

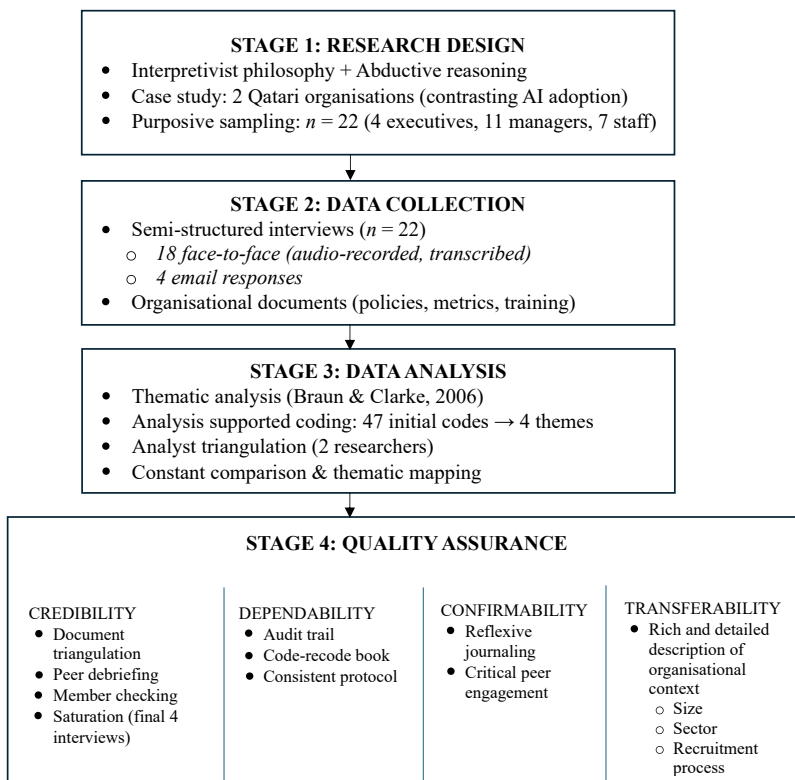


Figure 1. Methodological flow diagram. Source: Researchers

Table 1. Demographic details of interview participants

Participant	Role	Organisation
1	Senior Officer–Talent Acquisition	Firm A
2	Senior HR Generalist	Firm A
3	Group Financial Controller, IRO	Firm A
4	Marketing Manager	Firm A
5	Director of Media and Public Relations	Firm A
6	Senior Talent Acquisition Specialist	Firm B
7	Accounting Manager	Firm B
8	Member of Sales Team	Firm B
9	Chief Executive Officer	Firm B
10	Chief Human Capital Officer	Firm B
11	Talent Management Section Head	Firm B
12	Senior Manager HR Group	Firm A
13	IT Systems Manager	Firm A
14	Recruitment Coordinator	Firm A
15	Chief Technology Officer	Firm B
16	HR Business Partner	Firm B
17	Junior Talent Acquisition Specialist	Firm B
18	Operations Director	Firm A
19	Learning and Development Manager	Firm A
20	Data Analytics Specialist	Firm B
21	Digital Transformation Lead	Firm A
22	Employee Experience Manager	Firm B

The following ethics approval, semi-structured interviews were conducted between January and March 2025. Interview questions explored: (1) AI tools currently used and their functionality, (2) perceived efficiency changes (time-to-hire, cost and workload), (3) decision-making processes and human-AI interaction, (4) implementation challenges and training needs and (5) recruitment outcomes and quality-of-hire perceptions. Questions were tailored to respondent roles; for example, executives addressed strategic investment decisions, while HR staff focused on operational impacts. Eighteen interviews were conducted face-to-face (audio-recorded and transcribed verbatim), while four responded via email due to scheduling constraints.

Research quality was ensured through established trustworthiness criteria (Lincoln and Guba, 1985). Credibility was supported by triangulating interview data with organisational documents (AI implementation policies, recruitment metrics reports and training materials) to verify and contextualise participant accounts, and by peer debriefing sessions to test emerging interpretations. Transferability was enhanced by providing rich, thick descriptions of both organisations' contexts, including their size, sector, AI implementation approaches, organisational structures and recruitment processes, enabling readers to assess the applicability of findings to their own settings (Saunders *et al.*, 2019). Dependability was addressed through maintaining a transparent audit trail, with consistent application of coding frameworks and code-recode checks. Confirmability was supported through reflexive journaling and documentation of analytic reasoning. Thematic saturation was reached when no new codes or themes emerged across the final four interviews (Guest *et al.*, 2006).

Data analysis

The data were analysed using thematic analysis following Braun and Clarke's (2006) six-step framework (See Figure 2). This approach is suitable for identifying and interpreting patterns of meaning within qualitative datasets, while remaining flexible in terms of context and depth.

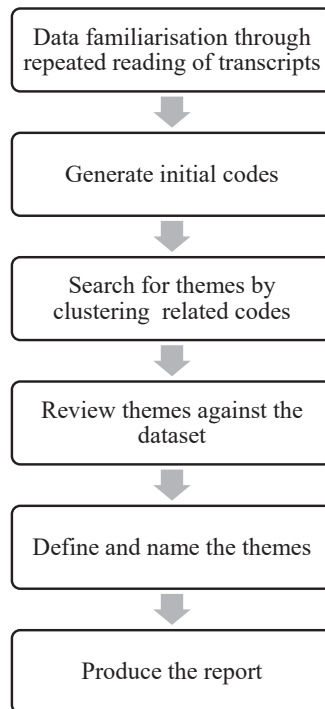


Figure 2. Thematic analysis procedure. Source: Adapted from [Braun and Clarke \(2006\)](#)

Thematic maps were used to visualise relationships and guide theme refinement. To enhance analytical rigour, analyst triangulation was applied, with two researchers independently coding and reconciling discrepancies ([Patton, 2015](#)). Member checking was conducted by sharing preliminary findings with participants for feedback, enhancing interpretive accuracy ([Lincoln and Guba, 1985](#)). Reflexive journaling (a process through which researchers documented assumptions, analytic decisions and evolving interpretations to enhance transparency and confirmability) was also used throughout the analysis to track analytic decisions and support transparency. [Table 2](#) presents the summary of the thematic analysis.

Results

From the analysis, four themes emerged: (1) process optimisation through AI integration, (2) subjectivity in AI-Powered recruitment, (3) recruitment strategies in the age of AI and (4) strategic investments in AI (See [Table 1](#)). These themes are discussed in this section.

Process optimisation through AI integration

The analysis revealed a significant focus on how AI-powered recruitment tools have transformed organisational processes. This theme captures efficiency enhancements following AI implementation and includes two distinct subthemes: organisational efficiency enhancement and process streamlining and standardisation.

Organisational efficiency enhancement. The implementation of AI-powered recruitment tools demonstrated significant impacts on organisational efficiency. At Firm A, the integration of an ATS transformed recruitment pipeline management by creating a unified database for CV

Table 2. Summary of thematic analysis

Theme	Subthemes	First-order codes	Illustrative quotes
Process Optimisation Through AI Integration	Organisational efficiency enhancement	Unified database creation, improved interdepartmental communication, rapid CV screening and administrative burden reduction	It's more like user-friendly from how we were sharing the CV with the managers, collecting data evaluations from the interviews, the feedback, comments and everything . . . it enhanced the communication and the accessibility . . . (Participant 18)
	Process streamlining and standardisation	Paperless transition, enforced procedural compliance, standardised templates, reduced administrative overhead, enhanced precision in candidate filtering	I can say that the managers must follow the procedure because everything they have to go through the ATS. Before, if they miss filling out the form . . . (Participant 21)
	Subjectivity in AI-Powered Recruitment	Bias mitigation through ai implementation	Objective screening criteria, reduced human partiality, filtering based on job requirements and ethical considerations in filtering
The human component		Necessity of human judgement, AI as an assistive tool, not a replacement, human intuition value, contextual understanding importance	Of course, you have to because, unfortunately, you might be looking for certain keywords or certain things that the applicant is not keeping in his CV. So, you still have to screen and have a screening telephonic interview even to be able to understand exactly what they have missed. (Participant 20)
Cultural fit assessment		Cultural fit as a critical hiring factor, beyond AI capabilities, linked to employee retention, interpersonal compatibility valuation	They go through a testing period, whether it's a replacement or a new hire. And this testing period has two parts. The first is the company's culture. Many companies, no matter how qualified the employee is and this is something that AI cannot measure, there has to be a work environment or atmosphere fit. (Participant 4)

(continued)

Table 2. Continued

Theme	Subthemes	First-order codes	Illustrative quotes
Recruitment Strategies in the Age of AI	Diverse sourcing channels in modern recruitment	LinkedIn prominence, social media utilisation, employee referrals importance and external expertise for specialised positions	About 30–40% of our sources are through social media. (Participant 4)
	Role type effect on recruitment	Position-specific approaches, varying recruitment timelines, headhunting for specialised roles and standard procedures for routine positions	Hiring time varies depending on the position, because some positions take a long time. (Participant 2)
Strategic Investments in AI-Powered Recruitment	Cost-benefit analysis of AI recruitment tools	Time efficiency correlation to financial impact, initial investment justification, long-term return expectation and productivity enhancement valuation	It's worth all the money and effort. (Participant 12)
	Strategic vision and implementation roadmap	Planned expansion of AI capabilities, comprehensive digital transformation, future implementation timelines and enhanced evaluation tools integration	Like the ATS, it's for us currently filtering or banking the CVs . . . Some other tools, like they evaluate the candidate, like we create a questionnaire or survey, or like video interviews . . . (Participant 19) Everyone might resist it. (Participant 21)
System Integration	Adaptation of employees to AI-powered recruitment tools	Initial resistance to change, proactive engagement strategies, training and education importance and external implementation support	
	Program customisation	Tool flexibility for specific workflows, manager-specific configurations, screening filters customisation and alignment with organisational processes	Customising the system, lots of customisation and lots of flows that we had to create . . . (Participant 2)

storage, retrieval and assessment. This centralised system particularly improved interdepartmental communication by replacing fragmented email-based processes.

It's more like user friendly from how we were sharing the CV with the managers, collecting data evaluations from the interviews, the feedback, comments and everything . . . it enhanced the communication and the accessibility. You can find anything easily in the records. (Participant 18, Operations Director)

The most dramatic efficiency improvements were described by the CEO of Firm B (Participant 9), who uses ChatGPT for CV screening:

I will submit the CV, and in a few seconds, it can scan 5 CVs, for example, of a CIO. In a few seconds, it will write them for me and will give me data, and then I can start asking questions . . . Who has more experience, for example in real estate, and it will say x . . . If I do this manually, it takes hours and maybe days.

These findings illustrate how AI-powered recruitment tools significantly streamline hiring processes, enhance communication and reduce administrative burdens. From ATS integration

to ChatGPT-assisted screening, the tools improve speed, accuracy and collaboration. Overall, AI adoption in recruitment not only boosts operational efficiency but also empowers decision-makers with timely, data-driven insights for more strategic talent acquisition.

Process streamlining and standardisation. The implementation of the ATS at Firm A facilitated a transition to largely paperless recruitment processes. Previously fragmented document management systems were consolidated. The AI-powered system improved procedural compliance and accountability through enforced process steps:

I can say that the managers must follow the procedure because everything they have to go through the ATS. Before, if they miss filling out the form, the interview report, this time, we cannot process on the net step unless they complete it. (Participant 21, Digital Transformation Lead)

This enforced compliance ensured complete documentation and reduced errors in the recruitment process. The standardisation of templates and communication pathways significantly reduced administrative overhead in applicant interactions, while enhanced precision in candidate filtering ensured that only qualified candidates progress through the recruitment pipeline.

Subjectivity in AI-powered recruitment

A recurring pattern in participant responses concerned the link between AI's objective assessment capabilities and the subjective dimensions of recruitment decisions. This theme emerged from participants' reflections on human judgement in an increasingly automated process. Three subthemes emerged: bias mitigation through AI implementation, human component and cultural fit assessment.

Bias mitigation through AI implementation. The integration of AI tools demonstrated potential for reducing human biases. Participants consistently acknowledged that AI systems can help mitigate partiality by implementing objective screening criteria:

Of course, yes, if you will, but exactly, because when you are posting the job on the career page, you have like, a screening out criteria. So, if you set it, if someone is required to have this X certificate, if you put this as a screen-out criterion, you will not even be able to see it. So of course, it's avoiding any partiality. (Participant 1, Senior Officer in Talent Acquisition)

However, an important distinction emerged regarding the use of AI systems to filter candidates based on specific criteria such as gender, language skills, or nationality. Participants emphasised that such filtering does not necessarily stem from bias but rather reflects legitimate job requirements:

There are options for that. So, when we are posting there are requirements. For example, we need a safety officer for the site for maintenance – of course, we will need only male because dealing with the thousands of labours all of them are males so specifically we have to mentioned male. (Participant 14, Recruitment Coordinator)

These findings reveal that while AI tools can reduce human bias through standardised and objective screening criteria, their use still reflects underlying human decisions regarding job requirements. Although filtering based on specific attributes may be necessary in certain roles, it raises ethical considerations. Thus, AI's bias mitigation potential depends on how inclusively and responsibly these systems are configured and applied.

The human component. Despite the advantages of AI in reducing bias and improving efficiency, participants unanimously emphasised the continued importance of human judgement in the recruitment process:

Of course, you have to because unfortunately you might be looking for certain keywords or certain things that the applicant is not keeping in his CV. So, still you have to screen and have screening telephonic interview even to be able to understand exactly what they have missed. (Participant 20, Data Analytics Specialist)

Participants positioned AI as an assistive tool rather than a replacement for human recruiters:

I didn't say AI would replace the human. It will assist you—the human aspects it will stay there, the humans are there, we need them, the AI will make my work more efficient and keep me focused more on more important things in my quality time. (Participant 9, CEO of Firm B)

These insights highlight that while AI enhances recruitment efficiency and supports bias reduction, it cannot fully replace human involvement. Participants view AI as a valuable assistant, not a substitute, recognising the irreplaceable role of human intuition, contextual understanding and interpersonal judgement in making nuanced hiring decisions and ensuring candidate suitability beyond algorithmic assessments.

Cultural fit assessment. The significance of cultural fit emerged strongly across participant accounts, highlighting it as a critical factor in hiring decisions that remains outside the current capabilities of AI systems:

They go through a testing period, whether it's a replacement or a new hire. And this testing period has two parts. The first is the company's culture. Many companies, like [Firm B], no matter how qualified the employee is—and this is something that AI cannot measure—there has to be a work environment or atmosphere fit. (Participant 4)

Poor cultural fit was commonly linked to higher rates of employee turnover:

They leave because, maybe, they are not culturally fit. So, this happens, and the AI doesn't have a role in that. They will not be able to identify if this is culturally fit or not. (Participant 22, Employee Experience Manager)

Organisations were found to weigh interpersonal compatibility alongside technical competencies:

The employee has to have a good relationship with the organisation and coworkers. Sometimes you'll accept someone with 60% qualifications and 40% attitude. (Participant 4)

These findings underscore the irreplaceable role of human judgement in assessing cultural fit, which remains beyond the reach of current AI capabilities. While AI supports technical screening, successful hiring decisions also depend on interpersonal compatibility, alignment with organisational values and workplace integration, factors critical for retention and long-term performance that are best evaluated through human insight.

Recruitment strategies in the age of AI

Despite embracing AI tools, participants consistently described maintaining diverse recruitment approaches tailored to specific circumstances. This theme emerged from participants' detailed accounts of their practical sourcing methods and strategic hiring decisions. The results are organised into two subthemes: diverse sourcing channels in modern recruitment and role-specific recruitment approaches.

Diverse sourcing channels in modern recruitment. Organisations in Qatar continue to utilise multiple sourcing channels despite implementing AI-powered recruitment systems. LinkedIn emerged as a predominant sourcing channel at Firm A, consistent with broader industry trends. Social media plays a significant role, with Participant 4 noting that “about 30–40% of our sources are through social media.” Employee referrals remained a cornerstone of Firm A's hiring strategy, accounting for approximately “40%” of their hiring according to Participant 19, the Learning and Development Manager. For specialised positions, Firm B occasionally turned to external expertise, with Participant 17 noting that sometimes they source candidates from a “relative, friend” or use “a recruitment agency.”

These findings show that even with AI-powered recruitment systems, organisations in Qatar maintain a diverse mix of sourcing channels. Platforms such as LinkedIn, social media, employee referrals and external recruitment agencies continue to play vital roles. This hybrid

approach allows firms to reach wider talent pools, leverage trusted networks and tailor sourcing strategies to specific hiring needs.

Role type effect on recruitment. Job role characteristics significantly influence recruitment strategies. Organisations seek candidates with specific qualifications to meet job requirements, but this process varies by position difficulty:

... Depends on the position—if they're looking for retail, you have to head hunt, not only post. [For corporate positions], we have different levels of recruitment, so we know already what we are looking for. (Participant 17)

The time required for recruitment similarly depends on role characteristics, with Participant 22 observing that “there are positions that are faster than before,” while Participant 2 indicated that hiring time varies “depending on the position because some positions take a long time.”

These findings highlight that recruitment strategies and timelines are heavily influenced by the nature of the job role. Specialised or hard-to-fill positions often require proactive sourcing methods like headhunting, while routine roles may follow standardised procedures. Consequently, recruitment duration and effort vary, underscoring the need for adaptive strategies aligned with specific role requirements.

Strategic investments in AI-powered recruitment

Financial considerations and future planning have emerged as significant concerns for organisations implementing AI recruitment technologies. This theme captures participants' strategic thinking about technological investment and long-term implementation planning. Analysis revealed two distinct subthemes: cost-benefit analysis of AI recruitment tools and strategic vision and implementation roadmap.

Cost-benefit analysis of AI recruitment tools. Organisations implementing AI-powered recruitment tools evaluate both immediate costs and long-term returns on their investments. At Firm A, the adoption of the ATS was viewed as a strategic investment aimed at addressing specific operational challenges. Participant 12 was unequivocal in their assessment: “It's worth all the money and effort.”

The CEO of Firm B (Participant 9) provided a detailed perspective on the relationship between time efficiency and financial impact:

Yes, I mean time is money. So, for example, time is money, how? Can we use you as an example? Let us say you are the HR, you are my HR. So, each one takes, for the sake of the discussion, how much, 20,000 each, 10,000, let's say 10,000, that's 30,000. Okay, and let's say you are costing me per day 300, plus or minus by your cost. So, you are costing per day 1,000 riyals. So, if I give you those CVs, you will take 3 days, five days, it will cost me 5,000. AI will give it to you in minutes, so you save the 5,000, and that's your daily work.

These insights underscore the perceived value of AI recruitment tools in terms of both efficiency and financial return. While initial investment costs exist, participants emphasised substantial time savings that translate directly into cost reductions. AI tools are thus seen not just as technological upgrades but as strategic assets that enhance productivity and deliver measurable economic benefits over time.

Strategic vision and implementation roadmap. Beyond current implementations, the interviews revealed clear strategic visions for expanding AI's role in recruitment processes. Firm A's current AI implementation focuses primarily on CV filtering and database management, but the organisation has identified specific expansion areas:

Like the ATS, it's for us currently filtering or banking the CVs. Alright, so you won't guarantee the data in the CV are actually, the candidate has the same information or has the experience that he mentioned in the CV. Some other tools like they evaluate the candidate, like, we create a questionnaire or survey or, like video interviews ... We are going to try to implement it next year. (Participant 19, Learning and Development Manager)

At Firm B, the strategic vision encompasses a more comprehensive digital transformation of the recruitment process:

We have a strategy that is yet to be implemented, inshallah [by God's grace] in 2025 . . . starting from the onboarding . . . from posting, the filtering of CVs, and the receiving of CVs, into hiring and recruitment, even till all the tests required for hiring. (Participant 10, Chief Human Capital Officer)

These findings reveal a forward-looking commitment to expanding AI integration in recruitment. Both firms recognise current limitations and are planning strategic enhancements, such as candidate evaluation tools, video interviews and full-cycle digital recruitment systems. This proactive vision reflects a broader goal of transforming recruitment into a seamless, data-driven and fully automated process aligned with organisational growth and innovation goals.

Discussion, conclusion and implications

This research sought to explore how AI integration affects recruitment process efficiency in Qatari organisations and to explore the connection between AI systems and human judgement in recruitment decision-making. The findings reveal a complex interplay between technological capability, human judgement and cultural context in shaping AI-assisted recruitment practices within Qatari organisations. While AI integration has undoubtedly enhanced efficiency, standardisation and transparency in recruitment, the evidence underscores that its value lies in augmentation rather than the replacement of human decision-making. Efficiency gains were not limited to faster candidate screening or reduced administrative workload; they also reflected a more strategic reallocation of human effort toward higher-value tasks requiring empathy, contextual interpretation and interpersonal evaluation. This shift supports [Wilson and Daugherty's \(2018\)](#) argument that AI enhances human capability rather than rendering it obsolete.

Participants' experiences demonstrate that AI streamlines repetitive tasks, such as CV screening, data management and interdepartmental coordination, corroborating earlier studies that highlight reductions in recruitment costs and time-to-hire ([El Ouakili, 2025](#)). However, efficiency in this context transcends metrics. It involves qualitative improvements in decision-making and organisational communication, aligning with STS theory ([Mumford, 2006](#)), which posits that technological progress is meaningful only when integrated with the human and organisational subsystems that support it. The transition to paperless, standardised recruitment workflows and the enforcement of procedural compliance, as seen in Firm A, epitomise how technology can restructure social processes by creating accountability and data coherence. These results reaffirm [Thomas's \(2024\)](#) argument that digital transformation's real impact lies in organisational redesign and behavioural adaptation rather than in the technology itself.

Despite these positive outcomes, the findings reveal persistent limitations in AI's analytical capabilities, particularly in qualitative and contextual assessments. The inability of AI systems to evaluate cultural fit, identified by participants as the most critical determinant of long-term retention, reflects a limitation well-documented in literature ([Mori et al., 2025](#)). Participants' emphasis on cultural compatibility as a factor "AI cannot measure" reinforces that effective hiring extends beyond data patterns to relational and affective dimensions. In Qatar's collectivist and relationship-oriented business culture ([Budhwar and Mellahi, 2016](#)), such qualitative dimensions are indispensable. Consequently, human evaluators remain essential in ensuring alignment between organisational values, interpersonal dynamics and candidate potential.

The findings further illustrate how AI-driven objectivity coexists with continuing human subjectivity. Participants viewed AI as a useful tool for mitigating human bias by standardising screening criteria. However, the same systems were configured to filter candidates based on gender, language, or nationality when these were deemed job-relevant. While participants rationalised such filters as practical necessities, they raised ethical concerns surrounding

algorithmic fairness and inclusivity (Raghavan *et al.*, 2020; Horodyski, 2023). This duality highlights what Leicht-Deobald *et al.* (2019) term the “standardisation paradox,” where efforts to enhance fairness through automation may inadvertently embed bias if human-defined parameters remain unexamined. The issue is especially salient in multicultural labour markets like Qatar’s, where cultural norms and localisation policies intersect with global standards of non-discrimination. Thus, AI’s promise of impartiality is contingent on transparent configuration and responsible governance, a finding consistent with Papagiannidis *et al.* (2025) and Fenwick *et al.* (2024), who advocate for human-in-the-loop systems that combine algorithmic rigour with contextual oversight.

Resistance to change emerged as another key dimension of AI implementation. Employees initially expressed apprehension that automation might devalue human expertise or threaten job security. Overcoming such resistance requires deliberate change management, continuous training and stakeholder engagement. These findings echo Weber *et al.* (2023), who emphasised that organisational readiness, user competence and trust are pivotal to realising AI’s potential. In both firms, gradual integration and customisation were critical to acceptance. Configuring AI systems to align with local workflows and managerial preferences enhanced usability and relevance, supporting Li *et al.* (2023)’s view that adaptable system design is essential for successful adoption. This also aligns with Venkatesh *et al.*’s (2016) context-sensitive technology adoption framework, demonstrating that perceived usefulness is mediated by organisational culture, user familiarity and leadership support.

The hybrid recruitment model observed in this study, where AI handles preliminary screening and humans conduct final evaluations, represents a pragmatic response to the automation–augmentation paradox (Raisch and Krakowski, 2021). Participants recognised that AI’s strengths in speed and consistency complement human recruiters’ nuanced judgement, creating a symbiotic relationship between machine precision and human discernment. Rather than displacing HR professionals, AI redefines their roles, shifting focus toward strategic and relational dimensions of talent acquisition. This echoes Karaboga and Vardarli’s (2020) argument that the future of recruitment depends on the effective orchestration of both human and technological contributions.

This study makes three significant theoretical contributions. First, it advances STS theory by demonstrating that AI adoption in HRM constitutes a fundamental reconfiguration of organisational relational architecture, not merely technical integration. Where Mumford (2006) posited alignment between technical and social systems, this study reveals how AI necessitates renegotiation of trust boundaries, decision authority and accountability. In relationship-oriented cultures, technological efficiency is subordinate to relational legitimacy, thus challenging techno-centric adoption models.

Second, the study introduces “contextual algorithmic governance” to technology acceptance literature. Unlike UTAUT’s focus on individual adoption determinants, our findings reveal that AI legitimacy depends on alignment with institutional logics, particularly how algorithmic decision-making accommodates nationalisation policies (Qatarisation), cultural norms around trust and local regulatory frameworks. This extends technology adoption theory by demonstrating that acceptance is mediated by socio-institutional compatibility, not only perceived usefulness.

Third, the research refines automation-augmentation discourse by demonstrating that augmentation is a cultural necessity in collectivist contexts, not a design choice. Where Western literature frames augmentation versus automation as strategic options (Raisch and Krakowski, 2021), this study reveals that in relationship-oriented cultures, AI without human oversight lacks legitimacy regardless of technical capabilities. This culturally-contingent constraint represents a novel boundary condition for automation theories.

Organisations should treat AI as an augmentative technology, preserving human judgement for final decisions (Raisch and Krakowski, 2021). Customisation should align systems with local workflows and values. Investment in training and communication mitigates resistance, while ethical governance ensures fairness (Papagiannidis *et al.*, 2025). AI’s commercial value

lies not solely in cost savings but in enabling HR professionals to focus on strategic activities, including relationship building, employer branding, talent development and driving competitive advantage.

In Qatar, where Qatarisation mandates prioritise national employment, AI recruitment must support nationalisation objectives. Policymakers should establish frameworks requiring compliance through audits. Building public trust requires transparency, mandating disclosure of AI use and rejection explanations. Educational initiatives are essential at the university level and through public campaigns. For wider GCC contexts, responsible AI adoption requires governance aligning innovation with societal values and policy objectives. This study focused on two large Qatari firms, potentially limiting generalisability. Longitudinal studies would trace AI system evolution. Future research should compare experiences across cultural settings and investigate candidate perspectives. As AI systems grow autonomous, inquiry into ethical boundaries, data privacy and accountability is needed.

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Corresponding author

Olatunji David Adekoya can be contacted at: o.adekoya@shu.ac.uk